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Essays on development and international economics

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Summary

My doctoral thesis comprises three chapters focussing on the impact of technology and trade on long-run economic development and political outcomes. The first chapter explores the effect of the early adoption of electricity at the end of the 19th in Switzerland on local economic development in the long-run. The second chapter explores the role of colonial trade on economic and political developments in British India during the 20th century. The third chapter analyses the effect of recent technological change, mainly automation, on the making of immigration policy in the United States since the 1970s.

The first chapter explores the effect of the early adoption of technology on local economic development. While timing and intensity of technology adoption are key drivers of economic divergence across countries, the initial impact of new technologies within advanced countries has been incredibly illusive. Resolving this puzzle, this chapter documents that the early adoption of electricity across Switzerland was conducive to local economic development not just in the short-run, but also in the long-run. Exploiting exogenous variation in the potential to produce electricity from waterpower, this chapter documents that electricity adoption at the end of the 19th century led to structural transformation. However, despite access to electricity becoming quickly universal in the early 20th century, due to the expansion of the electricity grid, economic development did not converge across areas. Instead, areas which adopted electricity early continue to be more industrialized and have higher incomes today. In particular, the geographical distribution of the newly emerging chemical industry was shaped by early electricity adoption, while employment gains through the building and operation of new power plants were mostly short-lived. The main mechanism through which differences in economic development persist in the long-run is through increased human capital accumulation and innovation, rather than persistent differences in the way electricity is used.

The second chapter explores the role of colonial trade in which colonies commonly specialized in the export of primary products in exchange for manufactured goods. Did this pattern of trade prevent industrialisation in colonies? And did the absence of industrialisation help to keep colonies under control? To answer these questions, the chapter examines the impact of the temporary trade collapse between Britain and India due to World War I, on industrialisation and anti-imperial feelings in India. Exploiting cross-

district variation in exposure to the trade shock, the chapter documents that districts more exposed to the trade shock experienced substantially faster industrial growth in 1911-21, placing them on a higher level of industrialisation which persisted up to today. Using the WWI trade shock as an instrument for industrialisation levels, it also highlights that more industrialised districts were more likely to express anti-imperial feelings in 1922, and to vote for the Indian National Congress in the landmark election of 1937.

The third chapter explores whether recent technological change, in the form of automation, affected immigration policy in the United States? The chapter highlights that as automation shifted employment from routine to manual occupations at the bottom end of the skill distribution, it increased competition between natives and immigrants, consequently leading to increased support for restricting low-skill immigration. This hypothesis is formalized theoretically in a partial equilibrium model with constant elasticity of substitution in which technology leads to employment polarization, and policy makers can vote on immigration legislation. These predictions are empirically evaluated by analysing voting on low-skill immigration bills in the House of Representatives during the period 1973-2014. First, there is evidence that policy makers who represent congressional districts with a higher share of manual employment are more likely to support restricting low-skill immigration. Second, the chapter presents empirical evidence that representatives of districts which experienced more manual-biased technological change are more likely to support restricting low-skill immigration. Finally, the chapter highlights that this did not affect trade policy, which is in line with automation having increased employment in occupations exposed to low-skill immigration, but not those exposed to international trade.

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Chapter 1

The long-run gains from the early adoption of electricity

Abstract

This chapter explores the effect of the early adoption of technology on local economic development. While timing and intensity of technology adoption are key drivers of economic divergence across countries, the initial impact of new technologies within advanced countries has been incredibly illusive. Resolving this puzzle, this chapter documents that the early adoption of electricity across Switzerland was conducive to local economic development not just in the short-run, but also in the long-run. Exploiting exogenous variation in the potential to produce electricity from waterpower, this chapter finds that electricity adoption at the end of the 19th century led to structural transformation. However, despite access to electricity becoming quickly universal in the early 20th century, due to the expansion of the electricity grid, economic development did not converge across areas. Instead, areas which adopted electricity early continue to be more industrialized and have higher incomes today. In particular, the geographical distribution of the newly emerging chemical industry was shaped by early electricity adoption, while employment gains through the building and operation of new power plants were mostly short-lived. The main mechanism through which differences in economic development persist in the long-run is through increased human capital accumulation and innovation, rather than persistent differences in the way electricity is used.

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1.1 Introduction

The adoption of new technologies is seen as being at the core of economic development. The timing and intensity of adoption is associated with a drastic divergence in incomes across countries (see e.g. Bernard & Jones 1996; Comin & Hobijn 2010; Comin & Mestieri 2018). Despite this apparent importance of the early adoption of new technologies, its effect within advanced countries remains elusive.[1] Many major technological breakthroughs, like electricity and information technology, that became universally adopted and had an important economic impact later on, initially diffused slowly and did not appear to have had an immediate positive economic effect (see e.g. Mansfield 1961; David 1990; Jovanovic & Rousseau 2005; Hall & Rosenberg 2010).[2]

This raises the question whether the pattern in which new technologies diffuse across advanced economies is at all important for local development in the long-run, or whether it might even be detrimental when considering some prominent historical examples of technological leadership within countries (e.g. the North of England, the Rust Belt in the USA, and the Ruhr area in Germany).

This chapter studies the role played by the early adoption of new technologies on the spatial evolution of economic development within an advanced country. In particular, I study (i) the extent to which the initial adoption of a new technology led to contemporaneous economic development,[3] (ii) whether differences continued to persist even as the technology became widely adopted and (iii) the mechanisms that can explain this persistent divergence in economic activity.

I examine these three questions empirically in the context of the early commercial use of electricity across late 19th century Switzerland. Electricity is a particularly well suited technology to answer these three questions. Usually, the adoption of new technologies is confounded by being embodied in equipment with the need for physical capital accumulation on-site, this equipment might subsequently become obsolete, but prevent the

[1]Recent empirical studies have started to look at the long-run impact of technology adoption within countries at the peak of their importance. While Lewis & Severnini (2019) find some positive lasting effect of rural electrification in the US during the 1930s on agriculture and sub-urban expansion, Franck & Galor (2019) finds that areas that most intensively had adopted steam engines during the 1860s in France are poorer today.

[2]Most is known about the way new technologies are adopted in agriculture expanding on seminal work by Foster & Rosenzweig (1995), but a set of papers recently started to also evaluate technology adoption in manufacturing (see Bloom et al. 2013; Atkin et al. 2017; Giorcelli 2019; Juhász et al. 2019).

[3]The effect of the adoption of new technologies in historic settings at relatively early stages has of course been documented before. For example, De Pleijt et al. (2020) looks at the effect the adoption of the steam engine across England by 1800, only about 30 years after James Watt's considerable improvements to its design. However, what my chapter is able to contribute here is that it looks at a particularly brief and well defined window of less than 20 years since the first commercial usage of the new technology. This represents a particularly brief time-window when considering the slow speed of adoption of new technologies in the 19th century. Specifically, I will focus on electricity adoption by 1900, which had only started to disseminate with its earliest relevant economic application dated between 1882 and 1894 (see Jovanovic & Rousseau 2005; Comin & Hobijn 2010).

adoption of newer technologies (see Boucekkine et al. 2008 for a summary).[4] Electricity is different as its usage does not necessarily require large investments on-site, as energy can be drawn as needed from a network even by small firms using varied types of machinery (Mokyr 2010). This also meant that after a slow initial adoption due to limitations in the available transmission technology, its use became quickly widespread in advanced countries as transmission technologies improved and the electricity grid expanded.

Late 19th century Switzerland provides an advantageous historic setting to evaluate the early adoption of electricity. I use the following terminology here: Adoption of electricity refers to both the generation and use of electricity, where within geographical areas the later was dependent on the former during the early phase of adoption.[5] First, the country was at the forefront of electricity adoption at the time. Second, the initial ability to adopt electricity depended on idiosyncratic geographical features, as before the creation of an extensive electricity grid in the early 20th century, the use of electricity relied on local waterpower for electricity generation.[6] Third, the differential exposure to electricity was only short-lived as after 1900 long-distance transmission was implemented, which made locally generated electricity available in other parts of Switzerland. This provides a unique empirical setting in which early adoption of a new technology was effectively randomly assigned to areas for the relatively brief period of about 20 years.

I find that the initial round of electricity adoption had a considerable effect on structural transformation. Locations that adopted electricity early experienced a contemporaneous fall in agricultural employment and an increase in manufacturing employment. I also find that despite the rapid expansion of the electricity grid in the early 20th century, areas that had adopted electricity earlier continued to be more industrialized over 100 years later. The earlier adoption of electricity did not just increase the level of industrialization. Manufacturing employment continued to diverge between areas which adopted electricity early and those which did not throughout the first half of the 20th century. This lasting positive effect on economic development is also reflected in higher median incomes today. This suggests that considerable first-mover advantages exists when it comes to the adoption of new technologies. Finally, I find evidence that earlier exposure to electricity led to an immediate increase in human capital accumulation and innovation

[4]For example, steam-power required the costly installation of boilers, engines, shafting, and belts throughout a factory and complementary skilled workers operating the equipment to provide energy (Du Boff 1967). This specialization potentially leads to technological hysteresis and a slow-down in the development of new technologies and industries (see e.g. Brezis & Krugman 1997; Franck & Galor 2019).

[5]I refer to generation or use of electricity individually to explicitly discuss to this aspect of electricity adoption. In addition, access to electricity refers to the possibility to use electrical power through having been connected to the emerging electrical grid.

[6]Note that, electricity from thermal power was not an economically feasible option on a large scale in Switzerland at the time due to (i) low thermodynamic efficiency in electricity generation and (ii) the high cost of imported coal (Bossard 1916). So that the vast majority of electricity generated was from waterpower until the building of nuclearpower plants in the 1960s (Weingartner 2016).

activity.[7] This in turn appears to have been the main driver of subsequent economic growth. Importantly, this is in contrast to the usage of electricity itself, where there is no evidence of persistent differences across areas after access became universal through the extension of the electricity grid.

To carry out my analysis, I have assembled detailed information on electricity generation, geographical suitability for electricity generation and measures of economic development from 1860 to the present day for 178 districts covering the whole of Switzerland. The crucial information on actual and potential electricity generation has been obtained from digitizing and geo-referencing a detailed survey of all existing and potential waterpower plants conducted in the early 20th century (see Bossard 1916). The information on economic development is collected from a wide range of sources with the pivotal information on sectoral employment coming from the Swiss censuses 1860-2011 (see Bundesamt für Statistik 1860-2011).[8]

The key challenge in studying the effect of technological change, and particularly its early adoption, is that the decision to adopt is not random. Rather the most advanced areas and the ones that have most to gain are likely to adopt a new technology first. This means any observed effect might potentially reflect underlying local advantages, e.g. human capital, institutions or culture. These factors seem well suited as an explanation for why differences in prosperity across areas persist even as technologies become obsolete or universally adopted. This issue appears of particular concern when looking at technology adoption across countries, where differences in the timing and intensity of technology adoption are documented to have the largest and most permanent impact. Accordingly, well identified micro-level evidence on early adoption of new technologies is crucial to understand what drives long-run differences in economic development.

Ideally, assessing the causal impact of early technology adoption requires an environment where: (a) adoption was initially as good as random, and (b) those initial differences only mattered for a short period. Switzerland's adoption of electricity in the late 19th century provides a unique setting, in which both these requirements are met. First, the country was poor in natural resources, which meant that the only economically viable way to generate electricity was to use waterpower. Importantly, this suitability of areas to generate electricity was based almost entirely on small local geographical variations (e.g. the gradient of a river). Figure 1.1 illustrates the relationship between electricity generation in 1900 across Swiss districts and the more than 1000 potential locations identified by

[7] This documented increase in human capital reflects an improvement in education of the local population with there being no evidence of increased in-migration.

[8] The data used is based on district level tables compiled in the original publications by the Swiss census bureau. No individual census records are available. The censuses are conducted about 8-12 years apart and not in all years the information is compiled in the required way. I newly digitized district-level information on sectoral employment for roughly every 20 years during the period 1860-2011.

Bossard (1916) as suitable for waterpower plants.[9] As it can be clearly seen, the number of available locations and their potential is crucial for the observed electricity generation by 1900. Second, these geographical features only mattered for the use of electricity for the initial 20 year period from 1880 till 1900,[10] as in this period, electricity had to be consumed near to the power source as transmission over long distances was uneconomical. From 1900 onwards this constraint was relaxed as long distance transmission lines were established from where electricity was most efficiently produced to wherever there was demand.[11] This provides a unique empirical setting in which the exposure to electricity was effectively randomly assigned to areas for about 20 years. Before and after this period areas had instead access to the same technology.

I use variation in the suitability to produce electricity from waterpower across areas, that occurs due to otherwise unimportant geographical differences, to instrument the actual adoption of electricity. In particular, the gradient of a river segment combined with complementary features like river bends or bifurcations appear crucial in determining the amount of electricity that could be generated at a site (see Bossard 1916, Volume 4, p.15-16). This meant that most potential locations are along small, rocky streams with little economic or geographic significance prior to 1880 rather than major rivers like the Rhine, Rhone and Aare. I call this the potential to generate electricity. The suitability of my instrument relies on two assumptions: First, the potential to generate electricity had to be as good as randomly assigned across areas. This appears to be the case as areas with and without potential electricity generation did not differ in industrialization or population density before the adoption of electricity.[12] Second, the exclusion restriction needs to hold, which means that the potential to generate electricity only affected economic development through electricity adoption. This also appears to be the case as the potential to generate electricity did not lead to economic development before the commercial adoption of electricity. Further, there is no relationship between the potential for electricity generation and the mechanical energy generated by watermills in 1880.[13]

[9] The engineers surveying these potential locations across the whole of Switzerland aimed to provide the optimal network of waterpower plants for energy generation based on the available geographic characteristics explicitly disregarding any pre-existing developments and economic considerations (see Bossard 1916, Volume 5, p.9-16).

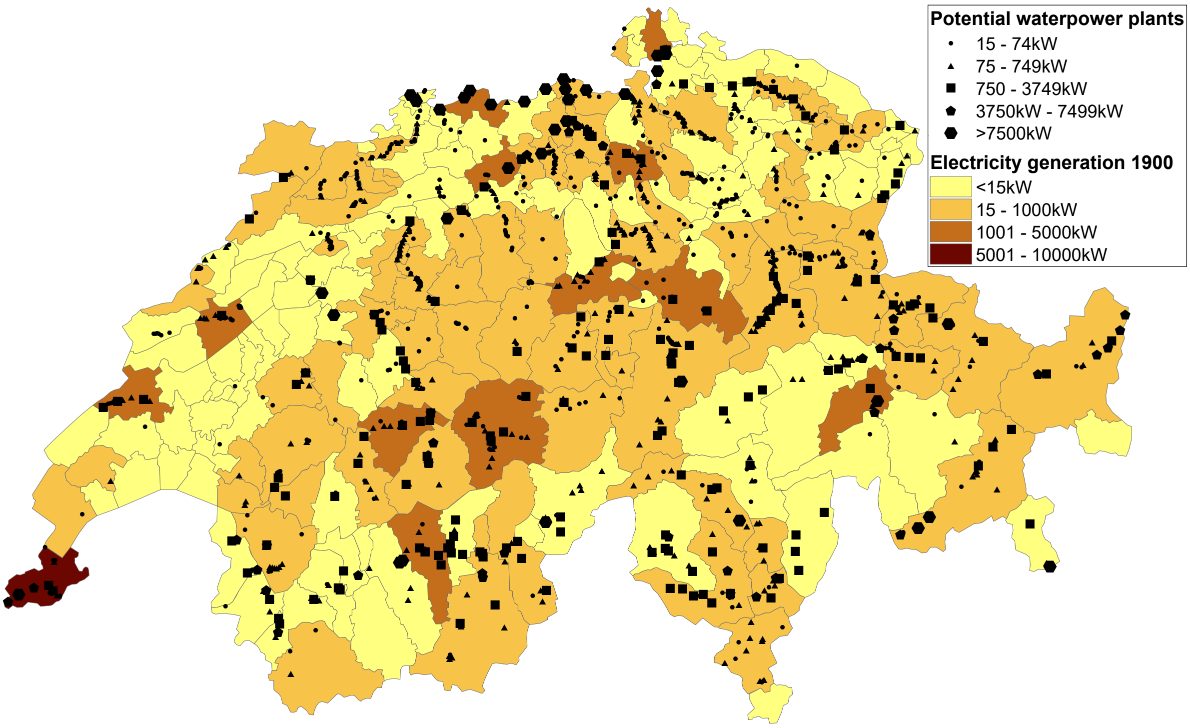
[10] Geographical features still continued to be relevant for electricity generation, however I'm able to directly observe any further extension of local electricity generation that occurred after the initial 20 years to distinguish this later extensions from the initial adoption of electricity.

[11] In 1901, the longest transmission line in Switzerland was only 35km, however the maximum transmission distance doubled every 3-4 years to 72km in 1904 and 135km by 1908 (see Department des Inneren 1891-1920).

[12] Appendix Figure A.1 provides additional descriptive maps.

[13] Watermills here refers to all energy generated from water that is exclusively transmitted via mechanical means, i.e. wheels, shafts, gears, and belts, and was not converted into electrical energy. It might appear surprising that mechanical power generation is not related to the potential to generate electricity, however this is for the simple reason that the materials used for mechanical transmission of energy were unable to transmit the considerable amounts of energy that waterpower could provide and also required

Figure 1.1: Electricity generation in 1900 and potential waterpower plants



Notes: The figure depicts electricity generation in kW from waterpower across Swiss districts in 1900. Black points represent all potential locations for waterpower plants of more than 15kW generation. The size and shape of the point corresponds to the location and kW generation of optimally located potential waterpower plants: (i) 15-74kW, (ii) 75-749kW, (iii) 750-3750kW, (iv) above 3750-7499kW and (v) above 7500kW (these groups correspond to historically used groups measured in HP with 1HP=0.75kW). Both measures are based on a survey of existing and potential waterpower plants conducted by a commission of Swiss engineers at the time, which was instructed to identify the maximum waterpower potential across the whole of Switzerland (Bossard 1916). More detail is provided in Section 1.3 and Data Appendix A.3.

An additional concern that emerges in the long-run is that the same geographic features are likely to remain relevant for the building of waterpower plants even after 1900. While the location of these plants are no longer important for the local use of electricity due to the extension of the supply network, they might still have a direct impact on economic development through construction and operation. I account for this by separately controlling for the building of plants after 1900. In this way, I disentangle the long-run effect of the adoption of electricity in between 1880-1900 from the effect of subsequent power-plant construction which might be correlated with the instrument.

My claim is that the observed divergence in economic development emerged solely due to a brief period in which electricity adoption differed across areas. However, the effect of early electricity adoption can be even further distinguished into the effect of its use and its generation. Electricity is well suited to distinguish these effects, as electricity genera-

that location of generation and use were in immediate proximity. See for example Du Boff (1967) on the crucial differences between mechanical and electrical power generation, transmission and use.

tion and distribution emerged as distinct industries.[14] Interestingly, I find that electricity usage rather than generation is the main route through which early electricity adoption affected economic development in the long-run. While in the short-run industries associated with the generation and use of electricity both experienced considerable employment growth, in the long-run the employment gains in industries associated with electricity generation declined.[15] In contrast, employment in industries exclusively using electricity further expanded in areas that had adopted electricity early. In particular, employment in chemical industries, where electricity was a crucial input in novel production processes, continued to expand even after 1900. Indeed, more than 70% of the modern-day spatial distribution of chemical industries can be explained by the early adoption of electricity.

Why did a 20-year period of early exposure to electricity have such important consequences on economic development? My preferred explanation is that earlier exposure triggered the accumulation of human capital and further innovation. In turn, this is what leads to the persistent differences in economic development. I find evidence that those areas which adopted electricity early immediately experienced improvements in educational outcomes. In particular, understanding of maths and general knowledge at the secondary level of schooling increased drastically, while literacy and other knowledge at the primary level of schooling improved little. One of the drivers for this increase in educational outcomes was the dual education system. I find evidence that both the number of institutions and students expanded more quickly in areas which adopted electricity earlier. For this, the cooperation of employers and local governments was crucial in the provision of knowledge through apprenticeships, industry- and technical-schools, which increasingly focused on providing theoretical rather than practical knowledge in the late 19th century as the need for an evermore skilled workforce increased (Wettstein 1987). The increased local importance of education is also underlined by increased support in national referendums for more central government investment in education. Crucially, these differences in the level of human capital that emerged at the end of the 19th century persist up to the present day: areas exposed earlier to electricity still have a higher share of secondary and tertiary educated individuals by 2010.

Consequently, it is not surprising that those areas remain more innovative with a higher rate of patenting. In contrast, the use of electricity per worker no longer differed by 1929 between areas which adopted electricity early and those that did not. This highlights

[14] This clear distinction in generation and use of electricity is for example different from steam power which was not only used in many factories, but required the installation of steam engines and skilled workers maintaining them within the same factory (see Nye 1992; Goldin & Katz 1998; De Pleijt et al. 2020).

[15] The employment growth associated with electricity generation in the short-run was mostly through industries associated with the construction of waterpower plants. These employment gains disappeared after 1900. In contrast, employment in electricity generation continued to persist and even expanded further after 1900. However, the economic magnitude of these employment gains are small throughout in comparison to the ones in industries that exclusively used electricity.

that differences in economic development from early exposure to electricity persisted even as access and utilisation became universal across Switzerland due to the extension of the electricity grid.

The initial geographic constraints on the early adoption of electricity in Switzerland meant that remote areas were heavily exposed to the new technology, rather than just urban centres, where new technologies are usually first adopted. How did high levels of human capital and innovation persist in this rather unusual setting? I find empirical evidence that the infrastructure network adjusted and in fact the Swiss rail network remains more dense, in terms of connections and passengers, in areas which had adopted electricity earlier.[16] This is further underlined by higher support for government infrastructure investment emerging after 1900 in these areas. This complementary change in the infrastructure network providing improved access to distant markets and knowledge helps explain how areas that had adopted electricity early were able to retain specialized industries and continue to innovate despite, in many cases, being rather remote and having a small population.

This chapter contributes to several strands of the literature. First, several papers have studied the spread of electrification in developed countries in the first half of the 20th century (Kitchens 2014; Kitchens & Fishback 2015; Gaggl et al. 2019; Lewis & Severnini 2019; Molinder et al. 2019; Leknes & Modalsli 2020).[17] The main innovation of this chapter is to study the initial adoption of electricity at the end of the 19th century and its long-lasting effect.[18] Looking at this early adoption is important as electricity has long been seen as one of the key technologies of the second industrial revolution (see e.g. Mokyr 1992), but, its impact on manufacturing between 1870-1914 has not been thoroughly analysed. The period 1880-1900 is also particularly relevant as it reflects a time of experimentation, where the economic gains of using electricity might not have been as clear as later on.[19] My chapter finds a considerable impact of electricity on industrialization as early as 1900. I am also able to separately investigate the role of

[16]That persistent differences in economic development from the early adoption of electricity are associated with human capital accumulation and changes to the infrastructure network appears a surprising parallel to recent findings by Dell & Olken (2020) on the positive long-run effect of the economic changes implemented by the Dutch Cultivation System on economic development across Indonesia today. Also with the crucial distinction that the change in the economic structures in Switzerland occurred naturally due to a change in technology rather than being imposed.

[17]A corresponding literature look at the effect of electrification in developing countries in the second half of the 20th century, for example Dinkelman (2011), Rud (2012), Lipscomb et al. (2013), Van de Walle et al. (2017), De Faria et al. (2017), Moneke (2019), Lee et al. (2020).

[18]To the best of my knowledge, the study with the earliest starting point so far is Leknes & Modalsli (2020). They study the adoption of electricity across rural Norway between 1891 and 1920. However, they explicitly treat the period 1891-1900 as the pre-electricity period for rural Norway (as in less than 2% of their sample a hydroelectric plant existed or was being build by 1900). The other papers focus on 1900-1920 (Molinder et al. 2019), 1910-1940 (Gaggl et al. 2019), 1929-1955 (Kitchens 2014), 1930-1960 (Lewis & Severnini 2019), 1935-1940 (Kitchens & Fishback 2015).

[19]Juhász et al. (2019) document that the initial adoption of a new technology can be rather tumultuous for mechanized cotton spinning in early 19th century France.

electricity generation and use. In particular, the early use of electricity explains where the chemical industry developed across Switzerland. This underlines the crucial role electricity played in facilitating new production processes in other emerging industries during the second industrial revolution.

Second, my chapter contributes to a literature emphasising the role of technical change on the formation of knowledge. It provides insights on the important question on whether technical change can foster human capital formation (see e.g. Galor & Moav 2006; Galor 2011; De Pleijt et al. 2020), and in turn on whether human capital is a main driver of economic growth (see e.g. Lucas 1988; Romer 1990). Notably, the switch from steam engines to electricity as a power source represents a drastic break point in the process of industrialization, which even changed the layout of factories (Du Boff 1967). My chapter shows that the introduction of electricity as a power source led to an immediate increase in human capital accumulation at the end of the 19th century.[20] These differences persisted with the early adopters of electricity continuing to exhibit higher levels of education and innovation today. This also appears to be the main driver of subsequent economic development, providing new insight on the contribution of electricity to fostering skill biased economic growth from the late 19th century.

Finally, my chapter contributes to a literature trying to explain persistent differences in the spatial distribution of economic activity. The seminal study of Davis & Weinstein (2002) highlights that location fundamentals were crucial in determining economic activity across Japan with the pattern of economic activity being robust to large temporary shocks caused by conflicts. Most closely related to my work here is a small set of papers which has studied the long-run impact of the adoption of specific technologies. Juhász (2018) shows that areas in France which adopted mechanized cotton spinning during the Napoleonic Blockade continued to be more specialized in spinning and had higher incomes for several decades, while Franck & Galor (2019) show that areas which had adopted more steam engines at the height of the industrial revolution fell behind in the long-run due to technological inertia. Lewis & Severnini (2019) highlight that rural electrification in the US between 1930-1960 led to an expansion in the agricultural sector, but had little effect on the local non-agricultural economy apart from driving suburban expansion. These studies suggest that while there are considerable short-run gains from the adoption of technology on economic development at the local level, the long-run gains across areas are rather elusive in developed countries.[21] However, what these papers have in common

[20] In general, the consensus is that technical change in the 20th century has favoured skilled workers (see e.g. Goldin & Katz 1998; Acemoglu 2002).In contrast, the impact of technical change throughout the 19th century is generally viewed as overall leading to deskilling and lower levels of human capital accumulation, even though recent empirical evidence provides a somewhat more nuanced picture (see Goldin & Sokoloff 1982; Atack et al. 2004; Katz & Margo 2014; Franck & Galor 2019; De Pleijt et al. 2020).

[21] In contrast, the literature using cross-country variation in timing and intensity of adoption of new technologies finds large persistent effects for a vast variety of technologies, see e.g. Comin & Hobijn

is that they look at the later-stages of a technology's adoption at the height of its importance rather than the pioneering adoption of a new technology during its infancy.[22] This chapter finds that areas that adopted electricity early continued to be more industrialized and have higher incomes even 100 years later. This is despite electricity adoption having differed across areas for only a short period of time (of about 20 years). I also provide evidence that the mechanism explaining this lasting effect is increased human capital accumulation and innovation in areas with early electricity adoption, which fostered further economic growth. Notably, as electricity became more widely used as a technology there no longer are any observable differences in its use as early as 1929 across areas.

The remainder of this chapter is organised as follows. Section 1.2 discusses the historical context of electrification and the second industrial revolution. Section 1.3 describes the empirical strategy and data used in the analysis. Section 1.4 presents the results for the contemporaneous effect as well as the long-run outcomes. Section 1.5 discusses potential mechanisms. Finally, Section 1.6 concludes.

1.2 Historical Context

1.2.1 The electrification of Switzerland

Switzerland was at the technological forefront in the adoption of electricity. The first recorded commercial use occurred in 1879 at the Hotel Engadiner Kulm in St. Moritz, where electrical lamps were supplied by a small waterpowered generator.[23] At the turn of the century Switzerland was leading in per capita electricity production (81.9kWh in 1902, and 166.9kWh in 1907, see "Elektrifizierung" in HLS 2020),[24] just in front of the United States (81.7 kWh in 1902; 125.2 kWh in 1907).[25]

(2010), Comin & Mestieri (2018), Gollin et al. (2018). These findings correspond well to Figure A.3 in the appendix, which shows a drastic persistent growth in per capita incomes in Switzerland, which was the largest initial adopter of electricity in the world till the 1900s, from around 1885 onwards.

[22]Another potential explanation for differences disappearing in the long-run is that this reflects considerable economic spillovers, e.g. through trade or migration, as well as government redistribution across areas, which attenuates the effect of the local adoption of technology within countries in the long-run.

[23]Electrical lighting, motors and dynamos were invented by the 1840s, however it took until the 1880s for electricity to become economically used as a source of power and light. The first electric tram started operating in Berlin in 1881. The first commercial power plant, Edison's Pearl Street Station, was opened 1882 in New York serving initially 400 lamps of 82 customers. In the same year, the city of Lausanne introduced electrical street lights. In 1886 the Thorenberg plant was opened in Switzerland, the first that used alternating current to provide electricity to consumers (Weingartner 2016).

[24]Converting the electric power of hydroelectric-plants recorded in my data, the electricity production per person is 144kWh in 1900, however this measure based on Bossard (1916) reflects maximum electricity that could be generated from the installed turbines conditional on available seasonal water-level variations, but does not account for power-generation being reduced due to lower demand or turbines being completely shut-off over night potentially explaining the observed discrepancies in measures. Taking into account that electricity (especially for manufacturing) is sparsely needed for 8 hours overnight and on Sundays suggests a very similar 82kWh electricity generation per person.

[25]Directly comparing installed capacity using primary sources provides a similar picture. Based on the data collected from Bossard (1916) the total installed capacity of Swiss electrical power-plants was

A key feature of Swiss electrification was its heavy reliance on waterpower due to the absence of fossil fuel deposits. This meant that use of this new source of energy was initially unequally distributed across Switzerland and dependent on the proximity to sites where the forces of nature could be used to produce electricity due to the absence of long-distance transmission. More than 1000 sites across Switzerland were deemed to be able to generate more than 15kW electricity. However, the potential electricity generation differed vastly across these sites with 126 of these being used to generate electricity by 1900 (see Appendix Figure A.2). The gradient of a river segment combined with complementary features like river bends or confluences were crucial in determining the amount of electricity that could be generated at a site (see Bossard 1916, Volume 4, p.15-16). Indeed this meant that most locations are along small, rocky streams with little economic or geographic significance prior to 1880 rather than major rivers like the Rhine, Rhone and Aare. This reliance on waterpower is also recorded in the Swiss statistical yearbook, which estimates that more than 99% of electricity produced was from waterpower plants by 1920 (see Data Appendix A.3 for more detail).

Interestingly, waterpower was not just crucial for electricity generation in Switzerland, but the development of electric power generation and transmission was in return crucial in allowing the exploitation of the available waterpower potential. This was due to mechanical energy generation and transmission by watermills having only been able to harness a fraction of the energy that waterpower was able to potentially provide. The main constraint was that waterwheels and transmission by shafts and belts was simply unable to handle and distribute large amounts of energy that turbines and electric transmission lines were able to exploit.[26] Even tough watermills were only able to exploit a very limited amount of power they still were of considerable historic importance in the early stages of industrialization until the advent of the steam engine (Mokyr 1992).

The emergence of electricity as a power source required investment in power plants and transmission lines. In the early stages of electrification, up to the 1890s, about 50% of electricity production was by industrial firms mainly for their own consumption (see Kammerer et al. 2012).[27] However, improvements in transmission technology led

69,000kW (548kW on average) in 1900. The US census of electrical industries (US Department of Commerce 1912) records 1,390 water and 5,930 steam turbines with a capacity of 328,854kW and 1,034,955kW in 1902, respectively. This suggests that installed electricity generation capacity per capita in Switzerland was about 20% greater than in the US. The reliance on however likely implied that this capacity was less intensively utilized than in the US as installed turbine capacity in Switzerland was about 1.7 times higher than the maximum electricity that turbines actually could generate due to fluctuations in the water-level throughout the year (see Bossard 1916). This historical electricity generation is tiny compared to the 698 Swiss plants operating in 2018 having an average capacity of 25572kW (Eidgenössische Amt für Wasserwirtschaft 1928-2018).

[26] A detailed historical description of the changes in generation and transmission technology from mechanical waterpower over steam to electrical power is provided in Volumes I-III of Hunter & Bryant (1979-1991).

[27] Some important examples are the chlorate factory in Saut-du-Day of the Pariser Société d'électrochimie, the calcium carbide, ethin and fertilizer production of Lonza, and the Alusuisse establishing

to electricity use rapidly becoming more widely available. This was in particular due to the emergence of a specialized electric utility industry which focussed exclusively on generation and distribution of electricity to consumers.[28] By 1895, only 5% of firms across Switzerland had access to externally generated electrical power (see “Elektrifizierung” in HLS 2020). However, the share of firms connected to the electricity grid quickly rose to 43% in 1911 and 95% in 1937. Further, the improvements in electricity transmission also meant that plants initially built to supply specific industrial plants increasingly supplied excess electrical energy to others (see Bossard 1916). Accordingly, as electricity became increasingly supplied by central power generation fixed investment was not necessarily required by individual firms to be able to use electricity.[29] In a similar way, in cases where power-plants had been initially built by firms for their own consumption, generation and use of electricity usually developed into distinct businesses as the electricity grid expanded.

The development of the Swiss electricity grid occurred in three distinct phases (see “Elektrizitätswirtschaft” in HLS 2020). In the early phase (1880-1900) electrification was dominated by private firms and focussed on local supply. In the second phase (1900-WWI) public producers and distributors became more important with electricity starting to be supplied over longer distances. In the last phase (after WWI) interconnected networks for delivering electricity across the whole of Switzerland were established. This transition was helped by improvements in technology leading to vast increases in transmission distances at the start of the 20th century. In 1901, the longest transmission line in Switzerland was 35km doubling to 72km in 1904 and 135km by 1908 (see Department des Inneren 1891-1920). Accordingly, the maximum number of municipalities supplied from a single power-plant increased ten-fold from 29 in 1901 to 232 in 1908. Consequently, local suitability to generate electricity only mattered for the first 20 years of electricity adoption, while after 1900 most locations were quickly connected to large waterpower plants by long-distance transmission lines. The clear dominance of waterpower plants in electricity generation only ended with the emergence of nuclearpower plants in the 1960s with current production almost equally split between the two (Weingartner 2016).

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the first aluminium plant in Europe as well as producing other electro-chemical products since 1888 (“Elektrizitätswirtschaft” in HLS 2020).

[28]The low cost of electricity usage is highlighted by balance sheet calculations of US engineer C. E. Emery in 1896 which suggest the total cost of generating one unit of energy from steam-power on site was about 4-5 times as expensive (especially due to the fixed capital investment required on-site) as the price charged for electrical energy supplied from a power-station off-site (see Emery 1896). This was particularly beneficial to small-scale firms which could draw energy as needed from the electricity network, in contrast to most technological developments during the industrial revolution which were scale-augmenting (Mokyr 2010).

[29]The investment required to use it varied greatly by application, for example small electric heaters versus large electric arc furnaces. That energy could be used as needed is generally seen as one of the advantages of electricity over steam-power, and why it was particularly beneficial to small-scale producers (Mokyr 2010).

1.2.2 The technological revolution: Chemistry and education

Landes (1969) describes the second industrial revolution as characterized by major advances in electrical and chemical sciences and a shift away from early-modernising sectors such as cotton textiles. The development of the chemicals industry was highly dependent on the commercial adoption of electricity itself. This was due to new methods in chemistry requiring high amounts of electricity, for example the electrochemical production of calcium carbide developed at the end of the 19th century.[30]

The development of the chemical industry in Switzerland did not receive direct support or protection by the state (Homburg et al. 1998). However, there was crucial cooperation between government and industry in education and research. For example, the Swiss Federal Institute of Technology (today ETH) founded in 1854 provided teaching and research laboratories imitating the German model. These institutes provided expertise in the application and development of chemical processes directly or through graduates to the chemical industry. It also led to the development of new occupations, for example that of the well-paid industrial chemists developing new chemical processes outside of academia (Homburg et al. 1998).

The underlying educational changes were much broader than just at the tertiary level. For example, as industrialization increased chemistry teaching had become well established in US secondary schools, including laboratory work, in the late 19th century (Fisher 1986). Switzerland saw similar developments in providing practical industrial-technical knowledge at the secondary school level, for example through cantonal industry-schools (Gonon 1997). These changes did not just occur with regards to the chemical industry rather the dual education system in Switzerland in the late 19th century more broadly started to focus on providing also theoretical rather than just practical knowledge as the demand for a more skilled workforce increased (Wettstein 1987). For example, in 1887 a Bernese politician bemoaned in a parliamentary motion the lack of technically well educated workers (especially in mid-level roles), which was followed by the opening of new polytechnic universities ("Technikums") in short successions during the 1890s to provide this type of education (see "Technikum" in HLS 2020). Vocational schools (secondary level) and technical colleges (tertiary level) that started to become more widespread during the end of the 19th century still remain a key part of the educational system in Switzerland providing both job-specific practical skills and more broad theoretical knowl-

[30]The importance of electrochemistry can hardly be understated for the Swiss chemical industries, but it should be noted that even before 1880 there existed chemical plants focussing mainly on the production of synthetic dyes with alizarin (red) being the main product (Homburg et al. 1998). These chemical plants established themself close to the pre-existent local textile industries, especially in Basel. Another advantage was that Switzerland had no patent-law till 1907 allowing the imitation and improvement of dyes already patented abroad (see "Chemische Industrie" in HLS 2020). However, many of the initial chemical companies producing basic and intermediate products disappeared with the spread of the railway as transportation costs went down and larger foreign plants started supplying the local industry (Homburg et al. 1998).

edge (see Wettstein 1987; Mägli 1989; Halbeisen et al. 2017). These new schools were often initially financed by employers, employer-, and employee-associations or municipalities, while the central government started to play a more important role only later on (see "Berufsbildung" in HLS 2020).

1.2.3 A historical example: The story of Lonza

Many Swiss chemical firms established at the end of the 19th century relied on the availability of cheap electricity (see e.g. Lunge 1901).[31] It seems illustrative to discuss the story of one of them in more detail. I choose Lonza as its name is based on the local river used to power the electrical generators.

Lonza was founded in 1897 in the small municipality of Gampel (population of 421 in 1880) with its own waterpower plant producing electricity to manufacture chemicals, in particular calcium carbide. The production of calcium carbide requires a large amount of energy and has not changed since its invention in 1892. For this purpose, Lonza operated two waterpower plants in Gampel with an average electricity generation of 1725kW and 3750kW built in 1898 and 1900 (see Bossard 1916). Local employment in chemical industries tripled from 5 in 1880 to 14 in 1900. Lonza quickly outgrew Gampel in the following years and opened an additional production site in the neighbouring municipality of Visp (11.9km away) in 1909 extending production to synthetic fertilisers, vitamins, acids,chemical intermediates and additives.[32] Lonza's production was mainly not destined for the local market and while a railway line to Geneva already existed in 1880, the opening of the nearby Lötschberg Tunnel in 1913 connected the Lonza plants directly with Central Switzerland (and through this to Germany). Today Lonza is the 7th largest chemical company in Switzerland (48th in the world) with a revenue of 5.5 billion CHF and 14,500 employees across 100 sites in 18 countries with the Visp-site being the largest production and research site with 2800 employees. Gampel, where the initial carbide oven was closed in 1964, also still boasts an extremely industrialized and high-skilled workforce with 4.7% being technical professionals or scientists in 2008 (see Bundesamt für Statistik 1860-2011).

The emergence of Lonza, and the chemical industry more generally, created new educational opportunities. This is for example illustrated by Paul Hermann Müller (son of a railroad employee), who was born in Olten in 1899. He started to work as a laboratory assistant at Dreyfus & Cie. in 1916 after dropping out of secondary school due to bad

[31]For example, AIAG (aluminium and potassium chlorate), Ciba (chlorine and sodium hydroxide), Compangie Electrique du Phosphor (phosphor), La Volta (sodium chloride), Lonza (calcium carbide), and Societe de Electrochemie (chlorate).

[32]It should be highlighted that while these waterpower plants were initially build to supply energy to the production of chemicals, in 1914 all of them are listed as supplying electricity more broadly to the electricity grid and not just to the chemical industry Bossard (1916). Corresponding to this, chemical plants and electricity generation evolved into two separately run operations.

marks. He then joined Lonza as an assistant chemist in their industrial laboratory of their electrical plant. There he acquired a wealth of practical knowledge which later stood him in good stead in his career as an industrial chemist (NobelPrize.org 2020). Finishing his educational apprenticeship combined with an additional year in school allowed him to enter Basel University, receiving a Doctorate in 1925. He than returned to work in the private sector starting his career with Geigy in Basel, working initially on vegetable dyes and natural tanning agents, moving to work on insecticides later on. He received the 1948 Nobel in Physiology or Medicine prize for his work on the synthesis of DDT, an important chemical compound in the eradication of malaria across the world. Again this provides only an example, but it helps to highlight the crucial interplay between the nascent chemical industry, education and individual careers.

These are only examples of how the adoption of electricity at the end of the 19th century transformed two rather small municipalities and individual opportunities drastically. However, as will be shown in Section 1.4 these are not only individual success stories, but rather were common across Switzerland.

1.3 Empirical Strategy

This section describes the empirical strategy and briefly summarizes the main data used. More detailed information on my data sources is provided in Data Appendix A.

What was the effect of the early adoption of electricity on economic development? To answer this question, I explore the empirical relationship between the district-level increase in the supply of electricity and indicators of development, while controlling for confounding factors.

Swiss districts ("Bezirke"), the administrative level directly below the Cantons, provide the preferred unit of observation to evaluate this empirically as they are large enough so that the required historic information is available, but small enough to provide sufficient variation across Switzerland. These units of observation reflect distinct local labour markets up to the middle of the 20th century.[33] The 178 districts in my sample also provide a consistent unit of observation from 1860 till today.

I construct a measure of district-level electricity adoption between 1880-1900 as follows:

$$\Delta E_{d,1900-1880} = \frac{W_{d,1900} - W_{d,1880}}{N_{d,1880}} \tag{1.1}$$

[33] The development of the railroad and tram networks in Switzerland in the late 19th and early 20th century mainly improved the transport of goods and short-distance passenger traffic (see "Verkehr" in HLS 2020). A sizeable geographic distinction between place of living and work only emerged with the building of motorways and mass motorisation beginning in the 1950s. To better account for this, I use employment data based on the location of the workplace after 1955, rather than residence (the only measure available initially).

where W is the electricity generated and N is the population of district d.[34] The measure $\Delta E_{d,1900-1880}$ captures electricity adoption in kW per person in each district between 1880 and 1900.[35] Crucially, electricity in Switzerland was nearly exclusively generated from waterpower and due to technological constraints was not yet supplied over long distances. Accordingly, this measure of electricity adoption reflects both the effect of local generation and use of electricity.

I estimate the following equation to capture the contemporaneous effect of the adoption of electricity on outcomes measuring economic development:

$$\Delta DEV_{d,1900-1880} = \beta \Delta E_{d,1900-1880} + \gamma' X_{d,1880} + \epsilon_d \tag{1.2}$$

where $\Delta DEV_{d,1900-1880}$ denotes a measure of economic development with d denoting district and 1900-1880 representing the time-period. I use alternative outcomes, but a particular focus is placed on the structural transformation from agriculture into manufacturing and service employment. These represent crucial measures of economic development as historically areas became rich through labour moving from agriculture into modern activities with higher productivity as well as productivity growth (see e.g. Kuznets 1957; Kuznets 1973; Gollin et al. 2014). $X_{d,1880}$ are controls observed at the beginning of the period capturing differences across districts in 1880 that might influence the adoption of electricity as well as future economic development, and ϵ_d is the error term.

An obvious concern with a causal interpretation of the role of electricity in Equation 1.2 is that the decision to build a power-plant is affected by both demand- and supply-side consideration. On the one hand, economic development potentially creates an upward bias through increasing local demand for electricity generation. On the other hand, economic development potentially creates a downward bias by complicating the building or extension of waterpower plants for electricity generation. In particular, already awarded water-concessions (usually lasting at least 50 years) as well as unclear ownership situations can create obstacles for the exploitation of the full waterpower potential for electricity generation (Bossard 1916).

To address the potential endogeneity of electricity adoption, I use the following First-Stage regression:

$$\Delta E_{d,1900-1880} = \varphi \log P_d + \phi' X_{d,1880} + \mu_d \tag{1.3}$$

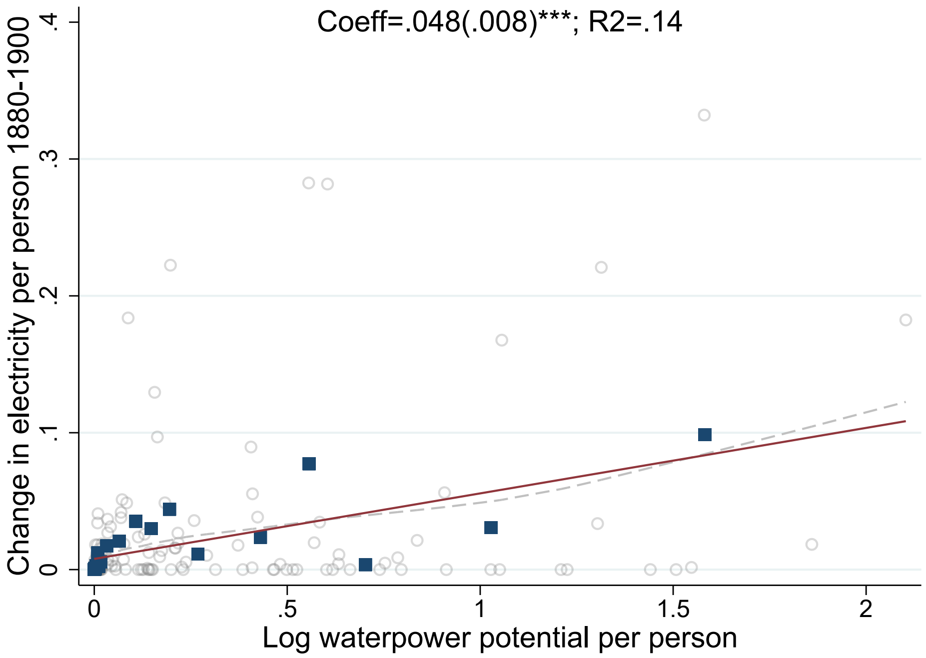
where the increase in the generation of electricity between 1880 and 1900 is instrumented by the log potential for energy generated from waterpower (in kW) per person in 1880,

[34] Note that while there was some hydroelectric electricity generation already in Switzerland by 1880 (the first having been build in 1879 see Section 1.2), these installations were so small that they did not exceed 15kW and are not recorded in the historic data used (see Bossard 1916). Effectively, $W_{d,1880} \approx 0$ across districts. The variable is specified as the change even though it equals the level in 1900 to immediately highlight that both variables represent the change that occurred since 1880.

[35] The measure is in kW (kilowatt) as it reflects the average power that the installed turbines in a waterpower plant can generate throughout the year conditional on the available water-flows.

denoted $\log P_d$.[36] The waterpower potential is based on a detailed plan — devised by engineers at the time — of all existing and potential waterpower plants and the energy they could generate in kW (see Bossard 1916). Importantly, the aim for the calculation of the waterpower potential is explicitly stated as aiming to optimally exploit waterpower for energy generation using the current level of technology disregarding i) any existing obstructions that could inhibit the building of potential waterpower plants, and ii) any economic considerations for the operation of potential waterpower plants (see Bossard 1916, Volume 5, p.9-16). Figure 1.2 highlights the relationship between the increase in electricity produced between 1880-1900 and the waterpower potential per person across districts.

Figure 1.2: First-stage relationship



Notes: The binned scatter plot illustrates the relationship as described in Equation 1.3 between the log waterpower potential per person and the change in electricity produced from waterpower between 1880 and 1900 across districts. Blue squares represent the binned observations with the solid red line being the linear fit. In the background hollow grey dots correspond to the underlying observations and the dashed grey line represents the locally weighted fit. N=178 in 20 bins.

A key question is whether the the potential to generate electricity is as good as randomly assigned across areas with regards to ex-ante economic development. First, I start with the extensive margin looking at whether districts that actually adopted any electricity (Panel A1 & A2 in Appendix Table A.1) and those that had any potential to adopt

[36]For simplicity I refer to the transformation as the log while the exact transformation used is the inverse hyperbolic sin which closely relates to a log-transformation in its functional form, i.e. $\log(x+((x^2+1)^{0.5}))$, but also allows 0 values to be transformed. I adopt a log transformation to capture that the marginal gain from electricity adoption is decreasing. Results are robust to using potential for energy produced from waterpower per person as the instrument with results displaying slightly wider confidence intervals.

electricity (Panel A3 & A4) differed from the remaining districts in the sample that did not adopt electricity or did not have any potential. While districts with and without electricity generation in 1900 differ in terms of economic development by 1880, there are no observable differences between districts with and without waterpower potential for electricity generation by 1880.[37] Next, Table 1.1 looks at whether potential electricity generation in kW, the intensive margin, is also unrelated to economic development by 1880 across districts. Panel A illustrates the relationship between potential kW per km^2 and important characteristics of economic development in 1880. This measures whether the distribution of waterpower potential is as good as randomly located across the area of Switzerland with regard to pre-existing economic development, i.e. each similar sized area has the same likelihood for waterpower potential independent of the economic development in the area by 1880. This appears the case as there is no significant relationship between potential kW per km^2 and population density, agricultural, manufacturing or services employment share across districts, both with and without controlling for major geographic differences. Panel B considers to which degree economic development and potential kW per person are unrelated.[38] While it initially appears that the potential per person is highest in the least developed areas, this relationship vanishes as soon as one controls for major geographic differences across Switzerland. This provides considerable support for the potential to generate electricity being as good as randomly distributed across districts with regards to initial economic development. Appendix Figure A.1 provides additional descriptive maps for electricity adoption, geography and economic development across Switzerland.

That the waterpower potential started to be relevant for changes in economic development at the time only through electricity generation is further supported by Figure 1.3. It shows that the waterpower potential is a strong predictor of the change in electricity produced across districts between 1880-1900 (left-panel), but it is not relevant for the energy generated by watermills, using only mechanical power generation and transmission, in 1880 (right-panel). The later might appear surprising at first, however it reflects that the equipment used for mechanical power generation and transmission, i.e.

[37]The potential electricity generation across districts only appears associated with some major geographical differences, but not population density, agricultural, manufacturing or services employment share. Districts are more likely to be situated in the east of Switzerland and have a 246m higher average altitude (with 960m being the average altitude across districts). Note that in the empirical strategy I control for altitude and use the first difference as the dependent variable, i.e. I control for any differences in development after 1880 that might be driven by altitude.

[38]Note that if potential to generate electricity is as good as randomly distributed across Switzerland with regards to geography and there are differences in population density across areas, that in a mechanical way more densely populated areas will have a lower potential per person. This can be illustrated in the following way, consider Switzerland was divided into 1x1km grid cells and each cell would have the same likelihood to be able to generate electricity independent of anything else. Even if potential electricity is random, more densely populated grid cells would have a lower per capita potential for electricity generation on average. Appendix Figure A.4 illustrates this relationship. However, conditioning for geographic factors that determine population density in the very long-run, e.g. altitude, the relationship across cells should again be as good as random.

Table 1.1: Evidence for randomness of potential to generate electricity

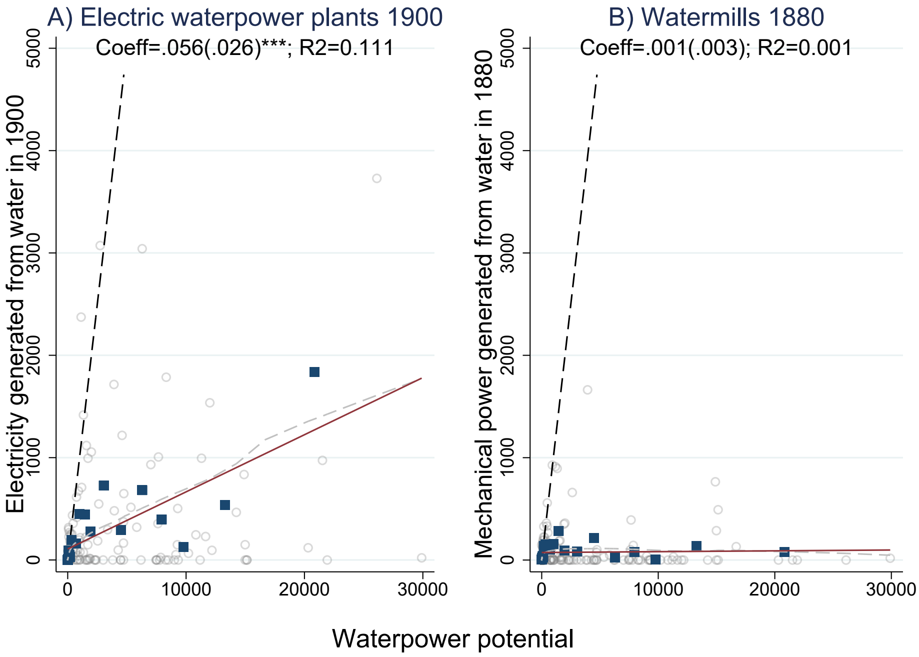
	Population density 1880		Share employment 1880 in Agriculture		Manufacturing		Services	
A. Geography	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Potential kW per km^2	0.004	0.004	-5e^{-4}	1e^{-5}	2e^{-4}	-3e^{-4}	2e^{-4}	2e^{-4}
	(0.002)	(0.002)	(5e^{-4})	(0.001)	(3e^{-4})	(4e^{-4})	(2e^{-4})	(2e^{-4})
Altitude (km)		-0.098***		0.082		-0.064		-0.018
		(0.032)		(0.061)		(0.054)		(0.024)
Longitude		0.034		-0.011		0.005		0.006
		(0.033)		(0.029)		(0.025)		(0.007)
Latitude		-0.026		-0.148*		0.180**		-0.032
		(0.056)		(0.079)		(0.075)		(0.019)
B. Population								
Potential kW per person	-0.056**	-0.019	0.102**	0.060	-0.101**	-0.061	-0.001	1e^{-4}
	(0.020)	(0.022)	(0.044)	(0.043)	(0.037)	(0.037)	(0.011)	(0.008)
Altitude (km)		-0.108***		0.056		-0.037		-0.019
		(0.033)		(0.062)		(0.057)		(0.024)
Longitude		0.036		-0.016		0.010		0.006
		(0.031)		(0.027)		(0.024)		(0.006)
Latitude		0.035		-0.148*		0.176**		-0.027
		(0.046)		(0.075)		(0.071)		(0.018)
N	178	178	178	178	178	178	178	178

Notes: Dependent variables are population density in 1880 in column 1 & 2, share of agricultural employment 1880 in column 3 & 4, share of manufacturing employment 1880 in column 5 & 6 and share of services employment 1880 in column 7 & 8. Panel A presents the relationship between potential to generate electricity in kW per km^2 and economic development in 1880 across districts. Panel B presents the same for potential to generate electricity in kW per person. Robust standard errors in parentheses are clustered at the cantonal level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

wheels, shafts, gears, and belts, were not able to transmit the considerable amounts of energy that waterpower could provide and also reflects that location of generation and use had to be located in immediate proximity further complicating the exploitation of the full waterpower potential before 1880 (see e.g. Du Boff 1967).[39] Accordingly, this means that the technologies available before electricity were unable to fully exploit the potential waterpower. This suggests that the specific geographic features relevant for electricity generation were otherwise economically irrelevant, including power generation in any other way, supporting the validity of the exclusion restriction. To even further alleviate any concerns, I will later also present estimates based on Equation 1.2 for the period 1860-1880, which show that the early adoption of electricity 1880-1900 is unable to predict any economic development in this pre-period.

[39]Most of the watermills in 1880 are watermills are used for milling flower or sowing wood that rarely generated more than 75kW (100PS) of energy and were initially build as far back as the middle ages. In comparison the majority of electric power plants generated vastly more energy than 75kW (see Apendix Figure A.2.)

Figure 1.3: Electric- versus mechanical-power generated from potential



Notes: The binned scatter plots illustrate the relationship between the total waterpower potential in kW of a district and a) electricity generation from waterpower by 1900 and b) the energy generated by watermills using exclusively mechanical power transmission by 1880 across districts. The x-axis give the potential kW from waterpower (based on the lowest water level during the year), while the y-axis gives the actual average kW of energy generated throughout the year. Blue squares represent the binned observations with the solid red line being the linear fit. In the background hollow grey dots correspond to the underlying observations and the dashed grey line represents the locally weighted fit. The blacked dashed line provides a 45-degree line of full exploitation of the minimum potential throughout the year. Some districts actual electricity generation is slightly above the 45-degree line because it varies with the water level throughout the year, i.e. turbines have been installed that operate at less than full capacity in parts of the year when the water level is low. Geneva with an electricity generation of 9900kW and a potential of 16785kW lays outside of the depicted range in the left figure. N=178 in 20 bins.

Next I study whether the contemporaneous effect persists in the long run: I analyse in separate regressions the effect of the early adoption of electricity on economic development. The equation below outlines the expanded empirical strategy:

$$\Delta DEV_{d,t-1880} = \beta_t \Delta E_{d,1900-1880} + \gamma_t' X_{d,1880} + \gamma_t \Delta E_{d,t-1900} + \epsilon_d \tag{1.4}$$

$$where\ t = 1900, 1920, 1941, 1955, 1965, 1975, 1985, 2011$$

$\Delta DEV_{d,t-1880}$ is the dependent variable of interest as in Equation 1.2, but where t denotes the respective end point of the time period. Each specification is being estimated separately for each of the listed ts. Accordingly, the effect of the early adoption of electricity and the initial controls is allowed to vary over-time, which is denoted by the subscript

t on the coefficients.[40] In addition to the previous specification I also control for extensions in electricity generation from waterpower that occur after 1900 ($\Delta E_{d,t-1900}$). While local supply of electricity in the long-run is unlikely to be influenced by this due to the development of long-distance transmission grids, this variable accounts for the potential correlation between the instrument and economic activity due to the construction and operation of waterpower plants for electricity generation that occurs after 1900.[41] The establishment of the electricity grid across Switzerland makes it no longer necessary for electricity generation to occur near its usage after 1900, so that the placement of power plants is driven by exogenous engineering considerations where best to construct new waterpower plants rather than endogenous reasons related to local electricity demand (see Eidgenössische Amt für Wasserwirtschaft 1928-2018). Accordingly, $\Delta E_{d,t-1900}$ is not determined by economic development caused by $\Delta E_{d,1900-1880}$.

A key advantage of the empirical strategy presented is that through taking the first difference and accounting for outcomes by 1880 the estimated results can not be driven by spatial autocorrelation between past and modern outcomes. This has been highlighted to be a key issue in the literature on persistence by Kelly (2020*b*), where the variable of interest is only observed several hundred years ago and regressed on modern day outcomes. Potential concerns about the persistence are further alleviated by results being consistently presented at a high frequency (on a historical perspective) of about 20 years. This will depict any time-varying persistence in the effect if present. Further to address another concern raised in Kelly (2020*a*) regarding spatial regressions, I will present standard errors for several different common ways of clustering.

Information on electricity generation across Switzerland between 1880-1900 comes from "The waterpower of Switzerland in 1914" (see Bossard 1916).[42] This source provides information on building and extension dates, energy generation, type of energy, and location for all waterpower plants in Switzerland with a generation capacity of more than 15kW. The same source also provides information on location and energy generation

[40] This is crucial as the effect of initial characteristics is unlikely to be constant over time. Apart from $\Delta E_{d,t-1900}$, the estimated coefficient β_t would be closely related to an event-study specification, where the observations are pooled and each included variable is interacted with time fixed effects.

[41] Consequently, my main variable of interest captures the causal effect of electricity adoption 1880-1900, while disentangling it from any later increase in electricity generation after 1900. In the case of not controlling for $\Delta E_{d,t-1900}$ the effect should rather be interpreted as the overall effect of electricity adoption from 1880 up to point t. In Appendix Figure A.8 this result is presented, which compared to the baseline specification (presented in Figure 1.6) suggests that the effect of electricity on industrialization is even larger. In line with the extension of the electricity grid after 1900 this difference in coefficients is explained exclusively by an increase in employment in electricity generation after 1900 (see Appendix Table A.7). To avoid noise from pure improvements in technology over time leading to increase in electricity generation, e.g. more efficient turbines, I focus on the number of newly build waterpower plants as control instead of kW electricity generated after 1920.

[42] This publication (Bossard 1916) and the later comparable publications (Eidgenössische Amt für Wasserwirtschaft 1928-2018) are official statistics published by the Swiss ministry of the interior, which tasked a group of mainly government engineers with the collection, calculation and composition of the reports, tables, and figures assessing the actual and potential waterpower of Switzerland.

Table 1.2: Summary statistics

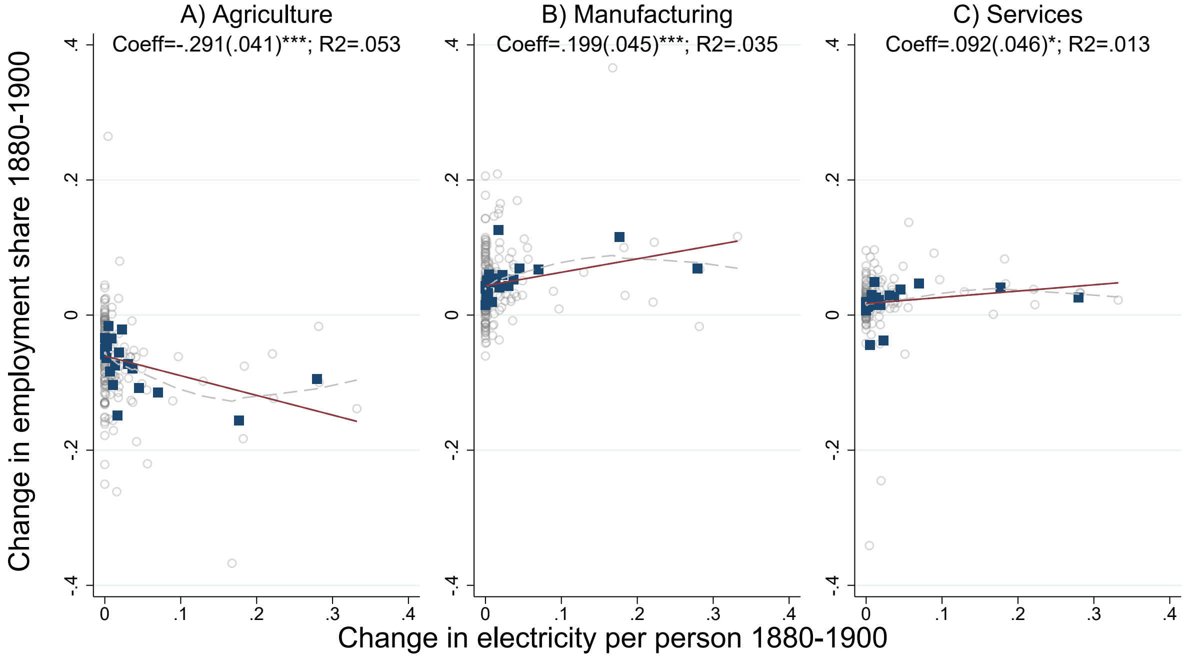
	Mean	SD	10th	90th	N
Panel A. Electricity adoption 1880-1900					
Δ Electricity pp 1880-1900	0.02	0.05	0.00	0.04	178
Log waterpower potential pp	0.23	0.40	0.00	0.79	178
Panel B. Agricultural employment share 1880-2011					
Share agricultural employment 1880	0.49	0.20	0.23	0.73	178
Change agricultural share 1880-1900	-0.07	0.07	-0.13	-0.00	178
Change agricultural share 1880-1920	-0.11	0.08	-0.22	-0.01	178
Change agricultural share 1880-1955	-0.17	0.13	-0.33	-0.00	178
Change agricultural share 1880-2011	-0.42	0.17	-0.64	-0.18	178
Panel C. Manufacturing employment share 1880-2011					
Share manufacturing employment 1880	0.37	0.17	0.16	0.63	178
Change manufacturing share 1880-1900	0.05	0.05	-0.01	0.11	178
Change manufacturing share 1880-1920	0.05	0.07	-0.03	0.14	178
Change manufacturing share 1880-1955	0.09	0.13	-0.05	0.24	178
Change manufacturing share 1880-2011	-0.08	0.17	-0.32	0.12	178
Panel D. Services employment share 1880-2011					
Share services employment 1880	0.13	0.07	0.07	0.22	178
Change services share 1880-1900	0.02	0.04	-0.00	0.05	178
Change services share 1880-1920	0.06	0.05	0.02	0.12	178
Change services share 1880-1955	0.08	0.08	0.01	0.17	178
Change services share 1880-2011	0.51	0.10	0.39	0.63	178

Notes: The table reports summary statistics for the main explanatory variables and main dependent variables. The columns report mean, standard deviation, 10th and 90th percentile and number of observations.

for all potential waterpower plants that could be build across Switzerland to maximise electricity generation at the time. From this, I calculate the electricity generation and potential electricity generation at the district level. Panel A in Table 1.2, which presents summary statistics for the main variables, highlights that the average electricity adoption 1880-1900 was 0.02kW per person. I augment this information on the number of waterpower plants and electricity produced for the period after 1914 with later publications of the “Statistics of waterpower plants in Switzerland” (see Eidgenössische Amt für Wasserwirtschaft 1928-2018), which extends the information on electricity generation from waterpower up to 2018. More detailed information on the electricity data is provided in Data Appendix A.3.

To study the effect on economic development I first collected information on structural change (employment across agriculture, manufacturing and services) from the Swiss Censuses focussing on the years 1860, 1880, 1900, 1920, 1941, 1955, 1965, 1975, 1985 and 2011

Figure 1.4: Electricity adoption and structural change 1880-1900



Notes: The binned scatter plots illustrate the correlation between the change in electricity generation 1880-1900 and change in share of employment 1880-1900 in a) agriculture, b) manufacturing, and c) services across districts. Blue squares represent the binned observations with the solid red line being the linear fit. In the background hollow grey dots correspond to the underlying observations and the dashed grey line represents the locally weighted fit. N=178 in 20 bins.

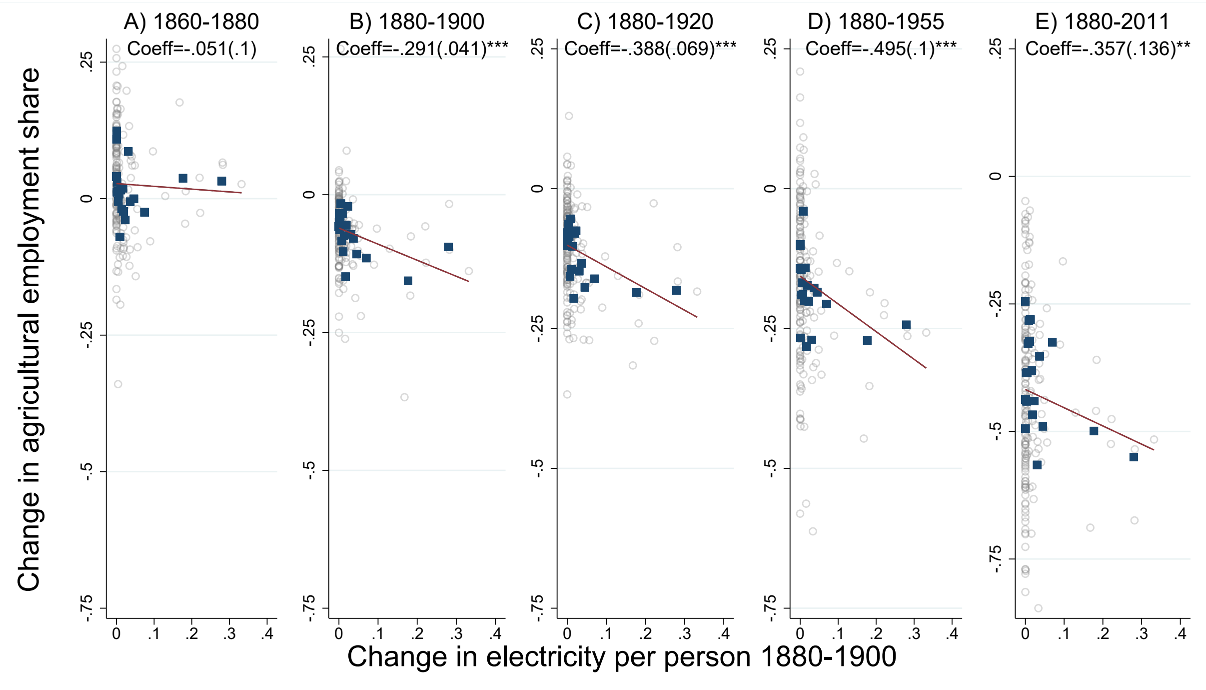
(see Bundesamt für Statistik 1860-2011).[43] These provide information on employment of individuals for the whole of the Swiss population at the district level. In addition, I also collect more detailed information on employment in different manufacturing industries for the years 1860, 1880, 1900, 1920 and 1975, identifying seven consistent groups out of the categories reported in the census: "Electricity generation", "Construction, wood & stone products", "Chemicals", "Textiles & apparel", "Food products", "Metal, machinery & watches", and "Other".[44] The category "Other" mainly comprises employment in mining, paper and typography. The additional breakdown by industries allows me to distinguish to which extend the effect of electricity adoption on manufacturing was due to electricity generation itself or rather due to the use of electricity. Additional information on the Census Data is provided in Data Appendix A.4.

Panel B-D in Table 1.2 highlights that by 1880 Switzerland was still a mainly agricultural economy, but that there was rapid structural change after 1880 with employment

[43]These sources are the official Census statistics aggregated and reported at the time by the statistical department of the Swiss ministry of the interior based on the 100% population censuses that had been conducted.

[44]Construction is included within manufacturing because even in the disaggregated historical information for 1880-1920 the construction of buildings is reported in one category together with the production of materials predominantly used for construction (wood and stone products). Accordingly, I follow the historic classification and count construction within manufacturing throughout.

Figure 1.5: Electricity adoption and structural change in the long-run



Notes: The binned scatter plots illustrate the correlation between the change in electricity generation 1880-1900 and change in share of employment in agriculture for a) 1860-1880, b) 1880-1900, c) 1880-1920, d) 1880-1955 and e) 1880-2011 across districts. Blue squares represent the binned observations with the solid red line being the linear fit. In the background hollow grey dots correspond to the underlying observations. N=178 in 20 bins (N=177 in A) 1860-1880).

first transitioning from agriculture to manufacturing and then to services. Combining the data on electricity adoption and employment, Figure 1.4 visualizes the correlation between the change in the share of employment in (i) agriculture, (ii) manufacturing and (iii) services with the adoption of electricity in the short-run 1880-1900. The figure shows a substantial decrease in agricultural employment for districts with a higher electricity adoption and a corresponding increase in manufacturing and to a smaller extent services employment. Figure 1.5 illustrates that this structural transition is not just short-lived. Even by 2011, the early adoption of electricity continues to be correlated with a stronger decrease in the agricultural employment share since 1880.

These two main sources are complemented by a large set of other data sources measuring electricity use, education, innovation, and infrastructure over the long-run to evaluate the potential mechanisms for the persistent effect and a set of data sources to used to construct additional controls. Data Apendix A.5 presents the data-sources for these variables.

1.4 Results

This section analyses the effect of early electricity adoption on economic development across districts in Switzerland. First, Section 1.4.1 shows that early electricity adoption led to structural change in the short-run. Second, Section 1.4.2 shows that the effect of early exposure to electricity persisted over time, despite the fact that the extension of the electricity grid allowed access to the new technology regardless of location. In Section 1.4.3 I show that early adoption of electricity had significant short-run effects on industries associated with the generation of electricity, but the long-run effect is mostly due to industries which benefited from the use of electricity.

1.4.1 Short-run effect of electricity

Table 1.3 Panel A analyses the effect of the adoption of electricity between 1880-1900 on the change in the share of employment in agriculture 1880-1900.[45] This corresponds to the estimation strategy outlined in Equation 1.2. Column 1 corresponds to the bivariate regression plotted in the first panel of Figure 1.4, and shows a substantial decrease in agricultural employment for districts with a higher electricity adoption. In the next columns I introduce controls accounting for initial differences across districts that might be correlated with both the adoption of electricity and economic development between 1880-1900.

A first concern is that electricity generation might be correlated with major geographic differences across Switzerland. These might also affect economic development. To account for this, I add altitude, longitude and latitude as controls in the second column, which accounts for major differences in Swiss geography that occur in terms of elevation, from north to south, and from east to west. A higher altitude is related with less transition out of agriculture. The coefficients for longitude and latitude suggest that areas in the North-West (South-East) experience the lowest (highest) transition out of agriculture.

A second concern is that electricity adoption is driven by the initial level of economic development, which might also be related to future economic development. In column 3, I control for the 1880 agricultural employment share, population density and average educational test scores. No clear pattern of convergence nor divergence in economic development is observable across districts.

A third concern is the pre-existing use of mechanical waterpower through watermills, which were the dominant source of power in Switzerland up to the middle of the 19th century until the steam engine overtook it in importance and crucial in the early stage of industrialization (Rosenberg 1972; Mokyr 1992). The previous use of waterpower through

[45] Standard errors are clustered at the cantonal level due to their administrative importance within Switzerland (25 clusters). Similarly, sized standard errors are obtained clustering for spatially correlated error terms with a 35km kernal (see Conley 2008; Hsiang 2010). The kernal size is based on the longest electricity transmission distance in 1900.

watermills might also influence electricity generation after 1880, so that industrialization due to the operation of watermills could be falsely attributed to the adoption of electricity after 1880. Column 4 controls for the mechanical energy generated per person in watermills by 1880. Indeed, the use of mechanical waterpower by 1880 is associated with a greater decline in agricultural employment 1880-1900. Consequently, the included control helps to disentangle any potential effect between the adoption of electricity after 1880 and any pre-existing usage of water as a power source.

A final concern is that there are region-specific unobservable in economic development which are correlated with electricity adoption. Accordingly, column 5 accounts for different trends in economic development across the seven major economic regions in Switzerland.[46] Across all specifications the main coefficient of interest remains similar in size. I choose column 5 as my baseline specification.[47] The -0.291 coefficient in column 5 implies that the share of agricultural employment in a district with a one standard deviation higher exposure to electricity decreased by 1.5 percentage points more than in a comparable district.[48]

Appendix Table A.2 highlights that the coefficient is robust to accounting for a vast set of other human characteristics that have been highlighted to be of importance for economic development: upper-tail human capital (Squicciarini & Voigtländer 2015), religion (Becker & Woessmann 2009), culture (Alesina & Giuliano 2015) and institutions (Acemoglu et al. 2011). These factors appear at most of limited importance for the transition out of agriculture in Switzerland between 1880-1900. This is not necessarily surprising as their effect on future economic development is potentially already well accounted for by controlling for the level of economic activity observed in 1880 included in the baseline specification. In addition, the table shows that the result is robust to controlling for a vast set of additional geographic characteristics (cropland, presence of major rivers, average water-flow of rivers, bioregions, ruggedness). In particular, the share of available cropland and the Po-Basin bioregion are associated with less transition out of agriculture. However, these measures are based on modern data, as no historical information is available, so while it is reassuring that the effect of electricity appears robust to including them,

[46]The 7 regions are Geneva-lake-region (Geneva, Vaud, Valais), Espace Mittelland (Bern, Fribourg, Jura, Neuchâtel, Solothurn), Northwestern Switzerland (Basel-City, Basel-Country, Aargau), Zürich (Zürich), Eastern Switzerland (Schaffhausen, Thurgau, St. Gallen, Appenzell Ausserrhoden, Appenzell Innerrhoden, Glarus), Central Switzerland (Lucerne, Uri, Schwyz, Obwalden, Nidwalden, Zug) and Tessin (Tessin) with the corresponding Cantons in brackets. These regions correspond to the European Unions NUTS-2 regions.

[47]Reassuringly the estimated standard errors are similar using several common ways of calculating them (see Kelly 2020*a*). First, using the Bell-McCaffrey small sample adjustment when clustering on Cantons the standard error is 0.04. Second, when changing the kernel to 100km and 250km the standard error changes to 0.07 and 0.04, respectively. Accordingly, the estimate in Column 5 remains significant at the 1% significance level in all these cases.

[48]The coefficient of -0.291 indicates that a 1kW increase in generated electricity per person (a standard deviation is 0.05kW, see Table 1.2) predicts a decrease in the employment share in agriculture of 29.1 percentage points.

they might provide bad controls as their measurement might be affected by the building of waterpower plants and later economic development.

Table 1.3: Effect of electricity on agricultural employment 1880-1900

A. Agriculture (OLS)	(1)	(2)	(3)	(4)	(5)
Δ Electricity pp 1880-1900	-0.291***	-0.315***	-0.321***	-0.314***	-0.291***
	(0.041)	(0.050)	(0.057)	(0.057)	(0.042)
	[0.050]	[0.046]	[0.052]	[0.051]	[0.037]
Altitude (km)		0.037**	0.045**	0.044**	0.061**
		(0.014)	(0.020)	(0.020)	(0.028)
Longitude		-0.004	-0.006	-0.005	-0.049***
		(0.004)	(0.005)	(0.005)	(0.014)
Latitude		0.047***	0.043***	0.045***	0.040
		(0.014)	(0.013)	(0.013)	(0.032)
Share agricultural employment 1880			-0.031	-0.037+	-0.020
			(0.028)	(0.027)	(0.033)
Population density 1880			0.003	0.001	0.006
			(0.007)	(0.007)	(0.006)
Average educ. grade 1880			-0.014	-0.012	-0.013
			(0.021)	(0.021)	(0.021)
Watermills 1880				-0.667+	-0.739*
				(0.413)	(0.399)
Region FE	No	No	No	No	Yes
adj. R^2	0.048	0.089	0.090	0.097	0.131
N	178	178	178	178	178
B. Agriculture (IV)					
Δ Electricity pp 1880-1900	-0.500**	-0.756***	-0.731***	-0.734***	-0.625***
	(0.238)	(0.260)	(0.251)	(0.249)	(0.212)
	[0.264]	[0.300]	[0.269]	[0.268]	[0.268]
First stage estimate	0.048***	0.051***	0.054***	0.054***	0.057***
	(0.008)	(0.011)	(0.012)	(0.012)	(0.014)
F-stat (1st stage)	36.56	20.51	19.96	19.98	16.66
Reduced form estimate	-0.024*	-0.038***	-0.039***	-0.039***	-0.036**
	(0.012)	(0.010)	(0.010)	(0.010)	(0.013)
C. Manufacturing (IV)					
Δ Electricity pp 1880-1900	0.417*	0.536**	0.570**	0.573**	0.532**
	(0.241)	(0.271)	(0.282)	(0.279)	(0.262)
D. Services (IV)					
Δ Electricity pp 1880-1900	0.083	0.220+	0.161	0.162	0.093
	(0.206)	(0.135)	(0.151)	(0.152)	(0.162)

Notes: The dependent variable is the change in the share of employment in agriculture between 1880 and 1900 across districts. Panel A presents the OLS-estimates for the effect of electricity adoption per person between 1880-1900. Panel B presents the corresponding IV-estimates for electricity adoption per person between 1880-1900 using log waterpower potential per person as instrument. Panel C and D present the IV-estimates using the change in the share of employment in manufacturing and services as dependent variable, respectively. Robust standard errors in parentheses are clustered at the cantonal level. Square brackets present alternative Conley standard errors accounting for spatial correlation. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B of Table 1.3 uses the instrumental variable strategy outlined in Section 1.3 to account for unobservable factors not accounted for so far. The estimated effect can be interpreted as the local average treatment effect of being assigned the option to generate a certain amount of electricity from waterpower. The first-stage coefficient is highly relevant across all specifications and suggests that a 40% (one standard deviation) higher potential to generate electricity per person leads to a 0.02kW per person higher electricity adoption by 1900.[49] Accordingly, this first-stage provides exogenous variation in the adoption of electricity independent of economic considerations.

The magnitude of the IV coefficient for the effect of electricity adoption roughly doubles in size compared to the OLS regressions across columns (1)-(5). A plausible explanation for this is the presence of unobserved constraints in the use of waterpower for electricity generation in areas developing more rapidly.[50] The key issue here appears to have been that water-concessions had already been allocated for purposes other than electricity generation and that legal ownership-rights were often unclear and difficult to resolve (see Bossard 1916, Volume 4, p.7-8).[51] The -0.625 coefficient in column 5, obtained using the IV strategy, implies that a district which had a one standard deviation higher exposure to electricity experienced a 3.1 percentage points decline in the share of agricultural employment.[52] A way to appreciate the overall magnitude of the effect is to work out the contribution of electricity to the overall change in agricultural employment between 1880 and 1900. Since average adoption of electricity was 0.02kW per person (see Table 1.2), the coefficient implies a decrease in the agricultural employment share of 1.3 percentage points between 1880 and 1900 in the average district. The average decline in agricultural employment over this period was 6.6 percentage points, so that this suggests

[49] Appendix Table A.3 suggests that similar results are obtained using modern day potential for the building of small-scale waterpower plants in Switzerland using data from Schröder et al. (2012) as instrument. However, the predictive power of this instrument is considerably weaker and it's measurement is potentially endogenous to any dams and waterpower plants that have been build since 1880. In addition, it's explanatory power comes exclusively from its correlation with the historical instrument.

[50] Figure A.6 in the Appendix provides suggestive empirical evidence for this. It highlights that areas which exploit a large share of their potential actually have a smaller marginal effect from electricity adoption compared to areas that are only able to exploit a small share of their potential. If there would be an upward bias in the OLS coefficient due to local demand for electricity generation driving adoption, areas which adopted a higher share of their potential should observe a larger marginal effect compared to areas which exploit a small share of their potential. Instead the observed pattern is consistent with areas that have the largest gains from electricity adoption having more constraints in actually adopting it, e.g. due to water-concessions, which creates the observed downward bias.

[51] The city of Basel, the pre-eminent centre of the Swiss chemical-dye industry by 1880, provides an excellent illustration of the problem. Despite the considerable potential waterpower that the Rhine could provide within the city to generate electricity and a plausibly large local demand for electricity, little was being exploited. The main users of waterpower continued to be an array of inefficiently small and fragmented watermills that in many cases date back to the middle ages (see Appendix Figure A.5). Electrification in Basel continued lagging behind until the city's main electric power plant with a generation of more than 2000kW was build in 1912 (Bossard 1916). Notably however, this relied on improvements in transmission technology, rather than a consolidation of ownership of local water-rights, as the power plant was located more than 10km away from Basel in the district of Liestal.

[52] Considering the standard errors, the effect range lies between -4.2 and -2.1 percentage points.

20% of the decline in agricultural employment between 1880 and 1900 was due to the adoption of electricity. This partial equilibrium estimate, of course, does not take into account any losses of industrial employment or positive spillovers in other districts due to the adoption of electricity.

Panel C and D of Table 1.3 show that the shift out of agricultural employment mainly increases manufacturing employment and there is little effect on employment in services. The coefficient for the manufacturing share (column 5) suggests that a one standard deviation higher exposure to electricity increased manufacturing employment by 2.7 percentage points. The average increase in manufacturing employment over this period was 4.7 percentage points, so the partial equilibrium estimate suggests that 23% of the increase in manufacturing employment in Switzerland between 1880 and 1900 was due to the adoption of electricity.

Table 1.4: Effect of electricity on employment and population growth

	Employment growth 1880-1900			
	All (1)	Agriculture (2)	Manufacturing (3)	Services (4)
Δ Electricity pp 1880-1900	1.242***	-0.553***	2.527**	1.203$^+$
	(0.456)	(0.180)	(1.255)	(0.839)
	Population growth 1880-1900			
	Municipality (5)	Canton (6)	Swiss (7)	Foreign (8)
Δ Electricity pp 1880-1900	0.199	0.425	-1.381	3.264
	(0.282)	(0.516)	(2.604)	(2.986)
Controls	Yes	Yes	Yes	Yes
N	178	178	178	178

Notes: The dependent variable is the growth rate in employment and population between 1880 and 1900 as specified in the column header. The presented IV-estimates for the effect of electricity adoption per person between 1880-1900 uses log waterpower potential per person as instrument. Column 1-4 present the effect on total, agricultural, manufacturing and services employment growth. Column 5-8 present the effect on population growth of individuals originating from the municipality, from another municipality inside the canton, from another canton in Switzerland and from outside Switzerland. Robust standard errors in parentheses are clustered at the cantonal level. $^+$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The adoption of electricity did not just lead to changes in the share of employment across sectors, but also increased the employment growth rate. Table 1.4 Panel A shows that the adoption of electricity led to overall employment growth and employment growth in manufacturing, while employment in agriculture declined. Notably, Panel B looking at the growth in the population originating from the respective municipality, the canton, Switzerland or a foreign country does not change due to the adoption of electricity. This highlights that there appears to be little labour migration between 1880-1900[53] and

[53]By 1900, still the majority of the population was born in the municipality they currently lived in with the second largest group having been born in the same Canton, while migrants from other Cantons

that the observed employment growth is due to an increase in employment of the local population.[54] This provides further evidence that the adoption of electricity led to local structural transformation through agricultural and surplus labour moving into manufacturing employment.

Table 1.5: Pre-trend analysis 1860-1880

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Electricity pp 1880-1900	0.087	0.388	-0.348	-0.210	0.260	-0.177
	(0.552)	(0.400)	(0.436)	(0.260)	(0.320)	(0.193)
F-stat (1st stage)	36.17	17.46	36.17	17.46	36.17	17.46
Controls	No	Yes	No	Yes	No	Yes
N	177	177	177	177	177	177

Notes: The dependent variable is the change in the share of employment in agriculture, manufacturing and services between 1860 and 1880 as specified in the column header. This represents a period before the commercial adoption of electricity. The table analyses whether there is any correlation between the instrumented electricity adoption per person between 1880-1900 and pre-trend outcomes 1860-1880. Robust standard errors in parentheses are clustered at the cantonal level. One less observation is available as two districts were created out of one in 1877. Initial controls are for 1860. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The crucial assumption for the IV results to be valid requires that the potential to produce electricity from waterpower affects employment shares only through electricity adoption. One way to test this is to study whether the instrumented adoption of electricity 1880-1900 is observed to have an effect on outcomes before electricity started to be adopted in the 1880s. I conduct this falsification exercise in Table 1.5 by replacing my dependent variables with the change in employment shares between 1860-1880.[55] There is no evidence that districts experienced a different pattern of development before electricity started to be adopted in the 1880s. No significant effect of the adoption of electricity 1880-1900 is observed on the change in the agricultural, manufacturing or services employment share 1860-80 without and with controls. The estimated coefficients even go in the opposite direction compared to Table 1.3 ruling out any pre-trends across districts that might drive the observed effect between 1880-1900.

and immigrants were rare apart from in the larger cities (see “Binnenwanderung” in HLS 2020). Much more common appears to have been trans-Atlantic emigration, even though this was already declining at the end of the 19th century (see “Auswanderung” in HLS 2020).

[54] Male labour force participation in 1880 Switzerland was nearly 100% amongst working age males. However, the census records about 3% of men as unemployed (no occupation and relying on some sort of financial support) in 1880. In contrast, female labour force participation at the time is less than 50%. Appendix Table A.6 highlights that the initial employment growth 1880-1900 is mainly due to men finding employment, while later increases are due to female employment growth.

[55] To be consistent I also change all initial controls for 1880 to 1860. Accordingly, I include the share of agricultural employment, population density, energy generated by watermills per person for 1860 instead of 1880 across district. No data for average education grade is available in 1860.

1.4.2 Long-run effect from the early adoption of electricity

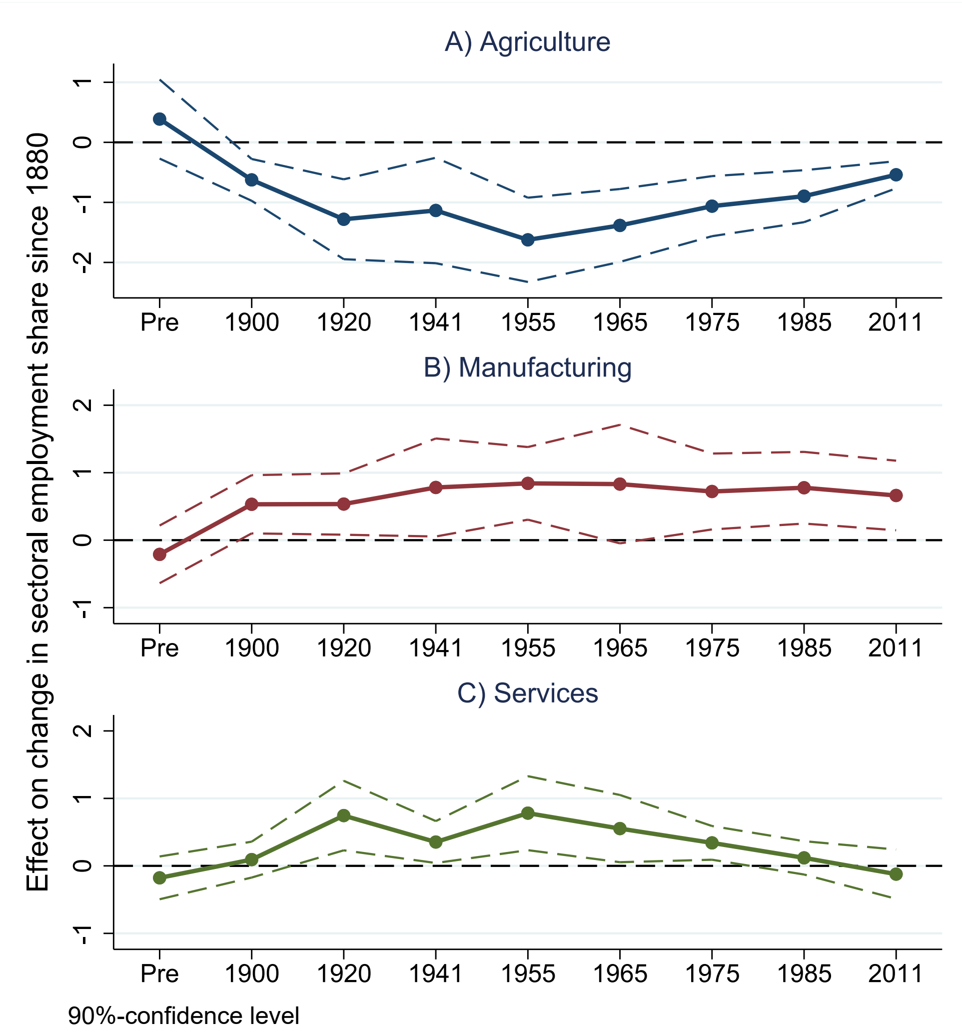
I now turn to my second key question: whether the effect of early adoption of electricity had a long-run effect on economic development. Figure 1.6 presents the IV estimates, based on Equation 1.4, for the effect of early electricity adoption on structural change in the long-run showing. The results highlight that the effect of early electricity adoption on economic development persists up to today.[56] The first-panel presents the coefficient for the effect of the change in electricity 1880-1900 on the agricultural employment share over time. The first two coefficients present the previously presented results for the periods 1860-1880 (pre-period) and 1880-1900 (contemporaneous-period) for comparison. The next coefficients presents the effect for the periods after 1900 with the size of the coefficient continuing to increase in magnitude till 1955. In 1955 the effect of the early adoption of electricity on the agricultural employment share is greatest with the coefficient of -1.624 suggesting a 8.1 percentage points smaller agricultural employment share in a district that experienced a one standard deviation higher electricity adoption 1880-1900. After 1955 the magnitude of the effect declines over time. However, the coefficient for the effect of electricity adoption 1880-1900 is still significant and of economic importance by 2011 as it suggests a 3.3 percentage points lower agricultural employment share for each standard deviation higher exposure to electricity 1880-1900. This suggests a considerable long-run effect of early electricity adoption.

The second panel of Figure 1.6 shows the effect of early electricity adoption on the manufacturing employment share. The coefficients suggest that early electricity adoption strongly contributed to increasing industrialization till the mid-20th century with the effect after this remaining relatively stable till 2011. To illustrate the economic importance, a district which had a one standard deviation higher increase in electricity between 1880-1900 had a 2.7, 3.9, 3.6, and 3.3 percentage point higher manufacturing employment share by 1920, 1941, 1975 and 2011, respectively.[57] This illustrates that the increase in electricity production between 1880-1900 triggered a process of industrialization in districts earlier exposed to electricity that reached its peak only several decades later and considerably contributed to different levels of industrialization across districts more than 100 years later.

[56] Appendix Figure A.7 present the corresponding OLS estimates. These despite being downward biased suggest also a considerable persist effect on structural transformation.

[57] This might appear surprising considering recent de-industrialization in most advanced economies. However, manufacturing still continues to represent a sizeable share of employment in Switzerland today (see Appendix Figure A.14). Further, productivity differences in manufacturing at least across countries appear remarkably stable over time compared to other sectors and economic convergence between countries mainly occurred through shifting labour out of agriculture into services (see e.g. Bernard & Jones 1996; Broadberry 1998). This might help explain why differences across districts persisted even as overall manufacturing employment started to decline, while there appears to be convergence in services employment despite it growing in importance overall.

Figure 1.6: Effect of early electricity adoption on structural change



Notes: The figure presents the IV-estimates for the effect of early electricity adoption per person between 1880-1900 on the change in the employment share across sectors from 1880 to the specified year (1900, 1920, 1941, 1955, 1965, 2011) as well as the pre-trend period 1860-1880. Log waterpower potential per person is used as the instrument. Regressions include the full set of baseline controls and robust standard errors are clustered at the cantonal level. The pre-trend period includes initial controls for the year 1860. The regression for the period 1880-1920 includes a control for the change in electricity produced per person between 1900-20. For the periods 1941, 1955, 1965, 1975, 1985, 2011 the change in the number of waterpower plants is included as an additional control. Each presented coefficient based on an individual regression with 178 observations (Pre-period N=177). Appendix Table A.4 presents the estimated coefficients for electricity adoption 1880-1900 and 1900-t for 1920-2011.

The final panel of Figure 1.6 presents the effect on the service sector. Here, the coefficients suggest a mixed effect, while there is some indication of early electricity adoption having increased the service sector share of employment in some periods the effect varies greatly with regards to the specific time-period and does not seem to be as persistent over time as the effect on the agricultural and manufacturing employment shares.

In general, this pattern is also observed when looking at overall employment across sectors. Areas exposed earlier to electricity continued to experience significantly higher employment growth (decline) in manufacturing (agriculture) throughout the 20th century, and not just a change to the level of industrialization (see Appendix Table A.5) with employment growth rates converging in the late 20th century. Despite the employment share in services converging again in the second half of the 20th century between areas which adopted electricity early and those which adopted electricity later, no corresponding difference in service employment growth is observable after 1920. This seems to suggest that the convergence in the share of service employment in areas that adopted electricity later is mainly driven by the local decline in employment in other sectors rather than actual faster employment growth in services compared to districts that had adopted electricity early.[58]

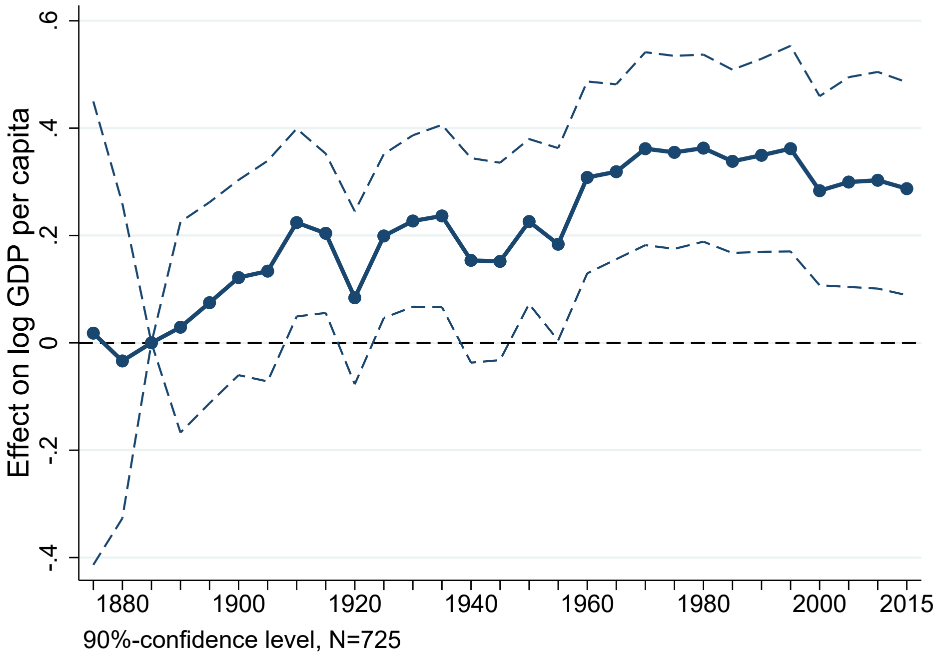
The different ways of measuring here reflect two distinct interpretations of the effect of early electricity adoption on economic development across districts. First, the measure using employment shares reflects differences in economic development across districts for the average person (corresponding to GDP per capita). Second, the measure using employment numbers reflects differences across districts in overall economic activity (corresponding to comparing overall GDP). The difference in estimates suggests that migration and commuting attenuated per capita differences across districts in Switzerland that occurred due to the earlier adoption of electricity in the long-run. Consequently, differences in economic activity per person appear less pronounced than in overall economic activity. Despite this, both the geographic distribution of economic activity as well as the per capita level of economic development continue to be affected by the early adoption of electricity more than 100 years later.

A natural question is whether these long-run differences in economic activity were associated with long-run differences in GDP per capita, as we would expect. No historic information is available for GDP per capita at the district level, so that I use data at the more aggregate Canton level. Figure 1.7 presents the effect of early adoption of electricity 1880-1900 on GDP per capita across cantons 1875-2015. In line with the pattern of structural transformation observed at the district level, GDP per capita increased faster in cantons with higher electricity adoption 1880-1900. The estimates suggest that GDP per capita growth was on average 0.8% higher per year between 1885-1910 in cantons with a standard deviation higher exposure to electricity 1880-1900. Only the first and second World War reversed the divergence in GDP per capita for short periods of time. However, the divergence in incomes continued after these disruptions. Only from the 1970s onwards the income differences stabilized at a relatively constant level that persists up to today.

Further evidence that the early adoption of electricity had a long-run effect on economic development can also be seen in Table 1.6, which presents the effect of the early

[58]Note also that the effect on the local service employment share peaks just as the construction of the Swiss motorway system starts. One interpretation of this is that this allowed services to be easier provided across districts suggesting potential positive economic spillovers from the early adoption of electricity on neighbouring areas, while at the same time attenuating the local estimate.

Figure 1.7: Effect of early electricity adoption on GDP per capita



Notes: The figure presents the IV-estimates for the effect of early electricity adoption per person on log GDP per person across cantons from 1875-2015 (with 5-year intervals). Estimates are based on an event-study, where the explanatory variable is interacted with time fixed effects so that the estimated coefficient can vary over time with 1885 being used as the reference year (the last year with no sizeable electricity adoption). The presented effect size is for a one standard deviation higher exposure to electricity. Canton and time fixed effects are included as well. GDP per person 1890-2000 from HSSO (2012) and after 2000 from BFS (2019). GDP per person 1875-1885 estimated based on changes to per capita tax revenues across cantons from Department des Inneren (1891-1920). N=725 with 25 cantons and 29 time periods.

adoption of electricity on the current level of economic development measured by education and income. First, Panel A column 1 presents the effect on median income in thousand Swiss francs across districts in 2010. Districts which had a one standard deviation higher exposure to electricity between 1880 and 1900 nowadays have a 2127 francs (4%) higher average income. A similar effect size can be observed for median incomes in column 2. A crucial determinant of higher earnings between individuals is usually the level of education Mincer (1974). In addition, secondary and tertiary education are also crucial determinants of future economic growth (see e.g. Goldin & Katz 2001). Accordingly, observable differences in educational outcomes across districts would further support that there is a lasting effect of the early adoption of electricity on economic development. Indeed, districts earlier exposed to electricity also have a higher share of individuals with secondary (column 3) and tertiary education (column 4).[59] Accordingly, in a district with a one standard deviation higher exposure to electricity between 1880 and 1900 the share of the population with at least secondary education is 2.02 percentage points higher and

[59]Secondary education is classified as at least having received the Matura or vocational training, while tertiary education is having received a degree from a university or technical college.

Table 1.6: Effect of early electricity adoption on current outcomes

	Income		*Education*	
A. Districts	*Average* (1)	*Median* (2)	*Secondary* (3)	*Tertiary* (4)
Δ Electricity pp 1880-1900	42.543*	26.922*	0.405***	0.196***
	(25.777)	(14.460)	(0.146)	(0.036)
Controls	Yes	Yes	Yes	Yes
N	178	178	178	178
B. Cantons				
Δ Electricity pp 1880-1900	233.3	224.1**	1.326+	0.863*
	(183.1)	(95.24)	(0.981)	(0.482)
Region FE	No	No	No	No
Other controls	Yes	Yes	Yes	Yes
N	25	25	25	25

Notes: The regressions present the IV results for the effect of electricity adoption between 1880-1900 on the level of modern development. Column 1 and 2 presents the effect on average and median income in thousand Swiss francs across districts in 2010. Column 3 and 4 presents the effect on the share of individuals with secondary and tertiary education in 2000, respectively. Panel A presents the effect across districts and Panel B presents the corresponding results across Cantons. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the share of tertiary education is 0.98 percentage points higher. Panel B presents the corresponding estimates at the Cantonal level. The estimated effects are considerably larger in magnitude. This again suggests that the observed local effect might be attenuated by spillovers through commuting and migration in the long-run, which plays less of a role the larger the geographic area of analysis.

Two features are crucial to be able to conclude that the effect is only from exposure in the initial 20 years of electricity adoption. First, the extension of the electricity grid across Switzerland rapidly equalised the use of electricity across districts after 1900. Access to electricity of firms in Switzerland rose from 5% in 1895 to 43% in 1911, and 94% in 1937 (see "Elektrifizierung" in HLS 2020). So while there was some initial difference in access to electricity across Switzerland, access to electricity rapidly became universal after 1900. Universal access might however still not be sufficient to support that the effect was only due to initial differences as areas that adopted electricity early might have continued to use electricity more intensively even after the extension of the electricity grid.[60] Table 1.7 analyses this formally, starting in Panel A by looking at the usage of electricity in factories in 1929. The effect of early adoption on electricity usage later on is shown in total kW (column 1), kW per firm (column 2) and kW per employee (column 3). In the first two cases a positive coefficient is observable, however per employee actually less

[60] Comin & Mestieri (2018) show that not just differences in the timing of adoption of new technologies, but also the intensity of use, account for a large share of the observed differences in incomes across countries.

electricity appears to be used, and all effects are insignificant.[61] This is further confirmed by Panel B showing that there is no considerable difference in electricity usage across all manufacturing and services firms also by 1955. These results suggest that the extension of the electricity grid in the early 20th century lead to a convergence in electricity usage between districts by at least the 1930s.

Second, one might be concerned that the persistent effect is mainly due to later increases in electricity generation which are correlated with the early adoption of electricity. For example, in France steam engines were more intensively adopted close to their first adoption in Fresnes-sur-Escaut (see Franck & Galor 2019). Importantly, due to controlling for the building of waterpower plants after 1900, the presented effect is purely from the early adoption of electricity, but not from future extensions in electricity generation that might be correlated with the initial adoption. This post-1900 increase in electricity generation also had a positive effect on industrialization itself (see Appendix Table A.4).[62]

Table 1.7: Effect of early electricity adoption on long-run electricity use

	Electricity use in kW per		
	District	Firm	Employee
A. 1929	(1)	(2)	(3)
Δ Electricity pp 1880-1900	6017.18	141.92	-6.92
	(8775.68)	(526.02)	(15.90)
B. 1955			
Δ Electricity pp 1880-1900	20655.16	25.24	-0.45
	(30241.94)	(38.77)	(7.03)
Controls	Yes	Yes	Yes
N	178	178	178

Notes: The regressions present the IV results for the usage of electricity in total, per firm and employee in 1929 and 1955. For 1929 the outcome measure includes only factories (Panel A), while for 1955 it covers all manufacturing and services (Panel B). In 1929, 5 districts report zero factories which are treated as missing values. The 1929 data only reports total energy used at the district level and measures were adjusted based on the usage of electricity versus other sources at the cantonal level. Notably, already 87.4% of the energy used in Swiss factories was reported as being electric in 1929 (451640kW electric of 516457kW in total). Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[61] The numbers in column 1 and 2 are also small in economic terms considering that electricity generation increased by 1571% from 119350kW in 1900 to 1994067kW in 1930 (see Figure **??**). So that the estimated effect from average early electricity adoption explains only about 1.5% of average electricity generation across districts in 1929 (corresponding to the higher manufacturing employment share, but not higher per capita electricity usage).

[62] Appendix Table A.4 highlights that electricity generation after 1900 had an effect on economic development as well and if not controlled for the effect of early electricity adoption on structural change would have falsely been estimated to be about 10%-20% larger across most results (see Appendix Figure A.8). However, in line with the rapid extension of the electricity grid across Switzerland, the effect of waterpower plants build for electricity generation after 1900 only increased employment in electricity generation itself (see Appendix Table A.7) and had no positive effect on other industries.

1.4.3 Decomposition of effect across industries

Table 1.8 analyses which industries are responsible for the observed persistent increase in employment in the manufacturing sector. Note, that the measured employment by industry here is based foremost on occupation rather than firm.[63] This provides two insights: First it allows to distinguish whether the adoption of electricity affected mainly industries associated with the generation of electricity or those that used electricity. Second, it highlights which industries were the ones that gained from the adoption of electricity. I focus on 7 consistently reported manufacturing industries "Electricity generation", "Construction, wood & stone products", "Machinery, watches, & other metal", "Chemicals", "Textiles & apparel", "Food products", and "Other". First, "Electricity generation" represents the direct rise in employment that is required for the generation and transmission of the electricity itself. The next two groups "Construction, wood & stone products" and "Machinery, watches, & other metal" are related on one hand to electricity generation through the need for building the electricity infrastructure and providing water-turbines. However, the latter were relatively easy to transport and did not necessarily need to be constructed locally.[64] On the other hand, these industries might also have been affected through using electricity. The remaining four industry groups use electricity, but are not related to its generation in any straightforward way. Panel A presents the effect of electricity in the contemporaneous period 1880-1900, Panel B presents the effect for 1880-1920, and Panel C for 1880-1975.

Column 1 presents the effect of the adoption of electricity on the change in employment share in occupations in the "Electricity generation" industry. Unsurprisingly, the adoption of electricity increased employment in its generation and distribution by 1900. Notably, the effect persists over time, which suggests that the electricity generation infrastructure continues to be in operation even after 1900. Column 2 shows that there is also a positive employment effect on "Construction, wood & stone products" for 1880-1900. This accounts for most of the employment gains in manufacturing between 1880-1900, which suggests a important short-term employment effect of electricity adoption likely through

[63]The enumeration in the historic Swiss censuses to industries is based foremost on main profession and the type of product produced by an individual rather than the industry of the firm. This means that for example in a firm that produced chemical products and also generated its own electricity, a part of this firm's employment was recorded as chemical industry employment and another part as electricity generating industry employment. For example Bundesamt für Statistik 1900, Volume 3, p.1-5 provides a detailed description of the enumeration system used. Bundesamt für Statistik 1920, Volume 3, p.31-34 provides a cross-tabulation of the employment in industries based on occupation versus firm for 1910. In general there is considerable overlap, but for example for "Electricity generation" the employment by occupation (5321) is about twice as high as by firm (2649) suggesting considerable employment of workers focussing on electricity generation within firms that specialise on producing different goods.

[64]That water-turbines were built somewhere else and transported to the site of usage is also underlined by the machinery industry having mostly developed beforehand in close proximity to the existing textile industry and that water-turbines accounted for 9% of Swiss exports in 1900 (see "Turbinen" and "Maschinenindustrie" in HLS 2020).

Table 1.8: Effect of electricity across manufacturing industries

	Generation	Mixed		Use of electricity only			
	Elec.	Con.	Mach.	Chem.	Text.	Food	Other
A. 1880-1900	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Electricity pp 1880-1900	0.037**	0.378*	-0.006	0.102**	0.135	-0.078***	-0.036
	(0.017)	(0.205)	(0.074)	(0.041)	(0.156)	(0.029)	(0.041)
B. 1880-1920							
Δ Electricity pp 1880-1900	0.066***	-0.009	-0.077	0.114***	0.354*	-0.067	0.105+
	(0.011)	(0.077)	(0.119)	(0.043)	(0.211)	(0.062)	(0.071)
C. 1880-1975							
Δ Electricity pp 1880-1900	0.138***	-0.174	-0.790***	0.604**	1.194***	-0.093	-0.156+
	(0.035)	(0.203)	(0.223)	(0.278)	(0.398)	(0.099)	(0.108)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	178	178	178	178	178	178	178

Notes: The regressions present the IV results for the effect of electricity on the change in the share of employment across manufacturing industries 1880 to 1900, 1920 and 1975. Log waterpower potential per person is used as instrument for the change in electricity produced per person between 1880 and 1900. The change in electricity produced per person 1900-1920 and waterpower plants built 1900-1975 are included as additional controls, respectively. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the requirement to construct the new generation and distribution infrastructure.[65] However, this effect is only short-lived as after construction finished the positive employment effect disappeared and no effect is observable by 1920 or 1975. Column 3 suggests that there is no local effect on employment in "Machinery, watches, & other metal". This is unsurprising as turbines were usually constructed somewhere else and transported to waterpower plants rather than produced locally. These three effects combined can be seen as the upper-bound of the direct effect of electricity generation on manufacturing employment. Together Column 1-3 explain most of the change in the manufacturing employment share in the short-run, but cannot explain the persistent effect observed by 1920 and 1975.

Column 4 presents the effect of early electricity adoption on employment in "Chemicals". This effect increases over time and explains 19%, 22%, and 83% of the higher manufacturing share by 1900, 1920, and 1975, respectively. This underlines the role of electricity in the establishment of the newly emerging chemical industry across Switzerland. The importance of electricity in new chemical production processes is presented in detail in Section 1.2.

The earlier ability to use electricity appears to not just have contributed to the emergence of new industries, but also made existing ones more competitive. This is suggested by column 5 as employment in "Textiles & apparel" was positively affected from 1920

[65] The observed effect might of course to some extent also be due to the building and extension of factories in other industries that use electricity.

onwards.[66] The use of electricity in the textile industry appears to have been especially beneficial for small scale producers and provided new prospects for the mechanization of certain production processes (Stiel 1933). First, this highlights that at least locally electricity as a technology did not lead to the replacement of workers in the textile industry and rather increased employment. Second, the positive effect here should be seen as slowing the decline of the textile industry and supporting the shift into new higher value products rather than necessarily creating new employment as overall the importance of the textile industry in Switzerland peaked in the late 19th century and declined after that (rising from 15% of total employment in 1860 to 19% in 1880 and declines to 18% in 1920 and 4% in 1975). By 1975, the remaining employment in the Swiss textile industry was in innovative firms, which produced specialised products (industrial textiles for cars and planes, medical textiles, heat and other resistant textiles etc.) and no longer bulk goods (see "Textilindustrie" in HLS 2020). Column 6 highlights that in line with the decline in agricultural employment also employment in "Food products" (predominantly the making of cheese and meat products) declined. However, employment recovered afterwards to some extent. This likely reflects that some workers moved from agriculture and food processing into construction, but returned afterwards. Column 7 highlights there is little effect on other industries.

The presented results suggest that the long-run effect of the early adoption of electricity on manufacturing employment was mainly from its use rather than its generation. By 1975, the employment growth in manufacturing observed is mostly due to a persistent effect of the early adoption of electricity on employment in "Chemicals" and "Textiles & apparel", and to a smaller extent in "Electricity generation" (the employment effect is less than a tenth in the other two). In all other industries lower employment is observed (with a significant decline for "Machinery, watches, & other metal"). This decline likely reflects increasing industrial specialization in the second half of the 20th century as most surplus labour had already left agriculture (see Appendix Figure A.14). Accordingly, the overall manufacturing employment share could no longer easily expand, but rather an internal reallocation in employment had to occur from the least competitive to most competitive manufacturing industries.[67]

[66] Appendix Table A.6 highlights that this is also reflected in female employment growth between 1900-1920 that made up most of the workforce in "Textiles & apparel". In contrast, male employment growth stagnated after 1900. This suggests that workers in "Construction, wood & stone products", predominately male, likely returned to their previous occupations in agriculture and food processing after 1900, rather than obtained employment in textile industries with the employment growth here likely being due to women newly entering the labour market.

[67] Notably, the persistent higher employment share in "Textiles & apparel" might also be interpreted as a technological lock-in of districts in less modern industries (compared to "Machinery, watches, & other metal") for a part of industrial employment. However as shown, the overall impact of the early adoption of electricity was clearly positive, which does not support that higher employment in these industries leads to districts earlier exposed to electricity having a lower overall productivity.

Employment numbers vary considerably across those industry groups, so that while the presented coefficient provide direct insight on the contribution of the respective industry group to the overall increase in manufacturing employment, it does not reflect the importance of the early adoption of electricity within the respective industry group. The average adoption of electricity 1880-1900 explains 27.1% (28.1%) of employment in "Electricity generation", 6.6% (-2.2%) in "Construction, wood & stone products", 46.8% (78.2%) in "Chemicals" and 1.5% (62.4%) "Textiles & apparel" across districts by 1900 (1975).[68] This suggests that the majority of the spatial distribution of chemical industries (and the survival of textile industries) across Switzerland is explained by the early adoption of electricity, which again underlines the influence the early adoption of new technologies can have on economic activity even several decades later.

1.5 Mechanisms

1.5.1 Implausible mechanisms

There are a number of potential mechanisms which might explain the persistent effect of early electricity adoption on economic development. However, on the basis of previously presented results a number of them can already be ruled out. The first potential mechanism that seems implausible is that the divergence in economic development is driven by persistent differences in electricity generation across districts. While there is a persistent effect of early electricity adoption on employment in electricity generation, the effect is economically small compared to the persistent employment effect on industries that only gained from the use of electricity (see Table 1.8).

The second potential mechanism that seems implausible is that differences in the use of electricity persisted even after the electricity grid extended across the whole of Switzerland. However, results in Table 1.7 show that, by 1929, early adoption of electricity had no significant effect on electricity use.

The third potential mechanism often able to explain persistence of differences in economic development even after initial advantages disappear is population or industry agglomeration due to sizeable economies of scale (see e.g. Krugman 1991; Bleakley & Lin 2012). However, again some of the already presented results appear to provide little support for this mechanism. First, there is no evidence of population growth as there is no increase in migration into areas that adopted electricity early (see Table 1.4). Instead local employment growth appears driven by successive increases in male and female labour

[68] Appendix Figure A.9 presents the corresponding employment shares for industries in 1860, 1900 and 1975. That the adoption of electricity explains only 27.1% of employment in electricity by 1900 likely reflects that employment is related to the number of waterpower plants rather than the electricity generated as larger ones generated a multiple of the energy of small ones while employment was rather similar. This is also why number of waterpower plants build is used as control after 1920, when electricity generation and use were definitely no longer correlated.

force participation (see Appendix Table A.6). Further, even the observed employment growth starts to slow after 1900, rather than accelerate over-time as in Bleakley & Lin (2012). Second, while the presented growth pattern of the newly developing chemical industries (see Table 1.8) would be in line with increasing returns to scale and a cumulative process of local industry development due to a historical accident —the early adoption of electricity— as highlighted by Krugman (1991). The increased survival of employment in the textile & apparel industries, which peaked in importance by 1880, in locations that adopted electricity earlier cannot be explained by this. This as well as the fact that geographic constraints meant that early electricity adoption occurred to a large extent in remote areas of Switzerland, i.e. with a initial low population density and high transport costs, suggests that increasing returns to scale do not provide a satisfactory explanation for the persistent effect of the early adoption of electricity on economic development.

1.5.2 Human-capital accumulation

The evidence so far suggested that persistent differences in the use of electricity or population agglomeration are implausible mechanisms for explaining the persistent effect of the early electricity adoption on economic development. Instead, I suggest that human capital accumulation and innovation are more plausible explanations for the long run effect of the early adoption of electricity. Recent contributions in growth theory suggest that technical change can increase human capital formation (see e.g. Galor & Moav 2006; Galor 2011),[69] which in turn is a main driver of economic growth (see e.g. Romer 1990; Goldin & Katz 2001). Notably, Table 1.6 already suggested higher levels of education today in districts that adopted electricity earlier. However, for this to be a crucial mechanism, there needs to be evidence of an immediate change in human-capital accumulation when electricity is adopted. I provide three pieces of evidence consistent with the hypothesis that the early adoption of electricity had effects on human capital formation and innovation. First, I show that educational outcomes immediately started to improve. Second, I show that the education system as well as demand for it increased. Third, I show that this translates into a higher level of innovation today.

Table 1.9 studies how the early adoption of electricity influenced educational outcomes measured through military test scores. Conscription was nationally organised since 1874, covering the whole male Swiss population so that military test scores reflect the education level at age 19 across different districts. Importantly, the test scores at the district level are based on the location of the primary school a recruit had visited as it was common at the time in Switzerland to migrate for secondary schooling. Here, the top-mark received closely relates to educational attainments at the secondary level of schooling rather than

[69]The mechanism in Galor & Moav (2006) is that the process of industrialization and the complementarity between capital and human capital lead to increasing support for the provision of public education that benefited both capitalists and workers.

primary schooling, while the worst two marks correspond to insufficient knowledge even at the level of primary schooling.[70] Two exemplary maths questions highlight the level of knowledge evaluated. For the lowest mark one needed to fail simple questions evaluating the ability to add and subtract, e.g.: "An army division counts 538 officers and 10472 soldiers. How many men in total?", while to receive the top-mark one needed to answer complex multi-part questions, e.g.: "Someone obtained a loan of 2160 Francs with $4\frac{1}{2}\%$ interest. He paid back 2207.25 Francs for capital and interest. How many days did the loan last?"

Table 1.9: Effect of electricity on human capital accumulation

	Overall	Reading	Writing	Math	General
A. Secondary education 1880-1900	(1)	(2)	(3)	(4)	(5)
Δ Electricity pp 1880-1900	0.530*	0.476+	0.667**	0.064	0.713**
	(0.306)	(0.351)	(0.338)	(0.358)	(0.310)
B. Secondary education 1880-1910					
Δ Electricity pp 1880-1900	0.932**	0.677*	0.784*	1.178*	1.089**
	(0.449)	(0.353)	(0.404)	(0.696)	(0.449)
C. Primary education 1880-1900					
Δ Electricity pp 1880-1900	0.088	-0.353**	0.154	0.037	0.310
	(0.316)	(0.178)	(0.460)	(0.327)	(0.612)
D. Primary education 1880-1910					
Δ Electricity pp 1880-1900	0.158	-0.259+	0.246	0.517	0.129
	(0.232)	(0.168)	(0.341)	(0.479)	(0.314)
Controls	Yes	Yes	Yes	Yes	Yes
N	178	178	178	178	178

Notes: The regressions present the IV results for the effect of electricity from waterpower on the change in the share of top marks received (corresponding to a secondary level of education) and share of passing marks (corresponding to basic primary education) across different subjects 1880 to 1900 and 1910. Marks are given between 1 and 5, with 1 being the best mark and 5 the worst (both 4 and 5 constitute a fail). Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A presents the effect on the share of top marks given to military recruits across four different subjects between 1880 and 1900. Column 1 shows the effect across all marks with there being a positive effect of electricity adoption on the share of top marks received. A standard deviation higher adoption of electricity increased the share of all top marks received by 2.7 percentage points. Column 2-5 provide the breakdown by the different subject areas tested. Column 2 presents the effect on reading scores, column 3 on writing, column 4 on maths and column 5 on general knowledge covering Swiss geography, history and politics. Reading was the easiest subject with 32% receiving the highest possible

[70] Only 8 out of 100 tested that only attended primary schooling received the top mark, while 65 out of 100 did so that attended secondary schooling. 20 out of 100 tested, which only visited a primary school, received a 4 or 5 constituting a failure to complete rudimentary tasks in the subject area, while non that attended secondary education did.

mark in a subject, while general knowledge was the hardest subject with only 17% of tested recruits receiving the highest mark. Between 1880 and 1900 the overall effect is mainly driven by improvements in writing and general knowledge test scores. However, educational improvements will not immediately be fully observed as military recruits aged 19 were likely only affected by changes in the latter years of schooling.

Panel B looks at the period 1880-1910 reflecting the effect on educational outcomes a decade later. Column 1 shows that the effect nearly doubled with a standard deviation higher adoption of electricity leading to a 4.7 percentage point increase in top test scores. By 1910, the largest improvement was in maths scores, while reading improved the least. The result suggests the greatest improvement in educational outcomes occurred in the more complex subjects, which at the time represented upper-tail human capital.[71] Further, Panel C and D highlight that there is no comparable improvement at the primary level of knowledge, basic reading ability appears to have even declined briefly.[72] These considerable improvements in the share of well educated recruits across different subjects provides some evidence towards human capital being a plausible mechanism for explaining the persistent effect of the early adoption of electricity over time.

The second piece of evidence comes from the education system. In particular, the Swiss dual education system seems a plausible driver of the observed improvement in secondary education outcomes as it provided practical and theoretical knowledge specific to occupations and industries in part funded by employers.[73] Table 1.10 looks at the effect of the early adoption of electricity on students in dual education in 1910 (Panel A) and newly established schools 1880-1910 (Panel B) based on the list of year-round operating schools reported in Grob (1887-1914). The effect is presented across all dual education, vocational schools at the secondary level of education, and polytechnic university departments at the tertiary level of schooling. Column 1-3 look at the effect across all districts for all dual education (Column 1), vocational schools (Column 2) and polytechnic universities (Column 3). Nearly no improvement in the dual education system is observable across these specifications. However, this might not be so surprising as districts with a small population usually had no dual-education institution of their own as they would be underutilized, so instead it was common for students to temporarily migrate for the purpose of schooling.[74] For this reason, I focus on districts with above average population

[71] The educational improvements associated with the adoption of electricity appear far broader than the limited (or even negative) effects found for the adoption of the steam engine in terms of working skills and literacy rates (see e.g. De Pleijt et al. 2020; Franck & Galor 2019).

[72] One explanation for this could be that some children in agricultural families, where child labour was still common at the time (see "Kinderarbeit" in HLS 2020), had less time to school as their labour needed to compensate for adult male workers that moved into manufacturing 1880-1900.

[73] The long-term income gains from vocational training in developed countries today have been highlighted for example by Neuman & Ziderman (1991). This type of education also provides exactly the kind specific training a labour force requires to utilize new technologies and therefore is critical in the diffusion of technology (Rosenberg 1972).

[74] The 1880 Census records nearly 1% of the population as pupils living outside their parents house.

in Column 4-6. Here a clear positive effect of the early adoption of electricity on number of students and newly established dual education institutions is observable in Column 4. The estimated effect suggests that the average exposed district had 115 additional students and 0.6 newly established education institutions in 1910. A considerable increase considering the rarity of these upper-tail educational institutions. Column 5 suggests that the increase in students in 1910 was nearly completely from an increase in vocational schooling at the secondary level of education, and that this increase in student number is at least in part through the establishment of new vocational schools. In contrast, Column 6 suggests that there is little increase in students in polytechnic universities, however an increase in the number of departments is observed, suggesting a reorganization rather than an extension of education.[75]

Further evidence on how the early adoption of electricity affected the education system is provided by Switzerland's direct democracy, which offers a unique opportunity to investigate individuals' historic support for the provision of government funded education. Table 1.11 Panel A presents the effect of early electricity adoption on support in referendums focussed on increasing government spending on education and science. Column 1-6 show that areas earlier exposed to electricity persistently displayed higher support for government spending on education and research in the six referendums on this issues between 1902 and 1978. A standard deviation higher early adoption of electricity increased support for government funded education by as much as 9%. These national referendums of course did not necessarily lead to improved local education, but they suggest that individuals in districts that adopted electricity earlier valued education more highly, which in turn likely led to higher individual and municipal investments into education. Indeed, national influence on education policy was low far into the 20th century so that local policy decisions where likely much more crucial for the provision of education. Some evidence for this is observable in increased municipal and cantonal spending, in particular for secondary education, across cantons (see Appendix Table A.8).

The third piece of evidence is that innovation persistently increased. This is one way through which human capital allowed manufacturing to persistently remain competitive and expand by consistently driving the development of new products. To evaluate this, I use data on geo-coded patents from De Rassenfosse et al. (2019) covering Swiss patents registered since 1980. Table 1.12 column 1 presents the effect of the early adoption of electricity on number of patents per inhabitant that have been registered over the last 40 years, which indeed suggests a higher level of innovativeness in areas that early adopted electricity. The estimate suggests that a district characterized by a one standard deviation

[75]The latter effect appears to be driven in particular by the establishment of four new departments at the polytechnic university in Geneva, which however had considerably less students by 1910 than earlier established ones.

Table 1.10: Effect of electricity on dual education institutions

	All districts			Population centres		
	Dual	Voc.	Poly.	Dual	Voc.	Poly.
A. Students	(1)	(2)	(3)	(4)	(5)	(6)
Δ Electricity pp 1880-1900	0.717^{+}	0.375	0.343^{+}	5.737^{**}	5.345^{**}	0.392
	(0.531)	(0.356)	(0.222)	(2.450)	(2.458)	(1.654)
B. Schools						
Δ Electricity pp 1880-1900	2.183	0.395	1.787	28.576^{**}	10.891^{*}	17.684^{**}
	(2.342)	(1.070)	(1.475)	(11.271)	(6.502)	(7.593)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	178	178	178	63	63	63

Notes: The regressions present the results for the effect of electricity on the provision of dual education. In both secondary-level vocational schools and tertiary-level polytechnic university that operated throughout the whole year. Panel A presents the effect on number of students in thousands by 1910. Panel B on the establishment of new vocational schools and polytechnic university departments 1880-1910. Results are presented for all districts as well as for population centres only. Vocational schools comprise professional ("Berufsschulen"), craft ("Handwerksschulen"), and commercial schools ("Handelsschulen"). The category of polytechnic universities (by department if reported) also includes all design schools ("Zeichnungsschulen" training architects, designers, etc.) which in some cases, but not always are parts of polytechnic universities. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Effect of electricity on education and infrastructure demand

	1902	1963	1964	1973	1973	1978
A. Support education	(1)	(2)	(3)	(4)	(5)	(6)
Δ Electricity pp 1880-1900	0.940^{+}	0.168^{+}	0.483^{***}	1.790^{***}	1.256^{***}	1.171^{***}
	(0.667)	(0.117)	(0.131)	(0.674)	(0.304)	(0.274)
	1877	1891	1897	1927	1945	1987
B. Support infrastructure	(7)	(8)	(9)	(10)	(11)	(12)
Δ Electricity pp 1880-1900	-0.696	-0.608	0.091	0.483^{*}	1.178^{***}	1.699^{***}
	(0.605)	(0.547)	(0.703)	(0.265)	(0.361)	(0.411)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	178	178	178	178	178	178

Notes: The regressions present the results for the effect of early electricity adoption on the pro-votes in Swiss referendums on central government education and research spending in Panel A and infrastructure spending in Panel B. The referendums used are reported in detail in Appendix Table A.10. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

greater early electricity adoption registered 28% more patents per person.[76] Column 2 and 3 look at patents before and after 2000 suggesting that the rate of patenting remained stable and that there is no convergence across Switzerland in patenting. Column 4, 5

[76] A one standard deviation higher exposure to early electricity adoption leads to 6 more patents per 1000 inhabitants since 1980 with the corresponding average number of patents being 21 per 1000 inhabitants suggesting that innovation increased by 28%.

Table 1.12: Effect of early electricity adoption on innovation today

	All patents (1)	Before 2000 (2)	After 2000 (3)	City (4)	Town (5)	Rural (6)
Δ Electricity pp 1880-1900	0.111***	0.053***	0.057***	0.003	0.042**	0.066**
	(0.033)	(0.016)	(0.021)	(0.009)	(0.020)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	178	178	178	178	178	178

Notes: The number of patents registered (1980-2017) per person (population in 2000) across Swiss districts using data from De Rassenfosse et al. (2019). Municipalities are classified based on 2000 population as city if more than 25000, town 10000-25000 inhabitants and rural less than 10000 inhabitants. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and 6 breaks the patenting down on whether the inventor was located in a city (>25000 inhabitants), town (10000-25000) or in a rural municipality with a population of less than 10000. The results suggest that early adoption of electricity mostly increased innovation in more rural areas. This would suggest that electricity at the end of the 19th century spread out innovation activities across Switzerland away from urban centres that usually are the main drivers of innovation to rather less densely populated areas. While it is impossible to evaluate the level of innovation in these areas in 1880 as no patent law existed in Switzerland at that time, it appears clear that these areas were not technologically leading at the international level at the end of the 19th century. This suggests that adoption of electricity allowed these areas to leapfrog to the forefront of innovation (see e.g. Brezis & Krugman 1997).

1.5.3 Infrastructure network

The evidence presented highlights the key role played by human capital formation and innovation in leading to persistent differences in economic development. However, the rather random nature of the early adoption of electricity across Switzerland, which was related to randomly located geographic characteristics rather than previous economic activity raises the question on how this high level of industrial specialization and innovativeness was feasible? In general, one would expect that high trade costs in these remote location should make high-levels of specialization in manufacturing and innovation unfeasible (see e.g. Eaton & Kortum 2002). One way in which this paradox can be resolved is that the infrastructure network adjusted to the early adoption of electricity reducing trade costs.[77] I evaluate this in Table 1.13 by looking at the level of integration of districts into the Swiss railroad network today (accounting for about a third of transported goods and people).

[77]This also seems of particular interest as for developing countries today it appears that big infrastructure investments only have a positive effect on industrialization when these are combined with access to electricity (see Moneke 2019).

Column 1 looks at the number of operation points, location where loading and off loading occurs, measuring the density of the railroad network. The benefit of this is that it not just measures whether a railway line passes through an area, but also if there is actual activity along the line. The coefficient suggests that the number of operation points per square kilometre is 23% higher in areas that had a standard deviation higher exposure to electricity between 1880 and 1900. Next, column 2 looks at the number of tunnels build. This provides a good proxy of how expansive the construction of infrastructure was in those areas as tunnels are the main cost factor per kilometre of railroad lines in Switzerland. Indeed more costly infrastructure investment was undertaken in districts adopting electricity earlier. Column 3 presents number of passengers per inhabitant today. Again a positive effect is observed.

This complementary role of infrastructure developments is further supported by Panel B of Table 1.11, which looks at the effect of early electricity adoption on support for government spending on infrastructure in referendums (1877-1987). The estimates suggest that there was no difference in demand before and during the period in which districts had an advantage in the adoption of electricity, but demand for infrastructure increased immediately after this advantages started to disappear in the early 20th century and persisted after that. In 1987, a one standard deviation higher exposure to electricity increased support for "Rail 2000", a major project of railroad improvements, by 8.5%. Accordingly, districts that adopted electricity earlier were able to become well integrated in the exchange of goods and knowledge. Here, of course Switzerland's unique geographic position in the centre of Europe might have been of crucial importance in allowing this. This observed improvement in infrastructure seems to be able to resolve the paradox that rather rural areas can have highly specialized firms and high rates of innovativeness. The presented increase in human capital and innovation in combination with this complementary change in connectivity provides a coherent explanation for how differences in economic development that emerged due to different electricity adoption for only 20 years continued to persist in the long-run despite electricity becoming adopted universally.

Table 1.13: Effect of early electricity adoption on the infrastructure today

	Operation points (per km^2) (1)	Tunnels (per km^2) (2)	Train journeys (per person) (3)
Δ Electricity pp 1880-1900	0.262*	0.056*	3.762***
	(0.151)	(0.030)	(1.253)
Controls	Yes	Yes	Yes
N	178	178	178

Notes: Swiss railway operation points on line as of 2020, tunnels as of 2019, passenger numbers as recorded at train stations in 2018. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6 Conclusion

This chapter documents that the early adoption of electricity between 1880-1900 persistently increased industrialization and incomes across Switzerland, even though differences in its use quickly disappeared due to the rapid extensions of the electricity grid after 1900. The persistently higher level of industrialization is related to the establishment of the chemical and pharmaceutical industry across Switzerland, which required electricity for many novel production processes, where the early adoption of electricity can explain a majority of the distribution of employment observed by 1975. In addition, in areas that adopted electricity early the textile industry, the pre-eminent industry by 1900, was more likely to outlast increasing competition during the 20th century.

Human capital accumulation and a complementary adjustment in the infrastructure network appear to be important mechanisms for the persistent divergence in economic development due to the early adoption of electricity. So that, areas earlier adopting electricity remained more innovative up to today. In contrast, electricity itself does no appear to be an important mechanism. Differences in the use of electricity quickly disappeared as the electricity grid expanded and persistent differences in electricity generation are small in terms of economic importance. Further, at leat initially no in-migration appears to have occurred suggesting suggesting that the change in the economic structure occurs internally.

To obtain these results I exploit exogenous variation in the potential to produce electricity from waterpower across Switzerland to deal with the issue that electricity adoption could be driven by economic considerations at the time. These initial geographic constraints on the adoption of electricity led to its early adoption not just in urban centres, where new technologies are usually first adopted, but equally in rural and remote areas. This is important as it highlights that early exposure to new technologies can foster economic development not just in urban centres, but also in rural areas. It also underlines that certain geographical features can have a lasting effect on economic development despite being relevant only for a short period of time.

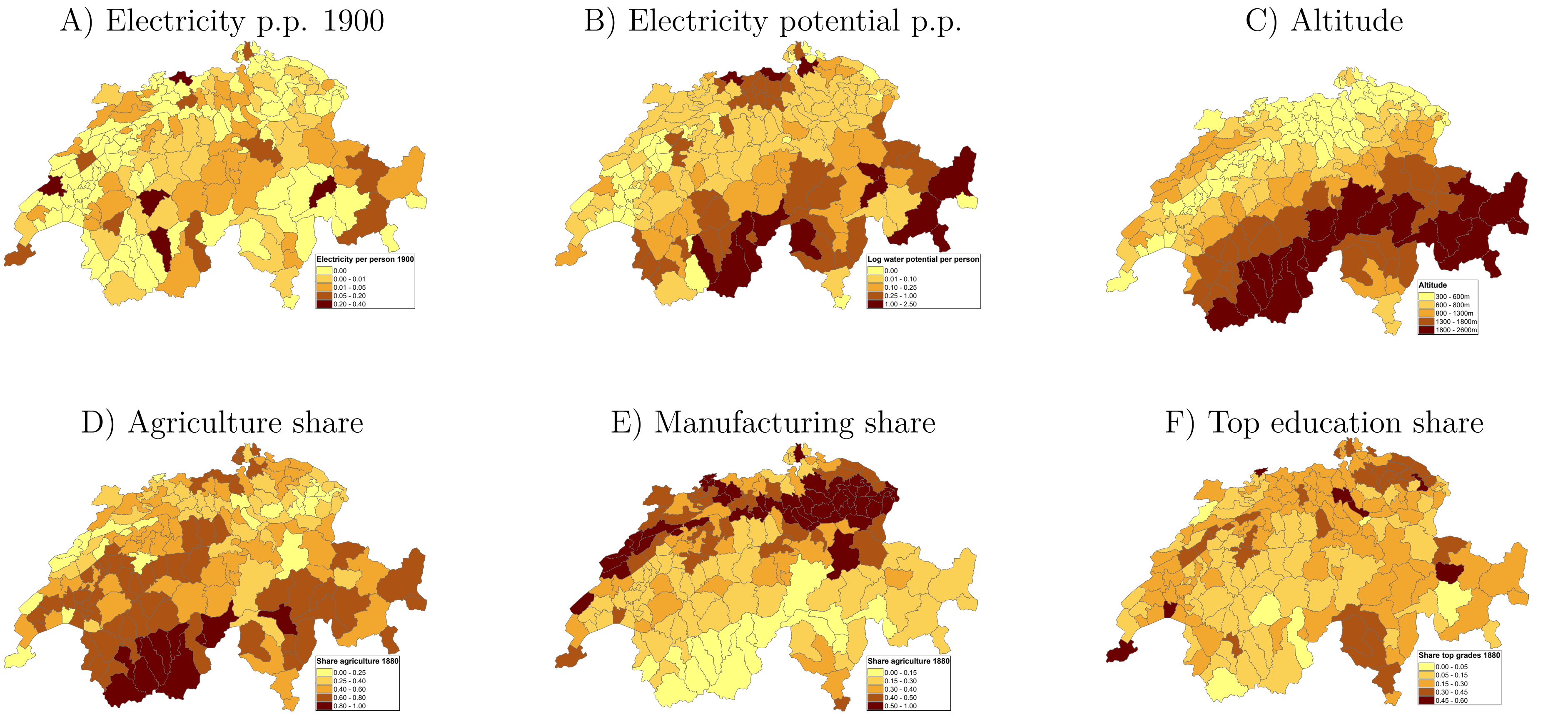
These results help explain how some countries were able to develop and retain their economic lead, when exposed to new technologies early. It also highlights that long run gains of new technologies might be quite heterogeneous with electricity having been far more beneficial compared to the steam-engine (see Franck & Galor 2019). Further, it highlights that countries might gain considerably from attracting skill-biased technologies and industrial sectors through positive externalities on human capital accumulation. It however also cautions that new general-purpose technologies like information and computer technologies might have long lasting positive and negative effects far beyond disruptions caused in the labour market during their implementation.

Appendix Chapter 1

A Additional Information

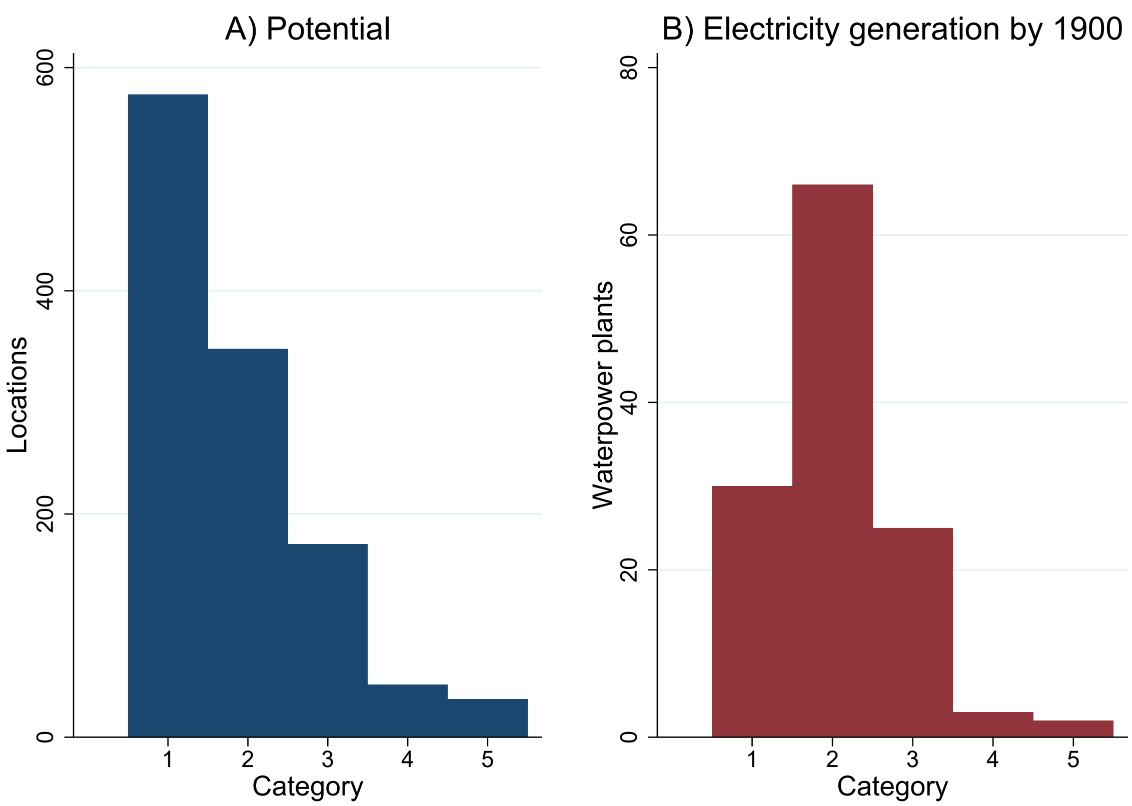
A.1 Figures

Figure A.1: Descriptive maps for Switzerland



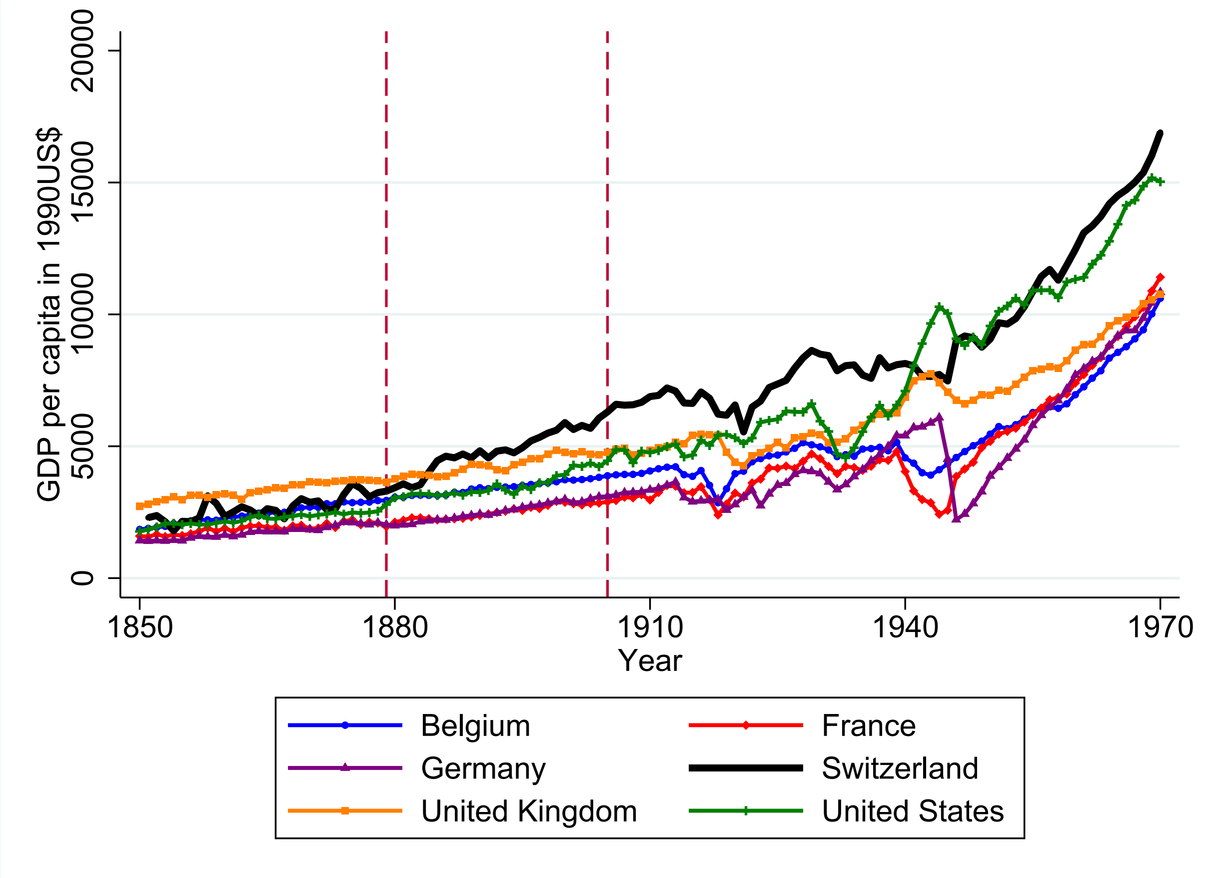
Notes: The figures depict A) kW of electricity per person in 1900, B) log water power potential, C) altitude, D) agricultural employment share in 1880, E) manufacturing employment share in 1880, and F) share of top marks in military education tests in 1880. More detail available when zooming into the respective figure.

Figure A.2: Size of potential and actual electric power plants



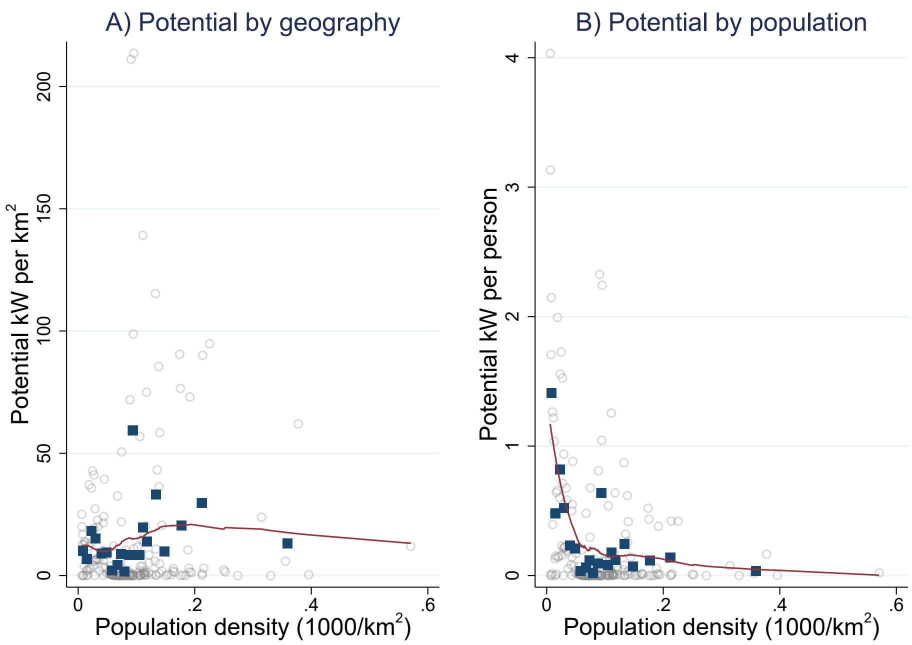
Notes: The histogram shows the number of potential and build water-power plants generating electricity in 1900 by size in Switzerland as reported in Bossard (1916). The 5 categories are: (1) 20-99HP, (2) 100-999HP, (3) 1000-4999HP, (4) 5000-9999HP and (5) above 10000HP with 1HP being equal to 0.75kW. The category of the build water-power plants in 1900 is based on actual energy produced, the potential of the location the power-plant is build on can be in a higher category. Locations requiring an embankment dam are not recorded (none of these were build by 1900).

Figure A.3: Economic output across countries 1850-1970



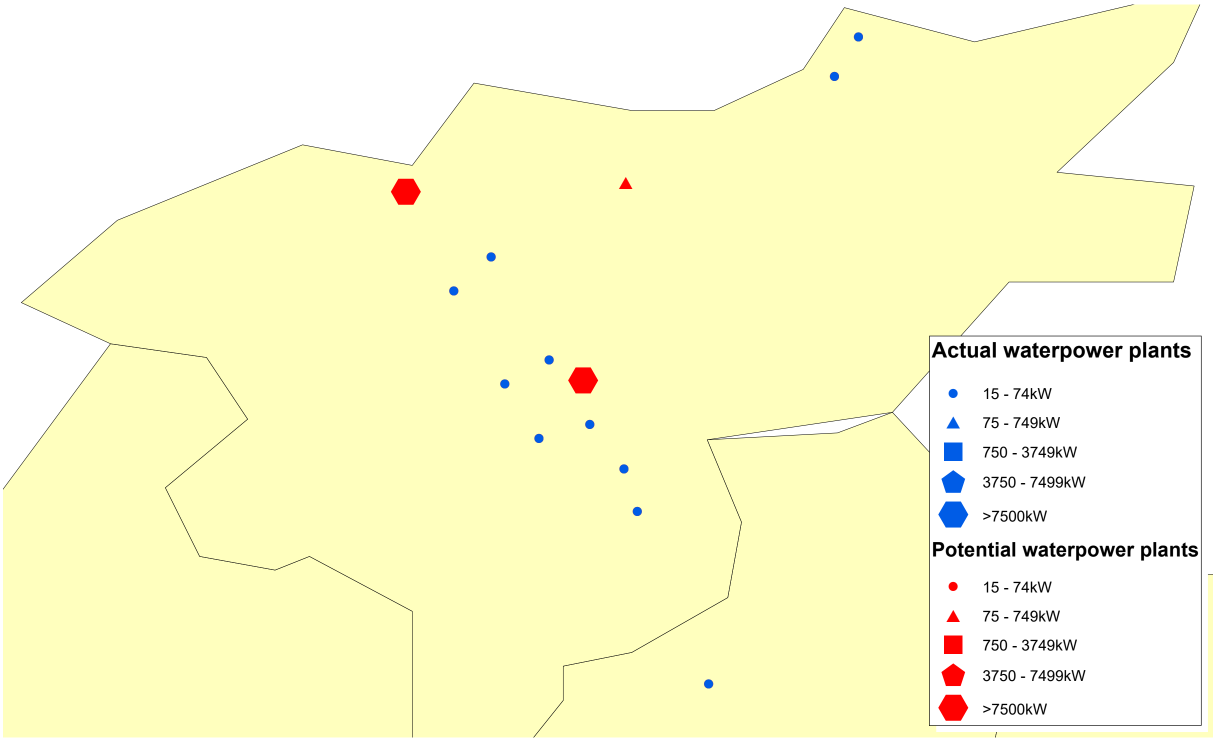
Notes: Real GDP per capita in 1990US$ across leading industrial countries from 1850-1970. The first line in 1879 reflects the initial commercial usage of electricity in Switzerland, the adoption of electrical lights at the Kulm Hotel in St. Moritz powered by a 7kW plant. The second line represents 1905 when Switzerland had the highest per capita production of electricity in the world with this leadership in adoption quickly diminishing in the following years (see "Elektrifizierung" in HLS 2020). Source: Bolt et al. (2018*a*)

Figure A.4: Random allocation across areas versus population



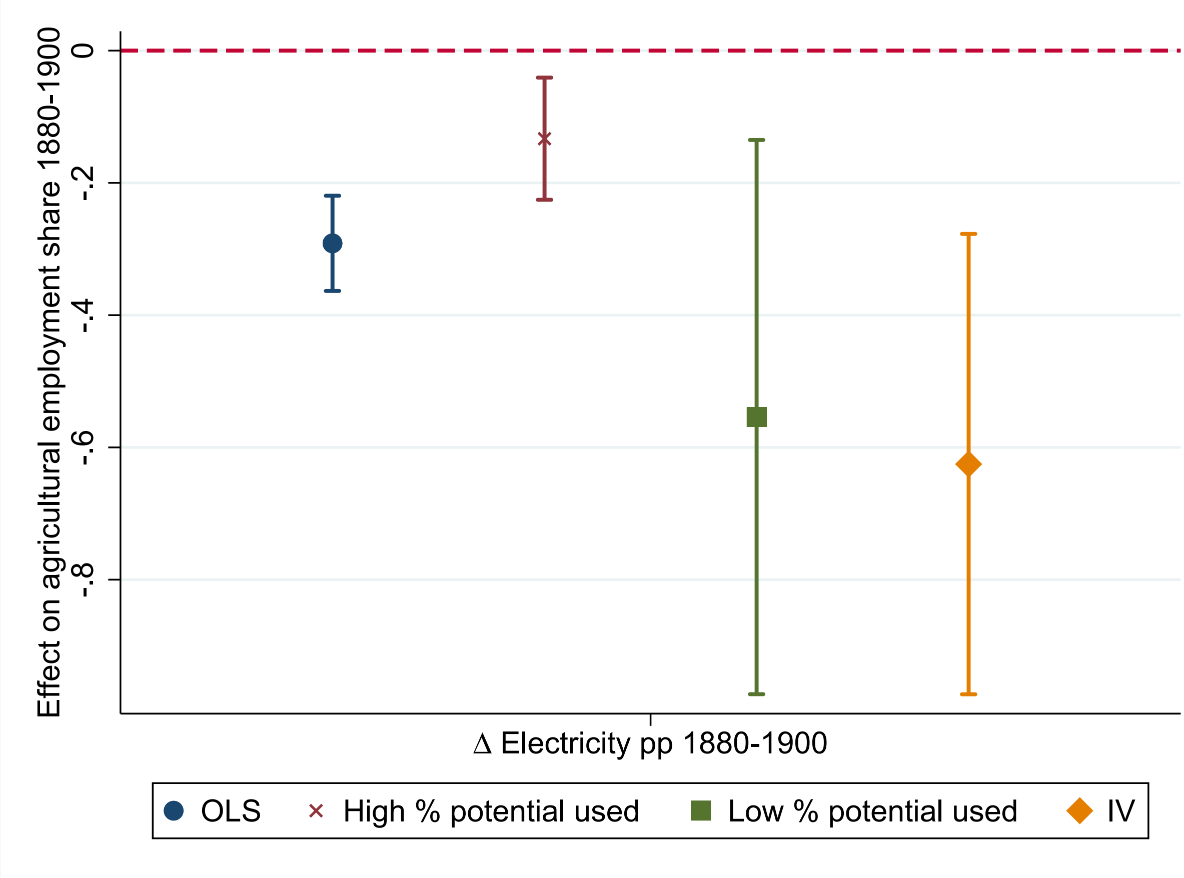
Notes: The figures illustrate the correlation between waterpower potential in (i) per km^2 and (ii) kW per person and population density in 1880. This illustrates that potential to generate electricity is relatively randomly distributed across Switzerland with regards to geography, but by definition this random allocation means that areas more densely populated will have less waterpower potential per person. That means if Switzerland was divided into 1x1km grid cells each cell would have the same likelihood to have potential to generate electricity independent of local population density. However, a more densely populated grid cell would have a lower per capita potential for electricity generation. Blue squares represent the binned observations with the solid red line being the lowess fit. In the background hollow grey dots correspond to the underlying observations. St-Gallen and Basel-Stadt with a population density far exceeding 1000 inhabitants per km^2 are not included in the figure.

Figure A.5: Existing and potential waterpower plants in Basel-City 1900



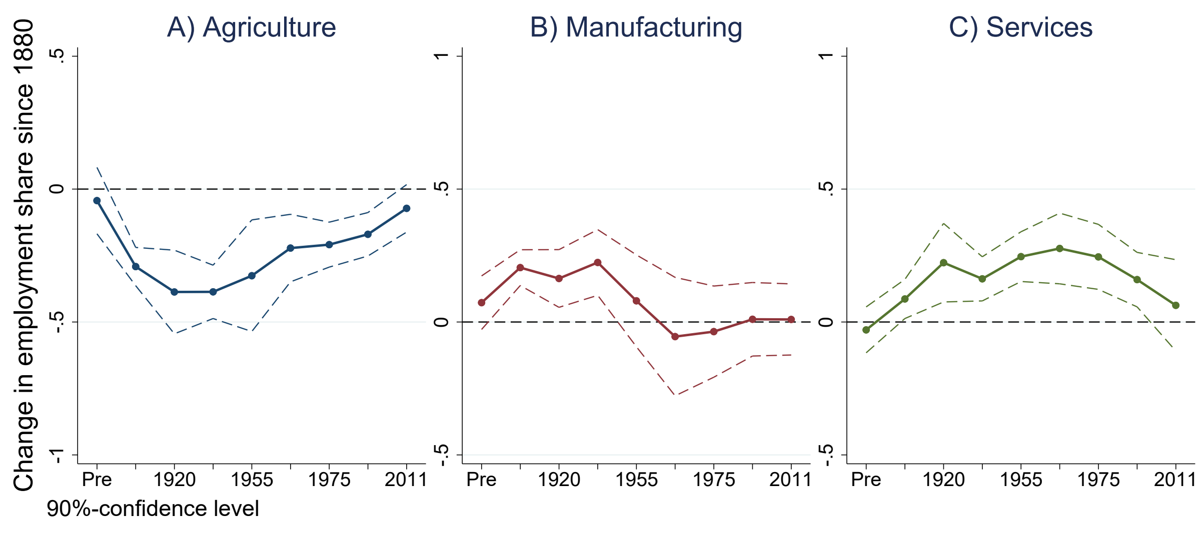
Notes: The map shows the existing (blue) and potential (red) waterpower plants in the Canton of Basel-City by 1900. The former are mostly watermills dating back to the middle ages. Source: Bossard 1916

Figure A.6: Evidence on source of bias in the OLS



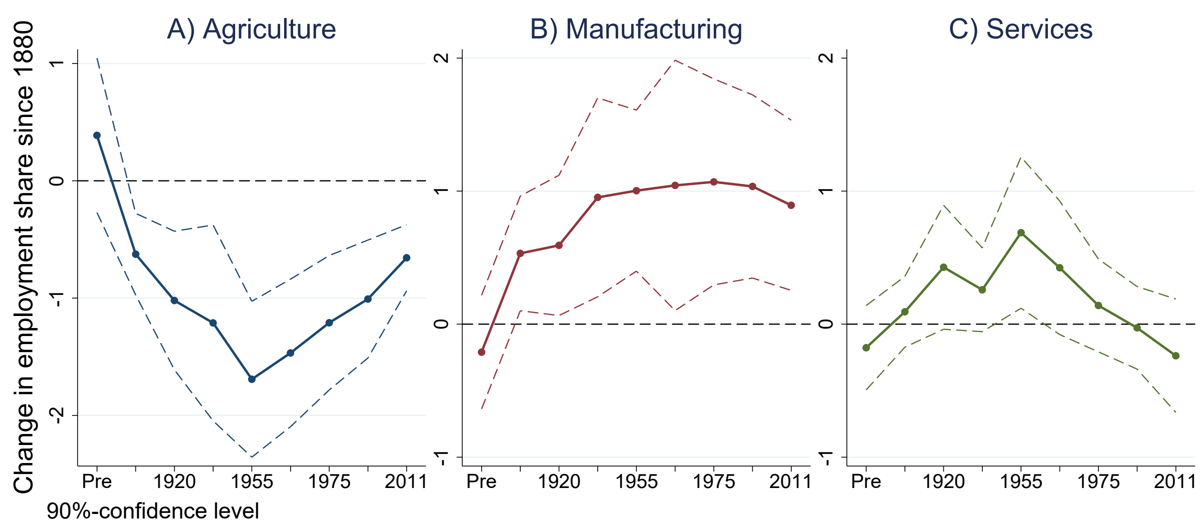
Notes: This figure presents baseline OLS and IV estimates and highlights that the downward bias in magnitude in the OLS is due to areas that utilize a large share of their potential for electricity generation (> 20%) as they have a smaller marginal effect from adoption compared to those areas that are only able to utilize a small share (< 20%). This provides evidence that areas that have the largest gain from electricity actually adopt less due to constraints in the adoption process (e.g. already allocated water-concessions). N=178; 66; 112; 178

Figure A.7: OLS estimates for the effect of electricity adoption



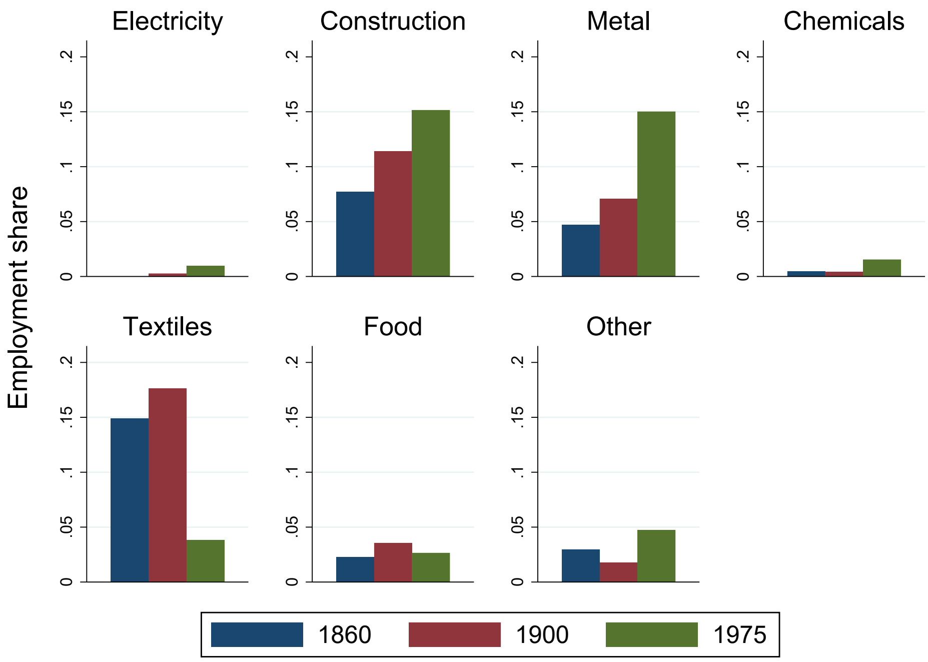
Notes: This figure presents the corresponding OLS estimates to Figure 1.6.

Figure A.8: Effect of electricity adoption confounded by later adoptions



Notes: This figure presents the corresponding estimates to Figure 1.6 without controlling for the adoption of electricity after 1900.

Figure A.9: Employment shares across industries 1860-1975



Notes: The figure presents employment shares of industry groups in total employment in 1860, 1900 and 1975. Employment shares represent the average across 178 districts in the sample.

A.2 Tables

Table A.1: Balance checks actual and potential electricity adoption

	Control		Treatment				
Variable	Mean	N	Mean	N	Diff	S.e.	P value
A1. Difference between no-electricity vs. electricty generation							
Share agricultural employment (1880)	0.51	93	0.47	85	0.041	0.029	
Share manufacturing employment (1880)	0.37	93	0.38	85	-0.009	0.026	
Share services employment (1880)	0.12	93	0.15	85	-0.032	0.011	* * *
Population density (1880)	0.11	93	0.15	85	-0.038	0.052	
Share secondary education (1880)	0.22	93	0.21	85	0.005	0.018	
Altitude (km)	0.90	93	1.02	85	-0.115	0.084	
Longitude	8.01	93	8.16	85	-0.143	0.147	
Latitude	47.00	93	46.96	85	0.034	0.067	
Ruggedness	0.23	93	0.30	85	-0.070	0.032	**
A2. Difference between no-electricity vs. top 33% of electricty generation							
Share agricultural employment (1880)	0.51	93	0.46	60	0.058	0.033	*
Share manufacturing employment (1880)	0.37	93	0.38	60	-0.013	0.029	
Share services employment (1880)	0.12	93	0.16	60	-0.045	0.011	* * *
Population density (1880)	0.11	93	0.17	60	-0.060	0.062	
Share secondary education (1880)	0.22	93	0.22	60	-0.001	0.019	
Altitude (km)	0.90	93	1.05	60	-0.150	0.094	
Longitude	8.01	93	8.15	60	-0.134	0.168	
Latitude	47.00	93	46.96	60	0.034	0.074	
Ruggedness	0.23	93	0.32	60	-0.087	0.035	**
B1. Difference between no-potential vs. any electricity potential							
Share agricultural employment (1880)	0.53	29	0.49	149	0.041	0.040	
Share manufacturing employment (1880)	0.34	29	0.38	149	-0.047	0.035	
Share services employment (1880)	0.14	29	0.13	149	0.006	0.015	
Population density (1880)	0.10	29	0.14	149	-0.037	0.070	
Share secondary education (1880)	0.24	29	0.21	149	0.033	0.024	
Altitude (km)	0.75	29	1.00	149	-0.246	0.112	**
Longitude	7.55	29	8.19	149	-0.633	0.193	* * *
Latitude	46.93	29	46.99	149	-0.064	0.091	
Ruggedness	0.16	29	0.29	149	-0.129	0.043	* * *
B2. Difference between no-potential vs. top 33% of electricity potential							
Share agricultural employment (1880)	0.53	29	0.57	60	-0.044	0.043	
Share manufacturing employment (1880)	0.34	29	0.29	60	0.046	0.034	
Share services employment (1880)	0.14	29	0.14	60	-0.002	0.019	
Population density (1880)	0.10	29	0.09	60	0.005	0.040	
Share secondary education (1880)	0.24	29	0.21	60	0.033	0.026	
Altitude (km)	0.75	29	1.29	60	-0.533	0.138	* * *
Longitude	7.55	29	8.21	60	-0.658	0.226	* * *
Latitude	46.93	29	46.78	60	0.145	0.108	
Ruggedness	0.16	29	0.41	60	-0.254	0.050	* * *

Notes: T-test between mean statistics for indicators of the level of development in 1880 and geographical characteristics across districts. Panel A compares the indicators across districts with electricity generation in 1900 (treatment) and those without electricity generation (control). Panel B compare the indicators across districts with potential waterpower (treatment) and without potential waterpower (control). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Additional robustness checks for the effect of electricity adoption on the agricultural employment share

	Additional human characteristics					Additional geographic controls					All
A. OLS	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ Electricity pp 1880-1900	-0.305***	-0.298***	-0.305***	-0.288***	-0.280***	-0.294***	-0.284***	-0.291***	-0.290***	-0.273***	-0.269***
	(0.042)	(0.047)	(0.046)	(0.044)	(0.033)	(0.038)	(0.040)	(0.044)	(0.044)	(0.049)	(0.052)
Share top math scores	-0.104^{+}										-0.067
	(0.065)										(0.083)
Share Catholic		0.008									0.016
		(0.022)									(0.030)
Share Jewish		-0.914									-0.360
		(0.792)									(0.781)
Share Romansh			-0.070^{+}								0.013
			(0.046)								(0.029)
Share Italian			-0.012								0.054
			(0.040)								(0.053)
Share French			-0.017								-0.009
			(0.022)								(0.049)
Liberal constitution (1833)				0.016							0.092^{+}
				(0.016)							(0.056)
Sonderbund member (1845)				0.031^{+}							0.199***
				(0.019)							(0.049)
Cantonal FE					Yes						Yes
					✓						✓
Cropland						0.085***					0.035
						(0.020)					(0.030)
River							-0.017**				-0.006
							(0.006)				(0.008)
Average water flow								-0.001***			-0.001***
								($3e^{-4}$)			($3e^{-4}$)
Alpine									-0.007		-0.004
									(0.016)		(0.022)
Po Basin									0.055***		0.073***
									(0.004)		(0.012)
Ruggedness										-0.093*	-0.096
										(0.047)	(0.086)
B. IV											
Δ Electricity pp 1880-1900	-0.661***	-0.575***	-0.595***	-0.585***	-0.497*	-0.600***	-0.512***	-0.546***	-0.635***	-0.601***	-0.406*
	(0.240)	(0.211)	(0.178)	(0.224)	(0.281)	(0.211)	(0.193)	(0.194)	(0.210)	(0.221)	(0.210)
F-stat (1st stage)	14.86	12.14	15.11	16.35	13.61	16.51	17.53	15.37	16.77	16.45	7.97

Notes: For all regressions the dependent variable is the change in the share of employment in agriculture between 1880 and 1900. Further controls included corresponds to the ones used in column 5 of Table 1.3. N=178. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Evaluating alternative instrument: Modern potential

A. Alternative IV	(1)	(2)	(3)	(4)	(5)
Δ Electricity pp 1880-1900	-0.428	-1.528*	-1.403*	-1.311*	-1.476*
	(0.440)	(0.794)	(0.752)	(0.733)	(0.888)
F-stat (1st stage)	12.37	6.01	5.96	5.69	3.79
B. Alternative Reduced Form					
Log waterpower potential pp (modern)	-0.003	-0.019***	-0.018***	-0.016**	-0.018***
	(0.003)	(0.005)	(0.006)	(0.006)	(0.005)
C. Alternative First Stage					
Log waterpower potential pp (modern)	0.008***	0.012**	0.013**	0.012**	0.012*
	(0.002)	(0.005)	(0.005)	(0.005)	(0.006)
D. Comparison instruments					
Log waterpower potential pp	0.048***	0.049***	0.051***	0.052***	0.055***
	(0.015)	(0.017)	(0.018)	(0.018)	(0.020)
Log waterpower potential pp (modern)	-4e^{-4}	0.001	0.002	0.001	0.002
	(0.004)	(0.009)	(0.009)	(0.009)	(0.010)
Controls	See controls included in Table 1.3				
N	178	178	178	178	178

Notes: The table illustrates an alternative instrument based on the potential of small hydropower plants in Switzerland (see Schröder et al. 2012). The data depicts the estimated electricity production potential of all natural flowing bodies of water in Switzerland (excluding main rivers as the Rhine, Rhone and Aare which are to large for small hydropower plants). Further, modern day structures of water-management alter the recorded potential. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Effect of electricity adoption on structural change

A. 1880-1920	Agriculture (1)	Manufacturing (2)	Services (3)
Δ Electricity pp 1880-1900	-1.281***	0.535*	0.746**
	(0.404)	(0.276)	(0.313)
Δ Electricity pp 1900-1920	0.028**	0.006	-0.034**
	(0.013)	(0.016)	(0.017)
B. 1880-1941			
Δ Electricity pp 1880-1900	-1.135**	0.781*	0.354*
	(0.534)	(0.442)	(0.189)
Change waterpowerplants 1900-1941	-0.005	0.011**	-0.006
	(0.004)	(0.005)	(0.005)
C. 1880-1955			
Δ Electricity pp 1880-1900	-1.624***	0.842**	0.782**
	(0.427)	(0.327)	(0.333)
Change waterpowerplants 1900-1955	-0.004	0.010**	-0.006^{+}
	(0.004)	(0.005)	(0.004)
D. 1880-1965			
Δ Electricity pp 1880-1900	-1.384***	0.831^{+}	0.553*
	(0.369)	(0.534)	(0.303)
Change waterpowerplants 1900-1965	-0.003	0.009*	-0.005^{+}
	(0.003)	(0.004)	(0.003)
E. 1880-1975			
Δ Electricity pp 1880-1900	-1.063***	0.722**	0.341**
	(0.304)	(0.342)	(0.152)
Change waterpowerplants 1900-1975	-0.005**	0.011**	-0.006^{+}
	(0.002)	(0.005)	(0.004)
F. 1880-1985			
Δ Electricity pp 1880-1900	-0.897***	0.777**	0.119
	(0.263)	(0.323)	(0.150)
Change waterpowerplants 1900-1985	-0.004*	0.008**	-0.005^{+}
	(0.002)	(0.004)	(0.003)
G. 1880-2011			
Δ Electricity pp 1880-1900	-0.540***	0.663**	-0.122
	(0.137)	(0.314)	(0.222)
Change waterpowerplants 1900-2011	-0.003**	0.005^{+}	-0.003
	(0.001)	(0.004)	(0.003)
Controls	Yes	Yes	Yes
N	178	178	178

Notes: The regressions present the results on the long-run effect. The dependent variables are the change in the share of employment in agriculture, manufacturing and services for the specified time-periods. All specification represent the IV-results using the potential waterpower per person as instrument for the change in electricity produced between 1880 and 1900. All specifications in addition to initial controls also include the change in the number of water-power plants per person between 1900 and the respective end date. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Effect of electricity adoption on employment growth by sector

	Employment growth rate		
	1880-1920	1920-1975	1975-2011
A. Agriculture	(1)	(2)	(3)
Δ Electricity pp 1880-1900	-0.922**	-0.333*	0.147
	(0.421)	(0.183)	(0.281)
B. Manufacturing			
Δ Electricity pp 1880-1900	6.103**	7.819**	0.881
	(2.608)	(3.815)	(0.866)
C. Services			
Δ Electricity pp 1880-1900	7.661**	2.452	-0.515
	(3.142)	(1.999)	(1.805)
Controls	Yes	Yes	Yes
N	178	178	178

Notes: The regressions present the results for the effect of initial electricity adoption on employment growth rates in agriculture, manufacturing and services for different periods. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Effect of electricity adoption on employment growth by gender

	Employment growth rate		
	1880-1900	1900-1920	1920-1941
A. Overall	(1)	(2)	(3)
Δ Electricity pp 1880-1900	1.242***	0.986*	-0.040
	(0.456)	(0.542)	(0.313)
B. Male			
Δ Electricity pp 1880-1900	1.549***	-0.369	-0.298
	(0.464)	(0.576)	(0.322)
C. Female			
Δ Electricity pp 1880-1900	0.021	2.105**	0.653
	(0.202)	(0.966)	(0.728)
Controls	Yes	Yes	Yes
N	178	178	178

Notes: The regressions present the results for the effect of electricity on the growth rate of employment for the periods 1880-1900, 1900-1920 and 1920-1941. Panel A presents the results on total employment growth in a district. Panel B and C present the corresponding effect for male and female employment growth, respectively. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Electricity adoption and industry employment 1900-1920

	Elec. (1)	Con. (2)	Metal (3)	Chem. (4)	Text. (5)	Food (6)	Others (7)
Δ Electricity pp 1900-1920	0.006***	-0.001	-0.001	0.001	0.002	-0.001	-0.002+
	($4e^{-4}$)	(0.004)	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	124	124	124	124	124	124	124

Notes: The regressions present the OLS results for the effect of the increase in electricity generation 1900-1920 on the change in the share of employment across manufacturing industries between 1900 and 1920. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Effect of electricity on education spending

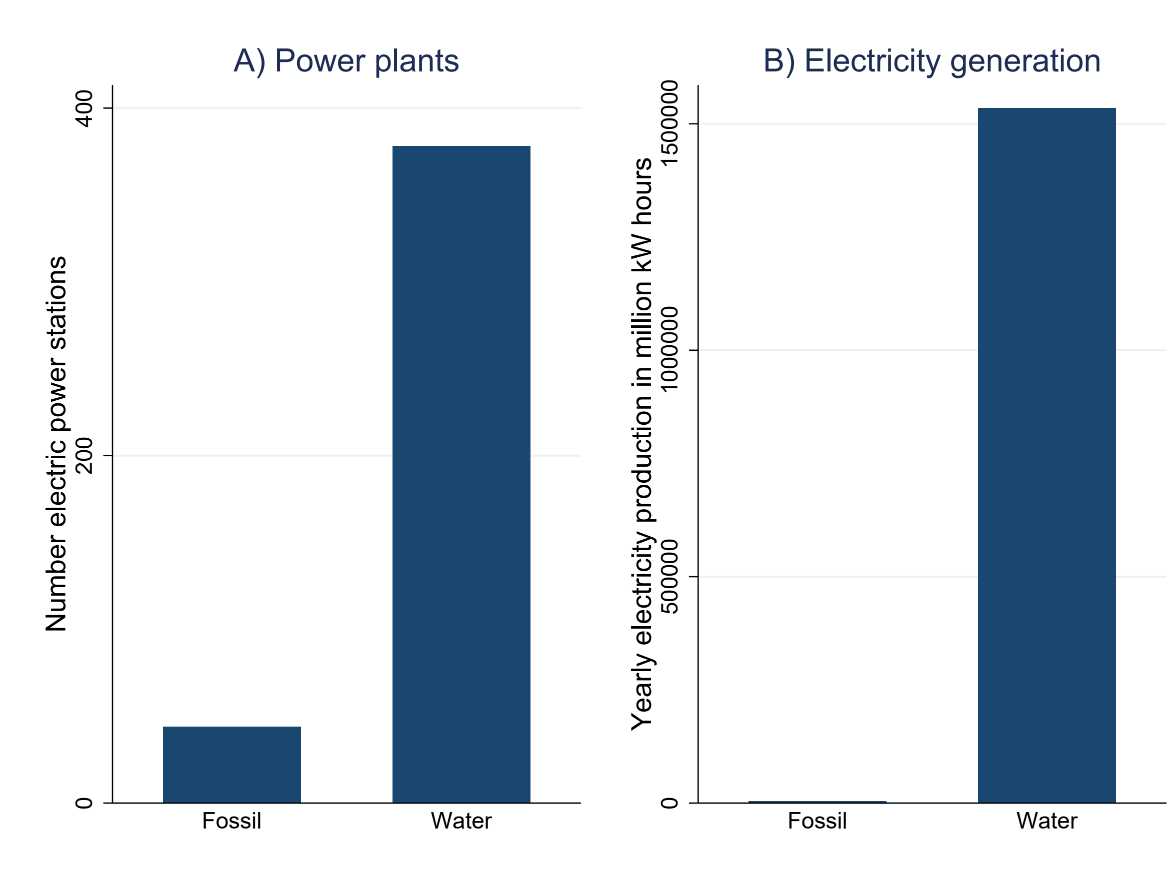
	Primary (1)	Secondary (2)
Δ Electricity per person 1880-1900	0.730*	9.846**
	(0.406)	(4.951)
Controls	Yes	Yes
N	25	24

Notes: The regressions present the results for the effect of electricity from waterpower on the change in the municipal and cantonal spending at the primary and secondary level. Data was only available at the cantonal level and from 1887 onwards. Robust standard errors in parentheses. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Data Appendix Chapter 1

A.3 Electricity data

Figure A.10: Electricity production in Switzerland by power-source



Notes: Type of primary power-plants by number and actual kW hours of electricity produced over a year in 1916. To the best of my knowledge 1916 is the earliest comprehensive survey of fossil fuel power plants available. Note, that of the reported fossil fuel power plants many appear to have been operated adjacent to waterpower plants. Source: Department des Inneren 1891-1920.

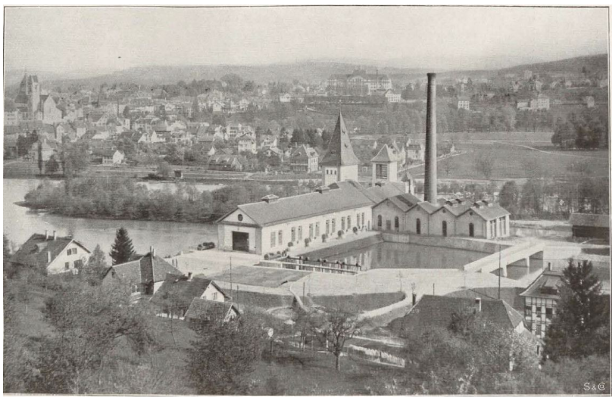
My data on electricity production by waterpower plants and waterpower potential is collected from "The waterpower of Switzerland in 1914" (Bossard 1916) compiled by the water-management agency ("Abteilung für Wasserwirtschaft") of the Swiss department of the interior ("Department des Innern").[78] The electricity produced from waterpower represented the vast majority of electricity production in the early stages of electrification in Switzerland (see Figure A.10). The low importance of fossil fuels for electricity production was due to Switzerland being scarce in natural resources and requiring expensive

[78]The historical information used was jointly created by a group of engineers working for the Swiss water-management agency, cantonal power-plants, the Swiss Federal Railway and Fa. Locher & Cie (a private construction company). The objective of the assigned project was to map all existing and potential waterpower plants in detail across Switzerland to obtain information of current generation and ownership of waterpower plants as well as plan the building of future waterpower plants across Switzerland with the aim to maximise national electricity generation.

coal imports making the generation of electricity from coal uneconomical (Bossard 1916). Even the remaining negligible generation of electricity from coal appears to have been mostly located at hydroelectric power-plants to compensate for variations in the water level (Roth 1920). Further, the distribution of electricity due to technological constraints was only possible over short distances until the beginning of the 20th century with many waterpower plants operating at low-voltages, supplying specific (usually industrial) establishments. Even the 49 high-voltage power plants that existed in 1901 on average supplied electricity over a maximum distance of 9.4km with the longest distance being 35km (2nd: 28km; 3rd 21km, see Department des Inneren 1891-1920).[79] In the cases waterpower plants lay within different administrative boundaries, the respective allocation of energy generated is reported for each administrative unit separately in Bossard (1916). Accordingly, between 1880 and 1900 the production and supply of electricity were extremely localised so that electricity needed to be produced in the district it was consumed.

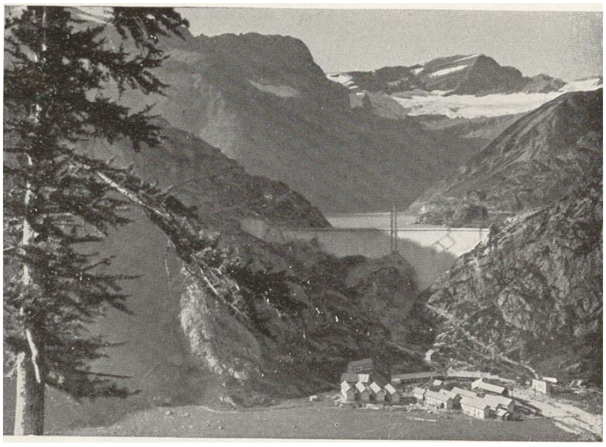
Figure A.11: Examples of waterpower plants

A) without embankment dam



Waterpower plant build in Aarau in 1894 owned by the municipality of Aarau with an electricity production of 705kW.

B) with embankment dam



Waterpower plant build in Barberine in 1923 owned by the Swiss Federal Railways with an electricity production of up to 15000kW and an embankment dam capacity of 39000000m^3.

First, "The waterpower of Switzerland in 1914" provides information on the water source (e.g. river, lake, etc), location (municipality and district), ownership, specific features of the plant, the minimum, average and maximum power generated, the installed

[79] Note that high-voltages (usually above 1000volt) are a prerequisite for providing electricity over long-distances to avoid excessive transmission loses. Even this select sample of high-voltage power plants in 1901 on average only supplied electricity to 5 municipalities (the average district had 18 municipalities). Even the "Société des forces électriques de la Goule" in Saint-Imier covering the longest distance of 35km supplied a mere 29 municipalities and 29000 people. In contrast, by 1908 the number of high-voltage power plants had increased to 280 with the longest transmission distance extended to 135km(See Department des Inneren 1891-1920). This pattern is in-line with the drastic shift in the production of electricity from small private suppliers of electricity to cantonal electricity companies at the start of the 1900s as described in HLS (2020) "Elektrizitätswirtschaft".

turbines, the different types of utilization of the power, construction (and extension if applicable) date and a vast set of other information of all mechanical and electrical waterpower plants with a capacity of at least 15kW (corresponding to 20HP, the unit in which energy was recorded in Bossard 1916). I use the average power generated as the measure of energy supplied by a power-plant and allocate this energy to two groups: (i) electric power plant if the power utilization specifies that the harnessed energy is converted into electricity, e.g. stating that the purpose of the energy was the transmission of electrical power or the supply of electrical light and (ii) mechanical power which is all other uses that are not indicating that the energy generated was converted into electricity. I use the location information to match the respective power plants to Swiss districts. The location information in the table is provided for districts ("Bezirke") and municipalities("Gemeinden") with a corresponding map providing precise geographic information as well that can be matched to the respective waterpower plants. Following this, I use the date of construction and extensions to construct measures of the electric and mechanical waterpower generated for specific time periods (allocating an equal weight to each extension date).

Second, for the instrument I digitize information presented in a map in "The waterpower of Switzerland in 1914" about the precise location of existing and potential waterpower plants and their specific features presented through illustrations of the existing and planned canals, pressure pipes towards and out of the turbine house, and whether a embankment dam is required. I geocode each existing and potential waterpower plant based on the proposed location of the turbine house. The mapping of whether a waterpower plant existed plants is based on 1914, however this does not affect my variable of the potential as I combine both existing and potential waterpower plants into a single measure for the potential. In correspondence with this, in cases were the map marks that both a waterpower plant already exists, but it could be extended to generate more energy, I use the maximum potential of the respective location, but do not count the already existing generation. This means my measure of potential electricity generation reflects the maximum potential electricity generation independent of whether any of this potential is already exploited or not.

The mapped waterpower plants can be distuinguished into two specific groups those not requiring an embankment and those requiring an embankment. Historic examples of the two types of waterpower plants are provided in Figure A.11. The first waterpower plant requiring an embankment dam was only build in 1908 and only two existed by 1914. Due to waterpower plants with embankment dams not being related to any actually build waterpower plants by 1900, including these would provide a less relevant first stage.[80]

[80] In addition, one might be more concerned that the decision on where to locate an artificial lake for the embankment dam might influenced by considerations other than maximising electricity output. However, the map does illustrate several embankment dams that would have required the flooding of multiple villages and smaller towns.

Table A.9: Embankment dams and early electricity adoption

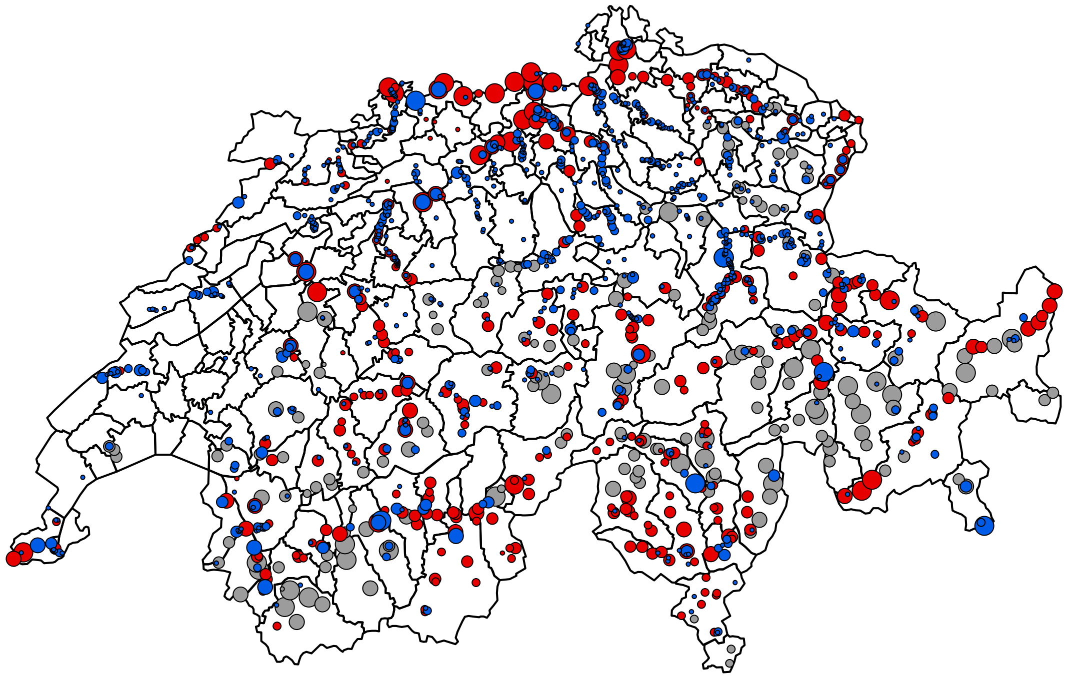
A. 1880-1900	(1)	(2)	(3)	(4)
Log waterpower potential pp	0.057***			
	(0.014)			
Waterpower potential pp		0.038***		
		(0.010)		
Log embankment waterpower potential pp			0.020	
			(0.017)	
Embankment waterpower potential pp				0.004
				(0.006)
B. 1900-2011				
Log waterpower potential pp	2.403***			
	(0.359)			
Waterpower potential pp		1.425***		
		(0.188)		
Log embankment waterpower potential pp			2.361***	
			(0.360)	
Embankment waterpower potential pp				0.589***
				(0.205)
Controls	Yes	Yes	Yes	Yes
N	178	178	178	178

Notes: Panel A Column 1 and 2 present the relationship between (log) waterpower potential per person, excluding all embankment dams, and actual adoption of electricity per person 1880-1900. Note, column 1 is the first-stage of the baseline specification Table 1.3 Column 5. Column 3 and 4 estimate the same relationship for embankment dams and electricity adoption. Panel B presents the relationship between the respective waterpower potential and the building of waterpower plants from 1900 to 2011. Robust standard errors in parentheses are clustered at the cantonal level. $^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Waterpower plants without and with an embankment dam are also distinctly marked on the historical map. For this reason, I code waterpower plants requiring an embankment dam separately and do not count their waterpower potential towards a districts total potential.

Table A.9 provides evidence that potential waterpower plants with embankment dams were indeed irrelevant by 1900. Panel A shows that potential power plants without embankment dams are highly relevant for the adoption of electricity, while when potential waterpower plants with embankment dams do not provide a relevant first-stage for the adoption of electricity by 1900. However as Panel B shows, potential waterpower plants with embankment dams become relevant after 1900 for the location of modern waterpower plants.

Figure A.12: Location of existing and potential waterpower plants 1914



Notes: The map shows the existing and potential waterpower plants in Switzerland in 1914. Blue dots represent existing and red dots represent potential waterpower plants. Both using available natural water sources. Grey dots represent existing and potential waterpower plants that require the building of an embankment dam. These are coded separately and not used for the instrument as the first of these was only build in 1908 and only two existed by 1914. The sites are coded into 5 categories represented by the size of the dot: a minimal power of (i) 20-99HP, (ii) 100-999HP, (iii) 1000-4999HP, (iv) 5000-9999HP and (v) above 10000HP with 1HP being equal to 0.75kW. Source: Bossard 1916

Figure A.12 presents the map of all digitized existing (in 1914) and potential power-plants with their location in Switzerland. An excerpt of the corresponding original map with the individual coding is illustrated in Figure A.13. The map provides the corresponding waterpower for existing and potential waterpower in 5 distinct categories: (i) 20-99HP, (ii) 100-999HP, (iii) 1000-4999HP, (iv) 5000-9999HP and (v) above 10000HP with 1HP equal to 0.75kW, for each categories its respective lowest value is used to construct the waterpower potential. The map measures power for existing and potential waterpower plants based on constant minimal kW (based on the lowest water level throughout the year). To construct the district level waterpower potential the capacity of all blue and red dots are summed up. These existing and potential waterpower plants marked with blue and red dots in Figure A.12 correspond to the locations of potential waterpower plants presented in Figure 1.1 in the main text.

A.4 Employment data

To assess the effect of electricity on economic development, I need data on employment by sectors (agriculture, manufacturing, services) across Swiss districts. This allows to measure structural transformation a key part of the process of economic development (see Kuznets 1957; Kuznets 1973). I collect this data from the Swiss Census focussing on employment across agriculture, manufacturing and services for the years 1860, 1880, 1900, 1920, 1941, 1955, 1965, 1975, 1985 and 2011 (see Bundesamt für Statistik 1860-2011).[81] These provide information on employment of individuals for the whole of the Swiss population at the district level. Further, I collect information on manufacturing sectors for the years 1880, 1900, 1920[82] and 1975 identify 7 consistent industry groups:[83] “Electricity generation”, “Construction, wood & stone products”[84], “Chemicals”, “Textiles & apparel”, “Food products”, “Metal, machinery & watches”, and “Other”. The category “Other” is mainly comprising employment in mining, paper and typography, but some newly emerging industries (e.g. rubber products) not associated with any of the other categories become of some importance after 1880.

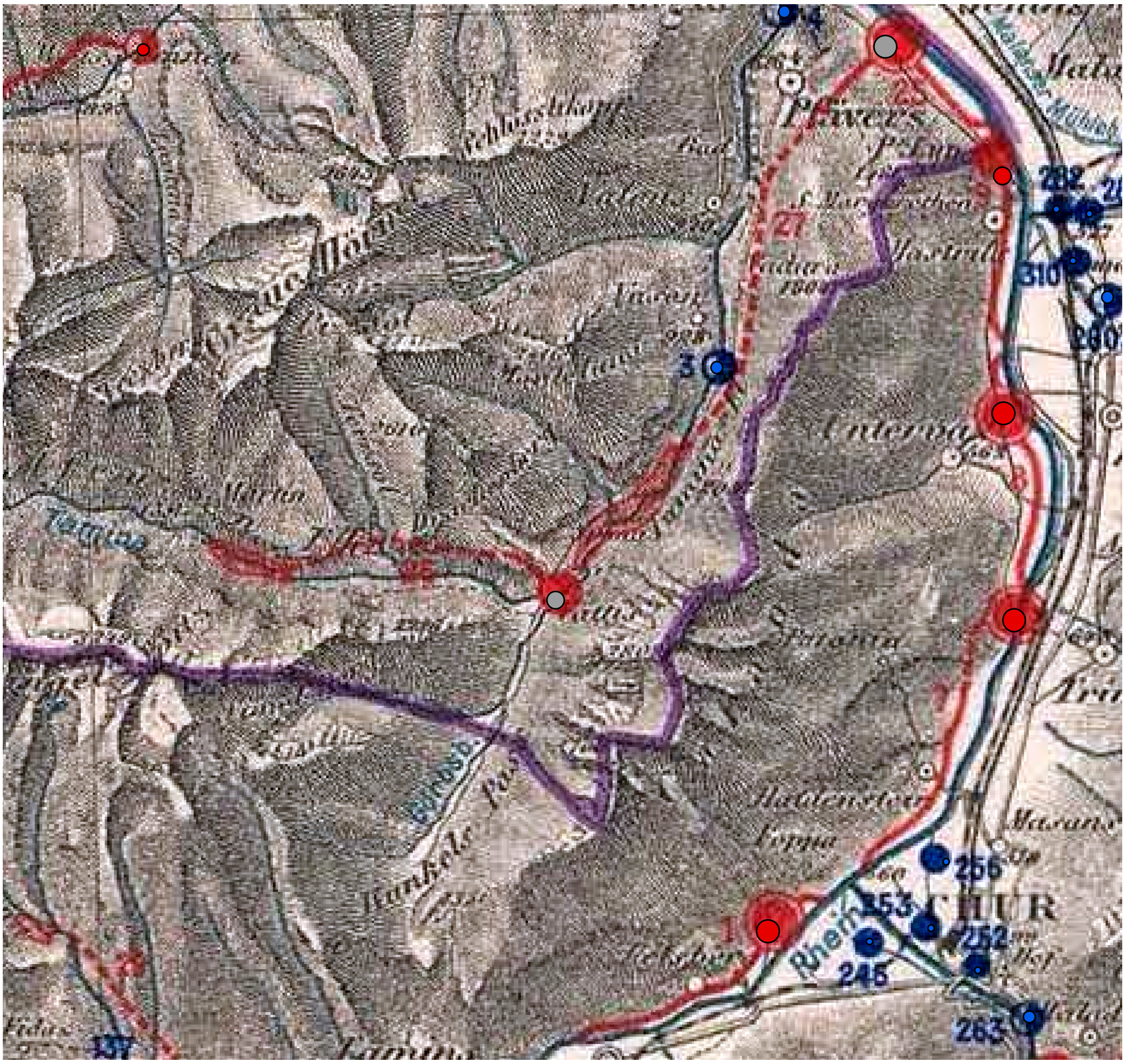
[81] Location of employment till 1941 is based on residence, and after 1955 on workplace (using the firm census instead of the population census). Initially, data is only available by residence from the population census, however differences between residence and workplace should be minor before the 1950s.

[82] For 1920 only information for 124 out of 178 districts were collected so far from the historical sources as it was impossible to obtain the remaining volumes required due to the current COVID-19 situation.

[83] While aiming to create as consistent industry groups as possible over time, in a few cases certain types of smaller occupations were reassigned from one industry category to another without there being detailed enough information at the district level to resolve this issue. For example in 1880, industry category “F4. Papier- und Holzstofffabrikation”, i.e. the making of paperstock (not paper), reported at the cantonal level is only reported within a more aggregate broader chemical industry category (“F. Chemische Gewerbe”) at the district level and matched to “Chemicals”. In 1900, paperstock is no longer reported individually, but within “118. Herstellung von Papierstoff und Papier”, the making of paperstock and paper, with paper being part of the more broad typography category (“D. Typographische und bezügliche Gewerbe”) in 1880, which was matched to “Others”. So that employment in both had to be matched to “Others” in 1900 despite employment in paper stock having been part of “Chemicals” in 1880. These discrepancies were impossible to resolve without losing an exorbitant amount of detail through further aggregating the 7 consistent industry groups, e.g. through aggregating the categories “Chemicals” and “Others”. However, this should only create measurement error as the initial distribution of employment in 1880 should be unrelated to the instrumented adoption of electricity.

[84] Construction is included within manufacturing because even in the disaggregated historical information for 1880-1920 the construction of buildings is reported in one category together with the production

Figure A.13: Extract from historic map of potential waterpower



Notes: The figure shows an extract of the map from Bossard (1916) of exploited and potential waterpower in Switzerland in 1914. In the map blue dots represent exploited waterpower, red dots represent potential waterpower. The sites are represented in 5 categories: a minimal power of (i) small circle representing 20-99HP, (ii) half filled big circle representing 100-999HP, (iii) filled big circle representing 1000-4999HP, (iv) filled circle with orbit representing 5000-9999HP and (v) square representing above 10000HP. 1HP is equal to 0.75kW. Straight and doted lines represent the connection between sites through pressure and tailback lines, when these lines originate at a point of the map it represents the source of the water used. I follow the original coding of sites (represented by the overlying circles) apart from cases where an embankment dam is required. This is denoted in the map by a red (blue) shaded area for potential (existing) dams. All sites requiring a dam are coded as a grey dot instead of their original colour, including sources that are partly supplied without a dam. Numbers associated with dots refer to additional data provided in additional tables for existing and potential waterpower plants. Purple lines represent administrative boundaries.

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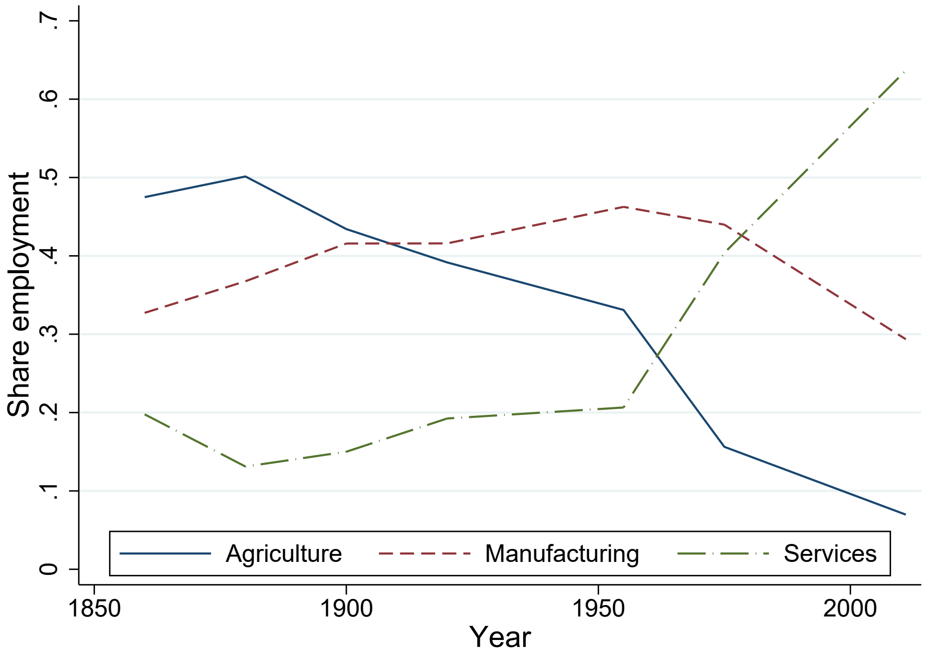
of materials predominantly used for construction (wood and stone products). Accordingly, I follow the historic classification and count construction within manufacturing.

Figure A.14: Structural change in Switzerland 1860-2011



Notes: The figure depicts the share of employment in (i) agriculture, (ii) mining and manufacturing and (iii) services. The share of employment reported is the average across the 178 districts in the sample. Sources: Bundesamt für Statistik 1860-2011

One issue faced when combining district level data for this long period is that geographical boundaries change. In general, administrative boundaries in Switzerland remained relatively stable over time. However, a few districts were merged or divided at some point in the sample period. I aggregate these into the larger unit for the whole sample period.[85] Figure A.14 depicts employment shares in agriculture, manufacturing and services for the time-period 1860-2011. The figure highlights that up to the 1950s a transition from agricultural to manufacturing employment occurred with the share of services employment having remained broadly stable. After the 1950s, the service sector share of employment increased while the share of agriculture and manufacturing in employment declined.

A.5 Other data sources

To analyse the channels through which the effect of early electrification persists I collect data on electricity usage for 1929 and 1955 from the (industrial) census to analyse whether

[85] This is the case for Bucheggberg-Kriegstetten, Dorneck-Thierstein, Geneva, Olten-Gösgen, Solothurn-Lebern and St.Gallen-Tablat. Some minor boundary changes that occur between districts that I do not account for between 1860 and 1975 due to their negligible nature are the following ones: Territory changes from Nidau to Biel district in 1920, Arbon to Bischofszell district in 1924, Arbon to Bischofszell in 1935, Moudon to Echallen district in 1960. From 1976 onwards the frequency of district boundary changes accelerates or districts get abolished as an administrative level in some Cantons altogether. I circumvent this issue by matching more detailed municipality-level or geocoded information to my historic district boundaries.

areas adopting electricity early still use more electricity at later points in time. Data on the education level of the population is collected from 1880-1910 military test scores reported in Statistischen Bureau (1880-1910) to see whether districts adopting electricity early experience higher levels of human capital accumulation. This is augmented with data on education spending at the cantonal level and information on number and students of dual education institutions from Grob (1887-1914), and on patenting by De Rassenfosse et al. (2019). Infrastructure data is obtained from SBB (2020). Swissvotes (2019) provides district level information on voting outcomes in Swiss national referendums since 1870 allowing to measure changes in political demands. A list of the referendums used by category is presented in Table A.10. HSSO (2012) and BFS (2019) are used for GDP data at the cantonal level from 1890 to 2015 and combined with information on tax revenue across cantons from Department des Inneren (1891-1920) to obtain proxies for GDP for the preceding years 1875, 1880 and 1885.

This is complemented by a set of datasources used in the construction of control variable. Longitude and latitude data is based on a digitized map of Swiss districts obtained from the 1900 census (see Bundesamt für Statistik 1860-2011). The average altitude of a district is calculated using topographical information (1km x 1km grid) from the elevation map of Europe (European Environment Agency 2004). The area of districts obtained in the same way is combined with population data from the census to construct 1880 population densities. Religion and primary language spoken across districts also comes from the 1880 census. The share of cropland is constructed based on Ramankutty et al. (2010). Information on main and tributary rivers is obtained from Kelso & Patterson (2009). Data on different ecoregions is from Olson et al. (2001). The intial education level is based on the military test scores (Statistischen Bureau 1880-1910). The remaining initial controls (agricultural employment share, population density, religion, language) used are obtained from the 1880 census (Bundesamt für Statistik 1860-2011).

Table A.10: List of Swiss federal referendums

	No	Date	Referendum	Direction	Yes	Turnout
	Investment education & science					
1	59	23.11.1902	Subsidies primary schools	Pro	76.3%	46.6%
2	205	08.12.1963	University & vocational training stipends	Pro	78.5%	41.8%
3	207	24.05.1964	Reform job related education	Pro	68.6%	37.0%
4	234	04.03.1973	Reform education system	Pro	52.8%	27.5%
5	235	04.03.1973	Support scientific research	Pro	64.5%	27.5%
6	286	28.05.1978	University subsidies	Pro	43.3%	48.9%
	Government infrastructure subsidies					
7	20	19.01.1879	Subsidies for the alpine railways	Pro	70.7%	61.9%
8	39	06.12.1891	Purchase of the Centralbahn	Pro	31.1%	64.3%
9	53	20.02.1898	Government purchase & operation railways	Pro	67.9%	78.1%
10	103	15.05.1927	Subsidies for alpine roads	Pro	62.6%	55.3%
11	138	21.01.1945	Debt relief of the SBB state railway	Pro	56.7%	52.9%
12	348	06.12.1987	Rail 2000	Pro	57.0%	47.7%

Notes: Referendums voted on in Switzerland on government education and science investment, government infrastructure investment, certain taxes, and the building and regulation of waterpower plants for electricity generation. I aimed at selecting the first 6 referendums that focus on an as clearly defined issue as possible and are comparable over time. For referendums on government investment in education and science I focus on expenditures, but do not include referendums focussed on the redistribution of power across different levels of administration. For government infrastructure subsidies On infrastructure referendums I focus on subsidies and expenditures of the central government that are not linked to any specific taxes financing these infrastructure projects. Data from Swissvotes (2019), which is also used for the classification of referendums.

Chapter 2

Trade disruption, industrialisation, and the setting sun of British colonial rule in India

with Roberto Bonfatti (Universities of Padua and Nottingham)

Abstract

Colonial trade encouraged the specialization of colonies in primary products. Did this prevent industrialisation in colonies? And did the absence of industrialisation help to keep colonies under control? To answer these questions, we examine the impact of the temporary trade collapse between Britain and India due to World War I, on industrialisation and anti-imperial feelings in India. Exploiting cross-district variation in exposure to the trade shock, we find that districts more exposed to the trade shock experienced substantially faster industrial growth in 1911-21, placing them on a higher level of industrialisation which persisted up to today. Using the WWI trade shock as an instrument for industrialisation levels, we also find that more industrialised districts were more likely to express anti-imperial feelings in 1922, and to vote for the Indian National Congress in the landmark election of 1937.

JEL Classifications: F14, F54, O14, N65.
Keywords: Colonial trade, India, Infant-industry argument, Decolonisation.
Current Version: Most recent version (Bonfatti & Brey 2020) can be found HERE.
Co-authorship: This chapter is joint work with Roberto Bonfatti (Universities of Padua and Nottingham).

2.1 Introduction

One common feature of European empires was the prominence of trade between the colonies and the imperial powers (Mitchener & Weidenmier 2008). This resulted in a pattern of specialisation whereby the colonies exported mainly primary products, and imported mainly manufactures. The imperial powers encouraged this specialisation, which simultaneously benefited their consumers of primary products, producers of manufactures, and investors in colonial plantations and mines. From the point of view of the colonies, however, two questions arise: did colonial trade prevent industrialisation in the colonies? And did it help keeping them under control, by making them dependent on trade with the imperial power?

We attempt to answer these questions empirically, in the context of early 20th century colonial India. This chapter is divided into two parts. In the first, we exploit the collapse in trade generated by World War I - which, as shown in Figure 2.1, more than halved Indian imports from Britain in real terms - to investigate the impact of an exogenous interruption in colonial trade (from now on, the "WWI trade shock") on industrial growth in India. In the second part, we investigate the impact of industrialisation levels on support for the anti-colonial movement in the 1920s and 1930s, using the WWI trade shock as an instrument for industrialisation levels.

This historical setting is well suited for what we intend to study, for three important reasons. First, India was exposed to unconstrained free trade in the second half of the 19th and early 20th centuries, which was associated with one of the most spectacular episodes of international specialisation in history (whereby Britain became the "workshop of the world", while India, once an important producer of manufactures, progressively de-industrialised). Second, many commentators have blamed colonial trade as one of the main reasons for India's poor industrial performance. Finally, WWI generated a large and exogenous interruption in colonial trade, allowing us to identify the impact of colonial trade on industrial growth. Importantly, the shock was also temporary. This allows us to investigate the persistence of its impact, and thus attempt to discriminate between alternative channels through which colonial trade may have affected industrial growth.

To discriminate between channels is important, because different channels have potentially different welfare implications. In a static trade model, a colony with a comparative advantage in primary products will benefit from trade, even though this will be associated with poor industrial performance. In contrast, in a dynamic model – featuring for example learning externalities, such as in the infant industry model – poor industrial performance might be welfare-decreasing (though it does not need to be). To adjudicate between the two cases, we take advantage of the fact that they have opposite predictions for the impact of a temporary trade shock. In particular, if the static trade model best describes colonial India, then the WWI trade shock should have had, at most, a temporary effect

Figure 2.1: Trade between India and Britain in real terms

Notes: Indian imports from and exports to Britain in our 105 traded sectors, in 1911 GBP. From 1923 the Irish Free State is no longer included in British imports and exports. Source: Annual Statement of the Trade of the United Kingdom

on Indian industry. In contrast, if the dynamic model is most appropriate (for example, if learning externalities were important), then the WWI trade shock should have had a persistent effect. Motivated by these considerations, we specifically look for persistent long-run effects of the WWI trade shock on Indian industry.

In the first part of this chapter, we investigate the link between exposure to the WWI trade shock and industrial employment growth across up to 235 Indian districts. We proceed in three steps. First, we compare product-level data on Indian net exports to Britain in 1913 and 1917 (the last full year of peace and war, respectively) to construct a product-level measure of exposure to the WWI trade shock, for India as a whole. Second, following Autor et al. (2013*a*), we match this product-level measure to district-industry-level employment data for 1911, to construct a district-level measure of exposure to the WWI trade shock. Finally, we regress district level industrial employment change from 1911 to various years between 1921-2011 on exposure to the WWI trade shock.

Consistent with a dynamic model of trade and industrialisation, we find that the WWI trade shock had a positive, large and highly persistent effect on Indian industry. Districts exposed to a greater 1913-17 increase in net exports to Britain experienced faster industrial employment growth in 1911-21. This placed them on a higher level of industrial employment which was still visible in 1926, 1936, 1951 and 2011 (the year of the last census). Net exports increased on average, so that the WWI trade shock is estimated to have had a positive effect on Indian industry. The impact of the shock was large: it accounted for between 29% and 40% of industrial employment growth in 1911-21, and for 4.4% of growth in 1913-2011. While long-run persistence might partly be driven by later shocks, we argue that persistence until at least 1936 was mainly driven by the WWI trade shock. These results imply that colonial trade did help to prevent industrialisation in India. Furthermore, the persistent effect of the WWI trade shock suggests to look at this through a dynamic model of trade and industrialisation, within which free trade can be welfare decreasing.

When we explore this further, we find some evidence that persistence was due to learning, and not to competing explanations (such that industries who benefited more from the WWI trade shock later expected or obtained a more favourable industrial policy, or that they experienced looser credit constraints due to war-time profits). First, the effect was entirely driven by variation in net exports of manufactures (as opposed to industries processing primary products), which in turn was dominated by a fall in imports. While manufacturing is where learning externalities should be more important, the effect on credit constraints might be expected to be similar in the two cases. Second, the WWI trade shock boosted the employment of Indian managers but not that of British managers, and the number of firms owned by Indians but not those owned by Britons. While both nationalities might have benefitted from a more favourable industrial policy, the former presumably had more to learn on how to operate a modern industrial firm. Finally, districts more exposed to the WWI trade shock experienced a temporary increase in the number of workplace accidents, which however returned to pre-WWI levels by 1921. A plausible interpretation of these results is that it took time for new unskilled workers to learn how to operate the machines safely.

In the second part of the chapter, we investigate whether more industrialised districts lent greater support to the anti-imperial movement in the 1920s and 1930s. This analysis is based on a classical argument on the role of commercial versus industrial colonial groups in supporting or opposing imperialism (see Markovits 2002, p.24), which has been reformulated recently by Bonfatti (2017). The argument is the following: Due to Empires having been trade-enhancing institutions, trade disruption were one of the costs of rebelling against them. However, such disruption would have affected different colonial groups differently. For commercial groups, involved in the export of primary products to the imperial power, trade disruption would have implied a cost. In contrast, for industrial groups involved in import substitution, it might have even implied a gain. Thus, commercial groups should support the empire, while industrial groups should oppose it. It follows that greater colonial industrialisation, by making the industrial groups more influential, should make a colony more rebellious. Within India, more industrialised districts should lend greater support to the anti-colonial movement.

We measure support for the anti-colonial movement at two key dates in the history of the movement: 1922 and 1937. The first year marked the end of the Non-Cooperation Movement of the Indian National Congress (INC). This was Ghandi's first attempt to resist British rule through non violence. In the summer of that year, the INC conducted an internal survey asking local party members how in favour they were of immediate civil disobedience against Britain. We observe the responses of up to 252 party members, located all over India. Our first measure of support for the anti-colonial movement will be the average response of INC members in a district. Fifteen years later, the INC had become the mass political party that would eventually lead the country to independence in 1947. The 1937 provincial election was the first to be held on a significant franchise, and also the first to be contested by the INC with full force. The result was a landslide for the INC, which formed governments in a majority of provinces. Our second measure of support for the anti-colonial movement will be the share of seats won by the INC in a constituency (a sub-division of a district).

Instrumenting for industrialisation levels in 1921 and 1936 using the WWI trade shock, we find that more industrialised districts featured stronger support for civil disobedience in 1922, and were more likely to elect an INC representative in 1937. A one percentage point increase in the industrial employment share is estimated to result in a 54% stronger support for civil disobedience in 1922, and a 6% higher probability of electing an INC representative in 1937. These large effects suggest that, although the INC's success in achieving independence was ultimately due to its capacity to mobilise the rural masses after the Great Depression, industrialisation levels had an important impact on support for the anti-colonial movement. The change in support of the rural masses was required due to the continued low levels of industrialisation in colonial India. Our results also imply that colonial trade did help to keep India under control: the interruption in trade which occurred in 1913-17 is estimated to have resulted in 6.8% stronger support for civil disobedience in 1922, and to have increased the number of seats won by the INC in 1937 by 2.4%.

In summary, our results suggest that colonial trade did help to prevent industrialisation in India, as evidenced by the fact that its interruption in 1913-17 led to a period of faster industrial growth and to a persistently higher level of industrialisation. The persistence of the effect highlights the importance of looking at colonial trade through a dynamic model, within which free trade can be welfare-decreasing for the colony. At the same time, colonial trade did help to keep India under control, as shown by the fact that its interruption in 1913-17, by leading to higher industrialisation levels, also led to stronger support for the anti-colonial movement in the 1920s and 1930s.

Our results have important implications. First, they suggest that the trade which took place within the European empires, while modernising the colonies in many respects, may have had a negative impact on the long-run growth of some of them. Second, our results provide a new way to rationalise the wide range of anti-industrial policies that the European colonisers adopted in their colonies in this period (O'Rourke & Williamson 2017, p.7). To the extent that industrialisation would encourage rebellion, it was in the imperial power's interest to discourage industrialisation. Finally, our result may explain why the imperial power that industrialised fastest, Britain, was also most successful at constructing and maintaining a colonial empire: its industrial growth boosted trade with the colonies, which in turn helped to keep the colonies under control.

This chapter is related to the economics literature on the infant industry argument, which has highlighted the importance of a dynamic learning process in industrialisation at least since John Stuart Mill (see Kemp 1960). The first formal model of the infant industry argument with learning externalities was provided by Bardhan (1971), while the most recent literature has explored more general or alternative settings (for a literature review, see Melitz 2005). Empirically, the literature has mostly tried to estimate the effects of policy-created trade protection by using partial equilibrium models to calculate the counterfactual of no-protection (see the literature review in Juhász 2018). The endogeneity of protection is clearly an issue in this literature. In an innovative recent paper, Juhász (2018) addresses this issue. She studies the effect of exogenous protection resulting from the Napoleonic Wars of 1803-1815 on the adoption of mechanised cotton-spinning in France. She finds that protection had a positive effect on technology adoption and value added per worker, both in the short-run and in the long-run. A second important contribution in this vein is Liu (2020). Using an identification strategy similar to Juhász (2018), she studies the impact of the WWI trade shock on textile manufacturing in China.[1] She finds that the shock induced firm entry, though this was delayed by a few years due the difficulty to import machinery during the war. The results presented in the first part of our work extend on those in Juhász (2018) and Liu (2020), as we use a different identification strategy and look at a broader set of industries, which allows us (among other things) to distinguish the effect of the disruption to trade on producers of primary products and manufacturers.[2] Further in contrast to these papers, we study a colony, and the impact of colonial industrialisation on anti-imperial feelings.

[1]To the best of our knowledge the only other paper on the trade shock effect of WWI is Fuchs (2018), who looks at the effect of increased demand for manufactures from belligerent countries on Spanish industrialisation and regional inequality.

[2]In Juhász (2018), the heterogeneous exposure of French departments to the trade shock is due to their geographical location, and the fact that the Continental Blockade made it more difficult for some region of France to import from Britain than for others. Instead, we follow Autor et al. (2013*a*) in constructing a measure of exposure that varies across Indian districts due to their initial industrial specialisation. Methodologically, we are close to the literature on trade liberalisation and deindustrialisation/political polarisation started by Autor et al. (2013*a*) and Autor et al. (2020). However we also depart from that literature substantially, in that we apply their method to a very different setting (a temporary drop in

This chapter also relates to two papers on how international trade shaped the colonial independence movements; the afore mentioned Bonfatti (2017), and Bhavnani & Jha (2018). Bhavnani & Jha (2018) is, to an extent, a precursor to our analysis. They analyse the link between the 1923-1933 drop in Indian exports caused by the Great Depression, and support for the INC across Indian districts. Their analysis focusses on the price decline in agricultural exports, which negatively affected rural producers of primary products, who according to the theory in Bonfatti (2017) should be a group in favour of empire. They find that districts with medium exposure to the drop in exports were those that provided the strongest support for the INC. They explain this by arguing that it was precisely in these districts that producers of primary products turned away from exporting, thus losing an economic motivation for supporting the empire. We add to the results in Bhavnani & Jha (2018) in two important ways. First, we establish the impact of an earlier shock to trade, which was mainly driven by a drop in Indian *imports*, on industrial growth in India. This allows us to comment on the role of colonial trade in promoting, or preventing, economic development in a colony, something which Bhavnani & Jha (2018) do not do. Secondly, we take advantage of the fact that our shock provides an exogenous source of variation in the industrial employment share, to identify the causal link between industrialization and anti-imperial feelings. This complements the results in Bhavnani & Jha (2018), providing a complete picture of the role of colonial trade in shaping anti-imperial feelings in India.

Our work has implications for how colonial trade policy affected industrial growth in India, thus is related to the literature on the economic legacy of colonialism. Most of this literature has focused on institutions, and on the very long run (e.g Acemoglu et al. 2001, Dell 2010), while we study the economic forces unleashed by colonial trade policy at the time. A similar focus on historical effects is in Donaldson (2018), who studies the welfare effect of the construction of the railways in colonial India. Dell & Olken (2020) study the economic forces unleashed in Indonesia by the production of sugar for export in the 19th century. Areas close to historical sugar factories are today more industrialised, and people tend to have higher levels of education and incomes. Dell & Olken (2020) explain this persistence through agglomeration forces and infrastructure investment that the production of sugar generated.[3] We instead focus on imports in colonial times, and the competition they generated for colonial manufacturers.

This chapter is organised as follows. Section 2.2 provides some historical background. Sections 2.3 and 2.4 describe our empirical approach, and how we collected and prepared the data. Sections 2.5 and 2.6 present our results on, respectively, industrialisation and political outcomes. Section 2.7 summarises our results and draws conclusions.

trade, in a colony) and to study a very different object (early-stages industrialisation, and anti-imperial feelings).

[3]Jedwab also show that colonial railroads persistently affected the distribution and aggregate level of economic activity in Africa.

2.2 Historical Context

As in a classical colonial setting, India exchanged mostly primary products for manufactures (Figure 2.1) at the start of the 20th century, and most of its trade (especially its imports) was with Britain, its imperial power (see Figure B.1 in the Appendix).[4] This was the result of a century-long process of deindustrialisation: a dominant producer and exporter of handcrafted cotton textiles until the 18th century, India was outcompeted by the industrial revolution in Britain (e.g. Gupta & Roy 2017, pp.230-31). As Britain industrialised and India de-industrialised, trade between the two expanded, and so did British colonial rule over India.

As the technologies of the industrial revolution spread around the world in the second half of the 19th century, Indian industry began to grow at what was actually a remarkable rate in comparison to other colonies in Asia or Africa. The main developments were the jute textile industry by British interests in Calcutta in the 1860s and 70s, and the cotton textile industry by indigenous business men in Bombay and Ahmedabad in the same period (a "probably unique" event in colonial economic history, Markovits 2002, p.8). Employment in large-scale industry grew from around 100,000 in 1860 to around 2 million in 1940, and the real output of manufacturing industries increased at a rate of 5.16% between 1900 and 1944 (Sivasubramonian 1997, p.140). Throughout this period, cotton and jute textiles remained the dominant sector, with iron & steel also becoming important after WWI. India accounted for 55 per cent of cotton spindles installed outside Europe, North America and Japan in 1910, and was, next to Britain, the world's greatest exporter of cotton yarn.[5] It also accounted for 50 per cent of the remaining steel produced in 1935 (Gupta & Roy 2017, p.232; Morris 1983, p.600-40).

Despite this relative success, large-scale industry remained a tiny share of the economy, and was outperformed not only by sovereign countries at a similar initial level of development, such as Japan, but also by more independent colonies such as Canada, Australia and New Zealand, and even by a dependent colony such as Korea. Wolcott & Clark (1999) estimate that Japanese labour productivity in cotton spinning increased five-fold between 1890-94 and 1935-38, while Indian productivity essentially stagnated. In Korea, the annual rate of growth of industry (including manufacturing and mining) was nearly 10% between 1910 and 1940 (Kohli 2004, p.48).

There is a long-standing view that blames the lacklustre industrial performance of India (and other dependent colonies) on colonial policy, but not everyone agrees with this. Many sovereign countries and independent colonies used protective tariffs in the late 19th century, and this was typically associated with faster industrial growth (Lehmann & O'Rourke 2011). In contrast, most colonies in Asia and Africa were more open to imports,

[4] India's main imports were cotton textiles, steel and iron products and machinery, while her main exports were tea, fibres, leather, raw cotton and fibre fabric (see Figure B.2) in the Appendix.

[5] China was an especially important foreign market.

and subject to a range of colonial policies that damaged their manufacturing growth (Tena-Junguito 2010, p.114-5; O'Rourke & Williamson 2017, p.7). In India, British *laissez-faire* meant that the country remained relatively open to imports (from all sources, not just Britain) compared to other independent countries and some colonies during the 19th and early 20th century. At the eve of WWI India was a nearly free-trading country and the few tariffs levied were aimed at providing revenue rather than protect domestic industries (see Arthi et al. 2020, Appendix 1). WWI changed this to some extend. First, the financial contribution of India to the British war effort required an increase in revenues which was in part provided through successive general tariff increases from 5% before 1916 to 15% in 1922. After 1923, increased autonomy for the Indian government meant that also some protective tariffs (e.g. on steel and cotton products). However, imports from Britain were often subject to differential protection with lower rates with imperial preferences being officially formalized in the Ottawa Conference in 1931. In effect the imposed tariffs, while lowering total imports, boosted Indian imports from the UK (Arthi et al. 2020). The protection India received was also relatively low compared to British dominions or other countries, for example the Japanese followed a more active industrial policy in Korea, and actively discriminated against Indian manufactures in government purchases (Kohli 2004; Tomlinson 2013, p.113). According to Bagchi (2000), these policies were largely responsible for India's poor industrial performance. However, not everyone agrees. For example, Roy (2002) argues that it was the scarcity of capital and skilled labour that held Indian industry back, while Wolcott (1994) and Wolcott & Clark (1999) argue that the reason why India underperformed Japan in textiles (and possibly other industries) is to be found in specific features of the Indian labour market.[6]

If historians cannot agree, the Indian nationalists of the time were of one mind in blaming Britain for India's backwardness. India was still under direct British rule on the eve of WWI, and various nationalist movements had formed to demand more autonomy. Among these was the Indian National Congress (INC). Founded in 1885 as a party of the urban elite, the INC progressively transformed into the mass party which would lead India to independence in 1947. There was much heterogeneity in the nationalists' strategies and goals, and the INC itself was internally divided. But one thing they had in common was the blame they assigned to British manufactures for having de-industrialised India, and the determination to secure some sort of protection against them (Clingingsmith & Williamson 2008, p.210). Indeed, even the limited protection that India obtained during the interwar years, while decreasing total imports, substantially boosted the import of British manufactures (Arthi et al. 2020)

[6]According to Morris (1983), pp.554-5 and 607-40, industrialisation held back by scarce domestic demand, due to the low per capita income, a low degree of monetisation of the economy, and the lack of industrialisation itself.

Unexpectedly, WWI provided such protection, though this was only a temporary event. Imports of British manufactures collapsed in real terms, reaching a low point in 1918 (Figure 2.1). This was reinforced by the prohibition to import from the Central Powers, most notably Germany, and was only partially alleviated by an increase in imports from war-allies such as Japan and the USA (see Appendix Figure B.1).[7] The collapse in imports from Britain was due to Britain's shift from production for export markets to production for the war effort (Morris 1983, p.600). Indeed, the greatest decline happened in war-related industries, such as steel, iron and copper products, and locomotives (see Appendix Figure B.2). Increasing trade costs, due to military utilisation of shipping capacity and an unrestricted German submarine warfare from late 1916, must have also played a role. Once the war was over, real imports of British manufactures rebounded rather quickly, though they remained below the 1913 peak (Figure 2.1).

When it comes to Indian exports, WWI had a mixed effect. Industries in high war-related demand such as leather, fibre (jute) fabric and flour, did well, while other industries such as raw cotton, sugar and timber, did poorly (see Appendix Figure B.2).

WWI also had non-trade effects on the Indian economy, due to recruitment, increased government demand for Indian products, and casualties. India sent almost a million Indian troops overseas, to fight or serve as noncombatants behind the Allied lines. For Punjab (the province which contributed most to the Indian army), Vanden Eynde (2016) finds that recruitment led to a significant rise in literacy in the recruitment grounds, most likely due to informal learning by serving soldiers. India's participation in the war effort also meant a greatly expanded public expenditure. The government of India paid for the soldiers it sent abroad, and must have therefore scaled up demand for locally-produced equipment. More generally, India became the supply centre for all Allied operations east of Suez (Morris 1983, p.600). An industrial commission was appointed in 1916 to survey the subcontinent's industrial resources and potential, and in 1917 a munitions board was created to accelerate the production of war materiels. By the end of the war, the munitions board played a huge role as a purchaser of industrial products (Lockwood 2012, p.37).[8] While this increased public demand for Indian products was in part a manifestation of the trade shock – the colonial government purchased locally what would have normally been imported from Britain – total public demand clearly increased. Finally, India reported around 75 thousand combat casualties, though this was dwarfed by the almost 14 million who died in the 1918-19 influenza pandemic (Chandra et al. 2012).

[7] Total imports remained roughly constant in nominal terms, but collapsed in real terms.

[8] For example, the Tata Iron and Steel Company began to receive Indian government support once the war started, and by 1916 was producing 100,000 tons of steel per year (Lockwood 2012, p.37; Gupta & Roy 2017, pp.240-41).

It has long been argued that the WWI trade shock had a positive effect on import-competing industries in India (and in other peripheral countries as well),[9] though this was initially constrained by the scarcity of imported inputs and machinery.[10] During the war, *THE Madras Times* wrote: "as far as the development of industries in India is concerned, the longer the war lasts the better. As soon as it is over, the flood of foreign goods will revive" (Lockwood 2012, pp.41-42). Morris (1983) argues that "As a consequence of wartime shortages and necessities, a variety of things were manufactured in India that had never been produced before [...]". Initially, Indian industries struggled to expand, as they lacked the raw materials, chemicals, machinery and spare parts normally imported from Britain or Germany. Skilled workers were also in short supply. In the second half of the war, however, they managed to overcome some of these constraints, by hiring more labour and working the machines around the clock. The real boom came in the aftermath of the war, as imports of replacement machinery boomed (Chaudhuri 1983, p.838) and the huge profits made by pre-existing firms attracted a flurry of investment (Gupta & Roy 2017, p.241; Morris 1983, pp.601-7). In a key industry like cotton textiles, the post-war boom was sustained by the fact that the British cotton textile industry took quite a few years to get back on its feet (Wolcott 1991).

It has also been argued that the war had *long-lasting* effects on industries in India (and other peripheral countries),[11] for three main reasons. First, some of the industries that expanded during the WWI boom learnt how to be competitive even in normal times, and progressively replaced imports in the 1920s.[12] The main examples are iron and steel, parts of the cotton textile industry, and cement (Morris 1983, pp.600-40).[13] Second, the attitude of the colonial government towards Indian industry became more benevolent in the inter-war period, for both military and political reasons.[14] The main implications were that the share of Indian products in public purchases progressively increased in the 1920s and 30s, and protective tariffs became available for selected industries from 1929 onwards

[9]Litman (1926) already noted that the war had considerable stimulated the industrialisation of economically backward countries. He explicitly cites Japan, China, India, Brazil, Canada, Australia and Argentina.

[10]On the contrary some *domestically* produced inputs, such as raw jute and cotton yarn, were made more abundant by the war, thus further supporting the growth of industry (Morris 1983, pp.601-7).

[11]Again, Litman (1926), p.25, notes how industrial developments in the periphery during WWI (and particularly their greater capacity to produce coarser manufactures) had a permanent effect on the composition of the manufacturing exports of the leading industrial countries.

[12]Other industries, such as chemicals, railway wagons and agricultural implements were less successful. According to Morris (1983) this was largely due to the lack of domestic demand, which in turn was due to the slow pace of industrialisation.

[13]e The iron and steel industry (essentially the Tata Company) could only survive thanks to protection from 1924 onwards, but this was largely due to the collapse in the international price of steel in those years (Morris 1983, pp.624-32).

[14]British officials realised that "[...] victory in Mesopotamia had been possible only thanks to rail provided by the Tatas" (Markovits 2002, p.11). At the same time, public opinion in India increasingly asked for an active industrial policy in the inter-war period (Tomlinson 2013, p.111-4).

(1924 for iron and steel).[15] But according to Tomlinson (2013), p.113, these changes were not large enough to represent a major new economic strategy. Finally, the WWI boom contributed to establishing the industrial dynasties which led the industrial development of India in the last thirty years of British rule (such as the Birlas and the Tatas). For these families, the large profits made during WWI were instrumental in allowing them to diversify into new industries in the 1930s and 1940s (such as sugar, paper, shipping, textile machinery, domestic airlines, and sewing machines).[16]

WWI also strengthened Indian nationalism, both as a result of indignation at Britain's behaviour after the war, and by laying the basis for greater frictions between Indian businessmen and the colonial government. During the war, Britain had promised to give India "dominion status", a position of substantial independence enjoyed by former colonies such as Australia and Canada. At the end of the war, however, it only conceded a partial transfer of power and a limited franchise, and ruthlessly repressed demonstrators.[17] Indian nationalism was stirred up by this, and the INC was no exception. WWI also created the basis for a growing rift between Indian businessmen and the colonial government. Until the early 20th century, India's leading businessmen were mainly merchants, who benefited from the market opportunities offered by the British empire. However, as industrial investments became more important, clashes with the colonial government became more frequent (Markovits 2002, p. 9-10).[18] The main elements of discontent were the scarcity of protective tariffs, the overvaluation of the rupee in the 1920s and 1930s, and, from the late 1930s onwards, the role of foreign capital. WWI accelerated this process for two reasons: it increased the relative importance of industrial investments, and it raised the policy expectations of Indian businessmen, who during the war had come to believe that the colonial government would provide greater support to Indian industry in the future. Importantly however, while creating large fluctuations in prices that affected the life of peasants, the WWI trade shock does not seem to have had as big an impact on peasants' support for the INC as the Great Depression did. The latter greatly contributed to making the INC a mass party with a strong rural support (Rothermund 1992). This likely reflects that the disruptions to trade caused by the two shocks affected very different sectors of the economy, while WWI mainly lessened competition from UK manufactures imports, the Great Depression mainly decreased demand for Indian primary products, but notably not tea, tobacco and sugar as during WWI (see also Bhavnani & Jha 2018).

[15] There was also a rise in revenue tariffs in the 1920s, with only mild protective effect (Tomlinson 2013, p.112; Wolcott 1991, p.3).

[16] See Tomlinson (2013), p.120. WWI generated both industrial profits and profits from speculation on basic commodities (Markovits (2002), p.11).

[17] These reforms led to the 1920 election, in which members of the central Imperial Legislative Assembly and Council of State were elected, as well as members of the Provincial Legislative Councils. In 1919, rising tension in the Punjab led to the Jallianwalla Bagh massacre, in which hundreds of demonstrators were shot dead by the army.

[18] It was over cotton textiles that the first significant clash emerged in 1895 (Markovits 2002, p. 9).

The INC began mass mobilisation shortly after WWI and went through a series of successes and setbacks before conquering power in the 1937 election, and then independence ten years later. The *non-cooperation movement* of 1920-2 was Gandhi's first attempt to deploy in India his famous methods of passive resistance. It comprised a boycott of elections as well as of British goods, education, courts, and honours to obtain dominion status within the British Empire. However, it failed after turning violent in February 1922, and it wasn't until the early 1930s that Gandhi could start a new campaign, this time aimed at full independence. The two Civil Disobedience movements of 1930-1 and 1932-4 were successful in mobilising the rural masses hit by the Great Depression (see Rothermund 1992 and Bhavnani & Jha 2018), but failed to extract significant concessions from the colonial government. Nevertheless, the India Act of 1935 devolved some powers to the provinces, and significantly enlarged the franchise. The INC participated in the 1937 provincial election, reporting a landslide.[19] It stayed in power until 1939, when it resigned in protest against India's participation to World War II. Gandhi was then incarcerated and almost died fasting in prison, but was eventually released and led the INC to another sweeping victory in the 1946 election. Exhausted by the war effort, Britain agreed on India's independence in 1947. In the years that followed, the partition of British India into India and Pakistan led to a refugee crisis and mass violence.

Indian big business became increasingly close to the INC in the 1920s and 1930s, as their dissatisfaction with the colonial government increased, and the INC managed to distinguish itself from a radical working-class movement. Initially, businessmen saw the INC mainly as an instrument of political pressure, as the expectation of a more benevolent government policy advised them against a complete alignment with the nationalist movement. Later, however, as the colonial government did not concede what they wanted, their support for the INC increased (e.g. Markovits 2002, p. 37; Kohli 2004, p. 253).[20] Even though the Great Depression did not hit industry as badly as the rest of the Indian economy,[21] it had the effect of further alienating the industrialists from the government, whose policy they saw as the main cause of the depression (Markovits 2002, p. 75). Big business largely supported the first Civil Disobedience movement of 1930-1, though its eventual failure created a split between pro-INC and anti-INC businessmen.[22] But as tensions with the government rose again, and businessmen realised that, without the INC,

[19]It won an absolute majority in six of the eleven provinces, emerged as the single largest party in Bombay and Assam, and fared badly only in the three predominantly Muslim provinces of Bengal, the Punjab and Sind (in which it nevertheless won most of the general non-Muslim seats).

[20]According to Markovits (2002), pp. 11 and 116-9, the colonial government was constantly preoccupied with trying to prevent the businessmen from joining the nationalist camp, but was limited in what it could do by the lobbying of British interests in London.

[21]While the contraction of internal demand was relatively small, due to the low initial purchasing power of the rural population and the rising real wages in the cities, Indian industry benefited from falling foreign competition and the drop in the price of raw materials (Markovits 2002, p. 41-2).

[22]Most notable on the anti-INC front were the Tatas, whose steel factories benefited more than anyone else from government purchases.

they had no way to pressurising the government, they returned to back the INC in the 1937 election. After this the alliance between big business and the INC was solidified, and survived throughout World War II despite the vast opportunities that the war opened to Indian capitalists (Markovits 2002, pp. 72, 80, 94, and 183). Crucial to this alliance was the INC's capacity to appear moderate at critical junctures. For example, the INC's anti-socialist resolution and moderate election manifesto of 1934 were specifically designed to win back the alliance of the capitalists (Markovits 2002, p. 98-100).

Even though business support was not the main reason for the INC's success – which lied in its capacity to mobilise the rural masses – it did play an important role, mainly but not exclusively by providing financial contributions. Already during the non-cooperation movement of 1920-2, businessmen made very large contributions (Krishna 1966, p. 426). Business support – in the form of financial help and participation in the boycott of foreign cloth – was an important factor in the initial success of the first Civil Disobedience movement, just as the weakening of such support helped convince Gandhi to call the movement off in 1931. In the elections of 1937, businessmen provided campaign contributions as well as votes in the special constituencies reserved for them. Systematic data on campaign contributions does not appear to exist, but voting patterns in the constituencies reserved for businessmen in 1937 are telling: of 21 seats, 12 went to either INC candidates or businessmen known to be pro-INC, while only 7 went to businessmen known to be anti-INC (Markovits 2002, p. 120-2). In 1939, the businessmen provided considerable political support to the INC by backing its rejection of a trade treaty with Britain (Markovits 2002, pp. 72-8, 119-24, 128-36 and 179-89). Key to the link between the INC and businessmen was Gandhi himself, a member of the Gujarati elite and friend of important businessmen such as G. D. Birla.

2.3 Empirical Approach

This section introduces our empirical approach. We present our main specifications in Section 2.3.1, and discuss threats to identifications in Section 2.3.2.

2.3.1 Specifications

Our main independent variable is a district level measure of exposure to 1913-17 changes in Indian net exports to Britain (in short, the "WWI trade shock"). We construct it as follows:

$$\text{EX-IM Shock}_n = \sum_{i=1}^{I} \frac{L_{n,i,11}}{L_{n,11}} \frac{\Delta(EX - IM)^{UK,India}_{i,17-13}}{L_{i,11}}. \tag{2.1}$$

The term $\Delta(EX - IM)^{UK,India}_{17-13,i}$ is the change in net exports to Britain in industry i between 1913 and 1917 (in 1911£), which we adjust by initial national employment in industry i, $L_{i,11}$ (we use 1911 as it is the year of the last pre-war census).[23] Adjusting by $L_{i,11}$ adjust for the industry specific absorption of the trade shock based on the initial size of an industry in India by 1911, i.e. it accounts for the fact that an increase or decrease in net exports for an industry has a relatively smaller effect in larger industries as the adjustment is distributed across a larger sector at the start.[24] From this industry level measure of exposure to the WWI trade shock, we construct a district level measure by weighing industries by their initial district employment ($L_{n,i,11}$) as a share of district population ($L_{n,11}$).

We start by exploring the effect of net exports as from a theoretical perspective the effects should be identical for imports and exports across different industries (see Autor et al. 2013*a*). However, one could reasonably expect that the effect of a change in imports of manufactures (e.g. infant industry argument) might have a different effect from a change in exports of primary products (e.g. Dutch disease argument). Accordingly, we will also separately estimate the effect of the change in (i) Indian imports of manufactures from the UK and (ii) Indian exports of primary products to the UK. This breakdown of the overall WWI trade shock follows the main colonial trade flows at the time where India exported primary products and imported manufactures from the UK. The two respective shocks are created following Equation 2.1, but only focus of the respective subset of industries i and EX and IM, respectively.

Our first set of regressions investigate the link between the WWI trade shock and industrial employment growth. Our baseline specification is

$$\Delta Industry_n = \beta_1 \text{EX-IM Shock}_n + X'_{n,11}\beta_2 + \epsilon_n, \tag{2.2}$$

where the dependent variable, $\Delta Industry_n = \sum_i \left(\frac{L_{n,i,21}}{L_{n,21}} - \frac{L_{n,i,11}}{L_{n,11}} \right)$, is the change in the share of industrial employment to total population in district n between 1911 and 1921. As the model is specified in first differences, it is closely related to a fixed effects regression (see Autor et al. 2013*a*) in which however the WWI trade shock only covers part of the differenced period. Accordingly, $X'_{n,11}$ is a vector of district level controls accounting for differential trends between districts based on observables in 1911.

We complement the baseline in (2.2) with a large number of alternative specifications, to be described in due course. For example, we decompose EX-IM Shock$_n$ into various sub-components, such as exports versus imports, or primary products versus manufactures.

[23]We measure trade in real terms because the shock was mainly on the import side, and was driven by a drop in British supply and by a rise in trade costs. This led to a simultaneous fall in volumes and rise in prices of Indian imports (which is visible from the fact that nominal imports fell less and rebounded more than real imports, see Figure 2.1 and Appendix Figure B.1). While both of these factors may have stimulated Indian industry, to measure imports in nominal terms would underestimate both, since they drive nominal imports in opposite directions.

[24]See also Autor et al. 2013*a* for the theoretical foundation for this. A generalized theoretical framework will be available in the next draft of Bonfatti & Brey (2020).

We decompose the dependent variable into five categories of employment by skills and nationality. We run a regression similar to (2.2), but at the industry level. We redefine the dependent variable to range between 1913 and all of the following years: 1915, 1917, 1919, 1921, 1926, 1936, 1951 and 2011 (the choice of a different start here is driven by data limitations).

Our second set of regressions investigates the impact of industrialisation levels on support for the anti-colonial movement, using the WWI trade shock as an instrument for industrialisation levels. Our second stage takes the form

$$Anticolonial_{n,j,t} = \beta_1 Industry_{n,t} + X'_{n,11}\beta_2 + X'_{j,t}\beta_3 + \epsilon_{n,j}, \tag{2.3}$$

where j represents the political unit of observation, and t the year. The variable $Anticolonial_{n,j,t}$ measures support for the anti-colonial movement in unit j and district n in year t. The variable $\text{Industry}_{n,t}$ is the industrial employment share in district n just before the political event.

We define $Anticolonial_{n,j,t}$ in two ways, the first of which measures the average strength of anti-imperial feelings by members of the Indian National Congress (INC) in district n in 1922. In this case, the political unit of observation is the district ($j = n$), and $Industry_{n,1921}$ is the industrial employment share in district n in 1921. In addition to our baseline controls ($X'_{n,11}$), we additionally include indicator variables for the 19 INC Provincial Committees, the average seniority of INC members within a district, and the proportion of them who belonged to the Khilafat movement ($X'_{j,22}$).

The second definition of $Anticolonial_{n,j,t}$ measures the share of seats won by the INC (and other political parties) in constituency j in district n in 1937 (constituencies are subdivisions of districts in the vast majority of cases). Now, $Industry_{n,1936}$ is the industrial employment share in district n in 1936, and we additionally control for constituency-type dummies ($X'_{j,37}$).

2.3.2 Threats to identification

The usual concern that the trade shock might not be exogenous, but driven by local demand or supply shocks, appears less serious in our context, since WWI was a truly exogenous shock to trade flows.[25] Three observations corroborate this point. First, Britain's exports to countries other than India also fell substantially during the war (see Figure B.7 available in the Appendix). Second, Indian imports from countries less affected by the war (such as the USA and Japan) boomed during the war (see Appendix Figure B.1).

[25]For example, if the fall in Indian imports from Britain was driven by a rise in Indian productivity, then one would observe a positive EX-IM Shock at the same time as a rise in industrial employment, but it would be a mistake to conclude that the former has caused the latter.

Third, Indian imports from Britain resumed very quickly after the war, both in real and in nominal terms (see Figure 2.1 & Appendix Figure B.1).[26]

Nevertheless, we include a specification in which we instrument for EX-IM Shock_n using the 1913-17 change in third countries' imports from Britain. This is a widely used strategy (e.g. Autor et al. 2013*a*), based on the assumption that shocks in third countries will be uncorrelated with shocks in the country of interest. We use as third countries Britain's exports to the rest of the World excluding India and individually each of Britain's top-five non-European export destinations other than India in 1911 (Argentina, Australia, China, Japan and the USA) supporting the exogenous interpretation of the WWI trade shock.

One concern that is specific to equation 2.2 is that WWI may have affected Indian industry through channels other than changes in India's net exports to Britain. To the extent that these other channels were correlated with EX-IM Shock_n, we would be erroneously attributing their effects to the WWI trade shock. We identify four such channels, and attempt to alleviate the related concerns in a series of robustness checks. First, the war clearly induced some substitution of imports from Britain with imports from British allies, chiefly the USA and Japan (see Figure B.1). To determine whether our coefficient of interest is downward biased by this substitution, we attempt to include a second trade shock, measuring the 1913-17 change in Indian imports from these countries. Second, since India contributed more than a million soldiers to WWI and became the supply centre for all Allied operations east of Suez, the related increase in public expenditure may have stimulated local industry. While district level expenditure on soldiers should be proxied by soldier presence in 1911 (a control included in the baseline), we further attempt to control for the effects of war-related expenditure by excluding war-related industries. Third, war casualties may have mattered, and we control for them directly. Finally, WWI gave way to the influenza pandemic of 1917-18, which hit India like no other country. We control for any related population loss by including district level population growth in 1911-21.

One concern that is specific to equation (2.3) is that our instrument for industrialisation levels (the WWI trade shock) might be correlated with pre-existing, deep-seated anti-imperial feelings. This concern arise from the fact that, unlike equation (2.2), equation (2.3) is specified in levels after the war, as opposed to differences before and after. This is done out of necessity, since the 20th century's incarnation of the anti-colonial movement only really started after WWI. To alleviate these concerns, we adopt a two-pronged strategy. First, the $X'_{n,11}$ and $X'_{j,t}$ vectors include possible determinants of pre-WWI anti-imperial feelings, such as province fixed effects (to control for different styles in government

[26]This is emphasised by Chaudhuri (1983): "That this [the fall of imports during the war] was due to disruptions on the supply side and not the lack of demand in India can be surmised from an inspection of the import figures in the immediate post-war years".

across British local administrations) and pre-WWI economic and social characteristics. Second, we conduct a falsification exercise in which we replace the dependent variable with a measure of district participation to the Indian Mutinies of 1857. The Mutinies were the most important act of rebellion against British rule before WWI (Krishna 1966, p.413). While not perfect, such an exercise should at least dispel the worry that there existed long-term factors causing both pre-existing anti-imperial feelings and exposure to the WWI trade shock.

2.4 Data and Descriptive Statistics

The analysis is based on three main blocks of data – trade data, industry data, and political data – which are briefly described in this section. A detailed description of the data is available in the Data Appendix B, which also provides summary statistics (Table B.14).

2.4.1 Trade data

Our first block of data is a hand-collected dataset on product-level net exports from India to Britain (in nominal and real term), yearly in 1911-24. Our main source is the annual Statement of Trade of the United Kingdom (see Customs and Excise Department 1911-1924). This source provides data on British trade by product and country, at up to four levels of product disaggregation. We identified 372 product categories that were traded between India and Britain (37 Indian export categories and 335 Indian import categories), and which could be best matched to Indian industrial sectors (on which more below).[27] We collected this data in values, and in quantities when available. We then used the available unit values to construct price deflators, allowing us to calculate real trade flows in 1911-24.

We complement this dataset with two similar datasets, one on British exports to the world and its top-five non-European destinations other than India in 1911 (Argentina, Australia, China, Japan and the US), and one on Indian imports from Japan and the USA (the latter comes from an Indian source, the "Annual Statement of the Sea-Borne Trade of British India with The British Empire and Foreign Countries", see Department of Statistics 1911-1921). These datasets span the same product categories collected for India-Britain trade, respectively for the years 1911-24 and 1911-21. We will use the first to construct an instrument for the drop in Indian imports from Britain, and the second

[27] We did not collect data at a further level of disaggregation than required by the matching procedure. We also did not collect data on manufacturing products apparently not produced in India, and on primary products not corresponding to Indian industrial sectors. The 372 product categories account for a vast majority of India-Britain trade in 1911: 82% of Indian imports and 72% of Indian exports. The difference is also to a sizeable part due to the aggregate data including Burma in British Indian trade flows, while our more detailed data does not include trade with Burma.

to assess whether India compensated for such a drop by importing more from Japan and the US.

Figures 2.1 describe the main patterns of real trade between India and Britain in 1911-24, as emerging from our data. Throughout the period, India imported mainly manufactures and exported mainly primary products (the classification of products comes from the Statement of Trade). Between 1913 and 1918, Indian real imports from Britain declined by a factor of 3, from £60 million to £18 million. By 1920, however, they had substantially recovered. In contrast, real exports remained rather stable over the period. All top Indian imports from Britain declined in real terms during WWI, while the picture for top exports was more mixed (see Appendix Figure B.2). The corresponding nominal trade flows are presented in Appendix Figure B.1, which typically declined less or increased more than their real counterparts, reflecting the high levels of inflation between 1914 and 1920 (Phillips 1958). During the whole period Britain remained by far India's most important trade partner for imports as well as exports.

2.4.2 Industry data

Our second block of data is a hand-collected dataset on industrial employment at the sector-district level in 1911 and 1921. The source of this data are the industrial censuses, which were run in these years alongside the population censuses (see Census Commissioner 1911, 1921). They provide information on employment in establishments with more than 20 employees (10 in 1921), by sector and district, covering the most developed part of the British Raj and more than 78% of its population.[28] The data from the industrial censuses has the advantage of focusing on employment in factories predominantly using mechanical power. This provides a more relevant measure of industrialization than manufacturing employment recorded in the population censuses as these numbers rather represent employment in artisanal and cottage production. The industrial censuses cover not only industrial factories, but also mines and plantations. Thus, the 262 sectors for which we have data can be divided into three broad categories: manufactures, raw materials and food. The latter two categories include both industrially processed raw materials and food (for example, ginned cotton and flour) as well as unprocessed food and raw materials produced on an industrial scale in mines and plantation (for example, iron ore, tea and rubber). Agricultural commodities not produced in plantations, such as uncleaned and unmilled wheat, are not included.

[28] We collected data from the industrial censuses for the seven major provinces of British India: Bengal, Bihar & Orissa, Bombay, Central Provinces & Berar, Madras, Punjab, and the United Provinces. These censuses provide data for the British-ruled districts of these provinces, as well as for 44 princely states which were included in them. Our sample does not cover a set of princely states, as well as the smaller provinces of Ajmer-Merwara, Adanamans and Nicobar, Assam, Baluchistan, Burma, Coorg, and the North-West Frontier province.

The data is further broken down by skills and nationality of employment, and by firm ownership structure. The breakdown of employment includes administrative staff (all employees related to direction, supervision and clerical work), skilled workers and unskilled workers, with the former two categories further subdivided into "Indians" and "Europeans and Anglo-Indians". Since most Europeans living in India will have been British, and Anglo-Indians were defined as British citizens living in India for a long time, for brevity, we rename the second subcategory "British". A non-negligible share of administrative and skilled workers were British in 1911: 14 and 1 per cent respectively (visualized in Appendix Figure B.9). Data on the number of firms by ownership and sector is only provided at the province level. We thus combine this data with data on the number of firms by sector and district to obtain an approximation of the number of firms by ownership, sector and district.[29] The ownership breakdown includes public versus private, with the latter category further subdivided into privately owned by Indians, privately owned by British, and companies. There was a large number of British-owned firms in India before WWI: Britons owned 23% of privately owned firms, and seemed to own a majority of companies (visualized in Appendix Figure B.10).

Although the industrial censuses provide us with the data we need to construct our measure of exposure to the WWI trade shock (which is based on 1911 industrial employment) it presents two important limitations when it comes to the construction of our dependent variable (the change in the industrial employment share).[30] First, the industrial censuses only allow us to construct the dependent variable for 1911-21. Second, the reduction in the threshold for census inclusion spuriously increases our dependent variable between 1911 and 1921, by counting as an increase the employment at firms that were in the 10-20 bracket in both years. Although this effect does not seem large on aggregate (firms in the 10-20 brackets account for only 2.5% of industrial employment in 1921, visualized in Appendix Figure B.11), we cannot fully rule out that this biases our results.

To circumvent these limitations, we complement the census data with data from the Factory Reports (available yearly in 1897-1948), and from the 1951 and 2011 censuses of independent India. The Factory Reports (Department of Industry 1897-1948), provide data on employment in firms covered by the 1911 Indian Factories Act, which were larger than those included in the industrial censuses, and did not include neither mines nor indigo, tea and coffee plantations.[31] Despite the narrower coverage, the Factory Reports

[29] For the province of Bombay, the province-level industrial classification does not match well with the one at the district level. We are thus forced to drop Bombay in regressions that use the breakdown by ownership.

[30] An additional small concern is that some administrative boundaries changed. To account for this we merge districts that underwent sizeable changes. More detail is provided in visualized in Appendix Section B.6.

[31] Between 1911 and 1922, the reports cover are all establishments which either (a) at any day of the year had at least 50 persons employed and used power driven machinery or (b) any premises with at least 20 employees that was declared a factory by the local government in the official Gazette (Prideaux 1917).

allow us to construct our dependent variable for periods other than 1911-21 (both shorter and longer). Furthermore, because the threshold for inclusion in the Factory Reports was the same in 1911 and 1921, they allow us to verify the robustness of our earlier results.[32] We also collected district level industrial employment from the Censuses of India of 1951 and 2011 (Census Superintendent 1951; Census Registrar General 2011). The data collected matches the industrial sectors covered by the Factory Reports, but all firms are included irrespective of the number of employees. Importantly, artisans are still reported separately.

After matching the 262 census industrial sectors to our 372 trade categories, we are left with 105 matched ("traded") sectors (of which 71 are import competing, 12 are exporting, and 22 are both import competing and exporting) and 45 unmatched ("non traded") sectors. A full list of sectors, classified by trading status and broad category (manufactures, raw materials, and food) is provided in Appendix Table B.15. The 45 non traded sectors are census industrial sectors for which we were unable to find a match with a trade category. In the vast majority of cases, this was because they produced non tradable products (e.g. "Waterworks"), or because they produced tradeable products which appeared not to be traded between Britain and India (e.g "Ice factories").

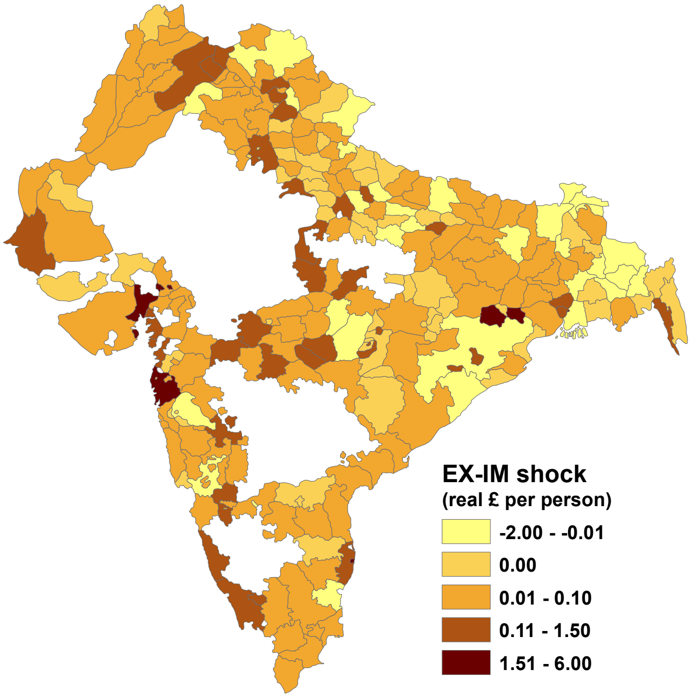
Aggregate industrial employment was 1.34 million in 1911, and increased by 37% to 1.83 million in 1921, i.e. from 0.55% to 0.75% of the population. When we focus exclusively on traded sectors, the greatest increase was for manufacturing, by 51% as compared to 21% for primary products. Employment in non-traded sectors was initially small, and essentially did not change in 1911-21. The composition in industrial employment is visualized in Appendix B.3.

Calculating 1913-17 changes in net exports to Britain in our 105 traded sectors and combining this information with district-industry level employment data from the 1911 census, we can now construct our measure of exposure to the WWI trade shock, as defined in equation 2.1. Exposure to the trade shock for the average district was £0.11 per person ($\approx$ US\$ 16.5 in 2017), or about 2% of annual per capita income (based on a per capita income of US\$ 895 in 1913, Bolt et al. 2018*b*). Figure 2.2 illustrates the geographical variation of the WWI trade shock across India. While the shock was particularly strong for some notable industrial districts (such as Ahmadabad, Bombay, Calcutta, Madras and Singhbum), there was considerable variation across the country, both along the coast and in the interior.

These thresholds were decreased to 20 and 10 in 1922, and to 10 and 5 in 1934. A detailed description of the firms covered by the Factory Acts over time is provided in Appendix Section B.7.

[32]The Factory Reports provide a coarser sectoral breakdown compared to the Industrial census, but this is not a problem for the construction of our dependent variable (for which we only need aggregate, district level industrial employment).

Figure 2.2: WW1 trade shock across India



Notes: The figure shows exposure to the change in net exports to Britain between 1913 and 1917 across British India. The depicted area covers the districts (British provinces and princely states) included in the censuses of Bengal, Bihar & Orissa, Bombay, the Central Provinces, Madras, Punjab and the United Provinces. The districts included represent 246,277,634 of the 315,156,396 population of British India (78%).

2.4.3 Political data

Our final block of data is on support for India's anti-colonial movement, which we use to construct the dependent variable $Anticolonial_{n,j,t}$. The dataset is divided in two parts: the first covers attitudes towards rebellion by members of the Indian National Congress (INC) in 1922, and the second the INC's electoral performance in 1937.

The data on attitudes comes from the Civil Disobedience Enquiry Committee Report of 1922 (Indian National Congress 1922). The report contains answers to the internal survey run by the INC in the summer of 1922, shortly after the failure of the Non-Cooperation Movement. The survey asked local party members how strongly they felt in favour of immediate civil disobedience, and whether or not they favoured particular forms of protests (such as a boycott of British products, British education, etc). The report provides the responses of up to 467 party members from all over India, 257 of which we are able to match to specific districts. For each question asked, we then construct an indicator variable which is one for "in favour" and zero for "against", and construct $Anticolonial_{n,1922}$ as the average response in each district. This procedure leaves us with a maximum of 92 (for the question on immediate civil disobedience) and a minimum of 42 (for the question on boycott of British products) district level observations. Of survey respondents, we also observe whether or not they were prominent members (participated in one of the 19 INC Provincial Committees, or in the All-India Committee)[33] and belonged to the Khilafat movement. Appendix Figure B.4 illustrates the geographical variation of $Anticolonial_{n,1922}$, when constructed as the average response to the question on immediate civil disobedience. As shown, our data covers most regions of India and, just like for exposure to the WWI trade shock, displays considerable variation across the country.

The data on electoral performance comes from the "Return showing the results of elections in India 1937" (India Office 1937).[34] We construct $Anticolonial_{n,j,1937}$ as the share of seats won by the INC (and by the other parties who contested the election) in constituency j (in almost all cases, constituencies were sub-division of districts). We cannot construct it as share of votes, since party affiliation and votes received are reported only for successful candidates. The electoral system and how we match Census districts to 1937 constituencies are described in Appendix Section B.8.

2.5 Results: Industrialization

This section analyses the effect of the World War I trade shock on industrial employment growth across districts in India. Figure 2.3 plots a bivariate regression of the 1911-21 change in the industrial employment share on exposure to the WWI trade shock. Districts exposed to a greater 1913-17 increase in net exports to Britain appear to have experienced faster industrial employment growth in 1911-21. We explore the robustness of this result, mechanisms for the increase in industrial employment and the long-run effect in the subsequent sections.

2.5.1 Baseline

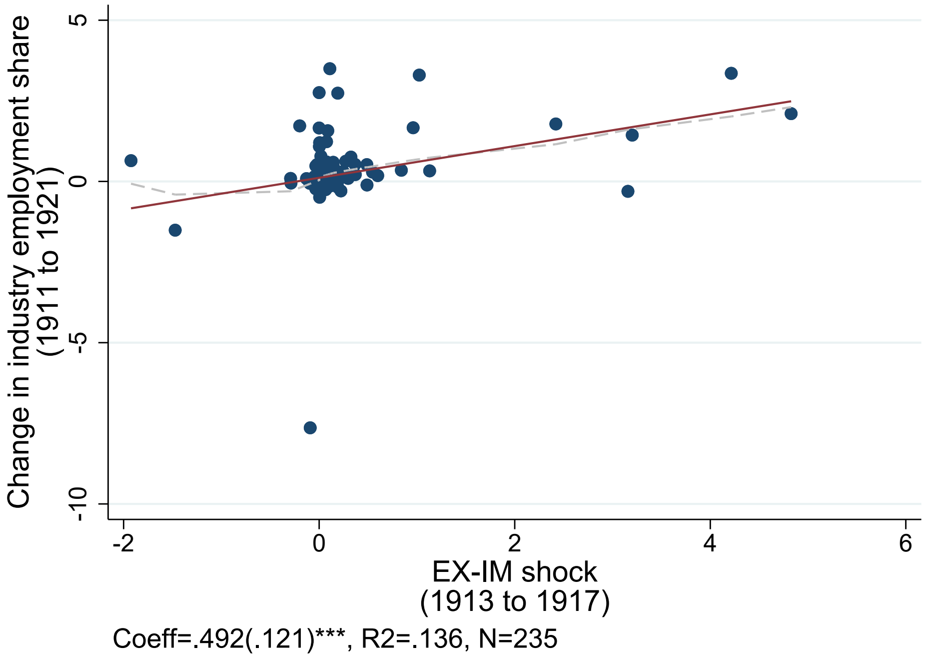
Our baseline results are presented in Table 2.1.[35] Column 1 is the relationship presented in Figure 2.3. It confirms that districts exposed to a greater 1913-17 increase in net exports to Britain, experienced faster industrial employment growth between 1911 and 1921, and this effect was highly significant. Column 2 adds as a control the initial industrial employment share. This addresses the concern that initially more industrialised districts might have been more exposed to the trade shock, while at the same time being on a faster growth trajectory. However, we do not find evidence of divergence across districts, and the coefficient on the WWI trade shock remains unaffected. Column 3 includes dummies

[33]There were more Provincial Committees than Provinces. For example, the Province "Central provinces & Berar" had three: "C.P. Marathi", "C.P. Hindustani", and "Berar".

[34]This data has been used before by Bhavnani & Jha (2018).

[35]Standard errors are clustered based on 41 province sub-divisions. Alternative standard errors accounting for spatial correlation with 100km kernal (as in Conley 2008), are presented in square brackets. Corresponding standard errors clustered at the industry level are presented in Appendix Table B.6. As shown, our preferred way of clustering on province sub-divisions provides the most conservative standard errors.

Figure 2.3: Effect of WW1 trade shock on industrialisation



Notes: Change in net British exports per person 1913-17 and industry employment share 1911-21 across Indian districts. The graph is equivalent to the first column from Panel A of Table 2.1. The grey shaded line in the background presents the corresponding locally weighted estimate.

for the seven provinces in our sample, thus absorbing any province-specific trends in the industrial employment share. Column 4 and 5 control for additional district level characteristics: whether they were coastal or not (accounting for any direct effect of the decline in maritime trade during WWI), and their initial population share of city-dwellers, militaries (a proxy for any rise in government demand for soldiers' equipment),[36] literates in any language and specifically in English, and of people at prime economic age. Only literacy in any language is associated with a faster industrial employment growth between 1911 and 1921. Our coefficient of interests remains very stable and statistically significant: a £1 higher exposure to the trade shock is predicted to increase the industrial employment share by 0.451 percentage points.[37]

Because the WWI trade shock was positive for the average district, the point estimate in our preferred specification (Table 2.1, column 5) implies that the shock had a positive effect on Indian industry. In particular, the shock accounted for 29 per cent of growth

[36] The military share is the number of serving army soldiers present in the district in 1911, divided by the district population. Assuming that districts where soldiers were located before the war were also those where the new recruits were equipped before deployment, and that the related industries were concentrated in these districts, then this measure should control for the direct effect that war had on Indian industry through public expenditure on soldiers' equipment.

[37] Reassuringly the estimated standard errors are similar using several common ways of calculating them (see Kelly 2020*a*). First, using the Bell-McCaffrey small sample adjustment when clustering on province sub-divisions the standard error is 0.16. Second, when changing the kernel to 250km and 1000km the standard error changes to 0.15 and 0.12, respectively.

Table 2.1: Effect of WWI trade shock on industrialisation

Dependent variable: Change industry employment share 1911-21					
	(1)	(2)	(3)	(4)	(5)
EX-IM Shock	0.492***	0.482***	0.486***	0.498***	0.451***
	(0.117)	(0.128)	(0.141)	(0.119)	(0.140)
	[0.092]	[0.113]	[0.116]	[0.106]	[0.130]
Industrial empl. share 1911		0.021	0.008	0.008	-0.002
		(0.071)	(0.072)	(0.081)	(0.084)
Military share 1911				0.065	0.032
				(0.088)	(0.148)
Urban share 1911				-0.001	-0.010
				(0.009)	(0.009)
Coastal				0.008	-0.110
				(0.244)	(0.201)
Literate share 1911					0.066***
					(0.023)
Literate English share 1911					0.015
					(0.130)
Age 20+ share 1911					-0.032
					(0.027)
Province FE	No	No	Yes	Yes	Yes
adj. R^2	0.132	0.132	0.128	0.118	0.142
N (districts)	235	235	235	235	216

Notes: The table presents the effect of the WWI trade shock measured as the change in £1 per person of net exports from Britain faced by a district between 1913 and 1917 on the share of employment in industry. Alternative Conley (2008) standard errors for 100km kernal in square brackets. Robust standard errors in parentheses clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in the industrial employment share between 1911 and 1921. That is to say, while the industrial employment share increased by 0.17 percentage points (from 0.64 per cent to 0.81 per cent), the increase due to the shock was 0.05 percentage points (29 per cent of 0.17). In terms of the dispersion of the effect, being at the 90th percentile of exposure to the shock as opposed to the 10th percentile meant a 0.09 percentage point higher industrial employment share by 1921, that is 14 per cent of the initial average (14 per cent of 0.64).[38]

The robustness of this result is evaluated in Appendix B.2 (including instrumental variable estimates in Table B.2, placebo exercises in Figure B.5 and Appendix B.3 provides a detailed description of the shift-share variable. In addition, we also analyse the effect of the WWI shock at the industry level and observe similar effects to the baseline result across Indian districts. Table B.4 in the Appendix shows that that industries that experienced a larger WWI trade shock 1913-17 experienced greater industrial employment growth

[38]The average trade shock was 0.11, so 0.451*0.11=0.05. The difference in exposure at the 90th and 10th percentile was 0.2, so 0.451*0.2=0.09.

1911-21. This result holds even after controlling for initial industry employment in 1911 and accounting for a variety of industry level fixed effects.

2.5.2 Mechanisms

We now attempt to discriminate between three competing explanations for the persistent effect of WWI on Indian industry (more evidence of persistence is provided in the next subsection). As explained in Section 2.2, three main hypotheses can be found in the historical literature. First, some of the industries that expanded during WWI simply turned out to be competitive even in normal times. This might be the result of learning what India was good at producing (in the spirit of Hausmann & Rodrik 2003), or of learning-by-doing more generally. For brevity, we call this the "learning" hypothesis. Second, Indian industry benefited from a more proactive industrial policy in the inter-war period (or at least the expectation of it), and this disproportionately benefited industries that did well during the war. We call this the "industrial policy" hypothesis. Third, the WWI trade shock generated large profits for some families, which could later be used to finance industrial expansion. We call this the "credit constraints" hypothesis.

We begin in Table 2.2, column 1, by showing that our baseline effect was driven by changes in imports, and not by changes in exports. We now decompose the trade shock defined in equation 2.1 in two parts: an import shock, only featuring $\Delta IM^{UK}_{i,17-13}$ in the numerator, and an export shock, only featuring $\Delta EX^{UK}_{i,17-13}$. We expect a negative coefficient on the former (indicating that Indian industry benefited from a decrease in imports), and a positive coefficient on the latter (industry also benefited from an increase in exports). Did changes in imports or exports have a persistent effect on industry? The coefficients on the two shocks have the expected sign and are similar in magnitude, both to each other and to the baseline coefficient.[39] However only the coefficient on the import shock is significantly different from zero.

Given that India imported mostly manufactures and exported mostly primary products, the last result may hide that it was changes in the trade of manufactures that mattered for persistence, and not changes in the trade of primary products. Columns 2-4 investigate this possibility. In columns 2 and 3, we further break down the import and export shocks into shocks to manufacturing industries and to industries processing primary products.[40] When we do so, we find that, indeed, changes in the trade of manufactures had a persistent effect no matter whether they were changes in imports or exports, whereas changes in the trade of primary products did not matter for employment 1911-21. The coefficients on the shocks to imports of primary products and exports of manufactures

[39] In fact, they are not statistically different from each other when taking the different directions of the shock into account.

[40] For example, the import shock to manufacturing industries is constructed using only $\Delta IM^{UK}_{i,17-13}$ in the numerator, and letting i vary over manufacturing industries only.

Table 2.2: Decomposition of WWI trade shock

Dependent variable: Change industry employment share 1911-21				
	(1)	(2)	(3)	(4)
IM Shock	-0.445*			
	(0.238)			
EX Shock	0.507			
	(1.824)			
IM Raw & Food Shock		7.906		
		(4.718)		
IM Manufactures Shock		-0.481***		-0.467**
		(0.155)		(0.231)
EX Raw & Food Shock			0.505	0.244
			(1.800)	(1.970)
EX Manufactures Shock			7.714*	
			(4.378)	
Controls	Yes	Yes	Yes	Yes
adj. R^2	0.138	0.145	0.118	0.136
N (districts)	216	216	216	216

Notes: The table presents the result for breaking down the effect of the WWI trade shock. Column 1 provides the effect of the trade shock by imports and exports on the change in the share of industry employment. A negative (positive) coefficient on the import (export) shock is going in the same direction as the positive coefficient for the net export shock. Column 2 further separates the import shock into primary (food & raw materials) imports and secondary (manufacturing) imports. Column 3 further separates the export shock into primary (food & raw materials) exports and secondary (manufacturing) exports. Column 4 separates the trade shock into the two main types of colonial trade: primary (food & raw materials) exports and secondary (manufacturing) imports. All columns include the full vector of control variables from column 5 of Table 2.1. Appendix Table B.7 confirms the robustness of the differential effect of colonial trade in more detail. Robust standard errors in parentheses are clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

are very large. This may be spuriously due to the fact that these trade flows accounted for a very small portion of India's trade, and only a few of her industries (Figure 2.1, Appendix Table B.15). For this reason, in column 4, we focus on the two components of the trade shock that best represent India's trade: the shock to imports of manufactures, and to exports of primary products. Results in this column confirm the pattern described earlier.[41]

Because the WWI shock to imports of manufactures was negative for the average district (imports of manufactures fell), the point estimate of its coefficient in column 4 implies that the manufacturing import shock had a positive effect on Indian industry.

[41]That only the change in the import of manufactures had a lasting effect is even more clearly confirmed in Appendix Table B.7, which digs even deeper into the separate effects of the two main WWI trade shocks.

In particular, it accounted for 40% of growth in the manufacturing employment share between 1911 and 1921 (as compared to 29% in the baseline).[42]

Table 2.3: Short-run effect of WWI trade shock

Dependent variable: Change in industry employment share				
Panel A1. Period effect, overall shock				
	(1)	(2)	(3)	(4)
	1913-15	1915-17	1917-19	1919-21
EX-IM Shock	0.039**	0.066***	0.199***	0.116***
	(0.019)	(0.017)	(0.070)	(0.030)
Panel A2. Accumulated effect, overall shock				
	1913-15	1913-17	1913-19	1913-21
EX-IM Shock	0.039**	0.105***	0.304***	0.420***
	(0.019)	(0.033)	(0.061)	(0.082)
Panel B1. Period effect, breakdown shock				
	1913-15	1915-17	1917-19	1919-21
EX Raw & Food Shock	0.323***	0.119	-0.029	-0.192
	(0.101)	(0.109)	(0.119)	(0.184)
IM Manufactures Shock	-0.008	-0.056***	-0.220***	-0.145***
	(0.016)	(0.016)	(0.068)	(0.024)
Panel B2. Accumulated effect, breakdown shock				
	1913-15	1913-17	1913-19	1913-21
EX Raw & Food Shock	0.323***	0.441**	0.412*	0.220
	(0.101)	(0.170)	(0.243)	(0.383)
IM Manufactures Shock	-0.008	-0.064**	-0.284***	-0.429***
	(0.016)	(0.027)	(0.068)	(0.084)
All specifications:				
Controls	Yes	Yes	Yes	Yes
N (districts)	190	190	190	190

Notes: For all regressions the dependent variable is the change in the share of employment in industry for the respective years. The number of observations is different from the baseline sample for the following reason: we only include districts in the sample that have been at least once reported in the annual Factory Reports. Note that mines and plantations are not included in the Factory Reports and that the threshold of industry was firms with at least 20 employees 1891-1922. Robust standard errors clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

If the WWI shock to exports of primary products did not have a persistent effect on industry, did it at least have a temporary effect? Table 2.3 uses Factory Reports data to break down our dependent variable into four sub-periods: 1913-15, 1915-17, 1917-19 and 1919-21.[43] Panels A1 looks at the overall WWI trade shock. Although the shock already had a positive effect on industrial growth in 1913-15, this increased over time to peak

[42]The manufacturing employment share increased by 0.14, from 0.26 in 1911 to 0.4 in 1921. Multiplying the average import shock on manufacturing industry (-0.12) by the coefficient (-0.467) we obtain 0.06, which is 40% of 0.14.

[43]Results for 1911-13 have already been discussed in the previous section.

in 1917-19, and growth remained high in 1919-21. The cumulative effect for 1913-21 is very similar to our baseline, which alleviates the concern that the baseline is biased by changes in the census inclusion rule between 1911 and 1921 (see Section 2.4.2). Panels B1 replicates the earlier panels, but distinguishes the shocks to exports of primary products and imports of manufactures. The former had an effect in 1913-15, but not after that. In contrast, the shock to imports of manufactures started to have an effect in 1915-17, peaked in 1917-19 and was still very strong in 1919-21. These results are consistent with the historical narrative according to which manufacturing boomed towards the end of the war, when capital and intermediates could be imported again (e.g. Morris 1983). Reassuringly, panels A2 and B2 find cumulative effects for 1913-21 which are very similar to our earlier results, even though the dependent variable is constructed using a different source of data.

Results so far seem most supportive of either the learning hypothesis, or the industrial policy hypothesis. Based on either, you would have expected the shock to imports of manufactures to matter the most. Learning is particularly important in manufacturing, and the inter-war period change in industrial policy was clearly focused on manufacturing. In contrast, if the credit constraints hypothesis was true, then you could have expected the shock to exports of primary products to also have an effect (in the next section, we show that not even in the long run did it have one). Districts exposed to a positive exports shock presumably made much larger profits than those exposed to a negative shock. Indeed, much of the profits made during the war came not from industrial profits, but from speculation on basic commodities (Tomlinson 2013, p.120; Markovits 2002, p.11).

Table 2.4, panel A, breaks down the change in employment by skills and nationality, finding that the WWI trade shock only boosted the employment of Indian administrative staff (as opposed to British ones). We repeat our baseline specification (Table 2.1, column 5) with the dependent variable now broken down into five categories of employment (British and Indian administrative staff, British and Indian skilled workers, and unskilled workers), so that the sum of the five coefficients equals the baseline coefficient. Unsurprisingly, 74% of the overall effect was due to an increase in the number of unskilled workers. However, WWI also had a significant effect on the number of Indian administrative workers, accounting for 8% of the overall effect. In other words, the WWI trade shock added about one Indian administrative worker per each ten unskilled workers. There was no effect on British administrative workers, or on skilled workers. The latter fact is perhaps not surprising, given that there was a great shortage of skilled workers in India in this period (Morris 1983, p.602).

Panel B provides a similar picture for industrial ownership. Here, we redefine the dependent variable to be the 1911-21 change in the number of industrial firms in a district. We look at the total number of firms, as well as its decomposition into four sub-categories: privately owned by Britons, privately owned by Indians, owned by a company, or owned by

Table 2.4: Industry employment & firm ownership breakdown

Dependent variable: See column header

Panel A. Change industry employment share by groups

	Administrative		Skilled		Unskilled
	British	Indian	British	Indian	Indian
EX-IM Shock	-4e^{-4}	0.036***	-5e^{-4}	0.084	0.332**
	(0.001)	(0.009)	(0.002)	(0.126)	(0.131)
Controls	Yes	Yes	Yes	Yes	Yes
N (districts)	216	216	216	216	216

Panel B. Change number of firms by ownership

	All firms	Personal		Company	State
	Total	British	Indian	Total	Total
EX-IM Shock	8.380*	-0.162	11.231*	-1.477	0.121
	(4.423)	(0.741)	(5.669)	(1.299)	(0.254)
Controls	Yes	Yes	Yes	Yes	Yes
N (districts)	183	183	183	183	183

Notes: Each column in Panel A presents the result for a subdivision of the industry employment share. Column 1 and 2 provides the result for the change in industry employment that is in administrative roles of British and Indian ethnicity, respectively. Column 3 and 4 provides the result for the change in skilled employment by British and Indian workers. Column 5 provides the result for the change in the share of unskilled employment that is exclusively Indian. Panel B presents the results on the change in the number of firms between 1911 and 1921. Column 1 presents the overall change in number of firms. Column 2 and 3 present the effect on the change in British and Indian privately owned firms, respectively. Column 4 present the result for the change in firms owned by a company with directors. Column 5 presents the result on government owned firms. Data on number of firms is available at the district level, while ownership data is constructed from province-industry cells that are matched to the district-industry structure. More information is given in Appendix B.6. The province of Bombay is excluded in Panel B due to the industry-classifications in the province-industry cells not being reported consistently in 1911 and 1921. Robust standard errors in parentheses clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the State. The WWI trade shock increased the total number of firms (column 1), through a compositional shift towards Indian privately-owned firms (columns 2-5).[44] This effect was small, though: only 1.2 Indian privately-owned firms are estimated to have been added by the WWI trade shock to the average district (multiply average exposure to the trade shock, 0.11, by the coefficient in column 3). It is possible that the shock mostly affected industrial employment at the intensive margin, or that it also created firms in districts where we would not expect to find them based on our empirical strategy.

The latter two results seem to reject the industrial policy hypothesis. If industries that did well during the war continued to expand because they expected to benefit from a change in industrial policy, then one could have expected this to apply to all firms in those industries, including those managed or owned by Britons. For example, it seems unlikely that the colonial government would discriminate against British managers and

[44] We looked for but could not find any differential effect of the WWI trade shock on companies, based on the nationality of directors.

entrepreneurs in its public purchase policy, and any change in trade policy would necessarily benefit all firms in affected industries.

Table 2.5: Change in workers accidents

Dependent variable: Change accidents per worker			
	(1)	(2)	(3)
	1913-17	1917-21	1913-21
EX-IM Shock	2.691**	-1.762***	0.930
	(1.178)	(0.594)	(0.916)
Controls	Yes	Yes	Yes
N (districts)	130	130	130

Notes: The table presents the impact of the trade shock on accidents per 1000 worker from 1913-1921. The vast majority of these accidents appear to be due to mishandling of machinery providing a good proxy for the ability of the workforce to use machinery. Robust standard errors clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Some evidence of learning by doing is provided by Table 2.5, which shows that districts more exposed to the WWI trade shock experienced only a temporary increase in the number of workplace accidents. We now replace our dependent variable with the number of accidents per worker in a district, which is reported by the Factory Reports for 130 districts and three years (1913, 1917 and 1921). Column 1 shows that districts more exposed to the WWI trade shock experienced a greater increase in the number of accidents per worker in 1913-17.[45] This pattern, however, was reversed in 1917-21 (column 2), with the result that Indian industry managed to expand in 1913-21 with no increase in accidents per workers (column 3). Information provided by the Factory Reports suggest that most recorded accidents were due to the incorrect handling of machines, and that workers do not seem to have worked longer hours during WWI.[46] A plausible interpretation of these results is that it took time for new unskilled workers to learn how to operate the machines safely.[47] The acquisition of such skills has been found to be a key aspect of human capital accumulation in the early industrial revolution (see De Pleijt et al. 2020 and references therein).

[45] The point estimate implies that a district with average exposure experienced an increase of 0.3 accidents per 1,000 workers.

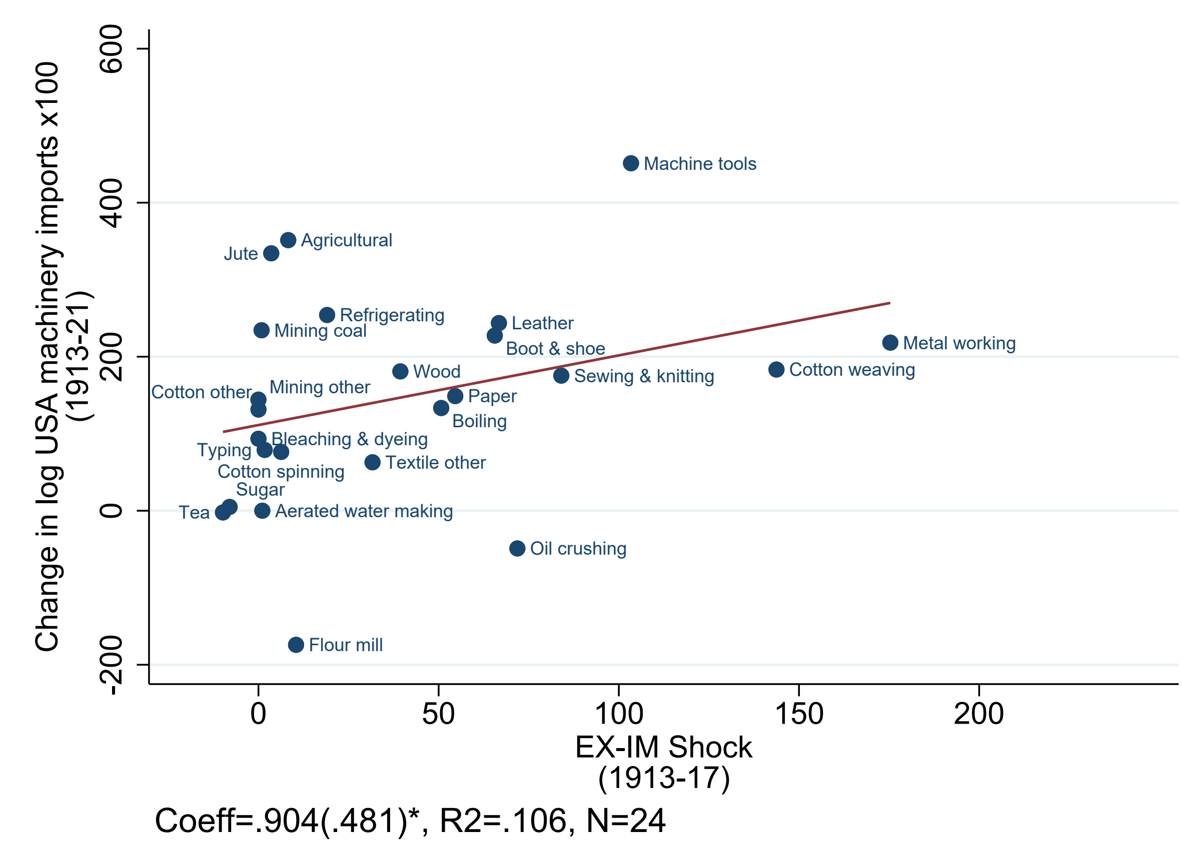
[46] The Bombay Factory Report of 1917 refers to the recorded accidents (28 fatal, 75 serious, 819 minor) in the following way: "The fatal accidents amounted to 27 and caused the death of 28 persons. Of the fatal accidents, 9 were due to machinery and the remainder were due to other causes, chiefly through gross carelessness on the part of the operatives. All accidents unconnected with the machinery and of very trivial nature have been excluded from this report. But fatal accidents of all kinds have been included.". The main cause of fatal accidents appears to be workers being caught by the line shaft (for power transmission) of machinery. Notably, information on shifts and working hours suggests most firms had similar hours of work and holiday set at the maximum level allowed, with no substantial change in the rules (or in the exemptions provided) observable over this period.

[47] A complementary explanation is that it took time for new managers to learn how to organise the production safely. However this hypothesis is not supported by data on prosecutions, which remained low throughout this period.

In summary, the evidence seems most supportive of the "learning" explanation for the persistent effect of the WWI trade shock. As one would expect if learning was important, the effect of the trade shock was mainly due to lagged response of manufacturing, it involved mainly Indian managers and entrepreneurs, and it resulted in only a temporary increase in accidents per workers. "Learning what you are good at producing", or "learning by doing", may both have played an important role. Of course, this is only a tentative conclusion given the limited evidence available.

2.5.3 Long-run

Figure 2.4: Effect of WW1 trade shock on machinery imports



Notes: Impact of WW1 trade shock 1913-17 on change in log machinery imports from the USA 1913-1921. To account for zero imports in some categories the value of imports is in 1000' GBP plus one. Due to limited information being available in the Indian statements of trade the data is collapsed at the level of the different types of machinery imported. The corresponding EX-IM shock is calculated by taking the weighted average across all matched categories from the baseline regression. For example, the categories "Cotton fabric" and "Cotton carpet" are matched to "Cotton weaving machinery" imports with the individual EX-IM shocks weighted by each categories share of employment in total employment of the two categories.

This section investigates the long-run persistence of the WWI trade shock, finding that it lasted throughout the 20th century and to the present day (2011, the date of the last census). To take such a long-term view, we now construct our dependent variable (the change in the industrial employment share at the district level) using two different sources: the Factory Reports, which provide yearly data between 1897 and 1948 for a subset of larger firms, and the censuses of post-independence India (we only focus on the Republic of India, and not on Pakistan and Bangladesh). All right-hand side variables are the same as in the baseline.

Some preliminary evidence of long-run implications is provided in Figure 2.4, which suggests that industries more exposed to the WWI trade shock were expanding their productive capacity more by 1921. The figure exploits the fact that, in Department of Statistics (1911-1921), imports of machinery from the USA are broken down by the type of work that the machinery performed (e.g. "metal working", "cotton spinning", etc).[48] We thus plot the 1913-21 change in imports of machinery from the USA by type, against the average WWI trade shock across sectors using that particular type of machinery. The relationship between the two variables is positive and significant. For example, some of the largest increase in imports are recorded for machinery used for "metal working" and "cotton weaving", two manufacturing activities exposed to a large drop in imports during WWI. In contrast, imports of machinery used in "tea" and "sugar" production (two sectors that were exposed to a drop in exports) stagnated over this period. Presumably, this indicates that industries which expanded during the war expected to retain their expanded position even after the war was over.

Our main long-run results are presented in columns 2-5 of Table 2.6 (column 1 replicates the 1913-21 regression presented earlier). Our selection of years for the post-1921 period (1926, 1936, 1951 and 2011) is driven by the following considerations. The first year is far enough from 1921, but before protective trade policies had a potential effect in the late 1920s. The second year is after the recovery from the Great Depression, and just before the 1937 election which is the subject of analysis in Section 2.6. Finally, the last two years are those of the first and last censuses of post-independence India.

Columns 2-4 find that districts more exposed to the WWI trade shock remained significantly more industrialised throughout the colonial period, and this long-run effect should be attributed to the WWI shock to imports of manufactures. Districts more affected by the WWI trade shock did not grow either faster or more slowly between 1921 and 1951 (Panel A1). As a consequence, they remained significantly more industrialised throughout this period (Panel A2). Most importantly for our purposes, they remained more industrialised in 1936, the year before the provincial election that projected the Indian National Congress into power. In the next section, we will exploit this exogenous variation to estimate the link between colonial industrialisation and support for an anti-colonial movement. In Panels B1 and B2, we focus on the two key components of the trade shock: the shock to imports of manufactures and to exports of primary products. We find that the above described pattern was driven by the shock to imports of manufactures, though

[48] US machinery imports of 198,120£ account for 5.9% of total Indian machinery imports (3,359,169£) in 1911. The main source of Indian machinery imports before WWI was the UK with 2,894,770£.

Table 2.6: Long-run effect of WWI trade shock

Dependent variable: Change in industry employment share					
Panel A1. Period effect, overall shock					
	(1)	(2)	(3)	(4)	(5)
	1913-21	1921-26	1926-36	1936-51	1951-2011
EX-IM Shock	0.420***	0.002	-0.039	0.003	1.099**
	(0.082)	(0.021)	(0.086)	(0.171)	(0.434)
Panel A2. Accumulated effect, overall shock					
		1913-26	1913-36	1913-51	1913-2011
EX-IM Shock		0.422***	0.383***	0.575*	1.674***
		(0.081)	(0.063)	(0.296)	(0.454)
Panel B1. Period effect, breakdown shock					
	1913-21	1921-26	1926-36	1936-51	1951-2011
EX Raw & Food Shock	0.220	-0.329	0.180	0.173	2.894*
	(0.383)	(0.196)	(0.318)	(0.487)	(1.596)
IM Manufactures Shock	-0.429***	-0.026	0.046	0.198	-0.548
	(0.084)	(0.028)	(0.082)	(0.176)	(0.575)
Panel B2. Accumulated effect, breakdown shock					
		1913-26	1913-36	1913-51	1913-2011
EX Raw & Food Shock		-0.109	0.071	1.320*	4.041***
		(0.557)	(0.325)	(0.710)	(1.526)
IM Manufactures Shock		-0.455***	-0.409***	-0.380	-1.126**
		(0.079)	(0.062)	(0.233)	(0.510)
All specifications:					
Controls	Yes	Yes	Yes	Yes	Yes
N (districts)	190	190	190	132	132

Notes: The number of observations is different after 1951 as the sample only covers the Republic of India and some districts had to be further merged to create a consistent unit of observation for this time period. More detail on the data is provided in Appendix B.7. Robust standard errors clustered on province sub-divisions till independence and robust standard errors after independence. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

results for the periods ending in 1951 already reflect some of the post-colonial patterns to be discussed next.

Column 5 finds that districts more exposed to the WWI trade shock are still more industrialised to these days. Panel A1 even finds a positive effect of the WWI trade shock on industrial employment growth in 1951-2011. However when we zoom into the key components of the trade shock (Panel B1), we find that it was only the WWI shock to exports of primary products which is significantly associated with industrial employment growth in 1951-2011, and less the WWI shock to imports of manufactures (also a large, but insignificant is observable). This suggests that what we are presumably picking up is a correlation between the disruption to India's export markets during WWI and after independence.[49] Even though the WWI shock to imports of manufactures did not lead to faster industrial growth 1951-2011, it did have a positive, cumulative effect in 1913-2011 (Panel B2). This indicates that districts shifted to a higher industrial employment share due to the disruptions to imports of British manufactures during WWI and continue to retain that higher industrial employment share even a century later.

Even though one must be cautious in attributing these long-run effects to WWI (since many other shocks have occurred since then), our results clearly point at a persistent effect of the WWI trade shock on Indian industry, at the very least throughout the 1920s and 1930s. The Indian economy has gone through many shocks and changes since 1921, the most important being the Great Depression (and the resulting rise in protectionism in the 1930s), World War II (which is known to have greatly stimulated Indian industry), independence (which led to the rise of a hyper protectionist state), and liberalisation after 1991. To the extent that some of these shocks were correlated with the WWI trade shock and had a similar effect on industry, our coefficients would be picking up their combined effect. Still, we believe our results until at least 1936 are truly indicative of a persistent effect of WWI. The year 1926 was before any other major shock, and before protective tariffs were introduced (with the exception of iron and steel).[50] The year 1936 came after the Great Depression and the granting of selective protection (mostly increasing imperial preference, not affecting imports from and exports to Britain). However, the Great Depression had a relatively small effect on Indian industry, and the protective tariffs that were granted before 1936 were not significant enough to represent a major change in industrial policy (Markovits 2002, pp.41-2; Tomlinson 2013, p.113).

[49] Being part of the British Empire meant that India was well connected with the rest of the world, and that exports of primary products were encouraged. Part of that connectivity must have been lost after independence, and the post-colonial governments were not particularly supportive of India's traditional exports. As a consequence, these performed poorly in the first few decades after independence (Vaidyanathan 1983, pp.972-3, Gupta & Roy 2017, p.245). Thus, the same districts that suffered from a disruption in their export of primary products during WWI suffered from a similar fate after 1951.

[50] Protectionist tariffs introduced in India during the interwar years indeed appear to have boosted imports of UK manufactures rather than reduced them (Arthi et al. 2020).

2.6 Results: Political Outcomes

We now turn to our second hypothesis, namely that greater industrialisation levels should result in greater support for the anti-colonial movement in a district (equation 2.3). Section 2.6.1 measures support using responses to the 1922 internal survey of the INC, while Section 2.6.2 measures it using the INC's performance at the 1937 election. Section 2.6.3 shows that there is no corresponding effect on rebelliousness in the Indian mutiny that occurred before WWI.

2.6.1 Industrialisation levels and 1922 survey responses

In this section, we study the link between industrialisation levels in 1921 (instrumented using the WWI trade shock) and the responses of local INC members to the internal survey run in 1922. The survey asked INC members whether or not they were in favour of different forms of rebellion. For each form of rebellion, we code their answers into a dummy, where 1 indicates in favour and 0 indicates against.

This information collected in Indian National Congress (1922) provides detailed insights on the attitudes of mid-level party members across India. The aim of the committee was to provide the leadership of the INC with a better understanding of the public's feeling on the measures of civil disobedience taken so far and to be taken in the future (see Indian National Congress 1922, p.4-5). Figure B.4 in the Appendix underlines that the local representatives interviewed are from a variety of districts across the whole of India and that there is considerable local variation in the responses given. This provides unique insight into the support for civil disobedience and specific policies across Indian districts by 1922.

All results are reported in Table 2.7, which reports five different versions of equation 2.3, one per each question asked. The dependent variable is defined at the district level and measures the average response of INC members in a district. In addition to our baseline controls, we include the share of members who were part of an INC committee above the district level (province or national level), the share of them who were part of the Khilafat Movement, and indicator variables for the 19 INC Provincial Committees, which in addition to geographic characteristics also accounts for differences in the timing of the interviews. Controlling for a large number of pre-WWI economic and social characteristics, as well as for province and INC committee fixed effects, helps us to alleviate concerns that our instrument (the WWI trade shock) might be correlated with pre-existing, deep-seated anti-imperial feelings.

Our main result is that more industrialised districts featured stronger support for immediate civil disobedience, the most general form of protest that INC members were asked about. The positive and significant coefficient in column 1 indicates that a one percentage point higher industrial employment share in 1921 was associated with a 54%

Table 2.7: Questions from the 1922 civil disobedience enquiry

Dependent variable: Whether in favour (=1) or not (=0) of reported action	(1) For immediate civil disobedience	(2) For boycott British products	(3) For private defense	(4) For boycott British education	(5) For boycott of courts in political cases
Industrial empl. share 1921	0.544***	0.729**	0.136	-0.289	-0.011
	(0.165)	(0.309)	(0.113)	(0.214)	(0.430)
Controls	Yes	Yes	Yes	Yes	Yes
N (districts)	92	42	62	69	63
F-stat (1st stage)	23.88	3.15	4.44	44.77	3.79
First Stage (EX-IM Shock)	0.496***	1.032*	1.090**	0.598***	0.775*
	(0.102)	(0.582)	(0.517)	(0.089)	(0.398)
OLS estimate	0.271***	0.752	0.148	-0.173	-0.009
	(0.091)	(0.875)	(0.182)	(0.180)	(0.468)

Notes: Each column presents the result for a different question related to independence asked in the civil disobedience enquiry committee report. Full vector of control variables from Table 2.1 plus INC province committee fixed effects and membership positions included. Industrial employment share 1921 is estimated with the WWI trade shock in the first stage. Due to the small sample, 2SLS might not be reliable, OLS results are presented as well at the bottom of the table. Robust standard errors in parentheses are clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

stronger support for immediate civil disobedience in 1922. In turn, this implies that the interruption in colonial trade associated with WWI, by leading to higher industrialisation levels, resulted in a greater support for the anti-colonial movement. In particular, the WWI trade shock is estimated to have resulted in a 6.8% support for immediate civil disobedience.[51] Even though the sample of districts is much smaller compared to before (91 observations), the F-stat on the first stage is sufficiently high for the instrument to be valid. Column 2 finds similar result for a boycott of British goods. Here, however, the sample is very much reduced (down to 42 observations) and the instrument is relatively weak. Columns 3-5 find no evidence that the WWI trade shock influenced views on other types of protest.[52] Considering the small sample size that is not well suited to estimate 2SLS, the corresponding OLS coefficients are presented at the bottom of the table. Coefficients are nearly identical to the IV-results, however the effect in column 2 is no longer statistically significant.

Table 2.8: Results of 1937 legislative election

Dependent variable: Share of seats won by reported party

Panel A. All constituencies

	(1) INC	(2) Muslim League	(3) Unionist	(4) Independents	(5) Other
Industry share 1936	0.044**	-0.006	-0.023**	-0.019	0.004
	(0.019)	(0.017)	(0.010)	(0.020)	(0.020)
N (constituencies)	878	878	878	878	878
F-stat (1st stage)	30.58	30.58	30.58	30.58	30.58
First Stage (EX-IM Shock)	1.281***	1.281***	1.281***	1.281***	1.281***
	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)
Panel B. Single-seat Muhammadan constituencies					
Industry share 1936	-0.011	-0.061	-0.044	0.109	0.007
	(0.011)	(0.072)	(0.038)	(0.082)	(0.045)
N (constituencies)	367	367	367	367	367
Panel C. Single-seat General constituencies					
Industry share 1936	0.060***	0.000	-0.014**	-0.030**	-0.016
	(0.019)	(.)	(0.006)	(0.012)	(0.020)
N (constituencies)	327	327	327	327	327
All specifications:					
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Panel A present the results for the share of seats won by different parties across all single- and multi-seat constituencies in the 1937 provincial legislative assembly elections. Only election results for "General" (predominantly Hindu) and "Muhammadan" constituencies are included in the sample. From left to right the columns report the effect on the Indian National Congress (INC), Muslim League, Unionist party, Independent, and other parties success to win a seat. Results when distinguishing by multi- and single-seats are nearly identical (not reported). In Panels B and C the sample is focussing exclusively on whether a party won a single-seat constituencies distinguishing by "Muhammadan" and "General" constituencies. Full vector of control variables from Table 1.3 plus constituency type fixed effects ("Rural Muhammadan", "General Urban" and "Muhammadan Urban") are included. Industrial employment share 1936 is estimated with the WWI trade shock in the first stage. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6.2 Industrialisation levels and 1937 election results

We now complement results in the previous section by studying the link between industrialisation levels in 1936 (instrumented with the WWI trade shock) and the INC's performance in the 1937 provincial election. We measure electoral performance as the share of seats won by the INC and by the other parties who contested the election.

[51]Multiply the average shock in this subset of districts (0.250) by the first-stage coefficient (0.496), and then by the the second-stage coefficient (0.544) to obtain a coefficient on the average shock equal to 0.068. Appendix Table B.9 highlights that the main result is robust to other potential channels through which WWI might have had an effect on civil disobedience. Here, WWI casualties and deaths in the 1918-19 Spanish flu are of particular interest for the political outcomes, while the other two columns are presented solely for completeness (likely providing bad controls).

[52]The much reduced sample in columns 2-5 are due to many respondents not explicitly answering all questions.

All results are reported in Table 2.8, where we estimate equation 2.3 using as dependent variable the share of seats won by the INC and by other political forces.[53] The dependent variable is measured at the level of constituencies, which in almost all cases were subdivisions of districts. In addition to our baseline district-level controls, we now also include constituency-type dummies: Muslim rural, Muslim urban and general (Hindu) urban (where the omitted type is general rural). The INC was the winner of the election (it won 617 out of 1109 seats in our constituencies), and the only party who promised to fight for the independence of all Indians irrespective of caste or creed (Pandey 1978). Following at a distance was the Muslim League, whose platform resembled in some respect that of the INC, but otherwise focused on the interests of Muslims, and the Unionist Party, which mainly represented the interests of Punjabi landlords and was most open to cooperation with the British. A considerable number of "independent candidates" represented a broad spectrum of varied opinions on mainly local issues, while the category "other" covers the remaining smaller parties.

Panel A finds that constituencies in more industrialised districts awarded a significantly higher share of seats to the INC, and a significantly smaller share to the Unionist Party. The panel includes both single-seat constituencies (694 out of 878) and multi-seat constituencies. The coefficient in column 1 implies that a one percentage point higher industrial employment share is associated with the INC winning an additional 4.4% of seats. In turn, this implies that the interruption in colonial trade associated with WWI increased the number of seats won by the INC by 10 out of 617, or 1.5% of the total.[54] This number is likely to underestimate the true effect of industrialisation levels, for two reasons. First, we are including all constituencies, even those where the INC was not an obvious choice (such as Muslim constituencies, or multi-seat constituencies with additional seats reserved for minorities). Second, our dependent variable measures the share of seats (as opposed to votes) won. This implies that, by construction, the effect will appear to be zero in all non-marginal constituencies, even though higher industrialisation levels may have implied more votes cast for the INC.

Panels B and C focus on single-seat constituencies, and find that industrialisation levels did not benefit the INC in Muslim constituencies but they benefited it especially strongly in general constituencies. The rationale for focusing on single-seat constituencies is that the additional seats of multi-seat constituencies were reserved for minority groups, either officially or unofficially (Indian Delimitation Committee 1936, pp. 13-14). Such groups might vote primarily for candidates representing their specific interests, and not

[53] Note that the Great Depression that occurred in the early 1930s is unlikely to bias the presented IV estimate. This is due to the industry level changes in trade flows, the identifying variation, during the Great Depression and WWI being plausibly uncorrelated. See Bhavnani & Jha (2018) for more detail on the very different trade shock created by the Great Depression in India and its political effect.

[54] We obtain the number 10 by multiplying the average trade shock in a constituency (0.155) by the first-stage coefficient (1.281), then by the second-stage coefficient (0.044), and finally by the total number of seats (1109).

for any of the big national parties. Note that, in single seat constituencies, our dependent variable (the share of seats won by the INC) can only take two values: 0 if the INC lost, and 1 if it won. The coefficient of interest can then be interpreted as the change in probability of an INC victory associated with higher industrialisation levels. Panel B finds that industrialisation levels did not affect the probability of INC victory in Muslim constituencies. This is as expected, since the INC was not a popular choice in Muslim constituencies (it won 10 out of 326), so that very few of them were likely to be marginal for it. The mirror image of this is panel C, which finds that, in single-seat general constituencies, industrialisation levels had a bigger effect on the INC's electoral performance than in the full sample.

Our preferred coefficient (panel C, column 1) implies that a one percentage point higher industrial employment share in 1936 was associated with a 6.0% higher probability of an INC victory in 1937. This implies that the interruption in colonial trade associated with WWI increased the number of seats won by the INC by 8 out of 327, or 2.4% of the total.[55] This is a relatively large effect, particularly given that it entirely relies on variation coming from constituencies turning to the INC, with no weight being given to constituencies merely giving more votes to the INC. Thus, our results suggest that although the INC's success was ultimately explained with its capacity to mobilise the rural masses, this was largely down to low levels of industrialisation in India. Industrialisation levels, per se, did have a large impact on anti imperial feelings.

2.6.3 Reduced form analysis and placebo

Table 2.9: WWI trade shock and Indian rebelliousness 1857-1937

Dependent variable: See column header			
	(1)	(2)	(3)
	Mutiny participation 1857	Support civil disobedience 1922	INC Seats 1937
EX-IM Shock	-0.026	0.271***	0.056**
	(0.034)	(0.088)	(0.023)
Controls	Yes	Yes	Yes
N	216	92	878

Notes: Column 1 present the effect of the WWI trade shock on the number of towns that rebelled during the 1857 mutiny collected from David (2003). Appendix Table B.10 confirms that no effect of the WWI trade shock is observed on the 1857 Indian mutiny across a wide set of different specifications. Column 2 present the direct effect of the WWI trade shock on support for civil disobedience in 1922. Column 3 present the direct effect of the WWI trade shock on seats won by the INC in the 1937 election. Column 2 and 3 present the respective reduced form results to Table 2.7 and Table 2.8 for comparison. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[55] We obtain the number 8 by multiplying the average trade shock in a constituency (0.148) by the first-stage coefficient (2.727), then by the second-stage coefficient (0.060), and finally by the total number of seats (327).

One potential concern is that even after controlling for a large number of pre-WWI economic and social characteristics and for a set of fixed effects, our instrument (the WWI trade shock) might still be correlated with pre-existing, deep-seated anti-imperials feelings.

To alleviate this concern, we conduct in Table 2.9 column 1 a falsification exercise, in which we study the reduced form effect of the WWI trade shock on a measure of district participation in the Indian Mutinies of 1857. The Mutinies were the most important act of rebellion against British rule before WWI (Krishna 1966, p. 413), and are sometimes known as India's "First War of Independence". The dependent variable is the number of cities and towns in a district in which a mutiny took place.[56] For comparability, columns 2-3 report the reduced-form effect of the WWI trade shock on our measures of support for the anti-colonial movement (support for civil disobedience in 1922 and share of seats won by the INC in 1937).

We do not find any significant correlation between the WWI trade shock and participation to the 1857 mutinies, alleviating the concern that there existed some long-term factors causing both pre-existing anti-imperial feelings and exposure to the WWI trade shock. In line with our earlier results, we find a strong reduced-form effect of the WWI trade shock on support for civil disobedience in 1922, and the share of seats won by the INC in 1937.[57]

2.7 Conclusion

In the *laissez-faire* world of the early 20th century, dependent colonies around the world were open to colonial trade, and this has been blamed for their poor industrial performance. We have found that colonial trade did help to prevent industrialisation in colonial India, as evidenced by the fact that its interruption in 1913-17 led to a period of faster industrial growth and to a persistently higher level of industrialisation. The persistence of the effect, and some evidence that this was due to learning, suggests to look at this through a dynamic model of trade, within which free trade can be welfare-decreasing. We also found that colonial trade did help to keep India tied to the British empire, as evidenced by the fact that its interruption in 1913-17 led to stronger support for the anti-colonial movement in the 1920s and 1930s. This is consistent with a classical argument according to which colonial industrialists were a force against empire.

If colonial trade hindered Indian industrialisation, then why did Britain knowingly insist on a policy of free trade? We can think of two explanations. First, promoting Indian

[56] Info on cities and town with mutinies is taken from Map 1 in David (2003). Similar results are obtained replacing the dependent variable with a dummy for any city or town in a district having had a mutiny (see Appendix Table B.10).

[57] Appendix Tables B.11 and B.12 present the coefficient on the controls and show that our results are robust to not including them.

industrialisation by restricting trade would have damaged British industry. India took as much as 22% of British manufacturing exports in 1911 (followed at a distance by Germany and the USA, who took 13% and 9% respectively), so British tax revenues and employment must have relied on free access to India's market. Our results suggest an alternative reason: Indian industrialisation would have led to greater support for the Indian anti-colonial movement, thus constraining Britain's capacity to extract resources from India, and increasing the chances of decolonisation. Both explanations are in principle valid to explain the wide range of anti-industrial policies that the European colonisers adopted in colonies in this period (O'Rourke & Williamson 2017, p.7).

Although our results suggest that free trade helped to prevent industrialisation in India, they should not be taken to imply that protectionist policies would have necessarily been better. First, evaluating the full impact of protectionist policies would require a careful comparison between all the different costs and benefits of protection, something that is beyond the scope of this chapter. Second, protectionist policies may easily degenerate. For example, the extreme policies introduced after independence clearly backfired, as is extensively shown by the literature on the liberalisations of the 1990s.[58] Politics seems to have played an important role in this degeneration. Some of the industrialists who benefited from the World War I trade shock and later supported the anti-colonial movement were amongst the signatories of the 1940s Bombay Pact, an agreement between business and the INC which laid the foundation of the future hyper-protectionist state (see Gupta & Roy 2017, p.242). In other words, the WWI trade shock contributed to the rise of a lobbying group that was able to secure permanent protection. This is a far cry from the temporary protection advocated by the infant industry argument.

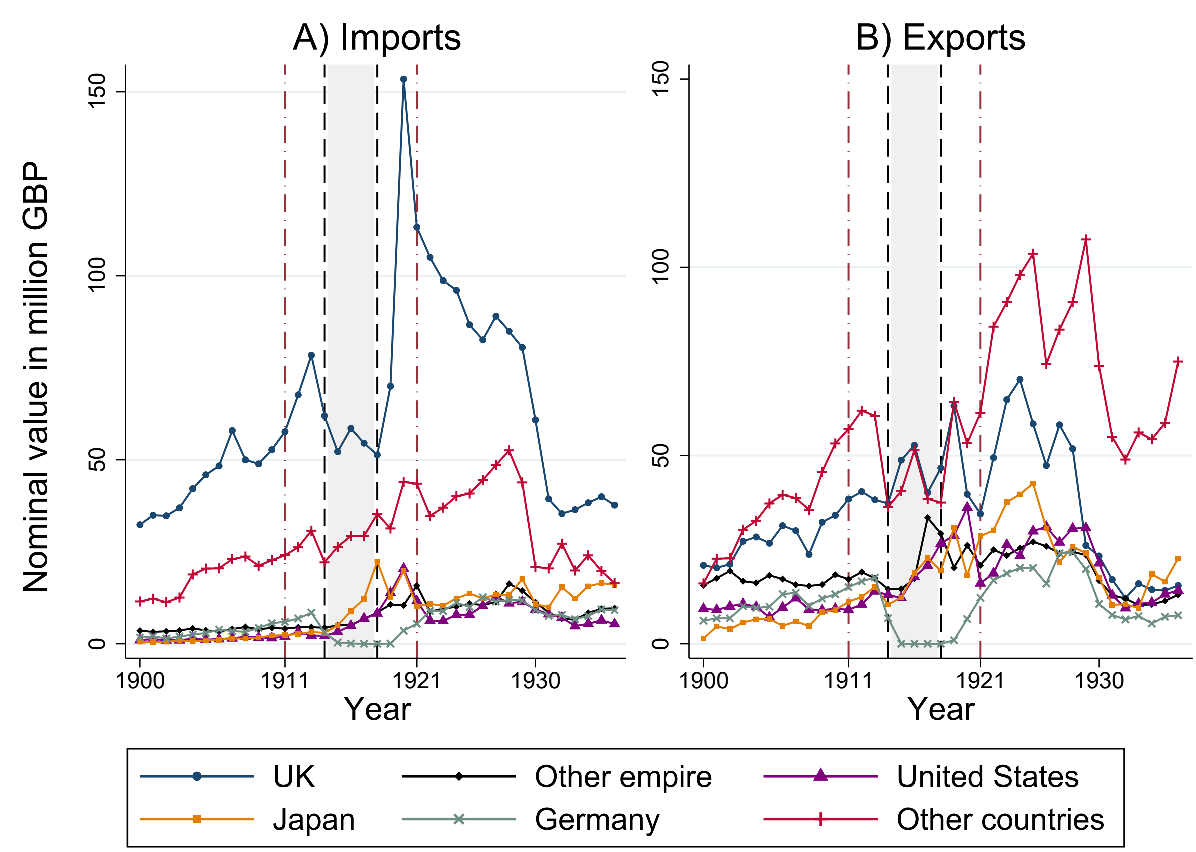
[58] Goldberg et al. (2009), Goldberg et al. (2010), and Topalova & Khandelwal (2011) all show that India's 1991 tariff reduction fostered growth, by making Indian firms more productive and inducing them to produce more products.

Appendix Chapter 2

B Additional Information

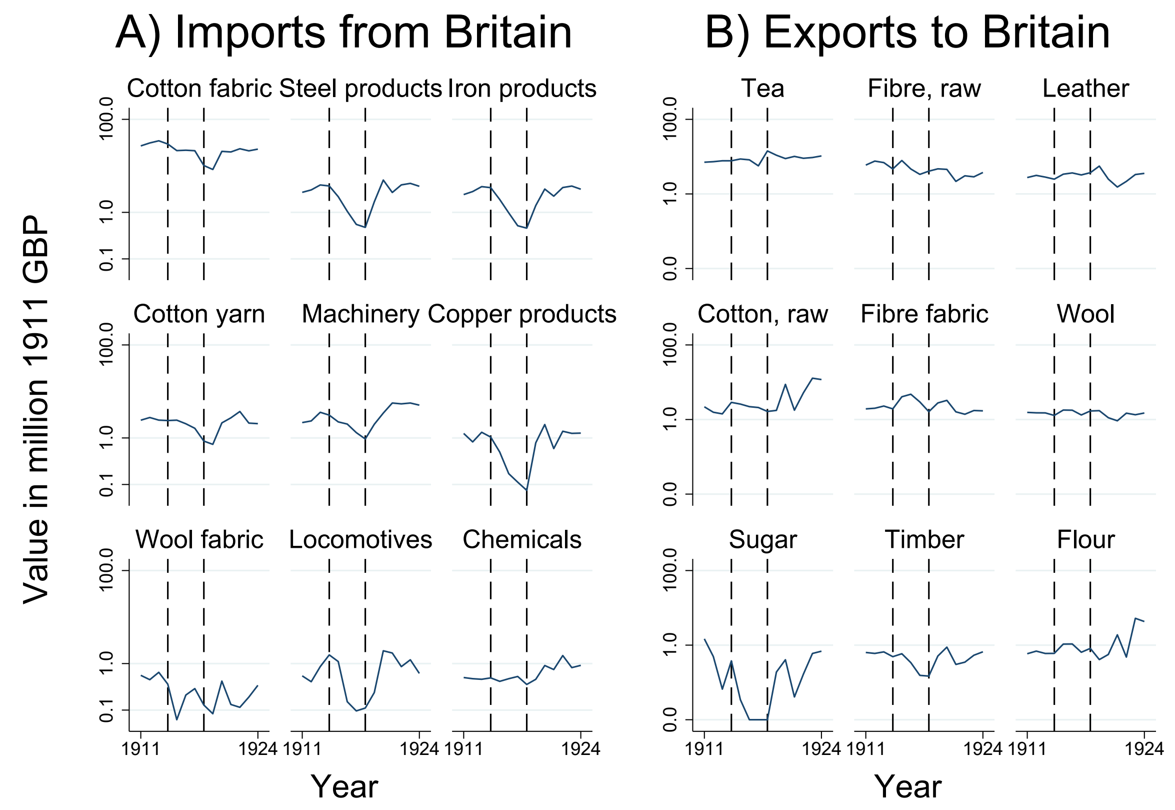
B.1 Figures

Figure B.1: Trade between India and main partners in nominal terms



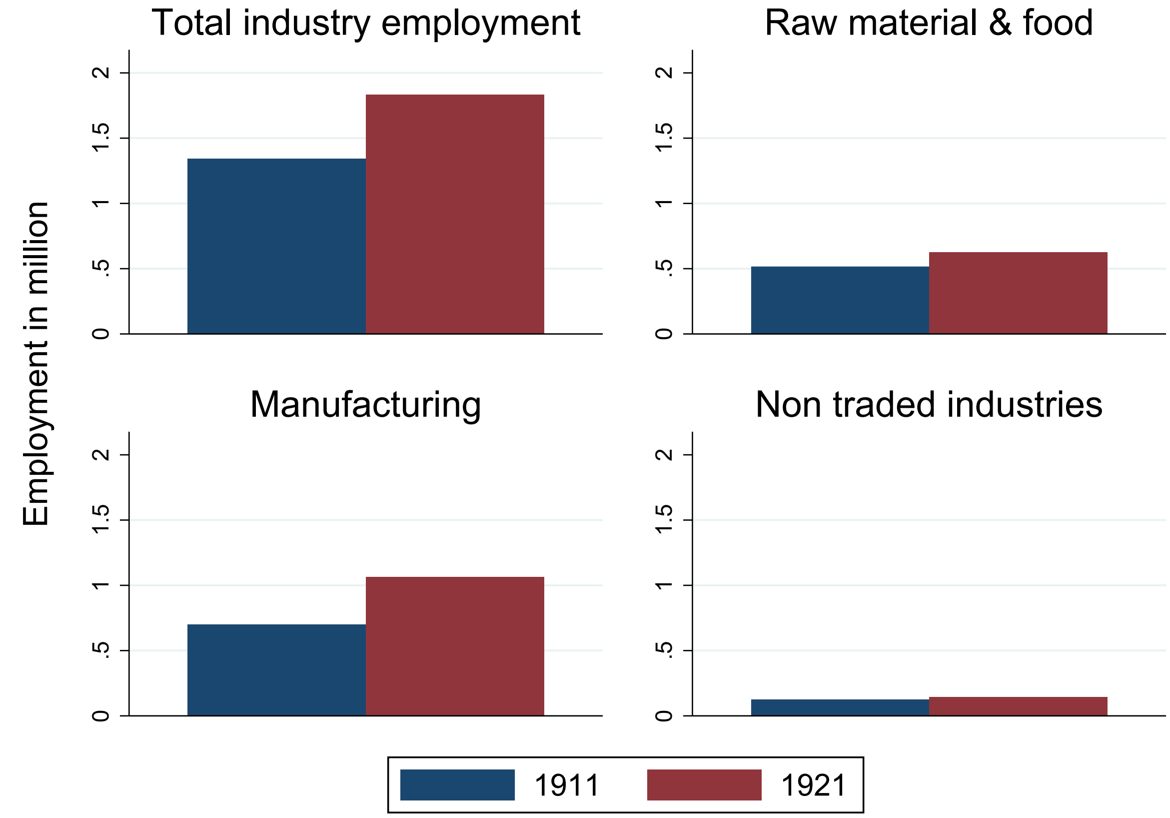
Notes: Total Indian imports and exports from top-4 partners in 1911 (by overall trade volume), in nominal GBP. The grey shaded area highlights World War I, while the red dashed lines for 1911 and 1921 highlight the years of the Indian census. Sources: RICardo Project (Dedinger & Girard 2017). However since this source did not provide Indian imports from Britain in 1929-37, we obtained this data in current Rupees from various yearly editions of the “Review of the trade of India”, and converted it into nominal GBP using the exchange rate dataset provided by the RICardo Project.

Figure B.2: Top 9 real imports and exports from Britain



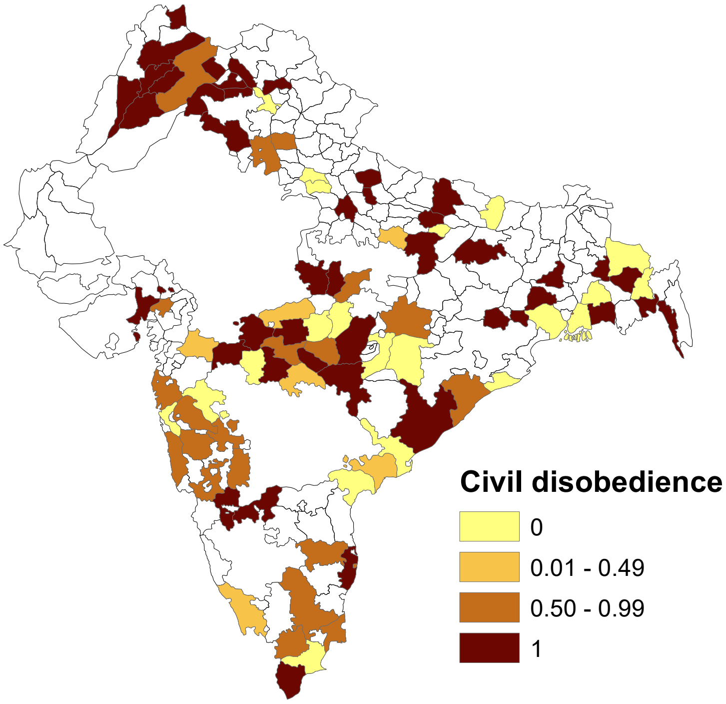
Notes: India-Britain trade in top-9 import and export sectors, in million 1911 GBP (deflator used: price index constructed using the actual prices of imported and exported goods, see Section 2.4 for details). Industries are ordered in descending value of imports from/exports to Britain in 1911. The term industries refers to the 105 traded industry categories in our dataset that have been merged out of the industry sectors reported in the Census of India and the product categories from the Annual Statement of the Trade of the United Kingdom. Source: Annual Statement of the Trade of the United Kingdom

Figure B.3: Industrial employment across sectors



Notes: The figure displays industrial employment in India for 1911 and 1921 by sector, for our 105 traded sectors as well as for our 34 untraded sectors. The graph on the top-left shows total number of workers employed in firms. The remaining graphs show the employment for three sectors of industries: (i) top-right depicts raw materials & food, (ii) bottom-left depicts manufacturing industries and (iii) bottom-right depicts non-traded industries. Classification of (i)-(iii) based on Annual Statement of the Trade of the United Kingdom. Source: Census of India

Figure B.4: Support civil disobedience across India



Notes: The figure shows the support for civil disobedience across Indian districts in 1922. Responses A-E (pro) are coded as 1 and F-G (against) are coded as 0 across individuals. The figure illustrates that the local representatives are selected from a variety of districts across the whole of India and that there is considerable local variation in the responses given. As described in Indian National Congress (1922) these responses provide important feedback to the INC leadership of local sentiments towards civil disobedience.

B.2 Robustness checks

Several robustness checks confirm the baseline result that the WWI trade shock had a positive effect on Indian industry, and this was not limited to specific industries or districts. This section reviews them.

Table B.1: Robustness of baseline results

Dependent variable: Change industry employment share 1911-21				
Panel A. Robustness excluding specific industries				
	(1)	(2)	(3)	(4)
	Ex. cotton interm.	Ex. cotton final	Ex. fibre	Ex. iron & steel
EX-IM Shock	0.391**	0.384	0.484***	0.298**
	(0.186)	(0.323)	(0.129)	(0.132)
	(5)	(6)	(7)	(8)
	Ex. military prod.	Ex. machinery	Ex. tea	Ex. tobacco
EX-IM Shock	0.480***	0.436***	0.708**	0.446***
	(0.124)	(0.137)	(0.267)	(0.141)
Controls	Yes	Yes	Yes	Yes
N (districts)	216	216	216	216
Panel B. Robustness of results to excluding specific districts				
	(1)	(2)	(3)	(4)
	No Shock	Outliers	Native	Boundaries
EX-IM Shock	0.491***	0.838**	0.520***	0.527***
	(0.154)	(0.335)	(0.123)	(0.124)
Controls	Yes	Yes	Yes	Yes
N (districts)	171	210	190	148

Notes: Panel A presents the results for the exclusion of important industries from the dataset. Column 1-4 (5-8) excludes main industries positively (negatively) affected by the trade shock. Column 1 excludes raw and intermediate cotton products, column 2 excludes cotton fabric and all types of apparel, column 3 excludes fibre (raw & fabric), column 4 excludes iron and steel products, column 5 excludes machinery, Column 6 excludes military products, arms and ammunition, column 7 excludes tea, and column 8 excludes tobacco. Panel B presents the results for the exclusion of specific geographical areas from the data. Column 1 excludes all districts that do not record a trade shock. Column 2 excludes districts with a trade shock that is outside the common range of -1.5£ to 1.5£. Column 3 excludes all princely states included inside the British provinces' censuses. Column 4 excludes all districts which experienced a change in boundaries between 1911 and 1921. All columns include the full vector of control variables from column 5 of Table 2.1. Robust standard errors in parentheses are clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a first step, we have verified that our results are not entirely driven by some of the most notable industries or districts in Table B.1. In terms of industries, we start by key sectors in terms of employment one at a time: cotton raw-to-intermediate products (waste, raw and yarn), cotton final products (fabric and all types of apparel) and other fibres (raw and fabric).[59] Next, to alleviate the concern that the WWI trade shock might be correlated with a war-related rise in public expenditure that benefited Indian industry, we

[59]Significance is lost when excluding cotton finals due to a large increase in the standard error, however the coefficient remains similar to previous estimates. This loss of significance in itself is not robust, since excluding only one severe outlier (Calcutta) makes the coefficient highly significant again.

also excluded, iron & steel and military products ("Ammunition", "Arms" and a residual category "Military products" including for example military and naval stores). We also separately excluded machinery, the fifth largest import from Britain after cotton fabric, steel and iron products, and cotton yarn. Finally, we excluded tea and tobacco, two sectors in contrast to others particularly negatively exposed to the WWI trade shock. In terms of districts, we excluded, one set at a time, districts with zero exposure to the trade shock, those with a trade shock above 1.5£ per person (Ahmadabad, Calcutta, Madras, Bombay and Singhbhum) and below -1.5£ per person (Darjeeling), those belonging to princely states that were not directly under British rule, and those which experienced a change in geographical boundaries between 1911 and 1921. In all these cases, the coefficient on the WWI trade shock remained strongly significant, never falling drastically in size and nearly doubling when tea and outlier districts were excluded. This underlines that our observed effect is driven by a wide set of shocks to different industries and districts.

Table B.2: IV strategy - British exports to other countries

Dependent variable: Change industry employment share 1911-21							
Instrument:	World	Top 5	East			West	
Export to	(ex. India)	(non-Eu)	Australia	China	Japan	Argentina	USA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EX-IM Shock	0.428*	0.445*	0.467*	0.347***	0.705***	0.455	0.721
	(0.237)	(0.234)	(0.269)	(0.124)	(0.094)	(0.395)	(0.787)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (districts)	216	216	216	216	216	216	216
F-stat (1st stage)	55.22	29.06	11.57	46.42	31.60	4.34	0.12
First stage	-0.280***	-0.501***	-1.033***	-0.778***	-4.155***	-1.253**	0.739
	(0.038)	(0.093)	(0.304)	(0.114)	(0.739)	(0.602)	(2.114)

Notes: Trade shocks instrumented with British exports to the world (excluding India), top 5 non-European destinations, Argentina, Australia, China, Japan, and the USA. All categories of military products are excluded from exports to the world to circumvent the issue of the drastic increase in military supplies provided to European allies during the War. Robust standard errors in parentheses clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2 addresses the concern that the 1913-17 trade shock might be endogenous to Indian demand or supply shocks, as opposed to exogenously driven by WWI. It instruments for Indian net exports to Britain using third countries' imports from Britain (we use imports rather than net exports because third countries might export very different products to Britain, compared to India). Thus, a negative sign is to be expected in the first stage. The construction of the instrument follows equation 2.1, but uses the change in imports from the UK 1913-17 for the respective destination j, i.e. $\Delta(IM)^{UK,j}_{i,17-13}$, instead of Indian net exports to the UK, i.e. $\Delta(EX - IM)^{UK,India}_{i,17-13}$, as the numerator. Column 1 uses as an instrument the rest of the world's imports from Britain (excluding India). The first stage suggests that a £1 decline in the rest of the world's imports from Britain is associated with a £0.3 increase in Indian net exports. The second stage is significant, and the coefficient of 0.428 is very close to our baseline estimate of 0.451. Column 2 focuses on the aggregate imports of Britain's top 5 non-European destinations in 1911: Argentina, Australia, China, Japan and the USA (together these accounted for roughly the same proportion of British imports as India, see Figure B.7). The results are essentially unchanged. Columns 3-7 consider these five countries individually. The results are very similar when considering countries in the Eastern Hemisphere (Australia, China, Japan), while they lose significance when considering Argentina and the USA. However, the F-stat for these two countries is very low, suggesting that their imports are weak instruments for Indian imports.[60]

Table B.3 alleviates the concern that the effect of the WWI trade shock was driven by omitted factors, or by the persistence of the shock. Column 1 addresses the hypothesis that the 1913-17 fall in imports from Britain was compensated for by a rise in imports from British allies less affected by the war. It adds to our baseline specification a second trade shock, constructed using the 1913-17 change in Indian imports from the USA and Japan. The coefficient of interest drops only marginally, and the coefficient on the second trade shock is positive but insignificant. This result seems consistent with the historical literature, which has pointed at supply constraints – and not competition from third countries – as the main constraint on industrial growth during the war (e.g. Gupta & Roy 2017, p. 241).

Column 2 further alleviates the concern that the WWI trade shock might somehow be correlated with soldier recruitment or casualties, two other channels through which the war may have affected Indian industry. For example, Vanden Eynde (2016) finds that recruitment led to a significant rise in literacy across the recruitment grounds of Punjab. Additionally, recruitment might be associated with greater wages or local public expenditure, and casualties with greater scarcity of labour. All of these may be correlated with industrial growth. To include a second proxy for both recruitment and casualties (in addition to the already included 1911 military share), we add to our baseline regression the number of casualties reported by each district during the war. Districts that experienced more WWI casualties experienced slightly faster industrial employment growth in 1911-21, however this effect is insignificant. Again, the coefficient on the WWI trade shock is unaffected.

Column 3 alleviates the concern that exposure to the shock might be correlated with deaths in the 1918-19 Spanish flu, another possible determinant of 1911-21 industrial growth. The pandemic hit India most severely than any other country: a recent estimate puts the death toll at up to 14 million people (Chandra et al. 2012). Reliable district level data on flu related deaths is not available (Chandra et al. 2012), so that we proxy for

[60] We suspect USA imports from Britain followed an exceptional pattern during the war (they were the only ones not to decline, see Figure B.7), possibly due to Britain's need to pay for the vast amount of food and raw materials it imported from this country (Litman 1926).

Table B.3: Other potential explanations for industrialisation

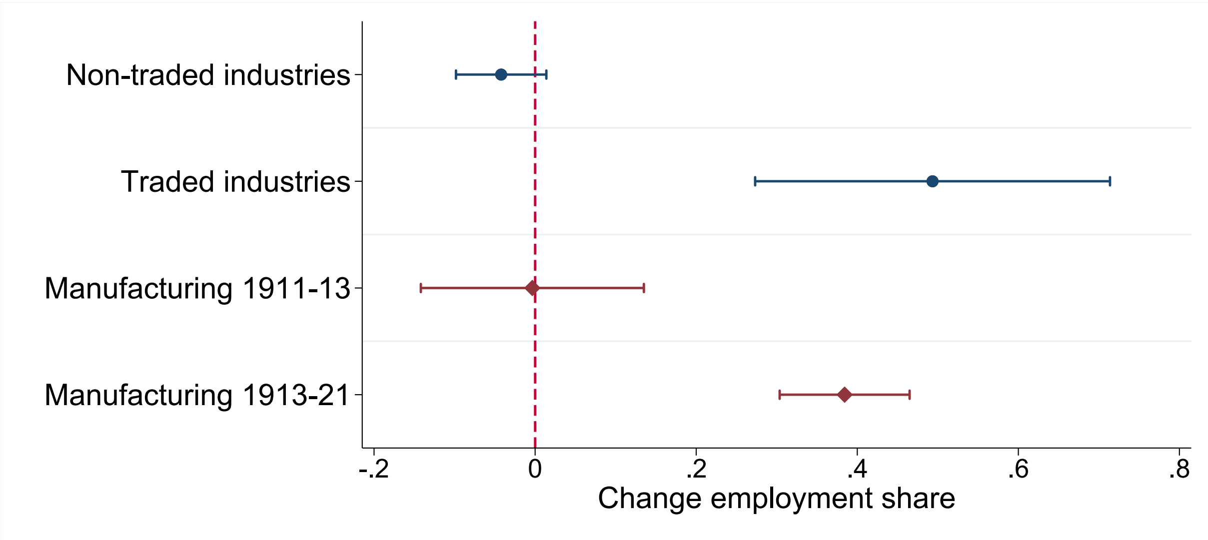
Dependent variable: Change industry employment share 1911-21				
	(1)	(2)	(3)	(4)
EX-IM Shock	0.365**	0.451***	0.421***	0.489***
	(0.146)	(0.141)	(0.147)	(0.115)
Imports Japan & USA	2.433			
	(2.853)			
WWI deaths (in 1000)		0.159		
		(0.456)		
Population growth			2.029	
			(1.528)	
IM Shock (Britain to USA)				-0.738
				(0.473)
Controls	Yes	Yes	Yes	Yes
N (districts)	216	216	216	216

Notes: Column 1 studies the effect of Indian imports from Japan and the USA (1913-17) substituting for British imports during WWI. Column 2 controls for the direct impact of WWI recruitment on industrialization. Column 3 controls for the change in population to account for the Spanish flu. Column 4 studies whether the rise in industrial employment in India can be explained by a persistent change in the structure of British exports (1913-21) not related to industrialization in India. Robust standard errors in parentheses clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

any unusual population loss using the 1911-21 district population growth. The estimated coefficient suggests that this did not matter for industrial growth, and the coefficient on the WWI trade shock is again unaffected.

Column 4 corroborates the view that the effect of the trade shock was still visible in 1921 because it was a persistent effect, and not a persistent shock. For example, Wolcott (1991) argues that the post-war boom of the Indian cotton textile industry was sustained by the fact that the British industry took quite a few years to get back on its feet. To control for persistent shocks to British productivity, we add to our baseline a second trade shock, constructed using the 1913-21 change in USA imports from Britain. We use the USA as the importing country, and not the other main British export destinations (India itself, Australia, China, Japan, Argentina) because those other destinations are all known to have benefited from import substitution during the war (Litman 1926, p. 25). These other destinations 1921 imports might therefore be endogenous to a similar local industrial expansion to the one we are trying to explain. While the coefficient on the additional trade shock is negative, indicating that faster industrialisation in India was indeed positively correlated with persistent British productivity shocks, it is not significant. Moreover, the coefficient on the 1913-17 trade shock is unchanged. These results go some way towards establishing that the WWI trade shock had a persistent effect on Indian industry. We provide more evidence of this in section 2.5.3.

Figure B.5: Placebo and pre-trend analysis



Notes: The first two coefficients (blue dot) present a placebo check where the first (second) estimate presents the effect of the trade shock on the change in the share of employment in non-traded (traded) industries across districts between 1911 and 1921. The other two coefficients (red diamond) present a pre-trend analysis where the third (fourth) estimate presents the effect of the trade shock on the change in the share of manufacturing employment between 1911-13 (1913-21). The full set of controls is included in all specifications with a 10% confidence interval depicted. The blue coefficients use the baseline sample (n=216). The red coefficients use the Factory Reports data as dependent variable with the number of observations (N=141) being different from the baseline sample for the following reasons: (i) we only include districts in the sample that have been at least once reported in the annual Factory Reports and (ii) district-level employment numbers were not reported in the Bengal Factory Report of 1911 (including Bihar & Orissa before the separation on 22nd of March 1912). For comparability the same sample (N=141) is used for 1913-21.

Figure B.5 presents the results of two falsification exercises. In the first, we split our dependent variable (the 1911-21 change in the industrial employment share) into traded and non-traded sectors (such as "Waterworks"). If what we are picking up is the trade effect of WWI, then we would expect this effect to be stronger for traded sectors then for non-traded ones, since the latter might at most be affected indirectly through backward and forward linkages. Results confirm this expectation: while the coefficient on the trade shock is similar in size to the baseline and strongly significant for traded sectors, it is negative and insignificant for non-traded sectors (the negative sign might indicate labour reallocation from non-traded into traded sectors). In the second falsification exercise, we use Factory Reports data on 1913 industrial employment to break our period into two, 1911-1913 and 1913-1921 (due to data limitations, this is only possible for 141 of the 216 districts in our baseline). If what we are picking up is the trade effect of WWI on Indian industry, then the effect should be present in 1913-21 but not in 1911-13. This is indeed what we find, and the coefficient for 1913-21 is also very similar in size to the baseline.

Finally, Table B.4 re-establishes our baseline result using cross-industry variation, as opposed to cross-district one. The dependent variable is now the 1911-21 percentage change in employment in industry i, while the WWI trade shock is the 1913-17 change

Table B.4: Effect of WWI trade shock at the industry level

Dependent variable: Change in log industrial employment (×100)						
	(1)	(2)	(3)	(4)	(5)	(6)
EX-IM Shock	0.167***	0.135***	0.114**	0.122***	0.163***	0.200***
	(0.027)	(0.039)	(0.045)	(0.043)	(0.042)	(0.037)
Log employment 1911		-10.573	-13.567	-9.429	2.801	16.573***
		(8.960)	(9.726)	(9.138)	(7.945)	(4.666)
One-digit industry FE	No	No	Yes	Yes	Yes	Yes
Two-digit industry FE	No	No	No	Yes	Yes	Yes
Only traded industries	No	No	No	No	Yes	Yes
Weighted	No	No	No	No	No	Yes
N (industries)	127	127	127	127	96	96

Notes: This table provides the industry level approach comparable to Acemoglu et al. (2016). For all regressions the dependent variable is the change in log employment at the industry level multiplied by 100. The coefficient for the WWI trade shock presents the effect of a £1 change in net exports per worker on percent employment growth. One-digit industries are the major categories "Raw Materials & Food", "Manufacturing" and "Non Traded Industries" based on the classification in the UK statements of trade. The two-digit industry categories are based on the broadest census classification (15 groups), and the three-digit industry categories are based on more detailed census-classifications subdividing the two-digit classification further (35 groups). Note that due to the different origin of the 1- & 2-digit industry categories the 2-digit industries are not sub-categories of the 1-digit industries. Employment in 1911 is used as weight in Column 6. Robust standard errors in parentheses clustered at the three-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

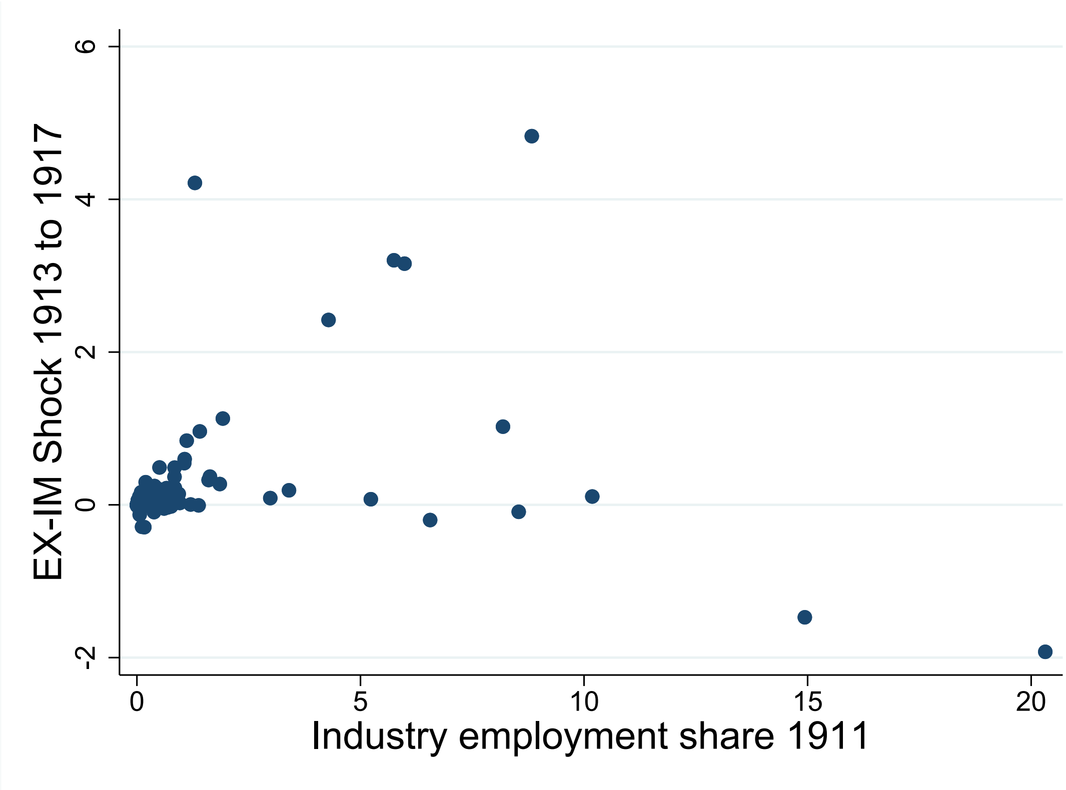
in net exports to Britain in industry i, per 1911 employee $(\Delta (EX - IM)^{UK}_{i,17-13} / L_{i,11})$. Subsequent columns present increasingly demanding specifications, consistently finding that the WWI trade shock had a positive and strongly significant effect on industrial employment growth. The point estimates in column 6 (where we focus on traded industries, weigh them by initial employment size, and control for initial employment as well as 1- and 2-digit industry fixed effects) indicates that the industry with average exposure grew 26% faster due to WWI.[61] Appendix Section B.3 provides more insight into the transition from industry to district level variation, addressing recent concerns regarding the use of shift-share variables (see e.g. Adao et al. 2019 and Borusyak et al. 2018). To the extent that our historical data allows, we do not find major reasons for concerns; rather, it appears that these concerns work against our results.

[61] The average trade shock was £132 per employee, so 132*0.1995=26.

B.3 Additional Shift-Share Checks

This section provides more insight into the nature of the variation our WW1 trade shock exploits. While our data has limitations due to its historic nature we hope to be able to sufficiently address recent concerns raised on the validity of shift-share variables in Adao et al. (2019) and Borusyak et al. (2018).

Figure B.6: Sources of variation in trade shock



Notes: This figure illustrates the relationship between initial industry employment share in 1911 and exposure to the WW1 trade shock across districts .

First we however start by evaluating whether the intensity of the WW1 trade shock across districts is associated with certain district specific characteristics in 1911. Figure B.6 illustrates the correlation between the industrial employment share in 1911 and the 1913-1917 trade shock. We do not observe a clear relationship between the two variables reflecting the considerable variation in the trade shock across industries and the industrial composition strongly varying across districts. We formally analyse this in Table B.5 which shows the relationship between the WW1 trade shock and a set of 1911 variables. In general the table suggests that the trade shock is not correlated with the 1911 manufacturing share, population, military share, police share, share of British employment, share of firms British owned, or share of firms government owned. However, it should be noted that the trade shock is positively correlated with a higher urban share, literate share and age over 20 share across districts. Also, more positively affected districts appear to be more likely to be coastal. Notably, the trade shock appears correlated with the the coastal location, literacy and age due to its correlation with the urban share. Considering the pattern of colonial trade (raw material & food exports and manufactures imports) and the disruption caused by WW1 it is not necessarily surprising that the trade shock had a more positive effect in urban areas compared to rural ones. This correlation underlines the importance of controlling for the urban share across districts, when evaluating the impact of the trade shock. However, reassuringly the trade shock does not in anyway seem to be associated with the British presence (military nor economic) in India by 1911. This would be particularly worrying as we are unable to observe any political outcomes just before WW1.

Table B.5: Balance check of trade shock

Dependent variable	Coef. (SE)		Coef. (SE)
% Manufacturing 1911	0.477 (1.007)	% Urban 1911	12.45*** (4.474)
Population in millions	-0.021 (0.073)	% Literate 1911	2.823** (1.243)
% Age 20+ 1911	1.387* (0.809)	Coastal	0.111* (0.061)
% Military 1911	0.028 (0.034)	% Police 1911	0.035 (0.039)
% British staff 1911	0.202 (0.122)	% Firms Brit. private 1911	-1.104 (0.817)
% Firms Brit. director 1911	-2.962 (2.593)	% Firms government 1911	-0.025 (0.582)

Notes: This table presents balance checks for the shift-share trade shock as suggested to be performed by Borusyak et al. (2018). It reports the coefficients of regressing exposure to the trade shock on 1911 characteristics across districts. Due to the historic data for these balance tests being unavailable at the industry-level, they are instead conducted at the district level. Robust standard errors clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Sensitivity shift-share coefficient

Dependent variable: Change industry employment share 1911-21				
	(1)	(2)	(3)	(4)
EX-IM Shock	0.452***	1.580***	1.601***	1.602***
	(0.107)	(0.234)	(0.262)	(0.261)
Controls	Yes	Yes	Yes	Yes
Weights		✓	✓	✓
Only traded industries			✓	✓
Excluding outlier industries				✓
N (industries)	139	139	105	95
adj. R^2	0.155	0.659	0.661	0.662
N	139	139	105	95

Notes: The table presents the analysis of the effects at the industry-level as suggested in Borusyak et al. (2018). All columns include the full vector of controls from column 5 of Table 2.1. The coefficient in column 1 differs slightly due to some districts not having any industrial employment in 1911 in the baseline specification. In addition to the baseline specification column 2 presents weighted results. Column 3 focusses exclusively on traded industries. Column 4 accounts for outliers being the top-5 industries with the highest and lowest exposure to the trade shock. Robust standard errors in parentheses clustered on three-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6 presents the evaluation of the shift-share variable as suggested by Borusyak et al. (2018) converting the variables of our shift-share dataset into a dataset of weighted shock-level aggregates. These results are presented at the industry level. Column 1 corresponds to our baseline specification (Column 5 of Table 2.1). The coefficient is slightly different as in our district level dataset some districts do not report any manufacturing employment in 1911 which are not considered in the presented result. Importantly, the standard errors are nearly identical to the ones in the baseline specification (0.140 versus 0.107) when clustering at the 3-digit industry level. This suggests that the concern raised by Adao et al. (2019) on the correlation of regression residuals across areas with similar industries is not an issue going in our favour. We opt for our more conservative clustering at the state sub-division level. Column 2 weights the regression by 1911 industry employment this increases the effect as in the industry-level results presented in Table B.4. However the increase in the coefficient size is even more pronounced. A similar change in the coefficient is observed when using 1911 manufacturing employment as weights in the district level specification. In contrast, when weighting our estimation by district population, results remain similar to the baseline specification. We favour our non weighted estimates for three reasons: (i) our focus is on newly emerging industries so it appears counter-intuitive to weight by initial industry size, (ii) not weighting by industry size provides us with a larger and more complete sample of Indian districts and (iii) the unweighted coefficients provide the more conservative estimate. Column 3 presents the effect when only looking at the sample of traded industries and Column 4 when excluding outlier industries (the 5 industries with the highest and lowest per worker exposure). The coefficient remains stable in both cases. The presented results confirm our findings in the baseline specification and suggest that those estimates might reflect a lower bound. It is however worth noting that our data set considerably differs from any of the modern datasets used as examples in Borusyak et al. (2018), so that there might be concerns specific to historical datasets that have not yet been highlighted in the literature.

Table B.7 provides some additional robustness checks for the breakdown along the lines of colonial trade. Column 1 and 2 highlight that the effect of the trade shock 1913-17 on industrial employment change 1911-1921 is driven by the effect of the change in imported manufacturers on employment in manufactures industries. In contrast, there is no spill over effect of the decline in competition in manufactures on industrial employment in raw materials and food. Further, there is no lasting effect of the change in export demand for raw materials and food on local industrial employment in manufactures nor raw materials and food. Column 3 and 4 further confirm this pattern looking exclusively at employment change in the respective industries experiencing either a change in import in manufactures (Column 3) or export of raw materials and food (Column 4). In these specifications we also control for the respective 1911 industrial employment share, which means we only exploit the variation in changes to trade between industries within the specific sector, while controlling for any overall trend observed for either imported manufactures industries or raw material and food industries. The observed effects again highlight that the effect is

Table B.7: Detailed breakdown WW1 trade shock

Dependent variable: Change employment share 1911-21 for specified sector

	(1)	(2)	(3)	(4)
	Manu	Raw & Food	IM Manu	EX Raw & Food
IM Manufactures Shock	-0.529***	0.026	-0.603***	
	(0.110)	(0.185)	(0.173)	
EX Raw & Food Shock	0.209	0.086		-0.133
	(0.479)	(2.125)		(2.345)
Industry share (traded)	0.040	-0.065		
	(0.051)	(0.228)		
Industry share (IM manufactures)			-0.167	
			(0.176)	
Industry share (EX raw & food)				-0.093
				(0.258)
Controls	Yes	Yes	Yes	Yes
N (districts)	216	216	216	216

Notes: The table presents the result for breaking down the effect of the WW1 trade shock along the pattern of colonial trade in additional detail. Column 1 analyses the effect of the two main types of colonial trade, raw material & food exports and manufacturing imports on employment in manufacturing industries 1911-21. Column 2 analyses the effect of raw material & food exports and manufacturing imports on employment in raw material & food industries 1911-21. In both columns we control for the share of industrial employment share in traded industries only. In Column 3 & 4 we are even more specific focusing exclusively on the sectors in question. Column 3 examines the effect of changes in manufacture imports on employment in industries importing manufactures 1911-21. Column 4 examines the effect of changes in raw material & food exports on employment in industries exporting raw material & food 1911-21. In column 3 and 4 we also control for the initial share of the respective industry employment. This means we exclusively exploit within variation in exposure to the trade shock across respective industry categories. Further, to reduce the number of confounding factors we focus exclusively on industries either exporting or importing in Column 3 & 4, but exclude those for which both imports and exports are recorded at the same time. Note, a negative (positive) coefficient on the import (export) shock is going in the same direction as the positive coefficient for the net export shock. Robust standard errors in parentheses are clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

driven by the change in import competition in manufactures, while there is no lasting effect of the change in exports of raw materials and food. Also noteworthy is that across all Column 1-4 we again observe that there is no significant effect of the respective 1911 industry employment shares. This seems to suggest that apart from the variation in trade due to WW1 there is no general pattern of industrialization observable across India between 1911 and 1921.

Table B.8 presents the results of a placebo exercise, where we randomly allocate the trade shock across industrial categories. From this we construct a placebo trade shock at the district level and present the average coefficient and the share of rejection at the 5% significance level for 1000 replications. Column 1 presents the result when we replicate our baseline specification (Table 2.1 Column 5) with the placebo trade shocks. We see that the average coefficient is 0 and that in 6 out of 100 regressions the coefficient was

Table B.8: Randomly allocated trade shock

	Baseline	Traded	Civil dis.
Avg. β	0.000	0.000	0.000
Share $p < 0.05$	0.060	0.099	0.008
Number replications	1000	1000	1000

Notes: This table presents the average result of the key regressions being replicated 1000 times with the trade shock randomly allocated across industries based on the observed mean and variance of the actual WW1 trade shock across industries. In column 1 the trade shock is randomly allocated across all industries and the dependent variable is the change in total industrial employment, while column 2 focusses exclusively on traded industries. Column 3 replicates the civil disobedience specification (reduced form). The reported statistics are the average coefficient obtained and the number of times the null-hypothesis for the EX-IM shock was rejected at the 5%-level. Controls and clustering of standard errors correspond to the respective benchmark specification replicated.

statistically significant at the 5% level (a minimal over-rejection). Compared to our actual significance level this issue appears rather minor. Column 2 repeats the replication using only the industry categories for which we observe trade flows. We accordingly randomly allocate the trade shock across traded industries and use the change in the share of manufacturing employment in traded industries as dependent variable. Further, we use the initial share of manufacturing employment in traded industries as a control variable (the other controls remain the same). We observe that in 10 out of 100 regressions the coefficient was statistically significant at the 5% level. This suggests an over-rejection of the null of no effect in the case of only focussing on traded sectors (however note the small number of industries in this case <100). Column 3 does the same exercise for our main political result (Table 2.7 Column 1). We observe that in only 1 out of 100 regressions the coefficient was statistically significant at the 5% level. Suggesting that when looking at political outcomes our specification might actually under-reject. This is reassuring considering the more limited data availability for political outcomes.

The papers of Jaeger et al. (2018) and Goldsmith-Pinkham et al. (2018) highlighting another set of concerns when using a shift-share variable should be mentioned here as well. However, the concerns raised seem unlikely to be an issue in our case. First, we do not expect our WWI trade shock to be related with previous trade shocks due to its war driven nature and neither Britain nor British India having been involved in any major war in previous decades. The uniqueness of the shock is supported by the relatively stable pattern of British import growth observed in Figure B.1. Second, as highlighted in Table B.1 that our coefficient is relatively robust to excluding main industries affected by the WWI trade shock making it unlikely that our result is driven by individual shocks to a specific industry. This is also supported by our industry level results, which are robust to the inclusion of 3-digit industry fixed effects as presented in Table B.4.

B.4 Political Results

Table B.9: Other potential channels support civil disobedience

Dependent variable: Whether or not in favour of civil disobedience				
	(1)	(2)	(3)	(4)
Industrial empl. share 1921	0.308	0.538***	0.543***	0.567***
	(0.542)	(0.167)	(0.161)	(0.173)
Imports Japan & USA	2.203			
	(4.166)			
WWI deaths (in 1000)		0.438		
		(0.456)		
Population growth			0.191	
			(0.808)	
IM Shock (Britain to USA)				-0.453
				(0.310)
Controls	Yes	Yes	Yes	Yes
F-stat (1st stage)	1.59	24.33	23.74	22.49
N (districts)	92	92	92	92

Notes: This table analyses other potential effects of WW1 on support for civil disobedience (analogous to Table B.3). Column 1 studies the effect of Indian imports from Japan and the USA substituting for UK imports during WW1. Column 2 controls for the direct impact of WW1 recruitment on industrialization. Column 3 controls for the change in population to account for the Spanish flu. Column 4 studies whether the rise in industrial employment in India can be explained by a persistent change in the structure of UK exports not related to industrialization in India. Robust standard errors clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Placebo 1857 mutiny

Dependent variable: Participation in 1857 mutiny				
	(1)	(2)	(3)	(4)
EX-IM Shock	-0.034	-0.026	-0.056	-0.027
	(0.024)	(0.034)	(0.039)	(0.053)
Controls	No	Yes	No	Yes
N (districts)	235	216	235	216

Notes: Columns 1 & 2 present the effect of the trade shock on the number of towns that rebelled during the 1857 mutiny collected from David (2003). Columns 3 & 4 present the marginal effect of the trade shock on a district having at least one town that rebelled. Columns 1 & 2 estimated with OLS and Columns 3 & 4 estimated with Probit. Robust standard errors clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Reduced form specification civil disobedience

Dependent variable: Whether or not in favour of civil disobedience					
	(1)	(2)	(3)	(4)	(5)
EX-IM Shock	0.062*	0.159***	0.236***	0.267***	0.271***
	(0.035)	(0.046)	(0.045)	(0.048)	(0.089)
Industrial empl. share 1911			-0.060*	-0.080***	-0.063*
			(0.032)	(0.026)	(0.037)
PCC or AICC member				0.419***	0.517***
				(0.108)	(0.112)
Khilafat member				-0.629**	-0.596**
				(0.279)	(0.292)
Military share 1911					0.003
					(0.078)
Urban share 1911					-0.016**
					(0.006)
Coastal					0.027
					(0.155)
Literate share 1911					0.065
					(0.047)
Literate english share 1911					0.034
					(0.092)
Age 20+ share 1911					-0.044**
					(0.022)
Province FE	No	Yes	Yes	Yes	Yes
INC Province Committee FE	No	Yes	Yes	Yes	Yes
N (district)	92	92	92	92	92

Notes: The table presents the reduced form result for the support of civil disobedience. It also presents the effect of the included control variables. The INC province committee FE in addition to accounting for geographic differences also capture differences in the timing of the interviews. Robust standard errors are clustered on province sub-divisions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Reduced form specification 1937 election

Dependent variable: Share of seats won by INC					
	(1)	(2)	(3)	(4)	(5)
EX-IM Shock	0.046*	0.057**	0.059**	0.044**	0.056**
	(0.026)	(0.027)	(0.026)	(0.019)	(0.023)
Industrial empl. share 1911			-0.001	-0.021***	-0.024***
			(0.008)	(0.008)	(0.008)
General-Urban constituency				0.141***	0.138***
				(0.033)	(0.031)
Muhammadan-Rural constituency				-0.731***	-0.727***
				(0.027)	(0.027)
Muhammadan-Urban constituency				-0.783***	-0.799***
				(0.031)	(0.032)
Military share 1911					0.042**
					(0.017)
Urban share 1911					0.003
					(0.002)
Coastal					-0.031
					(0.031)
Literate share 1911					0.019***
					(0.007)
Literate English share 1911					-0.071***
					(0.019)
Age 20+ share 1911					0.003
					(0.004)
Province FE	No	Yes	Yes	Yes	Yes
N (constituencies)	878	878	878	878	878

Notes: The table presents the reduced form result for the share of seats won by the INC in the 1937 province legislative assembly elections. It also presents the effect of the included control variables. The dataset includes all single- and multi-seat constituencies for "General" (predominantly Hindu) and "Muhammadan" constituencies. The constituency type fixed effects are individual dummy variables for the following categories of constituencies: "General Urban", "Rural Muhammadan" and "Muhammadan Urban" with "General Rural" being the reference category. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Data Appendix Chapter 2

This section of the Appendix provides additional information and summary statistics on the data sources we newly digitized for our analysis. Section B.5 provides additional information on the trade data used obtained from the "Annual Statement of Trade of the United Kingdom" and "Annual Statement of the Sea-Borne Trade of British India with The British Empire and Foreign Countries". Section B.6 provides additional information on employment and ownership data obtained from the 1911 and 1921 British Indian censuses and how the trade data is matched to it. Section B.7 presents more information on the data obtained from the Indian Factory Reports since 1911 and the modern Indian censuses conducted in 1951 and 2011. Section B.8 covers in detail the various data collected for our political outcomes. Section B.9 briefly describes the remaining data sources. Table B.14 at the end of this Appendix presents the summary statistics for all key variables used.

B.5 Trade data

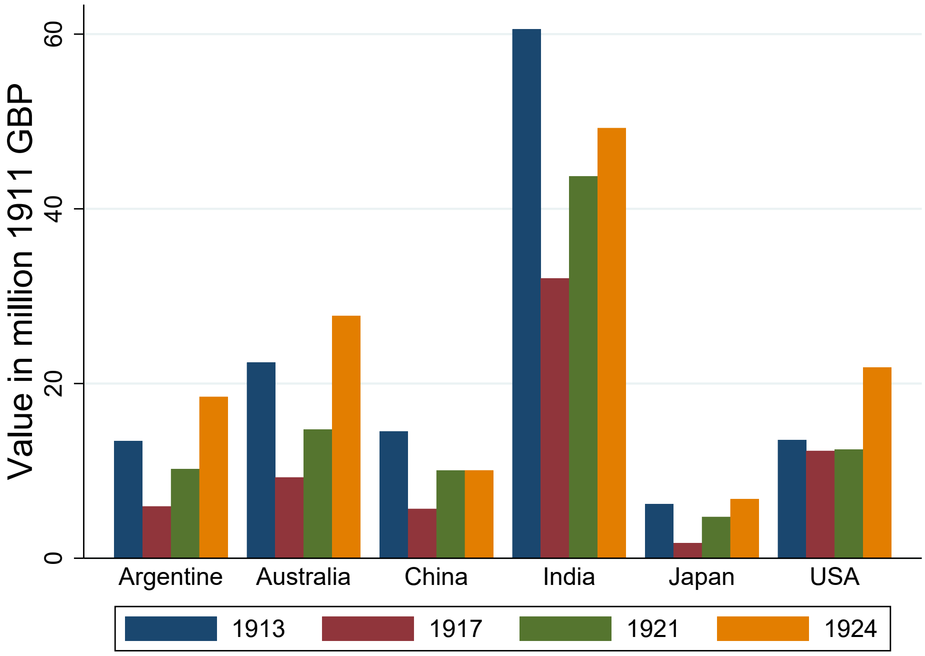
We collect our main trade data from the "Annual Statement of Trade of the United Kingdom" (see Customs and Excise Department 1911-1924). We focus on the 1914 and 1919 volumes, containing data on British exports and imports by country and product in terms of value and quantity, for the years 1911-1919. The trade categories are organised along a maximum of 4-levels of detail. In addition, we also collected data for 1920-1924 from the "Annual Statement of Trade of the United Kingdom" 1924 volume. From 1920, categories were disaggregated to 6-levels of detail. We aggregate this information back to the 4-level categories. In the following we mostly focus on discussing the 1911-1919 data, which is crucial for our main variables, however we adjust the data 1920-1924 following the descriptions outlined for 1911-1919 when needed.

We collect information on 372 trade categories for the years 1910-1919, to be matched to the industrial sectors for which we have census data. Of these trade categories, 335 cover Indian imports from Britain and 37 cover Indian exports to Britain. In 117 smaller British export categories trade is only reported for other British Possessions and not specifically India (comprising a considerable amount of categories, they only account for a fraction of British exports to India). In these cases we adjust the available data by India's share in total British trade with the relevant countries and dependencies. For example the trade category parts of iron and steel bedsteads is reported only for Australia, Canada and other British possessions. Accordingly, we first calculate India's share in total British trade for British possessions excluding Australia and Canada in 1911. Following this we adjust the value of "parts of iron and steel bedsteads" across all years by India's 1911 share in British trade for the specific group of countries in other British possessions. We do this for all 117 trade categories were trade is only reported for other British Possessions and not specifically India. For British imports the information is presented for British India across all categories of interest, so no adjustment is needed. Similarly, we do this adjustment only for British exports from 1911-19, but not after 1920 due to a further increase in the level of detail reported. We also do a similar adjustment for categories where Burma is not separately reported from the rest of British India.

To construct the trade shock, we need the value of Indian trade with Britain at constant prices (we choose 1911 prices). This requires calculating 1911-1919 prices for the 372 trade categories. Quantity and value data is reported for all Indian export categories, but is not always reported for import categories. This is because Indian imports are mostly manufactured goods which are reported in more detailed categories than Indian exports that mostly consist of raw materials and food. Due to the missing quantity data for Indian imports, we are required to create a price index at the 1st-level of detail (a weighted average of all sub-categories for which quantity and value data is available over the entire period), and use this index to deflate the subcategories. A simple example here is the trade in hats which is reported at the 1-level of detail as "Hats and Bonnets, Trimmed and Untrimmed" and is only further divided at the 2-level of detail into the subcategories "Felt", "Straw" and "Other Sorts". The first step in constructing a price index for "Hats and Bonnets, Trimmed and Untrimmed" is checking for which of the three 2-level categories data is available for value and quantity over the whole time period. Second, we create a price index by dividing value by quantity in each year for each of those 2-level categories. Third, we create a weight for the importance of the respective price index at the 1-level of detail based on the share of traded value in 1911 of all 2-level categories in "Hats and Bonnets, Trimmed and Untrimmed" were value and quantity data is available. Finally, we sum up all price indexes with regards to the constructed weight at the 1-level of detail and use this aggregate price index to deflate all value data of the 2-level categories. In case we have more levels of detail we follow the same procedure, but use the most detailed level for which we have data. Further, for categories where there is no consistent value and quantity data available for at least one subcategory we use instead the average price index across all products. This applies to the following categories: "Apparel", "Carriages", "Glass", "Instruments and Apparatus, Scientific (other than Electrical)", "Jewellery", "Perfumery and Articles used in the Manufacture thereof (except Spirits, Perfumed in Bond, and Essential Oils)", "Poultry and Game", "Saddlery and Harness", "Spirits, Foreign, Mathylated in the United Kingdom", "Umbrellas". For Indian export categories we adjust for each category's specific price as quantity and value data are always available.

We also adjust the 1920-24 data to be in 1911 prices, however the trade categories reported in Annual Statement of the Trade of the United Kingdom become more detailed after 1920 with the quantities sometimes being reported in different units of measurement. For example, this might be a change from "cwts." before 1919 to "pairs" after 1920 as the

Figure B.7: Real British Exports



Notes: British exports to main non-European destination countries in million 1911GBP for the years 1913, 1917, 1921 and 1924. Source: Annual Statement of the Trade of the United Kingdom

unit of measurement. Accordingly, we construct a separate price index along the same lines for 1920-24 (with the start year being 1920) and than adjust the values after 1920 to be in 1911 prices based on combining the 1911-19 and 1920-24 price indexes. This of course means we are only able to adjust for overall inflation between 1919 and 1920, but not category specific price changes. Accordingly, if there is considerable differences in inflation across products this will create measurement error in the constructed trade data for after 1920. Note however, that the data after 1920 is not used for our main explanatory variables, but mostly for descriptive purposes.

To formally assess the exogeneity of the WW1 trade shock we collect data on British imports and exports to the World, and the top-5 non-European trade partners (Argentina, Australia, China, Japan an the US) for 1911-1924 from Annual Statement of the Trade of the United Kingdom. Figure B.7 depicts British exports to the 6 main non-European destinations. It highlights the crucial role of India as a market for British exports and illustrates the general decline in British exports during WW1 and the subsequent recovery after the war across all countries (except the US). We use this data on British exports 1913-17 to other destinations at the industry level as instrument in Table B.2 to confirm the exogeneity of the India-Britain trade shock during WW1. Figure B.8 additionally illustrates this for the industry level. The left panel depicts the relationship between the decline in British exports 1913-17 to India per employee in Indian industry and the ratio of Indian industrial employment 1921 compared to 1911 across industries. The right panel present the corresponding relationship between the decline in British exports 1913-17 to

Figure B.8: Exogeneity of WW1 trade shock across industries

Notes: Change in British exports to India (left-panel) and the rest of the World (right-panel) per Indian worker and ratio of employment in 1921 to 1911 across Indian industries (y-axis). The corresponding first stage between the x-asis in the left and right panel is 0.269***. All axis are transformed using a symmetric log transformation: we take the log of the absolute value plus 1, and than multiply by the original sign. These transformations are done to make variations along the x- and y-axis easier to view. The circle size reflects the number of industry employees in 1911. The term industries refers to the 95 trade industry categories in our dataset that have been merged out of the industry sectors reported in the Census of India and the product categories from the Annual Statement of the Trade of the United Kingdom.

the rest of the World per employee in Indian industry and the ratio of Indian industrial employment 1921 compared to 1911 across industries. This highlights that the change in British trade across industries was driven by developments in Britain affecting both trade to India and the rest of the World.

Finally, we collect disaggregated data on Indian imports from Japan and the USA between 1911-21 from the "Annual Statement of the Sea-Borne Trade of British India with The British Empire and Foreign Countries" (see Department of Statistics 1911-1921). This allows us to analyse formally whether other countries compensated for the drop in imports from Britain (see also Figure B.1). The "Annual Statement of the Sea-Borne Trade of British India with The British Empire and Foreign Countries" is also the source of the data on machinery imports by type from the USA in 1913 and 1921.

B.6 Employment and ownership data

To assess the effect of the WW1 trade shock on Indian industry, we need data on industrial employment by Indian districts, and by sectors that can be matched to our trade categories, before and after the war. The most detailed source of this data are the industrial censuses of 1911 and 1921 (see Census Commissioner 1911, 1921), which were run alongside the main population censuses. They provide information on employment in establishments with more than a threshold number of employees (20 in 1911, 10 in 1921), by sector and district, covering the most developed part of the British Raj and more than 78% of its population. We collect data from the censuses of Bengal, Bihar & Orissa, Bombay, Central Provinces & Berar, Madras, Punjab, and the United Provinces of Agra & Oudh. In addition to the British ruled districts of these provinces, the 7 censuses also include information on 44 Indian princely states inside the surveyed area. The area of British India not covered in our dataset are the censuses individually collected by a set of larger princely states as well as the censuses for the smaller provinces Ajmer-Merwara, Adanamans and Nicobar, Assam, Baluchistan, Burma, Coorg and the North-West Frontier province.

The collected census data covers not only industrial factories, but also mines and plantations growing "special products" (of which tea accounted for 87% of employment in 1911, and coffee, indigo and rubber for much of the rest). Notably, plantations were in most cases involved in directly processing the agricultural products they produced, which explains why they are covered within industrial firms and makes them distinctly different from usual agricultural production. Thus, the 262 sectors for which we have data can be divided into three broad groups: manufacturing sectors, and sectors producing respectively food and raw materials (though not all such goods are represented in the data, e.g. basic agricultural products such as wheat are not, while the processing of wheat into flour is).

The data in the census comes by establishment types, and some types encompass two or more sectors. In these cases, we allocated their employment to sectors by weighing it by the inverse of the number of products produced. For example, half of the employment in "Cotton Spinning and Weaving"establishments was allocated to the "Cotton Yard/Thread" sector, and half to the "Cotton Fabric" sector.

After this we proceed with matching the census and trade data in four steps. First, we match all trade categories and census industrial sectors that are a perfect match. Second, we aggregate up groups of trade categories which together either comprise a perfect match with a broader census industrial sector, or at least a substantial subset of products of that sector. Third, we aggregate up groups of census industrial sectors to match broader trade categories. Finally, where this is not suitable we weight broader trade categories by the set of products included and match them to narrower census industrial sectors.

There are census sectors that are not matched to any trade category, for one of the following three reasons: 1) the sector produces a non tradable good, e.g. "Waterworks"; 2) the sector produces a good that is potentially tradable, but does not appear to be traded between Britain and India, e.g "Ice factories"; and 3) the sector does not match to any trade category because of a definition issue: this is the case for the census industrial sector "Bleaching and dyeing factories" which refers to a part of the production process of textiles of different materials (e.g. cotton, jute, wool), while in the Annual Statement of the Trade of the United Kingdom textiles are reported by the material. The first two cases are by far the most frequent. This provide us with an additional 45 non-traded sectors.

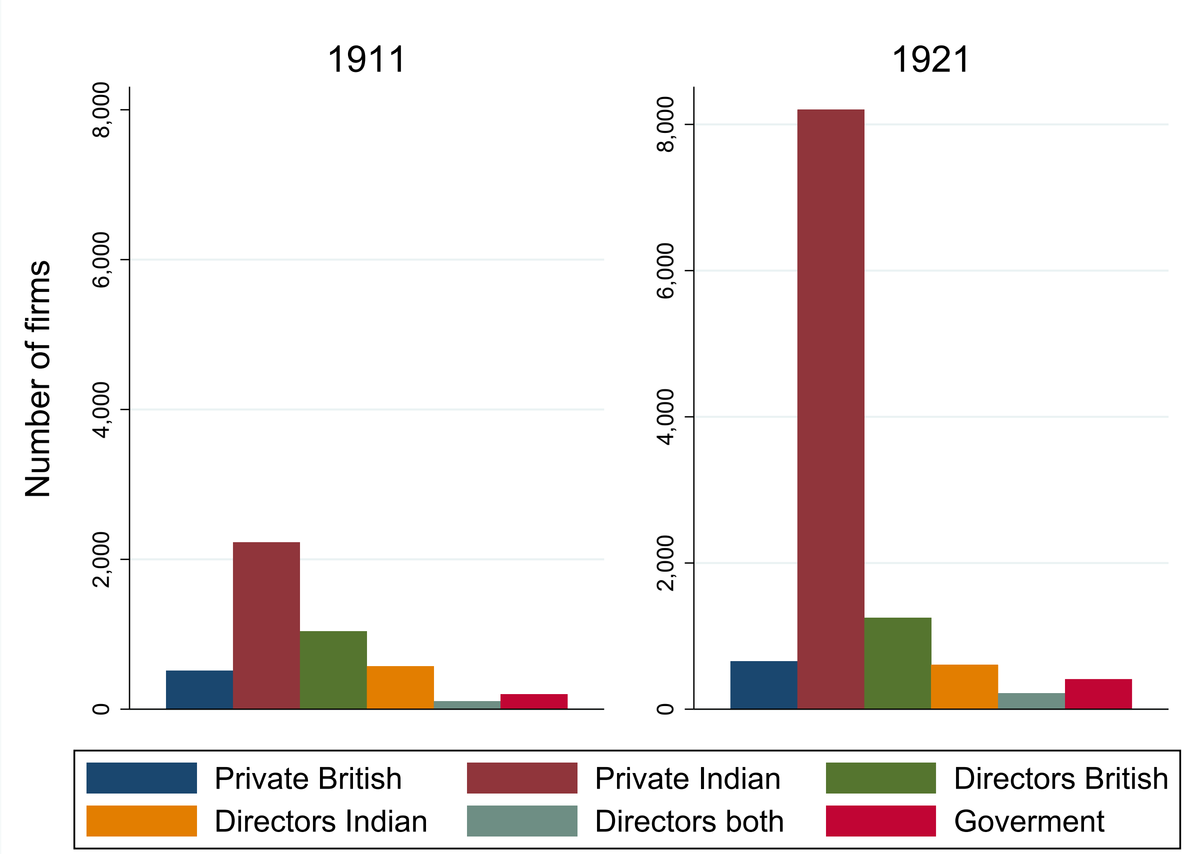
Figure B.9: Industrial employment across occupations

Notes: The figure displays industrial employment in India for 1911 and 1921 by occupation and nationality. Employment numbers are reported in thousands. Source: Census of India

From the 1911 and 1921 censuses, we also collect data on some additional industry breakdowns. We collect data on industrial employment by occupation and ethnicity. The breakdown is into administrative staff (including all employees related to direction, supervision and clerical work), skilled workers and unskilled workers. In addition, employment in administrative staff and skilled workers is further subdivided into Indian and British workers. Indian also includes a small fraction of worker from other non-European countries and British includes also other Europeans as well as Anglo-Indian workers. Figure B.9

presents the aggregate employment numbers for the different categories as reported for 1911 and 1921. Notably, nearly all skilled and unskilled workers employed in factories are Indians, while British administrative staff accounts for 12.3% of total administrative staff in 1911 and 11.1% in 1921.

Figure B.10: Firm ownership by type

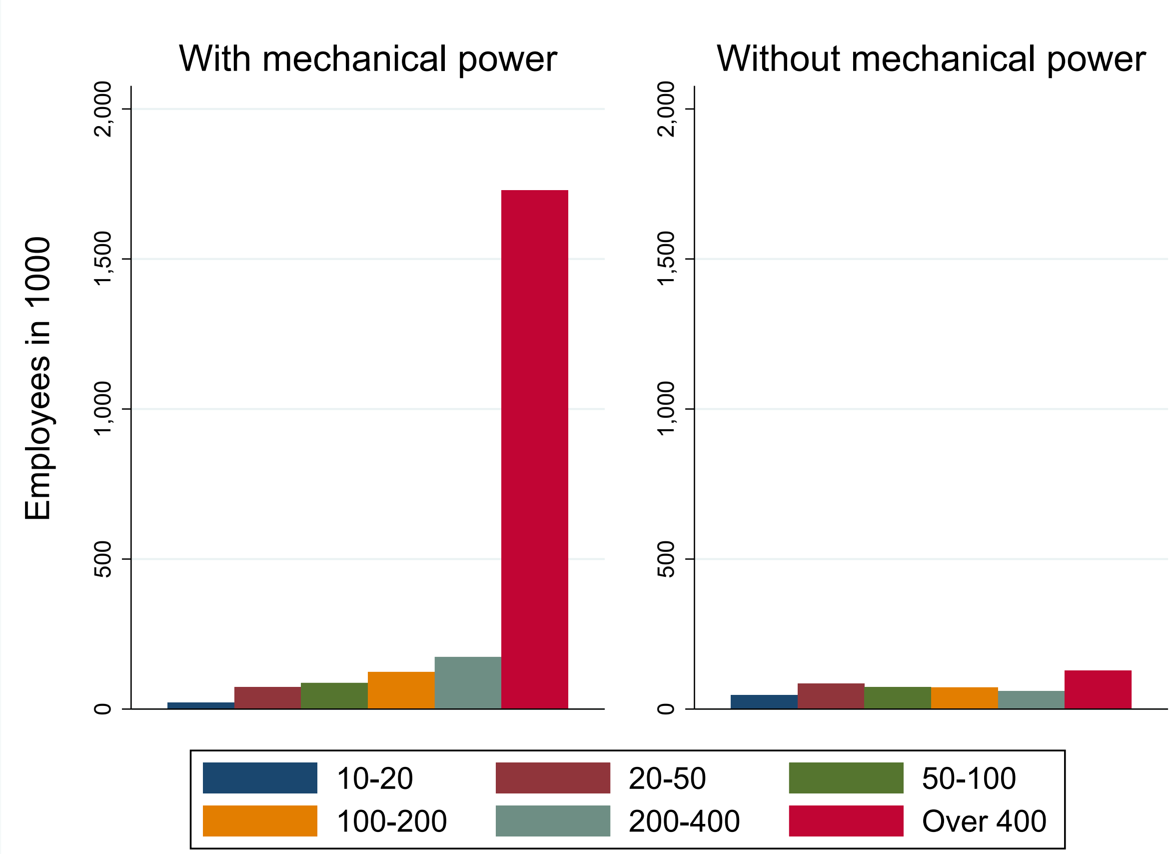


Notes: Number of firms across different types of ownership in 1911 and 1921. Firms covered changes from at least 20 employees in 1911 to at least 10 employees in 1921. This likely contributed to the rise in Indian privately owned firms reported. Even without this reclassification (attributing all firms in 1921 reported with 10-20 employees to be Indian privately owned) the number of Indian privately owned firms would have at least doubled compared to 1911. Source: Census of India

Data for ownership is also collected from the Census of India. However, the data is not provided at the district level, so that we collect the data on ownership for each province broken down by industry categories. For all data sources, apart from the Bombay 1911 census, the industry categories provided for the ownership data are nearly identical to the ones provided at the district level for firms and employment numbers. Accordingly, we match the data from the province-industry cells to the respective district industry cell, weighting the data by number of firms in the district industry cells. This gives us a good approximation of the number of firms in different ownership groups at the district level for 1911 and 1921. The following main types of ownership groups are reported in the census: (i) firms that are privately owned by a single individual, (ii) firms which are owned by a company with a set of directors and (iii) government owned firms. Group (i) privately owned firms is broken down into British and Indian owned firms, where the category British includes all Europeans and Anglo-Indian owners. For Indian privately owned firms ownership is further broken down by caste, but we do not utilize this information. Group (ii) firms owned by a company with a set of directors is further divided into the directors being exclusively British or Indian or from both groups. We than construct shares of ownership and total numbers of firms owned by each of these categories of ownership at the district level for 1911 and 1921. This is depicted in Figure B.10. Note that the threshold of included firms changed between the 1911 and 1921 census while the majority of firms appears to be covered in 1911 and 1921 this might in part contribute to the strong rise in reported Indian privately owned firms. However, even when subtracting all firms with 10-20 employees in 1921 reported for the whole of India from the Indian privately owned firms ownership would still have increased to more than 4000 firms (suggesting at least a doubling in Indian privately owned firms between 1911 and 1921). For each province apart from Bombay we also construct the change in the number of firms owned between 1911 and 1921 for each of these groups. We are unable to do this for the Bombay 1911 census as the ownership data reports industry categories only at a more aggregated level and does not cover all industry categories.

The data has two important limitations. The first issue is that the threshold above which establishments were included in the census decreased from 20 employees in 1911, to 10 in 1921. This mechanically increases our dependent variable, by adding firms that were in the 10-20 brackets both in 1911 and in 1921, and by not excluding firms which were in the 20+ bracket in 1911, but moved down to the 10-20 bracket in 1921. To the extent that these firms were more numerous in districts more exposed to the shock, this would lead us to overestimate our coefficient. Based on aggregate data, this issue does not seem to be a major concern, since firms in the 10-20 brackets account for only 2.5% of industrial employment in 1921 (see Figure B.11). That this is not a severe issue is also confirmed by using Department of Industry 1897-1948 as a complementary data sources were this is not a problem (more detail in Section B.7). The second issue that arises is that boundaries of some districts changed between 1911 and 1921. To deal with this, we lump together districts that have undergone changes of territory affecting more than 2% of the population of any individual district. We do this by comparing the population figure of a district in 1911, to the one reported for 1911 in the 1921 census, since the latter figure refers to contemporary (1921) district boundaries. The 1921 census also provides information on important boundary changes that occurred since 1911. For example, if district A has lost considerable territory and population to adjacent district B between 1911 and 1921, then we consider A and B as a single district both in 1911 and 1921. Accordingly, we construct 235 districts out of an initial 257 (253) districts reported in the 1911 (1921) census. The remaining changes predominantly occurred due to natural changes in boundary rivers and corrections of previous surveying errors. The average district in our dataset has a population of 1 million inhabitants and an area of 5 thousand square miles.

Figure B.11: Employment by firm size and power used



Notes: The figure presents total employment by firm size and power used for the whole of British India, as reported in the 1921 Census (thus, it includes both our traded and non traded sectors). Source: Census of India

B.7 Factory report and modern Indian census data

The first Factory Act in British India went into force in 1881 which covered premisses with (a) power driven machinery and (b) more than 100 employees with indigo, tea and coffee plantations having been exempt (See Prideaux 1917, p. xi). An amendment in 1891 reduced the employment cut off from 100 to 50 employees and the local government was allowed to designate establishments as factories of more than 20 employees through notification in the official Gazetteer. Mines were exempt and covered by the 1901 Mines Act. The 1911 factories act introduced considerable regulatory changes, but did not alter the coverage of factories. This was only done by the 1922 Indian Factories Amendment Act, which reduced the general coverage to at least 20 employees and the threshold for declaration by the local government to 10 employees (Turner 1923). The exemption of plantations and mines remained unchanged. No changes of importance for establishments or classes of workers were made in the 1923 and 1926 amendments (See Kapur 1949, p.2).

The 1934 Factories Act replaced the 1911 Factories Act after implementing recommendations made by the Royal Commission on labour in India, which than received minor amendments in 1944, 1945, 1946 and 1947 (See Kapur 1949, p.2). The 1934 Factories Act also reduced the threshold for factories to be covered in general to at least 10 employees and any establishment with at least 5 employees could be declared a factory. Census statistics on power usage and employment by firm size for the whole of India in 1921 suggest that the employment in firms of 10-20 and 20-50 employees only accounted for a minor proportion of employees (2.5% and 5.8%, respectively), and even less in firms using mechanical power (see Figure B.11). So that the threshold changes likely only had a minor effect. Following independence Pakistan kept the 1934 Factories Act, while India replaced it by the 1948 Factories act getting rid of exemptions and changing coverage to (i) any establishment with ten or more workers with the aid of power and (ii) twenty or more workers without power (See Kapur 1949, p.28). The pre-independence Factory Reports covered British ruled areas reporting statistics at the district level, but excluded de-regulated territories and scheduled districts therein. The Factory Reports also provides a sectoral breakdown, but only at a coarser level compared to the Industrial census. This is why we use it only as a secondary data source as this is not a problem for the construction of our dependent variable (where we only need district-level aggregate industrial employment).

Eventough the coverage of the Factory Reports data is narrower than the Census data we collected, it provides us with a measure of industrialisation that is consistent over time (at least for 1911-1921), and allows us to look at shorter as well as longer time periods. We were able to collect data for 1911, 1913, 1915, 1917, 1919, 1921, 1926 and 1936. We choose the 2-year intervals between 1911 and 1921 to have (i) a pre-war period covering 1911-13 to rule out any pre-trends, (ii) the periods 1913-15 and 1915-17 to analyse the time-horizon of the trade disruption to start affecting industrial employment growth, (iii) the period 1917-19 for analysing the effect during the transition from war to peace and (iv) 1919-21 to cover a full period of peace after the World War I and to match the time-horizon of the Census data. After 1921 we collect data at longer time intervals to study the long-run effect of the WW1 trade shock.

To be able to study industrial employment up to today we augment the information from the Factory Reports by data collected from the post-Independence Census of India in 1951 and 2011 (Census Superintendent 1951; Census Registrar General 2011).[62] Our data focusses on employers and employees (not including independent workers) in 1951 and main-workers in non-household industries (not including household industries and marginal workers) in 2011. This appears the most consistent classification as enumer-

[62] The partition of India and the need to aggregate some districts that underwent considerable boundary changes are the reasons for the smaller sample size of 132 districts after independence.

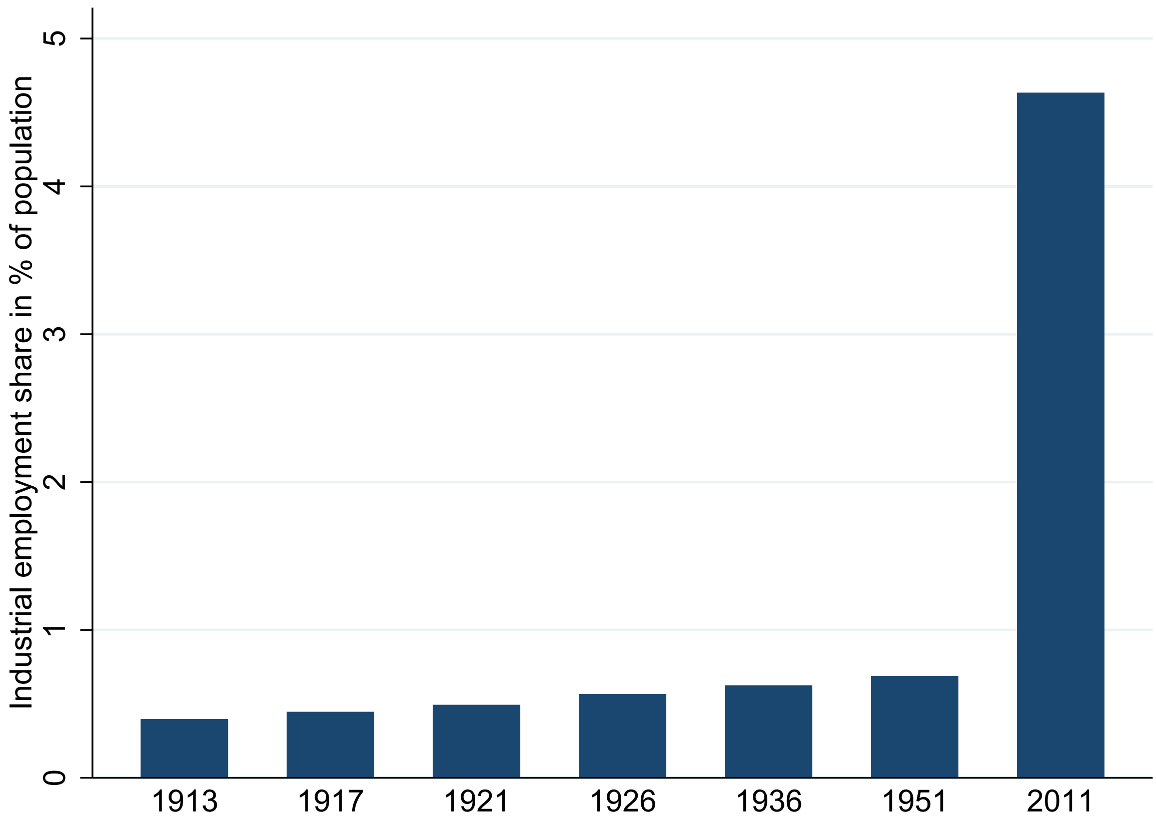
ated workers still exclude artisans.[63] However there is no longer a cut-off for minimum employment in the census so that all firms with at least one employer and one employee are included in the industrial employment share in 1951 and 2011. The industrial categories used from the 1951 Census are Division 2 "Processing and Manufacture- Foodstuffs, Textiles, Leather and Products Thereof", Division 3 "Processing and manufacture- Metals, Chemicals and Products thereof" and Division 4 "Processing and Manufacture- Not elsewhere specified" of the table on "employers, employees and independent workers in industries and services". The not included division are 0 "Primary Industries- Not elsewhere specified", 1 "Quarrying and Mining", 5 "Construction & Utilities", 6 "Commerce", 7 "Transport, Storage and Communications", 8 "Health, Education, Public Administration", 9 "Services- Not elsewhere specified". In 2011 we use divisions 10 "Manufacture of food products" to divisions 33 "Repair and installation of machinery and equipment" of the table on "industrial classification of main workers in manufacturing processing, servicing and repairs by household industry and non-household industry 2011". The not included categorise are 45 "Wholesale and retail trade and repair of motor vehicles and motorcycles" to 99 "Activities of extraterritorial organizations and bodies". The selected set of industries should reflect a consistent set of manufacturing industries that are reported in the Factory Reports, the 1951 Census and the 2011 Census. Accordingly, the decrease in the employment threshold of coverage (similar to revisions in the Factory Act in 1922 and 1932) reflects the only change in coverage. Figure B.12 illustrates the industrial employment share over time. Note, the industrial employment share is less than 1% of the population up to 2011 when only considering industrial employees and not artisans.[64] It highlights that changes to classification did not lead to a sudden jump in industrial employment numbers between 1913-51. This again is consistent with Figure B.11 which highlights that most industrial employment (excluding artisans) is in large firms with more than 400 employees.

Finally, we collect information on the total number of accidents reported in 1913, 1917 and 1921 across districts from the Factory Reports. The Bombay Factory Report of 1917 refers to the recorded accidents (28 fatal, 75 serious, 819 minor) in the following way: “The fatal accidents amounted to 27 caused the death of 28 persons. Of the fatal accidents, 9 were due to machinery and the remainder were due to other causes, chiefly through gross carelessness on the part of the operatives. All accidents unconnected with the machinery and of very trivial nature have been excluded from this report. But fatal accidents of all kinds have been included.” The main cause of fatal accidents appears to

[63] Note that for 1951 we continue using total population to construct the share of industrial employment, while in 2011 due to the introduction of compulsory schooling in India up to the age of 14 we use the population available to work, which consist of all workers, all marginal workers and all non-workers available to work. This considerably improves the precision of our estimate compared to using the total population in 2011.

[64] For example in 1951 artisanal (independent) workers account for 60% of total industrial employment (6 million in Divisions 2-4 in our sample).

Figure B.12: Industrial employment share over time



Notes: The figure presents industrial employment as share of the total population over time. For consistency, it depicts the mean industrial employment share across the 132 districts of modern India which our data covers past-independence. Source: Department of Industry 1897-1948; Census Superintendent 1951; Census Registrar General 2011

be workers being caught by the line shaft (for power transmission) of machinery. Notably, information on shifts and working hours suggests most firms had similar hours of work and holiday set at the maximum level allowed with there being no substantial change in the rules or exemptions provided observable across time. This suggests the number of accidents provides a decent proxy for the workforces knowledge of handling the machinery on-site.

B.8 Political data

For political attitudes we use the data given in the civil disobedience enquiry committee report (Indian National Congress 1922) set up by the Indian National Congress in 1922. Witnesses were heard on the committee's tour through India from the 30th of June toll the 16th of August. The main question focusses on support for civil disobedience with Table B.13 summarising the answers given. The answers range from supporting the immediate start of mass civil disobedience to being against any form of civil disobedience on principle grounds. Some respondents also provided a mix of answers from either category A-E or F-G, but those two groups are mutually exclusive. Accordingly we code an individual as supporting immediate civil disobedience of any form as 1 and an individual stating that his area is not ready for civil disobedience or opposes it on principle as a 0.

Table B.13: Responses given in civil disobedience enquiry

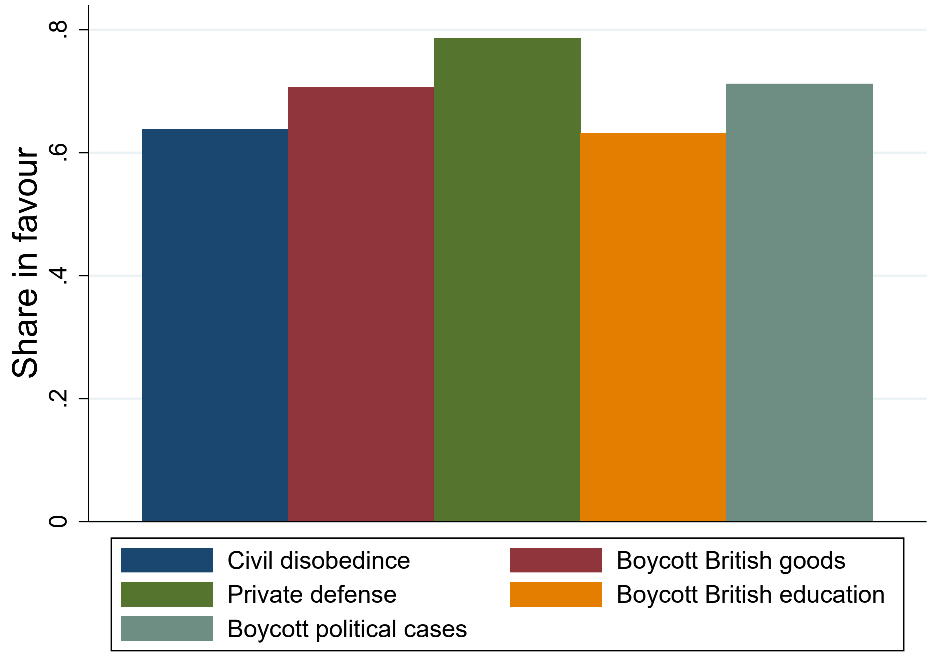
Nr.	Nature of Evidence	Immediate action	Witnesses
A	For immediate Mass Civil Disobedience	1	4
B	For immediate non-payment of taxes generally	1	3
C	For immediate Civil Disobedience limited to particular taxes and laws	1	5
D	For immediate Aggressive and Defensive Individual Civil Disobedience	1	100
E	For immediate Individual Defensive Civil Disobedience only	1	131
F	For Provinces or Districts not yet ready for Civil Disobedience in any form	0	161
G	Against any form of Civil Disobedience on principle	0	9

Notes: Responses given by witnesses on attitudes towards civil disobedience. The list only gives the unique responses. Some individuals gave as a response either a mix of answers A-E or F-G, but there is no overlap between the 2 groups. Accordingly we code the responses into either supporting immediate civil disobedience of any kind or not. Source: Indian National Congress (1922)

The remaining responses given on the boycott of British products, the use of private defence, the boycott of British education and the boycott of courts in political cases are all either reported as "for" or "against". Accordingly, these questions are all coded as 1 for support or 0 for being against the measure. Figure B.13 highlights that there is considerable variation in the responses given.

We match the political data to districts by the information on town or district provided for as many individuals as possible. We always attribute the WW1 trade shock based on the district even in cases where a representative represents a wider area than the district of residency. This occurs for example in cases where a representative is part of the provincial or the all India congress committee. The report also provides information on the provincial congress committee the interviewed person is from. This also acts as a control for the point in time the interview was conducted as it reflects the itinerary of the committee starting from Delhi over Madras to Calcutta with the aim of being representative of as much of India as possible. We are able to match up to a maximum of 257 individuals that provided a response to any of the outlined questions to our districts, which is about slightly above half of the maximum of 467 answers provided. This lower matching rate is due to three reasons: (i) There is no information provided on the origin of the individual. (ii) The individual is from an area outside the 7 major-census provinces we use in constructing our trade shock. (iii) A town/village is reported which is not covered

Figure B.13: Share of respondents in favour of question



Notes: Share of respondents reporting answers A-E (coded as in favour) of the question of civil disobedience and reporting "in favour" on the question of boycott of British products, private defence, boycott of British education and boycott of courts in political cases. Source: Indian National Congress (1922)

in the 1921 census and can not be matched to a district (the smallest towns reported are classified as cantonments with a population of above 200 individuals). Reason (i) is by far the most common one. Figure B.4 depicts the geographical variation on support for civil disobedience across districts for which responses are recorded.

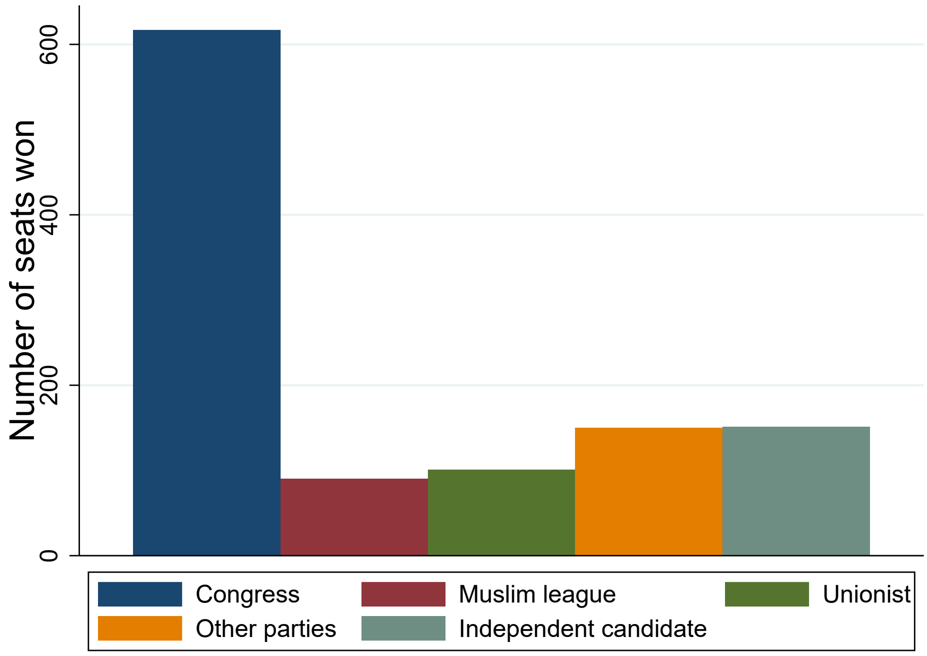
The second political data source we use are the provincial legislative assembly elections (India Office 1937). The 1937 provincial legislative assembly elections are the first elections held in British India in which a considerable share of the population was able to vote (around 1/6th of the adult population) as the Government of India Act 1935 had considerably increased the franchise. The elections were held for eleven individual legislative assemblies: Assam, Bengal, Bihar, Bombay Presidency, Central Provinces, Madras, North-West Frontier Province, Orissa, Punjab, Sindh and United Provinces with our collected census data covering all of these provinces apart from Assam and the North-West Frontier Province.

The winner of a specific seat was determined by having gained the highest number of votes in a constituency (first-past-the-post system), however the constituencies were not purely based on geographic boundaries, but also based on religion or reserved for some powerful interest groups (e.g. landowners, trade unions, universities). We focus on "General" and "Muhammadan" constituencies that provided elected representatives for the two main religious groups: Hindus and Muslims. This is done for two reasons: (i) they represented the two groups credibly vying for power after independence (which is reflected in the formation of India and Pakistan) and (ii) they are the only groups in homogeneous and geographically detailed constituencies across the whole of India enabling us to match Census data precisely to 1937 constituencies. The electoral system of the 1937 election is further complicated by some constituencies having more than one seat. These multi-seat constituencies were created to reserve seats for scheduled castes and tribes, Mahrattas or women as well as to avoid sub-dividing districts with large minorities into several small constituencies which would divide their voting power and deprive them of all chance of representation (see Indian Delimitation Committee 1936, Chapter 2 & 3). Further, the Bombay and Madras presidencies also had some multi-seat constituencies without reserved seats. For this reason, the clear first-past-the-post system in single-seat constituencies was augmented by the following three voting possibilities in multi-seat constituencies: (i) Single, non transferable vote: each voter had only one vote. This was perceived as providing more protection for minorities without a protected seat, (ii) Distributive vote: in an n-seat constituency each voter has n-votes, but can cast at most one vote per each candidate and (iii) Cumulative vote: in an n-seat constituency each voter has n-votes, and is free to cast them all for one candidate.

For matching the trade shock and other controls across districts to the 1937 election outcomes we use information on the mapping of constituencies, taluks (sub-divisions of districts) and towns from the "Report of the Indian Delimitation Committee" (Indian Delimitation Committee 1936) and the Census of India to match a unique district to the (usually smaller) constituencies. For the 43 constituencies (out of 878) which span multiple districts we use equal weights to match the district level information to the respective constituency. As an example the General-Urban constituency of "Bulandshahr-cum-Meerut-cum-Hapur-cum-Khurja-Nagina Cities" includes cities from the two districts of Bulandshahr and Meerut. Accordingly, we assign a weight of 0.5 to the two districts to construct the trade shock and controls for the constituency of "Bulandshahr-cum-Meerut-cum-Hapur-cum-Khurja-Nagina Cities" (we do not use population weights as we do not know the number of eligible voters for districts).

We focus on whether a party won a seat or not rather than the vote share as the party affiliation and number of votes polled are only reported for the successful candidate in the "Return showing the results of elections in India 1937" (India Office 1937). Figure B.14 presents the success –in terms of seats won– of the different parties across the constituencies in our sample. The INC appears to have been the only party that was well organized and fought the elections on a national front with the aim of the party being an independent and united India (Pandey 1978). This nation wide campaigning is reflected in the INC's dominant share of seats won. The remaining parties were much less organized and had less clearly defined political goals. The independent candidates represent a wide spectrum of varied opinions of which at least 10% of the successful candidates were clearly leaning towards either the INC or the Muslim league. The Muslim League's main standpoints in

Figure B.14: Results of 1937 legislative assembly elections



Notes: Number of seats won by the respective party in the 1937 province legislative assembly elections in our sample. Source: India Office (1937)

the 1937 election appear to have been similar to the Congress election programme, but with the especial emphasis on the protection of minority rights and the claim to be the representative of the Muslim electorate (Pandey 1978; Moore 1983; Kulke & Rothermund 2016). Despite winning the second most seats of all parties its number of seats won were far behind the INC's (see Figure B.14). This poor election result was suggested to be one of the reasons for the Muslim League to undertake a considerable transformation becoming clearly in favour of the creation of an independent Muslim state after the 1937 election (Moore 1983; Kulke & Rothermund 2016). The third most successful party and the one most clearly in favour of cooperating with British authorities was the Unionist party representing the interests of landlords. We here combine the votes of the Unionist and United parties as the United party had been modelled along the lines of the Punjabi Unionist party following the formation of Sind in 1936. As the Unionist party won less seats than the Muslim League on its own we refer to it as the third biggest party. Most of the remaining seats in the block of other parties were won by minor parties covering a vast spectrum of Hindu nationalists, smaller Muslim and other religious parties, anti-feudal parties, parties advocating for schedule cast rights and socialist and communist parties.

B.9 Other Data

In addition to the data already discussed, we collect data on number of World War I deaths by district from individual records of the Commonwealth War Grave Commission (where origin was reported). The variable for whether a district is coastal is constructed based on our geographical shape-file. The shapefile itself was digitized based on the "Map of India (Showing Provinces and Districts) in 1915" depicting the whole of British India published by the Surveyor General of India in combination with other maps when required. We than collapsed our digitized map to depict the merged district boundaries used in the baseline specification. Other baseline controls (number of persons employed in the army, navy and police, living in urban areas, being literate in English or any language and aged over 20 years) are collected from the census in 1911 (see Census Commissioner 1911, 1921).

Table B.14: Summary Statistics

	Mean	Std. dev.	10th Perc.	90th Perc.	Valid obs.
Panel A. Baseline variables					
Δ Industrial empl. share	0.17	0.76	-0.04	0.52	235
EX-IM Shock	0.11	0.57	-0.00	0.20	235
Industrial empl. share 1911	0.64	2.14	0.00	1.06	235
Military share 1911	0.21	0.61	0.00	0.58	235
Urban share 1911	10.43	14.00	0.90	20.44	235
Coastal	0.15	0.36	0.00	1.00	235
Literate share 1911	5.50	4.04	2.55	9.75	216
Literate English share 1911	0.72	1.64	0.11	1.13	216
Age 20+ share 1911	53.59	3.27	49.28	57.13	216
Panel B. Composition industries & trade shock					
Δ Industrial empl. share (traded)	0.16	0.77	-0.05	0.42	235
Δ Industrial empl. share (non-traded)	0.01	0.09	-0.01	0.05	235
Δ Industrial empl. share (primary)	0.02	0.58	-0.05	0.13	235
Δ Industrial empl. share (manufactures)	0.14	0.48	-0.01	0.31	235
IM Shock	-0.12	0.54	-0.15	0.00	235
EX Shock	-0.01	0.17	-0.01	0.03	235
Export raw materials & food	-0.02	0.17	-0.01	0.01	235
Import manufactures	-0.12	0.54	-0.15	0.00	235
Panel C. Employment & ownership composition variables					
Δ British admin empl. share	0.00	0.01	-0.00	0.00	235
Δ Indian admin empl. share	0.01	0.04	-0.00	0.05	235
Δ British skilled empl. share	-0.00	0.00	-0.00	0.00	235
Δ Indian skilled empl. share	0.06	0.26	-0.03	0.19	235
Δ Unskilled empl. share	0.10	0.66	-0.05	0.36	235
Δ Nr. firms	26.52	52.08	0.00	72.00	235
Δ Nr. private ownership (English)	0.24	4.44	-1.06	2.26	198
Δ Nr. private ownership (Indian)	22.91	40.28	0.00	74.22	198
Δ Nr. Directors	2.01	9.37	-2.68	7.89	198
Δ Nr. goverment ownership	0.62	2.63	-0.30	2.12	198
Panel D. Factory report industrial employment					
Δ Industrial empl. share 1913-15	0.03	0.12	-0.03	0.06	191
Δ Industrial empl. share 1913-17	0.04	0.18	-0.04	0.12	191
Δ Industrial empl. share 1913-19	0.08	0.27	-0.02	0.15	191
Δ Industrial empl. share 1913-21	0.11	0.36	-0.02	0.22	191
Δ Industrial empl. share 1913-26	0.17	0.48	-0.01	0.35	191
Δ Industrial empl. share 1913-36	0.21	0.56	-0.01	0.45	191
Δ Industrial empl. share 1913-51	0.29	0.56	-0.09	0.79	132
Δ Industrial empl. share 1913-2011	4.23	3.43	1.32	8.86	132

Summary Statistics contd.

	Mean	Std. dev.	10th Perc.	90th Perc.	Valid obs.
Panel E. Individual responses civil disobedience report					
Pro civil disobedince	0.64	0.48	0.00	1.00	227
Private defense	0.79	0.41	0.00	1.00	140
Boycott British goods	0.71	0.46	0.00	1.00	92
Boycott British education	0.63	0.48	0.00	1.00	144
Boycott political cases	0.71	0.45	0.00	1.00	139
Panel F. Results provincial elections					
No of Seats	1.26	0.58	1.00	2.00	878
Congress Seats	0.50	0.50	0.00	1.00	878
Independent Seats	0.15	0.36	0.00	1.00	878
Muslim League Seats	0.10	0.30	0.00	0.00	878
Unionist Seats	0.11	0.31	0.00	1.00	878
Other Party Seats	0.14	0.35	0.00	1.00	878

Notes: Summary statistics for main variables of interest. Panel A provides information on the variables used in Table 2.1. Employment shares are shares in total population. Panel B provides information on variables measuring the composition of employment growth and the trade shock by sector. Panel C provides information on variables related to nationality of employment and ownership. Panel D provides information on industrial employment change across time periods. Panel E provides information on individual answers given in the civil disobedience report. Panel F provides information on the outcome of the 1937 election.

Table B.15: Classification industries

	Import competing	**Export**	**Import competing & export**
Food	Dairy; Fish; Meat; Potatoes; Salt	Coffee, Raw; Pepper; Pigeon pea/Arhar splitting; Tea	Flour; Malt; Rice; Sugar
Raw materials	Coal; Granite; Stones	Copper ore; Cotton, raw; Fibre, raw; Manganese ore; Mineral oils; Rubber	Iron Ore; Manures; Raw Silk; Timber; Vegetable oil; Wool
Manufactures	Aerated Water; Ammunition; Animal Fat; Apparel; Arms; Bicycles; Boats; Boots and shoes; Brewery; Bricks; Brushes; Candles; Caps; Cardboard; Carpentry; Carriages; Cement; Clocks; Condiment; Confectionery; Copper products; Cutlery; Distillery; Electric lights; Electric tramways; Electrical appliances; Embroidery; Felt; Furniture; Glass; Harness; Hosiery; Instruments; Iron products; Jewellery; Leather manufactures; Locomotives; Machinery and Parts thereof; Matches; Medicines; Military products; Motor cars; Motors; Musical Instruments; Painters Colours and Materials; Paper, and Articles of Paper; Perfumery; Pig Iron; Pottery, red; Print; Processed coffee; Saddles; Silk yarn; Slates; Soap; Stationery; Steel products; Tiles; Tin; Umbrellas; Wood Products; Wool blankets; Wool fabric	Indigo; Opium	Animal Food; Chemicals; Coir yarn; Cordage; Cotton fabric; Cotton waste; Cotton yarn; Fibre fabric; Leather; Silk Fabric; Tobacco; Wool carpets
No trade	*Airplane*, Aluminium; Bakery; Buttons; *Chromite*; Cotton carpet; Cotton rope; Dockyards and boat repair; Dyeing and colouring; Electricity supply; Other food, nec; *Plantation fruits*; Gas works; *Cured ginger*; Gold ore; Graphite; *Processed groundnut*; Ice; *Kaolin*; *Kath*; Laundries; *Lead*; Local transport workshop; Locks; Metal typefaces; Other metal, nec; Mica ore; Mica manufactures; Mints; *Other processed grains, nec*; Other plants, nec; Other spices, nec; Public works; Railway servicing; *Rubber products*; Safes; Other stone, nec; Sugarcane; Telegraph; *Telephone*; Tents; Other textile, nec; Toys; Waterworks; Other wood, nec		

Notes: The table presents the 105 matched industries grouped by type of products and type of trade with the Britain and the 45 non-traded categories. Categories in cursive record no employment in 1911.

Chapter 3

The effect of recent technological change on US immigration policy

Abstract

Did recent technological change, in the form of automation, affect immigration policy in the United States? I argue that as automation shifted employment from routine to manual occupations at the bottom end of the skill distribution, it increased competition between natives and immigrants, consequently leading to increased support for restricting low-skill immigration. I formalise this hypothesis theoretically in a partial equilibrium model with constant elasticity of substitution in which technology leads to employment polarization, and policy makers can vote on immigration legislation. I empirically evaluate these predictions by analysing voting on low-skill immigration bills in the House of Representatives during the period 1973-2014. First, I find evidence that policy makers who represent congressional districts with a higher share of manual employment are more likely to support restricting low-skill immigration. Second, I provide empirical evidence that representatives of districts which experienced more manual-biased technological change are more likely to support restricting low-skill immigration. Finally, I provide evidence that this did not affect trade policy, which is in line with automation having increased employment in occupations exposed to low-skill immigration, but not those exposed to international trade.

JEL Classifications: F22; J24; J61; K37
Keywords: Political Economy, Voting, Immigration Policy, Technological Change
Current Version: Most recent version (Brey 2020*b*) can be found HERE.

3.1 Introduction

Immigration and immigration legislation have been a key area of policy debate in the United States since independence (Hatton & Williamson 2005). The US House of Representatives voted on more than a dozen bills regulating immigration since 1970 alone. During the same period the number of immigrants to the US increased from a relatively low level, when compared to the age of mass migration, to numbers not observed before.

Public views on immigration differ greatly between individuals. For example, one important determinant is competition with immigrants in the labour market. Low-skilled workers are considerably more likely to prefer limiting immigrant inflows than their high-skilled counterparts (Scheve & Slaughter 2001; Mayda 2006; O'Rourke & Sinnott 2006).[1] For political incumbents, casting roll-call votes ranks among the most visible activities to take clear policy positions and communicate them to their constituents (Mayhew 1974). Consistent with this, Facchini & Steinhardt (2011) find that the degree of potential labour market competition between natives and low-skill immigrants explains representatives' voting behaviour on immigration policy.[2] This raises the question, whether recent technological change, in the form of automation (see Autor et al. 2003; Acemoglu et al. 2011; Autor & Dorn 2013; Goos et al. 2014), has affected US immigration policy through shifting employment from routine to manual occupations, that face more competition from low-skill immigrants. In particular, the relative complementarity of automation with manual compared to routine tasks at the bottom end of the skill distribution, i.e. manual-biased technological change, appears crucial here, while the corresponding effect of automation on demand for abstract relative to routine tasks at the top end of the skill distribution should not influence competition between natives and low-skill immigrants.[3]

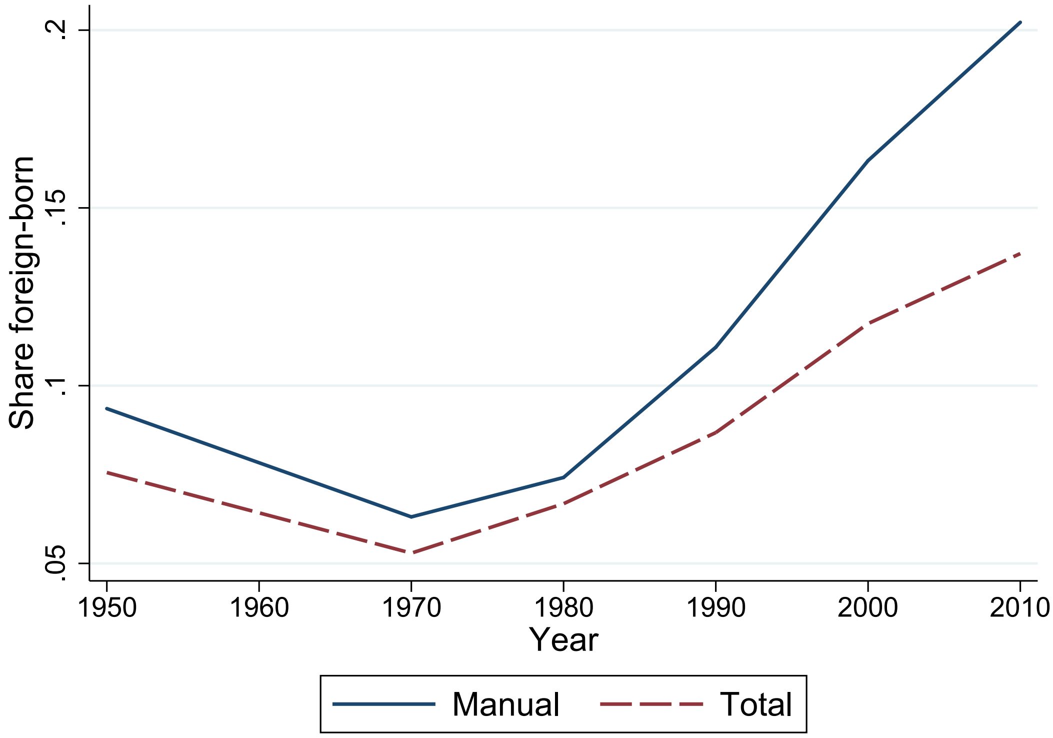
This chapter studies the role of technological change in the making of immigration policy. In particular, I study (i) the extent to which local manual employment is related to representatives being in favour of stricter low-skill immigration policies, and (ii) whether recent technological change affected the voting behaviour of representatives.

[1]The actual impact of immigration on local wages remains a vividly debated issue in the empirical literature. Borjas (2003), Borjas (2006), Borjas & Monras (2017) find evidence on the adverse effect of immigration on native workers' wages, whereas Card (1990) and Card (2009) find no or only minor effects, while Ottaviano & Peri (2012) finds positive effects. For a review on the literature see Dustmann et al. (2016). Allen et al. (2018) studying the impact of a specific immigration policy, the US-Mexico border wall, find it to change migration routes and create a modest income gain (loss) for low-skill (high-skill) workers. Burstein et al. (2020) highlight that the impact of competition from immigration on natives is much larger in non-traded compared to traded sectors.

[2]Note that I use the term native to refer to individuals with the right to vote (including previous cohorts of immigrants), while immigrant refers to individuals that have migrated to the US (legally or illegally), but do not have the right to vote.

[3]The latter effect of higher complementarity of automation with abstract compared to routine tasks might influence competition between natives and high-skill immigrants if these are substitutes in abstract occupation. However, as high-skill immigration is less contested and the House of Representatives has only voted on three bills focussing on this issue I will focus exclusively on the effect of recent technological change on low-skill immigration legislation.

Figure 3.1: Share of migrants in manual employment 1950-2010



Notes: The figure illustrates the share of foreign-born individuals in manual employment in total US manual employment from 1950 to 2010. It also depicts the share of foreign-born individuals in the total US population. Manual employment is defined based on an occupation being in the top-33% of manual task intensity in 1980. A detailed description on the construction of manual employment and task intensity is provided in Section 3.3.

I examine these questions theoretically and empirically. First, I formalise the hypothesis that automation, which led to a shift from manual to routine employment, increased competition between natives and immigrants, and consequently lead to increased support for restricting low-skill immigration in a theoretical model. Second, I empirically evaluate the theoretical predictions by analysing the effect of (i) the manual employment share and (ii) manual-biased technological change across congressional districts on voting on low-skill immigration bills in the House of Representatives from 1973 to 2014.

The extremes of the skill distribution in the US consistently record a higher share of immigrants than the middle of the skill distribution (Card 2009). This reflects a concentration of immigrants in manual and abstract employment due to disadvantages of immigrants in routine employment, like clerical and retail occupations, that require better communication skills which are difficult to transfer across language barriers (Lewis & Peri 2015). Figure 3.1 highlights the consistent over-representation of foreign-born individuals in manual occupations, like agricultural, construction and low-skill services. Accordingly, natives in routine employment experience little competition from low-skill immigrants, while natives in manual employment are in strong competition with low-skill immigrants.

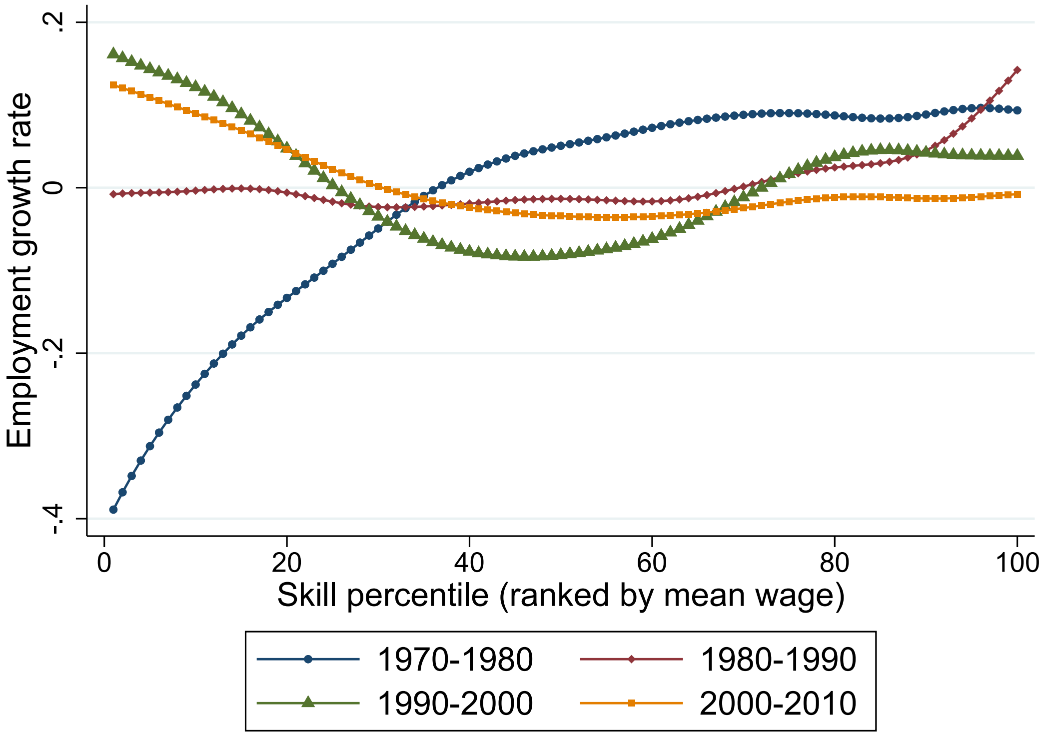
Figure 3.2: Employment tasks and voting on immigration policy

Notes: Employment share of natives across tasks in 1980 and voting on liberalizing low-skill immigration between 1983 and 1992 across corresponding congressional districts. Classification based on occupations being in the top 33% of task intensity at the national level. Employment data is taken from the census and matched to the respective votes reported in Appendix Table C.1. A detailed description on the construction of employment shares is provided in Section 3.3. Overall differences across votes subtracted. N=1673 in 50 bins.

If labour market competition between natives and low-skill immigrants in manual employment is indeed greater, one would expect this to affect policy preferences. Accordingly, representatives from districts with a higher share of manual employment should be observed to vote against liberalizing low-skill immigration, while representatives from districts with a higher share of routine and abstract employment should vote in favour of liberalizing low-skill immigration. In line with this, Figure 3.2 shows that representatives of congressional districts that had a higher manual employment share in 1980 were more likely to vote in favour of restricting low-skill immigration 1983-1992, while the opposite is the case for representatives in a district with a high routine or abstract employment share.

Recent technological change in the US, in particular automation (see Autor et al. 2003; Acemoglu et al. 2011; Autor & Dorn 2013; Goos et al. 2014), led to considerable labour market polarization in which employment declined in routine occupations, but expanded in manual ones at the bottom end of the skill distribution. Figure 3.3 illustrates this recent change in US employment growth along the skill distribution from 1970-2010. This

Figure 3.3: US employment growth by skill percentile



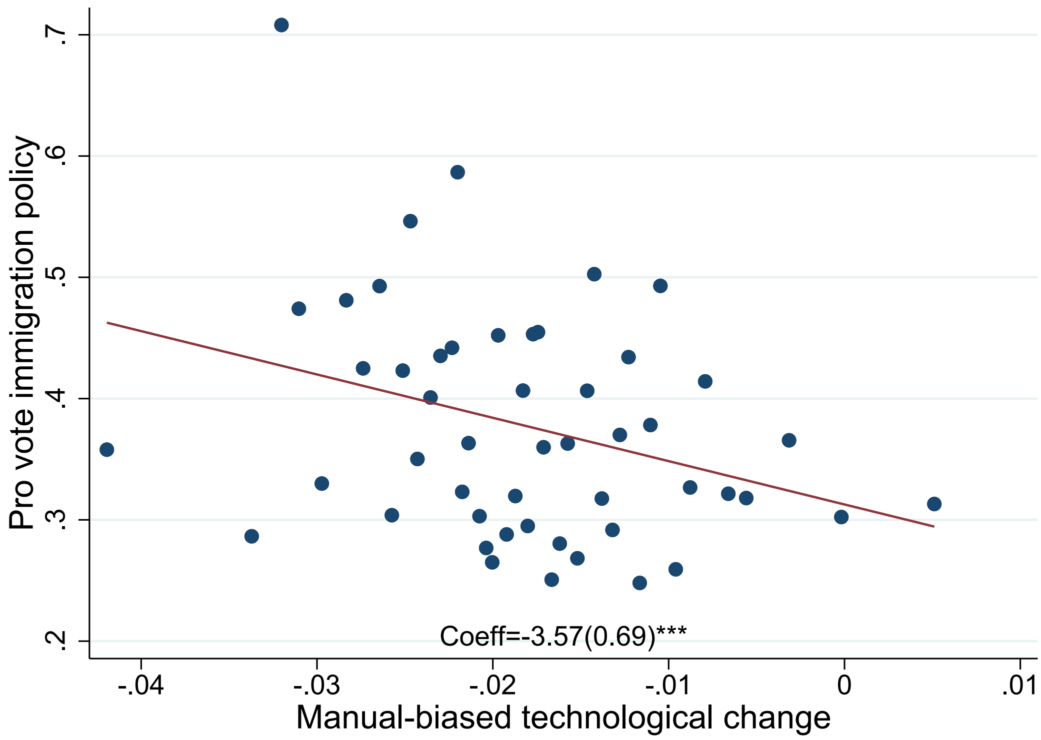
Notes: The figure displays smoothed US employment growth rates ranked by skill percentile for decades 1970-2010. The figure highlights the transition from skill-biased technological change (1970-1980) to employment polarization (1980-2010). The 2000s might even be described as unskilled biased. Employment growth rates are measured as the deviation from the average employment growth rate in the respective decade. The skill percentile of occupations is constructed based on the mean hourly wage in 1980.

suggests that while up to 1990 employment growth mostly occurred at the upper end of the skill distribution, since 1990 employment growth increased at the bottom end. This would suggest that until 1990 the share of natives in competition with low-skill immigrants was decreasing, while afterwards it increased again. This in turn should affect representatives votes on immigration policy. In general, one would expect that representatives become more likely to vote in favour of restricting low-skill immigration in areas where technological change was more favourable to manual employment increasing through the share of natives in competition with low-skill immigrants. This is highlighted in Figure 3.4 which shows that representatives from congressional districts that experienced more manual-biased technological change are more likely to vote in favour of restricting low-skill immigration.[4] Manual-biased technological change is measured as the change in the manual wage premium—the wage in manual occupations relative to other occupations—by industry at the national level since 1950 interacted with the initial

[4]Notably in Section 3.5 I will even provide evidence that exposure to manual-biased technological change altered the voting behaviour of the same elected representative and not just had an effect through the replacement of pro- with anti-immigration representatives (i.e. reflecting an adjustment in voting behaviour along the intensive margin).

industry structure of a congressional district in 1950. Accordingly, this measure proxies for technological change leading to a change in demand for manual tasks relative to other tasks across congressional districts.

Figure 3.4: Technological change and migration voting



Notes: The figure displays the relationship between manual-biased technological change and support for liberalizing low-skill immigration policy across congressional districts. The manual-biased technological change variable measures the complementarity of recent technological change that occurred since 1950 with manual employment across congressional districts. A detailed description on the construction of the manual-biased technological change variable is provided in Section 3.3. Overall differences across votes subtracted. N=5719 in 50 bins.

This outlined pattern is formalized in a partial equilibrium model in which technological change leads to employment polarization, low-skill immigrants compete with natives in manual employment and policy-makers respond to their constituencies' preferences towards immigration. First, my model predicts that in districts with a higher manual employment share the representative is more likely to support restricting low-skill immigration. Second, technological change which is complementary to manual tasks—for example the case of automation—increases the support for restricting low-skill immigration.[5]

[5] I focus in the empirical analysis on manual-biased technological change, rather than just automation for the following reasons: (i) the nature of technological change varies considerably across the time period 1970-2010 with automation accelerating only at the end and (ii) the key driving force is the shift into or out of manual employment caused by technological change which is plausibly better proxied for by changes in the manual wage premium than measures of automation as the latter also leads to a shift from routine to abstract employment at the top end of the skill distribution creating considerable noise.

I test these two predictions of the model empirically. I find that a one percentage point higher manual employment share in a congressional district makes it 3.7 percentage points less likely that a representative votes in favour of liberalizing low-skill immigration. Further, I construct a measure of manual-biased technological change by looking at the national level change in the manual wage premium by industry over time, exploiting the fact that the geographic distribution of industries is predetermined and that the possibility to implement technological changes differs across industries. I find that a one percentage point increase in the manual-biased technological change increases the likelihood of a representative voting in favour of restricting low-skill immigration by 3.9 percentage points. This supports the model's predictions that automation has made it less likely that representatives vote in favour of liberalizing low-skill immigration policy. Notably, I do not find any corresponding effect of technological change on voting on trade liberalization.[6]

This chapter contributes to several strands of the literature. First, several papers have studied the economic determinants of attitudes towards immigrants and immigration policy-making in the US. In particular, the role of substitutability between migrants and natives in the labour market (see Goldin 1994; Gonzalez & Kamdar 2000;Scheve & Slaughter 2001; Fetzer 2006; Mayda 2006; Facchini & Mayda 2008; Facchini & Steinhardt 2011; Conconi et al. 2020). I add to this literature through emphasizing the role played by key tasks performed within occupations and their role in shaping the substitutability between natives and immigrants and consequently voting on immigration legislation.

Second, it adds to an emerging literature focussing on how economic shocks affect support for nativist and protectionist political parties and policies. While most attention here has been on the political consequences of rising Chinese trade exposure in the US and Europe (see e.g. Feigenbaum & Hall 2015; Che et al. 2016; Colantone & Stanig 2017; Colantone & Stanig 2019; Autor et al. 2020), some recent studies have started to look at the impact of technological change. Frey et al. (2018) find that areas affected by the implementation of more industrial robots were more likely to vote for Donald Trump in the 2016 US Presidential Election. Gallego et al. (2018) find that in the UK individuals in industries that introduced more information and communications technology are more likely to support the UK Independence Party. However, they also highlight that the winners from automation were more likely to support mainstream parties. This chapter contributes to this literature in two ways: First, it focusses on the effect of technological change on policy outcomes rather than individual attitudes ot support for parties.[7] This

[6] Autor et al. (2013*b*) note that exposure to automation and Chinese import competition are largely uncorrelated and affect different local labour markets. Further, automation mainly led to a rise in low-skill services at the bottom end of the skill distribution (see e.g. Autor & Dorn 2013), which appear largely non-tradable and should not be exposed to foreign competition.

[7] Many bills were highly contested and decided by as little as 5 votes out of 429. So while my outcome is the voting behaviour of a congressional district's representative the estimated effect size for manual-biased technological change suggests this played an important role for overall outcomes in many cases.

seems important as an increase in support for extremist parties might not necessarily translate into changes in policy if these parties remain at the fringes. Second, I highlight that the effect of recent technological change increased support for restricting low-skill immigration, but did not have a corresponding effect on support for trade liberalization. This seems in line with automation having increased employment in occupations exposed to low-skill immigration, but unaffected by foreign competition.[8]

The remainder of this chapter is organized as follows. Section 3.2 presents a theoretical framework. Section 3.3 describes the data and Section 3.4 outlines the empirical strategy and presents my main results. Section 3.5 evaluates the sensitivity of the key results and presents additional findings. Finally, Section 3.6 concludes the chapter.

3.2 Theoretical Framework

This section aims at providing a theoretical framework to illustrate how employment polarization caused by technological change (see e.g. Autor et al. 2003 and Autor & Dorn 2013) can lead to a change in immigration policy. To do this, I set up a partial-equilibrium model with constant elasticity of substitution of factor inputs (manual, routine, abstract) in the production process, individuals choosing their level of education and policy-makers deciding on the supply of immigrants based on their constituents' preferences.

3.2.1 Production

Consider $d = 1, ..., D$ economies, each representing one US congressional district (with D representing all congressional districts). Each of these economies is characterized by a representative firm. Representative firms vary by their routine task automating technology ($Z_{d,t}$) and fixed production technology (α_d, β_d). I assume $Z_{d,t}$ to vary across (i) time, characterizing general advances in the automation of routine tasks, and (ii) districts, reflecting that there is some idiosyncratic variation across representative firms in the possibility to automate routine task (e.g. differences across industries). Further, the differences in α_d and β_d create local comparative advantages, which leads to fixed differences across districts in occupational specialisation across manual, routine and abstract intensive tasks. Firms combine labour inputs A, R and M in a constant elasticity of substitution production function to produce a final good Y:

$$Y = \left(\alpha_d M^{\frac{\theta-1}{\theta}} + \beta_d (Z_{d,t}R)^{\frac{\theta-1}{\theta}} + (1 - \alpha_d - \beta_d) A^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \tag{3.1}$$

[8] That automation increased employment mainly in non-tradable sectors, rather than traded ones, might also have been crucial for the observed effect on policy outcomes as recent evidence by Burstein et al. (2020) suggests that local labour market competition between natives and immigrants is much larger in the former set of occupations than the later.

The parameter θ measures the elasticity of substitution (being complements, i.e. $\theta < 1$) between the three inputs. A is the amount of abstract tasks performed. R is the amount of routine tasks. M is the amount of manual tasks performed. A, R, M are all supplied by the labour force while $Z_{d,t}$ reflects the tasks performed by automation technology.[9] Given $Z_{d,t}$ at time t each firm solves the following problem to maximise output:

$$\max_{M,R,A} Y - w_M M - w_R R - w_A A \tag{3.2}$$

Under the assumption that markets are perfectly competitive, the return on factor inputs will be at equilibrium equal to their marginal productivities. Consequently, combining the first order conditions of the optimal choice problem of the different labour inputs gives the manual($\hat{w}_M$) and abstract ($\hat{w}_A$) task wage premiums:

$$\hat{w}_M = \frac{w_M}{w_R} = \frac{\alpha_d}{\beta_d}\left(\frac{R}{M}\right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-\theta}{\theta}} \tag{3.3}$$

$$\hat{w}_A = \frac{w_A}{w_R} = \frac{1-\alpha_d-\beta_d}{\beta_d}\left(\frac{R}{A}\right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-\theta}{\theta}} \tag{3.4}$$

The manual and abstract task wage premiums are increasing in $Z_{d,t}$ leading to the polarization of wages due to technology being complementary to manual and abstract inputs in the production process, while substituting for routine ones. This affects the employment decision of individuals and leads to employment polarization.

3.2.2 Individuals' occupation choice

Each congressional district is populated by a set of native individuals. Individuals i have ability levels $\mu_i \geq 1$, distributed $F(\mu_i)$. Given $Z_{d,t}$ at time t individuals face the following occupation choices: (i) they can either work in manual occupations, (ii) obtain some education equivalent to a high-school degree/vocational training required for routine occupations, or (iii) obtain a college-degree to work in abstract occupations. Education costs are proportional to consumption, decreasing in μ_i and increasing in the complexity of the occupation. When an individual decides to obtain the level of education which is required for a routine occupation, the individual's consumption is adjusted by the learning cost $g_R(\mu_i) \in (0,1)$. Further, an individual can decide to obtain the level of education required for an abstract occupation with the additional learning cost being $g_A(\mu_i) \in$

[9]Classical skill-biased technological change could be characterized by $Z_{d,t}$ augmenting M instead of R. In this case it is analogous to show that policy-makers become more favourable towards low-skill immigration policy due to the decline in the manual employment share as technology is substituting instead of complementing manual labour inputs.

(0, 1). For both types of education $T \in (R, A)$ the cost is decreasing in ability $g'_T(\mu_i) > 0$. Consequently, consumption of individuals performing manual tasks is $c_M = w_M$; individuals performing routine tasks consume $c_{i,R} = g_R(\mu_i)w_R$ and individuals performing abstract tasks consume $c_{i,A} = g_R(\mu_i)g_A(\mu_i)w_A$. Given the learning costs, equilibrium wages for manual, routine and abstract occupations are ordered accordingly $w_A > w_R > w_M$. The education decision of individuals follows the respective cut-off conditions:

$$g_R(\mu_R^*) = \hat{w}_M = \frac{w_M}{w_R} \tag{3.5}$$

$$g_A(\mu_A^*) = \frac{1}{\hat{w}_A} = \frac{w_R}{w_A} \tag{3.6}$$

Consequently, individuals take up the following occupations depending on their ability; (i) manual if $\mu_i \in (1, \mu_R^*)$, (ii) routine if $\mu_i \in (\mu_R^*, \mu_A^*)$ and (iii) abstract if $\mu_i \in (\mu_A^*, \infty)$. The total supply of abstract, routine and manual tasks by natives in the economy in district d at point t is:

$$\begin{aligned} A &= \int_{\mu_A^*}^{\infty} f(\mu_i)di \\ R &= \int_{\mu_R^*}^{\mu_A^*} f(\mu_i)di \\ M_N &= \int_{1}^{\mu_R^*} f(\mu_i)di \end{aligned} \tag{3.7}$$

The subscript N denotes the aggregated manual tasks supplied by natives as through immigration the overall supply of manual tasks can be increases. Tasks supplied by foreigners are denoted with subscript F, i.e. $M = M_N + W_D M_F$. W_D is the nationwide low-skill immigration policy either allowing low-skill immigration ($W_D = 1$) or restricting it ($W_D = 0$). $Z_{d,t}$ is the only factor in the model changing exogenously across t which leads to a reallocation of labour across sectors between periods t and $t+1$ in a congressional district. Formally, thresholds μ_R^* and μ_A^* change with regards to technology in the following way:[10]

$$\frac{\partial \mu_R^*}{\partial Z_{d,t}} = g_R^{-1}\left(\frac{(1-\theta)\alpha_d}{\theta\beta_d}\left(\frac{R}{M}\right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-2\theta}{\theta}}\right) > 0 \tag{3.8}$$

[10]Analogously to Basso et al. (2017) a higher amount of low-skill immigrants M_F, through changing wages, affects the education decision leading to less natives in manual occupations. Notably, the expectation about the number of immigrants does in general not change when a policy change of the local representative occurs. This only occurs (for all districts) if the pivotal representative is expected to change his vote. In turn, this will lead to an additional reallocation of locals across tasks. In this case, the reallocation effect of technology from routine towards manual tasks is even stronger (due to $\frac{\partial M}{\partial Z_{d,t}} < 0$).

$$\frac{\partial \mu_A^*}{\partial Z_{d,t}} = g_A^{-1}\left(\frac{(\theta-1)\beta_d}{\theta(1-\alpha_d-\beta_d)}\left(\frac{A}{R}\right)^{\frac{1}{\theta}} Z_{d,t}^{-\frac{1}{\theta}}\right) < 0 \tag{3.9}$$

This highlights that when technology increases, a higher share of individuals decide to work in manual and abstract occupations compared to routine occupations. This is because the marginal return of routine tasks compared to manual tasks decreases, while the marginal return of abstract tasks compared to routine tasks increases.

3.2.3 Immigration policy

Due to the concentration of immigrants at the extremes of the US skill distribution, low-skilled immigrants in the model are assumed to work in manual occupations.[11] For this reason a change in low-skill immigration policy W_D is equivalent to an increase or decrease in the supply of aggregate manual tasks. In each period t the politician votes on setting low-skill immigration policy W_D.[12] Accordingly, an increase in a factor of production decreases the wage paid for the factor itself while increasing the wage of the other factors of production:

$$\frac{\partial w_M}{\partial M_F} = -\frac{w_M(w_R R + w_A A)}{\theta M Y} < 0 \tag{3.10}$$

$$\frac{\partial w_R}{\partial M_F} = \frac{w_R w_M}{\theta Y} > 0 \tag{3.11}$$

$$\frac{\partial w_A}{\partial M_F} = \frac{w_A w_M}{\theta Y} > 0 \tag{3.12}$$

This highlights that individuals working in routine and abstract task intensive occupations gain from low-skill immigration while individuals working in occupations intensive in manual tasks lose out from low-skill immigration. I assume the vote of a politician on low-skill immigration policy W_d is based on a median-voter equilibrium as described by

[11] The fact that low-skill immigrants supply manual tasks more intensively than natives, as shown in Figure 3.1, has also been highlighted by Basso et al. (2017).

[12] I model this as a binary choice for representatives between having immigration or not to reflect that when voting on a final bill in the house of representatives they are only able to vote "yes" or "no", but cannot vote for their preferred level of immigration. This binary setup also corresponds to the outcome variable of interest in the empirical analysis.

Downs (1957). Accordingly, the politician will focus on the effect immigration has on the median voter, characterized by the ability level $\bar{\mu}$:[13]

$$W_d = \begin{cases} W_d = 0 & if \quad \bar{\mu} \in (1, \mu_R^*) \\ W_d = 1 & if \quad \bar{\mu} \in (\mu_R^*, \mu_A^*) \\ W_d = 1 & if \quad \bar{\mu} \in (\mu_A^*, \infty) \end{cases} \tag{3.14}$$

Finally, all the votes are summed up setting the new national immigration policy:

$$W_D = \begin{cases} W_D = 0 & if \quad \frac{\sum W_d}{D} < \frac{1}{2} \\ W_D = 1 & if \quad \frac{\sum W_d}{D} > \frac{1}{2} \end{cases} \tag{3.15}$$

The key element for the decision of the representative to be in favour of restricting low-skill immigration is the size of the manual share of natives in a congressional district, which depends on two underlying factors; (i) the fixed local comparative advantage and (ii) technological change complementary to manual tasks. Accordingly, the spatial equilibrium of the model provides two main empirical implications that I will test in Section 3.4:

1. Higher α_d: Representatives of districts that have a fixed comparative advantage in manual task intensive production, and for this reason a higher share of natives in manual occupations, will be more likely to vote in favour of restricting low-skilled immigration.

2. Increase in $Z_{d,t}$: Manual-biased technological change, through increasing the wage premium for manual tasks, will make it more likely that a representative will vote in favour of restricting low-skilled immigration.

Two elements omitted from the model deserve some additional consideration. First, the assumption that natives are not mobile across regions. Allowing for internal migration in my set-up would lead to similar results as regions being more strongly affected by technological change would attract more abstract and manual task intensive individuals, while areas with lower levels of technological progress would observe an out-migration of those groups. This would not change the association between technology and the voting behaviour. However, if only high-skilled labour is mobile at the local level, it might be observed that, in areas with high rates of technological change, the manual employment

[13] One can simply extend this to allow for an orthogonal dimension of immigration that influences a representatives decision that varies across congressional districts d. For example, $p_d \in [0,1]$ is the share of individuals prioritizing other factors over economic gains and $c_d \in [0,1]$ is the share of individuals being in favour of restricting immigration based on these other reasons in d. Accordingly, the representative votes on low-skill immigration based on his constituency's preferences in the following way:

$$W_d = \begin{cases} W_d = 0 & if \quad p_d c_d + (1-p_d)\frac{M_N}{M_N+R+A} > \frac{1}{2} \\ W_d = 1 & if \quad p_d c_d + (1-p_d)\frac{M_N}{M_N+R+A} < \frac{1}{2} \end{cases} \tag{3.13}$$

share is decreasing. This would lead to a local representative in a district subject to high level of technological progress becoming more favourable towards liberalizing low-skill immigration policy. The nationwide effect between technology and voting behaviour would remain the same, while local measurement would be biased against my hypothesis. However, labour mobility mitigating local economic shocks is also faced by other papers (e.g. the local differences in exposure to Chinese trade Autor et al. 2013*a*), where there is little evidence of adjustment through internal migration of low-skilled workers.

Second, I assume immigrants are split equally across areas. However, it appears that immigrants move to districts more strongly affected by increased technological change in ICT (see Basso et al. 2017). This might slow natives' reallocation from routine to manual occupations. Accordingly, it is crucial to observe the share of manual occupations in native rather than in total employment to correctly observe attitudes towards low-skill immigration induced by natives' competition with them. In addition, local wages for different occupations are not fully representative of the effect of technological change. I circumvent this issue in the empirical part of this chapter by exploiting the quasi-fixed local industry mix and the industry specific technological change at the national level over time.

3.3 Data

I use US house of representatives roll call data from Poole & Rosenthal (2000) to obtain information on the voting behaviour of legislators for 17 bills focussing on immigration policy between 1973 and 2014, updating the list of immigration bills identified by Facchini & Steinhardt (2011). Following their methodology, I use bills that focus on legal and illegal immigration, which are most directly linked to the inflow of foreign labour. Furthermore, I restrict the analysis to the final passage vote of bills to reduce the amount of strategic voting in the data and obtain a better reflection of the underlying interests of the legislator's constituency. A full list of bills is presented in Table C.1 of the Appendix. I code these bills into primarily focussing on low-skill immigration or high-skill immigration legislation and bills being in favour or against increasing the number of immigrants. I exclude bills coded as relating to high-skill immigration from the main analysis as they, in contrast to low-skill immigration bills, should be unaffected by manual-biased technological change as it does not impact natives' competition with high-skill immigrants.

I combine the voting data with individual level economic information matched to congressional districts from the Census Integrated Public Use Micro Samples [IPUMS-USA; Ruggles et al. 2019].[14] The most rigorous way of testing the hypothesis that manual-

[14]IPUMS data is available at the following geographic areas: State Economic Areas in 1950 (not including Alaska and Hawaii); County Groups in 1970 and 1980; Public Use Microdata Areas in 1990, 2000 and 2010. The national random sample covers 1% of the population in 1950 and 2010, 2% of the

biased technological change influences policy-makers to tighten immigration policy would be by identifying when the introduction of new technologies leads to the median voter changing his occupation from routine or abstract employment to manual employment. Unfortunately, technological change $Z_{d,t}$ and the median voter identified by ability μ_i are unobservable. But as data on individual wages and occupations and their respective task intensity is available, it is possible to construct measures of the overall task intensity as well as changes in the wage premium for a certain task across congressional districts. I combine the IPUMS data on individuals' occupations with information on manual, routine and abstract task intensity of occupations in 1980 from Autor & Dorn (2013) denoted $T_{i,80} = \{M|R|A\}$.[15] However, occupations vary in their overall task content. For this reason, I estimate the share of an occupation's wage that is paid for the manual tasks performed to obtain a measure of relative task intensity. I first use a hedonic regression on the hourly wage to price the manual, routine and abstract tasks in 1980, with the estimated wage rate of a respective task denoted $\hat{w}_{T,80}$.[16] After this I divide the estimated wage paid for manual tasks performed by the total estimated wage paid for all tasks. Accordingly, the manual wage share for individual i is:

$$MW_{i,80} = \frac{\hat{w}_{M,80} M_{i,80}}{\sum\limits_{T=\{M,R,A\}} \hat{w}_{T,80} T_{i,80}} \tag{3.16}$$

with $MW_{i,80}$ being constant across individuals and time for each occupation. I use the estimated wage share related to manual tasks $MW_{i,80}$ in an occupation as the measure of relative manual task intensity, ordering all occupations along their relative task intensities. Appendix Table C.2 provides information on the top-10 manual, routine and abstract intensive occupations by employment in 1980. Following this, I construct the manual employment share across congressional district and years based on the share of individuals

population in 1970, and 5% of the population in 1980, 1990 and 2000. The variables relying on the use of individual level data, i.e. the main explanatory variables requiring individual level data, are constructed based on US citizens by birth or individuals that have been naturalized and are over the age of 18. Individuals living in prisons and psychiatric institutions are excluded. See Figure C.3 in the Appendix for more details on the conversion of data across geographical areas. For economic and non-economic variables used as controls I use data from Manson et al. (2019) available at the congressional district level. Variables at the congressional district level from Manson et al. (2019) and corresponding ones constructed from Ruggles et al. (2019) individual records are highly correlated and results are similar when using data from Ruggles et al. (2019) to construct controls.

[15] Appendix C provides additional information on the different tasks.

[16] Hourly wages are constructed from the available data for wage income, hours worked and weeks worked. I account for top-coded wages (varying by state and year) by excluding the highest 5% of incomes in each state in each year. In addition I restrict the sample to individuals that reported to having worked close to full-time over the last year and exclude the top and lowest 1% of observations for the hourly wage data in case reported hours (usually for last week) are not representative of weekly hours worked over the whole year.

that hold an occupation that was in the top 33% of manual task intensive occupations at the national level in 1980 (analogous to the threshold used in Autor & Dorn 2013):

$$MSH_{d,t} = \frac{\sum_{i=1}^{I} L_{d,t,i} * 1[MW_{i,80} > MW_{i,80}^{P66}]}{\sum_{i=1}^{I} L_{d,t,i}} \tag{3.17}$$

The considerable variation in the manual employment share across the US in 1980 is illustrated in Figure C.1 in the Appendix.

To investigate whether technological change has influenced the voting behaviour of representatives I need to measure the complementarity/substitutability of technological change with manual tasks. I do this by exploiting changes in the manual wage premium across congressional districts. This is based on the assumption that if technological change is complementary to manual tasks, i.e. increasing demand for them relative to other tasks, this will raise the relative wage paid for manual tasks compared to other tasks.

A key obstacle is that local supply shocks in manual tasks, for example through immigration, led to a change in the manual wage premium that is not related to demand changes due to manual-biased technological change. Accordingly, for changes in the manual wage premium to be a measure of factor-biased technological change my measure needs to reflect changes in demand for manual tasks due to technological change but be unaffected by local supply shocks. For this, I exploit the fact that the possibility of implementing new technologies varies by industries and that this is determined at the national level. Accordingly, I construct the following Bartik-type variable ($MP_{d,t}$) that measures the local manual-biased technological change experienced by a congressional district through combining industry-level changes in the manual wage premium at the national level since 1950 with the pre-existing distribution of industries across areas:

$$MP_{d,t} = \sum_{j=1}^{J} EmpSH_{j,d,1950} \times \Delta\left(\frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}}\right) \tag{3.18}$$

$EmpSH_{j,d,1950}$ describes the employment share of industry $j \in j, ..., J$ in 1950 for a congressional district. I interact this with the industry manual wage premium, which I construct by dividing the median hourly wage in the US among native workers in industry j working in manual occupations ($\bar{w}_{M,j,t}$) by the median wage of industry j ($\bar{w}_{j,t}$) in decade t.[17] A potential source of variations in the manual wage premium between industries—not related to technological change—are time-fixed industry characteristics. To account for

[17] I consider the overall median wage in the industry rather than the median routine wage to avoid capturing compositional changes to routine employment. Otherwise a demand driven change in employment from high-paying routine to abstract occupations would lead to an increase in the manual wage premium $MP_{d,t}$ that is only driven by changes at the upper end of the skill distribution.

this unobserved heterogeneity I subtract the industry specific manual wage premium in the initial year 1950 from the observed manual wage premium in decade t: $\Delta\left(\frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}}\right) = \frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}} - \frac{\bar{w}_{M,j,1950}}{\bar{w}_{j,1950}}$. This Bartik-type variable is a logical proxy for the varying degree of substitutability/complementarity of technological change with manual employment across districts assuming that intra-industry wage changes reflect changes in demand for certain tasks and are driven by the adoption of new technologies (see Katz & Murphy 1992; Krueger 1993). Crucially, focussing on the intra-industry change in the wage premium is not related to overall changes in demand or foreign competition faced by an industry, but only reflects relative changes in the demand for manual tasks compared to other tasks within an industry's production function.

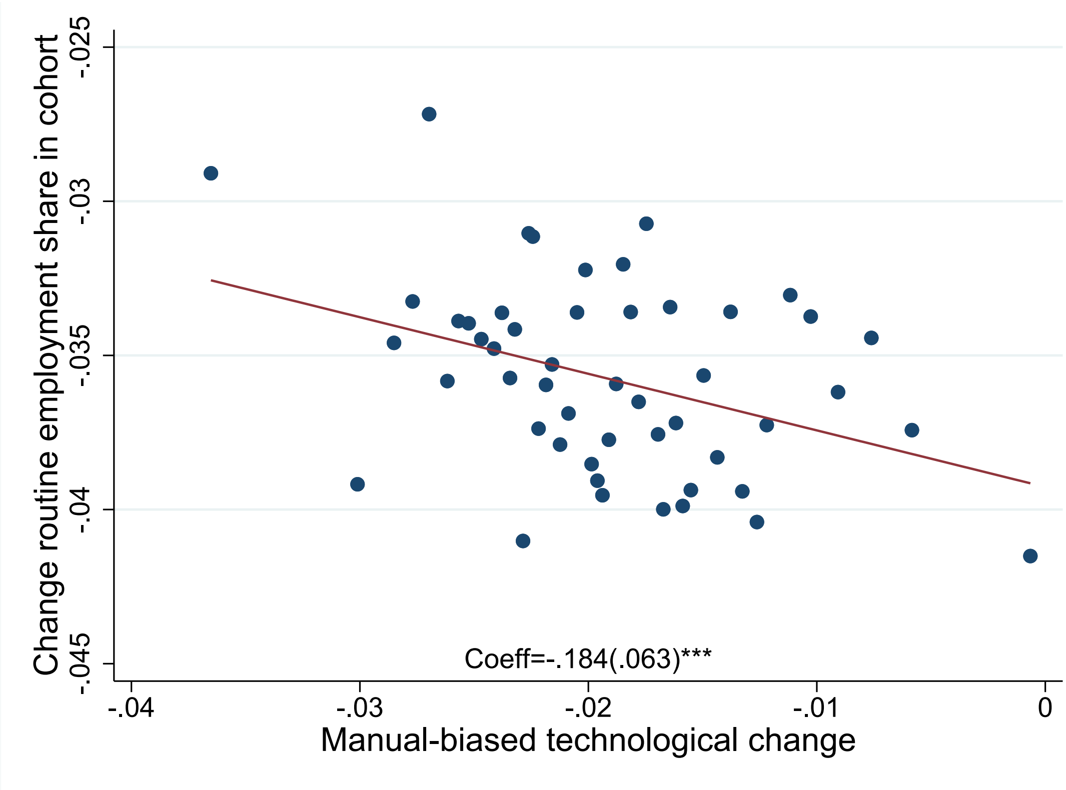
It should be highlighted that while the outlined measure is not affected by changes in the trade in goods at the industry level, recent advances in transportation and communications technology have made it increasingly possible to separate tasks in time and space within a production process (see e.g. Feenstra & Hanson 1999; Grossman & Rossi-Hansberg 2008). This "offshoring" of tasks within the production process certainly could affect the relative price of manual compared to other tasks within an industry at the national level and will accordingly be captured in my measure of manual-biased technological change. Importantly, this is in line with the aim of the measure to capture any type of technological change biased towards manual tasks compared to other tasks. Here, it is however important to point out that while offshoring had some important effects on US labour markets, the results in Autor & Dorn (2013) suggest that offshorability did not play a role in the growth in demand for manual tasks at the bottom end of the skill distribution. So, while feasible, it does not appear to be the case that manual tasks are offshored at any different rate than routine and abstract tasks.

Accordingly, congressional districts in which technological change was more biased towards manual task, e.g. due to automation, should observe a greater decline in routine employment. Figure 3.5 underlines this, it illustrates that in congressional districts that experienced more manual-biased technological change, more individuals leave routine employment.[18] Automation, of course, while likely the most important type of technological change in the period of interest, is not the only form of technological change. The adoption of skill-biased technologies might still have been more important than automation in certain industries potentially leading to a transition from manual towards routine or ab-

[18]The individual census records are repeated cross-sections and do not report specific individuals over time. For this reason, I cannot observe individual's employment transition directly. Instead I focus on the change in routine employment of cohorts over the previous 10 years. That is the change in the share of routine employment for individuals aged 35-55 in t compared to the same cohort when they were aged 25-45 in t-10 in congressional districts. In this case it seems unlikely that these individuals change from routine to abstract employment as their obtained occupation is fixed so that they can only change to occupations that require less or equivalent qualifications, i.e. reflecting a transition from routine to manual employment. Focussing on cohorts also circumvents the issues that the observed change in routine employment might be due to individuals that have not entered the labour market in t-10 changing educational choices or migrating as well as that older individuals might change their retirement decisions.

stract employment (e.g. in manufacturing industries, see Beaudry & Green 2005; Beaudry et al. 2010; Lewis 2011). Also, skill-biased technologies were likely more important than automation technologies for overall technological change till the 1980s (see Figure 3.3). Importantly, the impact of different types of technologies is consistently accounted for by my measure of manual-biased technological change as it simply captures how any type of technological change affected the relative demand for manual tasks compared to other tasks.

Figure 3.5: Manual-biased technological change and automation



Notes: The figure displays the relationship between manual-biased technological change and automation as measured by the decline in the routine task share within a cohort (age 35-55 in t and 25-45 in t-10). The observation are for congressional districts and census years 1970, 1980, 1990, 2000 and 2010. State and year differences accounted for. N=2142 in 50 bins.

Table C.3 in the Appendix provides an idea of what drives the variation in the manual wage premium showing the 5 industries with the highest employment share in 1950 as well as depicting the 5 industries with the highest and lowest increase in the manual wage premium between 1950 and 2010. It appears that industries in the retail, personal services and accounting sectors have seen the highest relative rise in manual wages, while industries in the manufacturing, business and professional services sectors have experienced the strongest decline in the manual wage premium.[19] The increase in the manual wage premium for the respective industries appears to be in line with the high share of

[19]Interestingly, Autor & Dorn (2013) make the puzzling observation that there is no wage decline for routine-intensive retail and clerical occupations overall, however when looking at wage changes inside the

routine-intensive clerical and retail occupations. While the strong decline of the manual wage premium in manufacturing industries seems to be in line with studies suggesting that manual task replacing technological change still dominates there (see e.g. Beaudry & Green 2005; Beaudry et al. 2010; Lewis 2011). This also suggests that the manual wage premium indeed provides a good proxy for measuring manual-biased technological change across congressional districts. Appendix Table C.4 presents the data sources for the remaining variables used as controls in the empirical analysis. Appendix Table C.5 presents summary statistics.

3.4 Empirical Analysis

3.4.1 Tasks and voting on immigration

The first thing I evaluate is whether differences in the manual employment share influence representatives voting behaviour on low-skill immigration policy. For this I estimate the following Probit equations:

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\alpha MSH_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

where $Vote_{d,t} = 1$ is a dichotomous variable taking a value of one if the representative of district d votes for a bill liberalizing unskilled immigration at time t, $\Phi(.)$ represents the cumulative distribution function of a standard normal, $MSH_{d,t}$ is the manual employment share. Accordingly, I move from the commonly used theoretical framework of the median voter model to estimating more standard marginal effects reflecting the complexity the representative faces in actually observing the median voter and having to vote on a large bundle of different bills, not just immigration policy, that the median voter cares about. $X'_{d,t}$ is a vector of controls including congressional district and representative characteristics. Finally, γ_s and γ_t denote state and vote fixed effects, respectively.[20] To simplify interpretation the estimation tables report marginal effects (at means) which represent the change in probability of a representative voting in favour of liberalizing low-skill immigration due to a change in the independent variable. Table 3.1 presents the Probit

related industries a strong rise in the manual wage premium is observable in line with the high routine task content in these sectors. This appears to suggest that the relatively stable wages for retail and clerical occupations might be explained by industry specific factors (e.g. little exposure to foreign competition) and that wage growth would have been even higher without automation in these occupations.

[20] The state level is the smallest geographical unit that remains consistent in its borders across the whole time period as the borders of congressional districts are redrawn up to every 10 years. Also, as I'm interested in the quasi-fixed differences in manual intensity across congressional districts in this section even if possible congressional district fixed effect would be problematic as they would account for all of the important variation between congressional districts. If controlling for them my estimation would instead only capture the remaining changes in manual employment over time due to demand (technology) and supply (migration) factors.

estimates for the measure capturing the manual employment share of a representative's congressional district on voting outcomes.

Table 3.1: Effect manual task share on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)						
	(1)	(2)	(3)	(4)	(5)	(6)
Manual share	-0.223	-3.435***	-2.287***	-1.107**	-1.332***	-1.356***
	(0.166)	(0.433)	(0.426)	(0.443)	(0.443)	(0.440)
	[0.258]	[0.433]	[0.372]	[0.399]	[0.397]	[0.397]
log(family income)		-0.317*	-0.0550	-0.0584	0.0387	0.0538
		(0.175)	(0.164)	(0.155)	(0.145)	(0.148)
Poverty		3.465***	2.074***	0.587	0.499	0.513
		(0.498)	(0.426)	(0.470)	(0.452)	(0.448)
Republican			-0.551***	-0.497***	-0.494***	-0.493***
			(0.0256)	(0.0253)	(0.0255)	(0.0254)
Foreign-born				0.848***	0.880***	0.858***
				(0.265)	(0.264)	(0.270)
Hispanic				0.516***	0.349**	0.374**
				(0.169)	(0.160)	(0.174)
African-American				0.725***	0.568***	0.578***
				(0.117)	(0.123)	(0.126)
Unemployment rate					2.645***	2.672***
					(0.791)	(0.792)
Age 65+						0.220
						(0.396)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5755	5755	5755	5755	5755	5755
Pseudo R^2	0.167	0.258	0.412	0.437	0.439	0.439

Notes: The table presents the effect of the manual employment share on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The table reports marginal effects at means of probit regressions. Panel A of Table C.6 in the Appendix presents the corresponding OLS results. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 1 in Table 3.1 shows that the effect of the manual employment share has the expected negative sign, however the effect is insignificant. A potential issue here is that manual employment is correlated with lower incomes. Notably, an abundant literature has highlighted the role of the welfare state channel as influencing individual and legislator attitudes on immigration policy (Hanson et al. 2007; Dustmann & Preston 2007; Facchini & Mayda 2009). Accordingly, legislators from wealthier constituencies are expected to exhibit less favourable attitudes towards low-skill immigrants as their constituencies carry the main fiscal burden of immigration. Consequently in column 2 I account for this confounding effect of the welfare state channel through controlling for average incomes and poverty share. Indeed, the coefficient suggests that representatives of richer areas are more averse to immigration. When disentangling the income effect and the subsequent higher fiscal cost of migration through redistribution from the competition of natives and migrants in manual tasks, I find that the estimated effect of the manual employment share increases considerably in magnitude and is now highly significant. A second concern is that representatives' party affiliation shapes voting on immigration policy (see Gimpel & Edwards 1999). Column 3 controls for Republican representatives showing they are indeed more averse to increasing immigration. A third concern is that previous rounds of migration affect the manual employment share as well as representatives' support for liberalizing immigration policy (Gimpel & Edwards 1999; Fetzer 2006). Column 4 shows that, in line with previous studies, the share of Hispanics and African-Americans has a positive effect on voting in favour of low-skill immigration. Note, also that when controlling for race and origin the importance of the welfare channel disappears. A fourth concern is that tighter labour markets might affect manual employment as well as support for liberalizing immigration policy. Accordingly, column 5 controls for the unemployment rate. I find that there is a positive relationship between the unemployment rate and support for liberalizing immigration policy. While counter-intuitive a positive correlation between a congressional district's unemployment rate and voting behaviour has been previously observed in the empirical literature (Gimpel & Edwards 1999; Facchini & Steinhardt 2011). This positive effect appears driven by the 1970s and 80s, while in later periods the effect turns negative (see also footnote 23). Accordingly, one explanation for the positive association between unemployment and pro-immigration voting of representatives might be the strong role of labour unions at the time, which were traditionally anti-immigration and might have also been associated with higher unemployment rates (see e.g. Gimpel & Edwards 1999). Most importantly, the effect of the manual employment share is nearly unaffected when controlling for the unemployment rate. A final concern is that an ageing population requires more manual employment in care services, often provided by immigrants, but age also shapes attitudes towards immigration (Espenshade & Hempstead 1996; Chandler & Tsai 2001; Haubert & Fussell 2006). Column 6 controls for the share of the population over 65 years, however this appears to be of little importance. A sizeable negative and significant relationship is observable in columns 2-6 between the size of the manual employment share and representatives support for liberalizing immigration policy. The benchmark specification (column 6) suggests that a one percentage point higher manual employment share is associated with the representative being 1.36 percent less likely to vote in favour of liberalizing low-skill immigration policy.

Table 3.1 so far explored the relationship between the manual employment share in a congressional district at the start of the period and subsequent voting decisions of congressmen on low-skill immigration bills in the following decade. Variation in the manual employment share can be attributed to; (i) fixed differences in the production structure, (ii) demand and (iii) supply shocks. To illustrate this, consider the observed manual employment share at point t as fixed differences in the production structure MSH_d^* and idiosyncratic shocks $v_{d,t}$:

$$MSH_{d,t} = MSH_d^* + v_{d,t}$$

Changes to the manual employment share due to unobserved factors $v_{d,t}$ are not necessarily a problem for identification as long as they are affecting a representatives vote on low-skill immigration purely through changing the competition between natives and migrants. However, certain idiosyncratic shocks $v_{d,t}$ might affect a representatives' voting behaviour not just through changing manual employment, but also through another channel. For example, a short-run boom in demand for a congressional district's routine-task intensive manufacturing outputs might lead to a reallocation of low-skilled workers from manual to routine occupations. However, this will likely also locally reduce financial anxiety more generally, which has a direct effect on individual attitudes towards immigration (see Goldstein & Peters 2014). This would lead to an upward biased OLS estimate on the effect of the manual employment share on representatives' voting on immigration policy. A corresponding demand shock for manual task intensive products (e.g. agricultural products) would have the reverse effect and lead to a downward biased OLS estimate. In addition, even short-run idiosyncratic shocks $v_{d,t}$ that are not directly affecting voting outcomes create the issue of introducing considerable measurement error at the time the vote on immigration policy actually occurs leading to regression dilution. I deal with the outlined concerns by following the approach of Autor & Dorn (2013) to construct a long-run, quasi-fixed measure of employment, but for manual rather than routine employment.

To do this I use the historical differences in industries across areas in 1950 combined with the nationwide manual employment share for industries in 1950:

$$\overline{MSH}_{d,1950} = \sum_{j=1}^{J} EmpSH_{j,d,1950} \times MSH_{j,-d,1950}$$

$MSH_{j,-d,1950}$ describes the manual employment share in a given industry in the whole of the US excluding area d and $EmpSH_{j,d,1950}$ is the local employment share of industry j in 1950. Accordingly, $\overline{MSH}_{d,1950}$ provides me with a predicted value of the long run, quasi-fixed manual employment share for each congressional district MSH_d^* unaffected by any local shocks $v_{d,t}$. I interact $\overline{MSH}_{d,1950}$ with decade dummies D_t giving the following first-stage equations:

$$\widehat{MSH}_{d,t} = \sum_{t=Decade} \phi_t * \overline{MSH}_{d,1950} * D_t + X'_{d,t}\beta + \gamma_s + \gamma_t + \varepsilon_{d,t}$$

Table 3.2 presents the corresponding IV-Probit results. The first-stage, presented at the bottom of the table, shows that the used instruments are highly predictive of the observed manual employment share. Also observable is that the magnitude of the predictive relationship decreases over time as initial conditions become less important. The IV-estimates for the effect of the manual employment share on the voting behaviour of representatives increase in magnitude compared to the OLS-estimates and are now similar in size across all specifications presented in Table 3.2.

The IV-Probit marginal effect in column 6 of Table 3.2 is -3.37, which suggests that a one percentage point increase in the manual employment share, from the average of 31% to 32%, makes it 3.37 percent more likely that a representative of a congressional district votes in favour of restricting low-skilled immigration. This suggests that even though far less than half of voters are in competition with low skill immigrants, an increase in share of natives in manual employment still influences a representative's voting behaviour. Indeed, the marginal effect of the manual employment share on representative's voting behaviour is largest at 29% with an effect of -3.46. One might interpret this as the pivotal median voter that has a decisive influence on a representatives voting decision on low-skill immigration policy being most frequently located towards the bottom-end of the skill distribution rather than at the middle as one might a priori expect.

3.4.2 The effect of technological change

So far, my estimates highlighted the relationship between relatively fixed differences in the competition of natives and low-skill immigrants across congressional districts in the labour market and the effect it has on the voting behaviour on immigration policy of representatives. We now turn to the second question: did recent technological change lead to changes in the voting behaviour of representatives.

First, I ask whether manual-biased technological change made representatives more likely to vote in favour of restricting immigration policy. To analyse this, I estimate Probit specifications of the following form:

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\gamma MP_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

where γ measures the effect of manual-biased technological change $MP_{d,t}$ on the voting outcome $Vote_{d,t}$ of a representative from congressional district d at time t. As described in Section 3.3, $MP_{d,t}$ proxies for manual-biased technological change by capturing the demand driven variation in the manual wage premium that occurred since 1950 across congressional districts d and decades t.

Second, I examine whether manual-biased technological change, in the form of automation, through causing declining routine employment led to representatives voting in

Table 3.2: IV-effect manual task share on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)						
	(1)	(2)	(3)	(4)	(5)	(6)
Manual share	-2.697***	-3.883***	-3.591***	-2.199**	-3.313***	-3.368***
	(0.368)	(0.385)	(0.490)	(0.859)	(0.965)	(1.000)
	[0.537]	[0.427]	[0.473]	[0.841]	[0.939]	[0.971]
Controls	See controls included in Table 3.1					
F-stat (1st stage)	296.6	135.1	131.3	115.1	125.0	123.6
Endogeneity test	0.000	0.000	0.001	0.064	0.005	0.005
Observations	5719	5719	5719	5719	5719	5719
First-Stage:						
Manual share 1950*D_{1970}	1.009***	0.760***	0.727***	0.637***	0.648***	0.649***
	(0.045)	(0.042)	(0.044)	(0.046)	(0.047)	(0.048)
Manual share 1950*D_{1980}	0.964***	0.647***	0.647***	0.544***	0.505***	0.500***
	(0.033)	(0.031)	(0.031)	(0.025)	(0.022)	(0.022)
Manual share 1950*D_{1990}	0.912***	0.469***	0.462***	0.400***	0.387***	0.384***
	(0.049)	(0.038)	(0.036)	(0.044)	(0.047)	(0.046)
Manual share 1950*D_{2000}	0.762***	0.356***	0.347***	0.249***	0.245***	0.242***
	(0.030)	(0.021)	(0.021)	(0.024)	(0.023)	(0.023)
Manual share 1950*D_{2010}	0.757***	0.357***	0.330***	0.253***	0.242***	0.232***
	(0.038)	(0.037)	(0.040)	(0.041)	(0.041)	(0.042)

Notes: The table presents the effect of the manual employment share on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The estimates are IV-Probit estimates corresponding to column 1-6 of Table 3.1. The estimates report marginal effects at means. Panel B of Table C.6 in the Appendix presents the corresponding 2SLS results. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

favour of restricting low-skill immigration. For this I estimate the following IV Probit specification and first stage:

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\delta \Delta RSH^{Cohort}_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

$$\Delta RSH^{Cohort}_{d,t} = \varphi MP_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t$$

where $\Delta RSH^{Cohort}_{d,t}$ is the change in the share of a cohorts' routine employment over the previous 10 years. Accordingly, it measures the recent change in routine employment for the same group of individuals when aged 35-55 years in t compared to when 25-45 years old in $t-10$. I instrument this change with the observed manual-biased technological change ($MP_{d,t}$) across congressional districts in the first stage. This should illustrate the mechanism through which recent technological change affected representatives voting on immigration policy, i.e. through the automation of routine tasks. However, it should be noted that given the varied nature and effects of technological change, it is not possible to fully rule out that the estimated effects are (partly) driven by other forces than through the transition out of routine occupations. For this reason, I view the effect of the change in cohort routine employment presented here more as suggestive, rather than conclusive evidence on the effect of automation of routine tasks on voting on low-skill immigration policy.

Nevertheless, while it is not possible to rule out every channel, other than the transition out of routine into manual employment, via which manual-biased technological change may effect voting on immigration policy, I present both the IV-Probit and the corresponding reduced form estimates across all specifications. Even if the exclusion restriction did not hold, the reduced form specifications would still identify the effect of manual-biased technological on representative's voting decision under the weaker assumption that manual-biased technological change is uncorrelated with other determinants of the outcome variable of interest. So while the latter cannot narrow the effect down to automation specifically, it provides conclusive evidence on the important role of technological change more broadly for the setting of immigration policy.

Table 3.3 Panel A presents the Probit estimates which analyse the effect of manual-biased technological change on the voting behaviour of representatives. In line with expectations the coefficient for the manual-biased technological change variable is negative. This implies that areas where technological change was more favourable to manual tasks compared to other tasks representatives became more averse to low-skill immigration. The estimated coefficient is similar in size and significance across column 1-6, when including controls for the welfare channel, party affiliation, migration networks, labour market conditions and demographic factors.The baseline specification in column 6 suggests that a one percentage point increase in manual-biased technological change makes it 3.8 percent less likely that a representative votes for liberalizing low-skill immigration. Accordingly, moving a congressional district to experience a standard deviation higher manual-biased technological change (2.1 percentage points) leads the corresponding representative to be 8.0% less likely to be in favour of liberalizing low-skill immigration policy.

Table 3.3 Panel B presents the IV-Probit results looking at the effect of changes in a cohorts routine employment share in the previous period instrumented with manual-biased technological change. The first stage estimate suggests that manual-biased technological change indeed captures the automation of routine tasks that occurred as an increase in it is related to transition out of routine employment. The second stage depicts a positive coefficient for the cohort change in the routine employment share. Accordingly, individuals changing from routine to manual occupations and the corresponding increase in natives competition with low-skill immigrants leads to the local representative becoming more likely to vote in favour of restricting low-skill immigration. This result suggests that the possibility of the automation of routine tasks, corresponding to manual-biased technological change, increased the likelihood of representatives voting in favour of restricting low-skill immigration policy in the US. The estimated effect of a change in a cohorts routine employment share is considerable as the marginal effect suggests that at mean each 1 percentage point decline in routine employment made the representative 10.6% more likely to vote in favour of restricting low-skill immigration. Accordingly, the individuals affected seem pivotal in influencing a policy makers voting behaviour on low-skill immigration policies.

Table 3.3: Effect of technological change on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)	(1)	(2)	(3)	(4)	(5)	(6)
A. Effect manual-biased technological change						
Manual premium	-5.270***	-4.926***	-3.639***	-3.213**	-3.827***	-3.827***
	(1.151)	(1.305)	(1.347)	(1.328)	(1.381)	(1.381)
	[1.737]	[1.663]	[1.433]	[1.402]	[1.433]	[1.433]
Controls	See controls included in Table 3.1					
Observations	5719	5719	5719	5719	5719	5719
Pseudo R-sq	0.171	0.235	0.395	0.424	0.427	0.427
B. Channel: Automation of routine tasks						
Δ Routine task (35-55)	12.95***	10.54***	9.426***	9.035***	9.539***	10.58***
	(0.896)	(1.929)	(2.587)	(2.505)	(2.234)	(2.670)
	[1.371]	[2.449]	[3.006]	[2.951]	[2.711]	[3.229]
First stage (MP)	-0.140***	-0.150***	-0.147***	-0.175***	-0.166***	-0.169***
	(0.042)	(0.043)	(0.043)	(0.042)	(0.041)	(0.041)
F-stat (1st stage)	11.269	12.011	11.647	17.534	16.086	17.332

Notes: Panel A presents the effect of manual-biased technological change on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The table reports marginal effects at means from probit regressions. Panel C of Table C.6 in the Appendix presents the corresponding OLS results. Panel B presents IV-probit estimates were the decline over the last 10 years in routine employment for a cohort (aged 35-55 in period t and 25-45 in $t-1$) is estimated with the manual-biased technological change. This corresponds to automation being a key way in how manual-biased technological change affects the voting behaviour of representatives. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5 Additional Results

This section presents additional results. First, Section 3.5.1 analyses the sensitivity of my measure for manual-biased technological change to variations in its specification. Second, Section 3.5.2 provides a falsification exercise where manual-biased technological change that occurs in the future is regressed on votes on low-skill immigration policy that occurred before. Third, Section 3.5.3 considers additional economic and political factors that might have played a role. Fourth, Section 3.5.4 considers the role of increased competition from China on US immigration policy and the effect of technological change on US trade policy.

3.5.1 Measurement

An important concern is that the estimated effect of manual-biased technological change is sensitive to changes in the definition of the variable. Table 3.4 analyses this by considering alternative ways of constructing the measure for manual-biased technological change. In column 1, I use a narrower definition of manual task intensity, classifying only the top 25% of occupations as manual instead of the top 33%. The coefficient on the measure of manual-biased technological change is nearly identical to my preferred specification (column 6 of Table 3.3). Column 2 presents the result when the definition of manual task intensity is instead widened to 40%. The coefficient decreases sightly in magnitude and becomes borderline insignificant. This seems consequential considering that through extending the definition of manual task intensity the measure is more likely contaminated by occupations falsely classified as being manual task intensive, when indeed they are more intensive in routine or abstract tasks. This leads to an increase in random measurement error in the explanatory variable, which compared to the baseline specification reduces the magnitude of the coefficient. In column 3, I replace the change in the manual wage premium with the change in manual employment across industries as proxy of manual-biased technological change. In contrast to the manual premium, this measure reflects the realized change in manual employment across industries at the national level rather than the change in demand for certain tasks across industries.[21] The estimated effect confirms previous results. The size of the coefficient suggests that a one standard deviation (3.3 percentage points) increase in manual employment since the 1950s leads to a representative being 6.4% less likely to be in favour of liberalizing low-skill immigration policy which is roughly equivalent to the effect measured by the manual wage premium.

3.5.2 Falsification exercise

Another concern is that manual-biased technological change might be a symptom of increasing anti-immigration sentiment rather than a cause. To verify that my results capture the period-specific effect of exposure to manual-biased technological change, and not some long-run common causal factor behind both the representatives support for restricting immigration and increased manual-biased technological change, I conduct a falsification exercise by regressing past voting outcomes on future manual-biased technological change.

For this, I construct measures of manual-biased technological change for congressional districts that will occur over the next 10, 20 and 30 years. Table 3.5 shows the correlation

[21] I prefer manual premium as measure of manual-biased technological change as it compares wages between occupations in the same industry with similar working hours and days, while changes in the employment share in a industry might be more likely subject to the extension of part-time employment at the bottom end of the skill distribution. Indeed, changes in relative wages across tasks should be the driving force behind workers reallocation within industries, so that the later is an intermediate outcome of the former. In line with this, the manual wage premium is the driving force behind workers reallocation across tasks in Equation 3.5 of the model.

Table 3.4: Measurement of manual-biased technological change

Dependent variable: Vote on low-skill immigration policy			
	(1)	(2)	(3)
Manual premium (25%)	-3.822***		
	(1.076)		
Manual premium (40%)		-2.359	
		(1.440)	
Δ Manual employment since 1950			-1.953***
			(0.622)
Controls	Yes	Yes	Yes
Observations	5719	5719	5719

Notes: The table analyses the robustness of the main result to changing the way manual-biased technological change is measured. The manual task intensity threshold is changed from 33% to 25% and 40% of national employment in column 1 and 2, respectively. Column 3 uses the change in the manual employment share instead of the manual wage premium interacted with the initial industry shares as explanatory variable. Presented estimates include all controls from column 6 of Table 3.3. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

between voting outcomes and the change in future manual-biased technological change. Column 1 looks at future manual-biased technological change over the next 10 years, column 2 at the next 20 years, and column 3 at the next 30 years. The presented correlations provide little evidence that would suggest reverse causality. In column 1 an insignificant, positive relationship between voting in favour of liberalizing low-skill immigration policy and future manual-biased technological change can be observed, while in column 2 and 3 the relationship turns negative, but remains insignificant. This exercise demonstrates that representatives of congressional districts that will experience more manual-biased technological change in the future were not becoming more unfavourable towards low-skill immigration beforehand.

3.5.3 Additional economic and political factors

This section shows that the main results are robust to accounting for a large set of additional economic and political factors. I focus on the robustness of manual-biased technological change, but corresponding robustness checks are presented for the manual employment share in Appendix C.3. I start with additional economic factors in Table 3.6. A first concern is that the degree of manual-biased technological change in a congressional district might be correlated with long-run differences in the importance of manual employment between congressional districts capturing the quasi-fixed higher competition between natives and low-skill immigrants rather than changes to it due to technology. Accordingly, column 1 includes the manual employment share in 1950. It shows that both the manual-biased technological change and the manual employment share in 1950

Table 3.5: Falsification exercise

Dependent variable: Vote on low-skill immigration policy			
	(1)	(2)	(3)
Manual premium (t+10)	1.285		
	(2.981)		
Manual premium (t+20)		-1.714	
		(1.857)	
Manual premium (t+30)			-0.923
			(1.861)
Controls	Yes	Yes	Yes
Observations	2798	2384	474

Notes: The table presents a falsification exercise, where the manual-biased technological change that occurs over the next 10, 20 or 30 years in the future is regressed on votes that occurred beforehand. For example, the future manual-biased technological change that occurred during the 2000s (t+1) is regressed on votes on low-skill immigration policy during the 1990s (t). The sample declines in size as no data is available on manual-biased technological change after 2010. Presented estimates include all controls from column 6 of Table 3.3. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

have their expected negative signs and are significant. This implicitly alleviates potential concerns that the effect of changes in technology since 1950 on the level of voting behaviour at point t are both driven by the initial level of manual employment at the start. Indeed there is little correlation between the historical manual employment share in 1950 and exposure to manual-biased technological change (correlation=-0.038) since 1950 and even this correlation suggests that areas initially less manual intensive experienced more manual-biased technological change, which would reduce the magnitude of the observed effect. This seems also in line with the minimal increase in magnitude of the coefficient compared to the baseline.

In column 2, I further explore the role played by competition between natives and low-skill immigrants. In particular, I modify the benchmark specification to include the share of college graduates as an alternative measure to control for competition between natives and low-skilled immigrants across congressional districts as used by for example by Facchini & Steinhardt (2011). As expected a higher share of highly-skilled individuals increases the likelihood that a representative will vote in favour of liberalizing low-skill immigration, however the effect of manual-biased technological change remains the same. This seems to suggest that competition due to tasks performed in the labour market and through education are two distinct mechanism that affect voting behaviour of representatives on low-skill immigration.[22]

[22]The manual employment share and the college share are highly negatively correlated across congressional districts. But as observable in Table C.8 in the Appendix competition characterized by tasks and education are not fully overlapping and both coefficients despite decreasing in magnitude have their expected sign and are significant.

Over the study period union membership has more than halved. Trade unions usually have been opposed to increasing immigration inflows fearing a deterioration of wages and working conditions through an extension of the labour force (see Gimpel & Edwards 1999). In addition, changes in union membership might have affected wages differently across occupations within industries. Column 3 accounts for the changing importance of trade unions in the US labour market. The share of trade union members appears to have indeed a negative effect, however the effect is not significant.

Another concern is that technological change varies between urban and rural economies and that this difference also shapes changing opinions on immigration. Column 4 accounts for differences between rural and urban labour markets with representatives from districts with more constituents in rural areas being slightly more likely to vote to restrict low-skill immigration, also the effect is insignificant.

Finally, column 5 accounts for a congressional district's employment share in five major industry categories: transport, retail, manufacturing, construction and agriculture. Again there is a general correlation between substitutability of low-skill immigrants with natives (apart from in agriculture) and the voting behaviour of representatives observable. I observe a strong negative effect of a higher employment share in construction, manufacturing and transport industries on the likelihood of representatives liberalizing low-skill immigration. This again does not weaken the observed effect of manual-biased technological change, if at all it's importance increases by controlling for major industry differences across congressional districts.

Up to this point, I controlled for the ideology of a legislator by using party affiliation. This however might not be a sufficient proxy for a representative's true views on low-skill immigration. Table 3.7 explores the impact of differences between legislators in further detail. Column 1 of Table 3.7 includes being a member of the republican party as a time-varying dummy control. By doing so, I allow for the degree of party influence on members' roll call votes to vary over the studied time period (see Snyder Jr & Groseclose 2000). It is clearly observable that republican representatives have become more averse to low-skill immigration over time compared to democrats.

Column 2 controls for the DW-1 nominate score as measure of a politicians left-right (or liberal-conservative) orientation and DW-2 nominate score reflecting secondary cultural political issues in particular civil rights for African-Americans or gun-rights as constructed by Poole & Rosenthal (2000). Accordingly, these measures account for the political ideologies of representatives beyond party affiliation. These measures should account for the general polarization of US politics over recent decades (Poole & Rosenthal 1984; Hare & Poole 2014). Having a more conservative attitude towards economic and cultural issues, even after controlling for party affiliation, makes it less likely that a representative votes in favour of liberalizing low-skill immigration.

Table 3.6: Robustness checks - Other economic factors

Dependent variable: Vote on low-skill immigration policy					
	(1)	(2)	(3)	(4)	(5)
Manual premium	-4.274***	-3.728***	-3.785***	-3.986***	-5.099***
	(1.395)	(1.328)	(1.391)	(1.389)	(1.381)
Historical manual share	-1.172***				
	(0.380)				
College		1.723***			
		(0.252)			
Union membership			-0.309		
			(0.596)		
Rural				-0.132	
				(0.086)	
Transport					-1.902**
					(0.876)
Retail					2.032**
					(0.960)
Manufacturing					-1.054***
					(0.184)
Construction					-2.366***
					(0.827)
Agriculture					-0.322
					(0.455)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of the main result to other labour market channels. Presented estimates extend on column 6 of Table 3.3 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 3 includes the share of votes the democratic candidate received as recorded by the Federal Election Commission (1970-2014), which seems to have a small positive but insignificant effect. This accounts for how competitive the election in a congressional district was for a democratic/republican representative.

These different characteristics might however still not fully account for a legislator's position on immigration, as a number of other individual characteristics are unobservable. These characteristics might be related to the task and industry composition of a congressional district. For this reason, I estimate column 4 including individual legislator fixed effects. This controls for time-invariant unobservable characteristics of representatives, therefore only exploiting the variation in manual-biased technological change across time while a representative remains in office. Accordingly, I estimate whether a representative adjusts his support for low-skill immigration policy with regards to the changing degree of manual-biased technological change in his congressional district. Importantly, the sign and significance of my key explanatory variables remains similar to the baseline specification across column 1 to 4 of Table 3.7.

Table 3.7: Robustness checks - Other political factors

Dependent variable: Vote on low-skill immigration policy				
	(1)	(2)	(3)	(4)
Manual premium	-5.020***	-4.977***	-3.614***	-5.092***
	(1.517)	(1.395)	(1.372)	(1.721)
Republican (93rd-97th)	-0.0221			
	(0.053)			
Republican (98th-102nd)	-0.285***			
	(0.035)			
Republican (103rd-107th)	-0.535***			
	(0.078)			
Republican (108th-112th)	-0.803***			
	(0.040)			
Republican (113th-117th)	-1.286***			
	(0.078)			
DW-1 nominate		-0.873***		
		(0.070)		
DW-2 nominate		-0.130***		
		(0.035)		
Democrat voteshare			0.074	
			(0.058)	
Representative fixed effects	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	5719	5719	5578	5719

Notes: The table analyses the robustness of the main result to a vast set of other political factors. Presented estimates include all controls from column (6) of Table 3.3. Columns 1, 2 and 3 report marginal effects at means for Probit regressions. Column 4 is estimated using OLS due to the high number of fixed effects. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, Table 3.8 checks for robustness of my results with respect to the timing of legislation, the geography of immigration and voting on high-skill immigration. In column 1, the sample of bills is restricted to the 2000s, a period characterized by considerable automation of routine occupations and a large number of roll call votes on bills aimed at restricting low-skill immigration.[23] Column 2 presents the effect for the periods before 2000. Column 3 exclusively focuses on states with a high immigrant share (the 15 states with the highest foreigner share during the study period). Column 4 instead excludes these 15 high-immigration states. The coefficient on my main explanatory variable remains similar to the benchmark specification across columns 1-4 suggesting that manual-

[23] Interestingly, when looking at later time-periods the coefficient on the unemployment rate turns negative and insignificant, which is in line with expectations. The positive coefficient on the unemployment rate in the baseline specification appears to be exclusively driven by the 1970s & 1980s.

biased technological change had a similar marginal effect across different time-periods and geographic regions. Rather than restricting the sample, column 5 includes votes on high-skilled immigration. A vote in favour of bills aimed at increasing high-skilled immigration has been coded as a "0", whereas a vote against it as "1". This is done as manual-biased technological change should, if at all, decrease competition of natives with high-skilled immigrants.[24] Extending the sample to include votes on high-skilled immigration seems to reduce the coefficient size as the link between manual-biased technological change and competition with high-skilled workers is likely weaker, but remains significant.

Table 3.8: Robustness checks - Effect across sub-samples

Dependent variable: Vote on low-skill immigration policy					
	Bills 2000s	Bills pre-2000	High immigration states	Low immigration states	High-skill bills included
	(1)	(2)	(3)	(4)	(5)
Manual premium	-4.387*	-3.857**	-3.599*	-3.755***	-2.191**
	(2.351)	(1.943)	(2.126)	(1.100)	(0.976)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1968	2798	2423	3296	6919

Notes: The table analyses the robustness of the main result across different sub-samples of the data. Presented estimates extend on column 6 of Table 3.3 reporting marginal effects at means for Probit regressions. Column 1 and 2 study the effect on votes in the 2000s and pre-2000, respectively. Column 3 (4) comprises (excludes) the following 15 states with the highest foreigner share: Arizona, California, Connecticut, Florida, Hawaii, Illinois, Maryland, Massachusetts, Nevada, New Jersey, New Mexico, New York, Rhode Island and Washington. Column 5 also includes high-immigration bills, which are coded in the opposite direction to low-skill immigration bills as high-skill immigration should be complementary to manual employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.4 Trade and trade policy

The politics of immigration and trade are often viewed as being shaped by similar forces (see e.g. Colantone & Stanig 2019; Conconi et al. 2020). Also, apart from technological change, trade in goods appears to have been the major factor in recent labour market developments in the US, in particular in the form of rising Chinese import competition (see Autor & Dorn 2013; Autor et al. 2013*a*).

First, one might be concerned that manual-biased technological change is correlated with increases in foreign competition, in particular from China, at the local level. To rule this out, I control for increased Chinese competition across congressional districts and the

[24]I also evaluated whether abstract-biased technological change increased support for restricting high-skill immigration, however I did not find any significant effect. This might simply reflect the limited number of bills (3) focussing on high skill immigration that were voted on in the house of representatives. In particular, as there is only limited time variation available as these three bills were passed in 1998, 2011 and 2012, respectively.

effect it might have had on immigration policy in Table 3.9. The political consequences that China's integration into the world economy had on US politics has been highlighted for example by Che et al. (2016) and Autor et al. (2020). I construct a measures of trade penetration in levels corresponding to the differenced version used by Autor et al. (2013*a*). The details of the specification used can be found in Appendix Section C. Column 1 and 2 present the effect of import penetration (in 1000$) per employee from China across congressional districts. Both coefficients, imports (column 1) and net imports (column 2), are negative and significant. Accordingly, rising competition from China made representatives more likely to vote in favour of restricting low-skill immigration. This negative effect is also what one would expect from the findings of Colantone & Stanig (2017) that Chinese import competition increased support for nationalist and isolationist parties in Western Europe. Trade competition however seems to be rather a complementary explanation for tighter immigration legislation as the main variable of interest is little affected by the inclusion of the variables controlling for Chinese import competition.[25] This is actually less surprising when considering that automation mainly led to a decline in non-traded routine occupations, like clerks and secretaries, and an increase in manual occupations in the low-skill services sector. That is the types of occupations most affected by automation are in general not affected by trade, so that there is little possibility for correlation between the two shocks across local labour markets (see also Autor et al. 2013*b*).

Table 3.9: Robustness checks - China trade shock

Dependent variable:	Vote on low-skill immigration policy	
	(1)	(2)
Manual premium	-3.862***	-3.862***
	(1.382)	(1.382)
China-US IM	-0.009***	
	(0.003)	
China-US IM-EX		-0.008***
		(0.003)
Controls	Yes	Yes
Observations	5719	5719

Notes: The table analyses the robustness of the main result to controlling for the China trade shock. Presented estimates extend on column 6 of Table 3.3 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, an important question is whether technological change might have led to a broader increase in anti-globalization policies, that is not just increasing immigration

[25] Corresponding robustness checks for the manual employment share are presented in Appendix Table C.10.

restrictions, but also leading to protectionist policies on trade. While technological change increased natives' competition with low skill immigrants, it should not have increased exposure to foreign competition. This is because as noted before most of the jobs lost as well as created are in non-trade sectors (see Autor & Dorn 2013). In contrast, trade liberalization has mainly affected specific industries within manufacturing and led to an overall employment decline in these industries (Autor et al. 2013*a*; Pierce & Schott 2016). Accordingly, an effect on the latter would suggest that manual-biased technological change led to broad discontent with globalization, even if there appears to be little economic gain from increased trade protection for individuals affected by manual-biased technological change. In this case an observed effect on trade policy could either reflect a protest vote due to increased economic hardship or a misperception of the real causes of local labour market changes. In contrast, if there is no observable effect of manual-biased technological change on trade policy, this would be in line with the voting of representatives being driven by underlying changes in competition between natives and low-skill immigrants in the labour market.

Table 3.10 presents the results of manual-biased technological change on the voting behaviour of representatives on trade policy. For this I collected 17 bills voted on in the House of Representatives for the corresponding time period, which are reported in Appendix Table C.7. Conconi et al. (2020) show that in general factor endowments of congressional districts affect voting on immigration and trade policy in similar ways. So that, voting on trade policy provides a good placebo test for whether technological change affected voting on immigration policy due to increasing competition between natives and low-skill immigrants or rather due to other factors. Column 1 shows that the effect of manual-biased technological change on trade policy also has a negative sign, but this effect is insignificant and less than a fifth in magnitude of the corresponding coefficient in Table 3.3. Columns 2-6 shows that when controlling for other factors the effect of manual-biased technological change on trade policy remains insignificant and even changes sign across specifications. This finding supports the argument that manual-biased technological change affects voting on immigration policy through increasing competition in the labour market between natives and immigrants in the US as it does not appear to have fostered general discontent against globalization.[26]

In contrast to this, trade shocks did not just increase representatives' support for restricting low-skill immigration, but also increased support for restricting free trade. This is highlighted in Table 3.11 which shows that rising Chinese import competition led representatives to be less favourable to free trade (not just with China). This suggests that in contrast to recent technological change increasing competition from China fostered

[26]Table 3.11 in the Appendix presents the effect of the China shock on voting to liberalize trade policy. In contrast to technological change, the effect of the China trade shock is comparable and significant for both voting on liberalizing trade and immigration. This is despite most bills focussing on legislation not related to US-China trade.

Table 3.10: Effect manual-biased technological change on trade policy

Dependent variable: Vote on liberalizing trade policy (1=Pro; 0=Against)						
	(1)	(2)	(3)	(4)	(5)	(6)
Manual premium	-0.836	0.211	-0.202	-0.728	-0.363	-0.384
	(0.969)	(0.990)	(1.006)	(1.014)	(1.019)	(1.018)
log(family income)		0.204***	0.326***	0.393***	0.325***	0.277***
		(0.054)	(0.054)	(0.060)	(0.063)	(0.065)
Poverty		-1.219***	0.199	0.685***	0.857***	0.829***
		(0.160)	(0.161)	(0.205)	(0.213)	(0.213)
Republican			0.417***	0.398***	0.396***	0.394***
			(0.013)	(0.014)	(0.014)	(0.014)
Foreign-born				-0.124	-0.185	-0.146
				(0.122)	(0.123)	(0.124)
Hispanic				-0.038	0.078	-0.002
				(0.083)	(0.090)	(0.096)
African-American				-0.265***	-0.163***	-0.202***
				(0.054)	(0.062)	(0.064)
Unemployment rate					-1.831***	-1.866***
					(0.532)	(0.533)
Age 65+						-0.677**
						(0.263)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7153	7153	7153	7153	7153	7153
Pseudo R-sq	0.149	0.184	0.297	0.300	0.301	0.302

Notes: The table presents the effect of manual-biased technological change on voting on trade policy. Vote in favour of freer trade coded as 1 and 0 otherwise. The table reports marginal effects at means from probit regressions. The list of votes used is reported in Table C.7. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

discontent with globalization overall not just trade policy. Understanding why Chinese competition has such broader consequences compared to technological change is left for further analysis.

Table 3.11: Effect of China shock on trade liberalization

Dependent variable:	Vote on liberalizing trade policy	
	(1)	(2)
Manual premium	-0.326	-0.323
	(1.019)	(1.019)
China-US IM	-0.005**	
	(0.002)	
China-US IM-EX		-0.005**
		(0.002)
Controls	Yes	Yes
Observations	7153	7153

Notes: The table analyses the effect of manual-biased technological change and the China trade shock on voting to liberalize trade policy. Presented estimates extend on column 6 of Table 3.10 reporting marginal effects at means for Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusions

This chapter documents that recent technological change that favoured manual tasks, for example automation, led to a tightening of low-skill immigration policy in the United States. This is because it increased the share of natives in manual employment that are in competition with low-skill immigrants, which in turn affects representatives' voting behaviour on low-skill immigration bills.

This finding is based on theoretical as well as empirical evidence. The empirical results are obtained by combining US Census data, which provides measures for manual employment and manual-biased technological change, with US House of Representatives roll call votes on immigration policy across congressional districts from 1970-2014. First, the obtained results highlight that the task composition of congressional districts matters and the degree of substitutability between natives and low-skill immigrants influences representatives' voting on low-skill immigration policy. Second, they provide evidence that representatives of congressional districts which were more exposed to manual-biased technological change increased their support for restricting low-skill immigration. Further, there is evidence that in particular the automation of routine tasks played an important role in the restriction of low-skill immigration to the US.

Importantly, manual-biased technological change did not have a corresponding effect on trade policy. This is consistent with the change in voting behaviour of representatives being due to increased competition in the labour markets between natives and low-skill immigrants rather than more broad discontent with globalization. This is in marked contrast to increased import competition from China, which I find increased support for policies restricting trade as well as immigration.

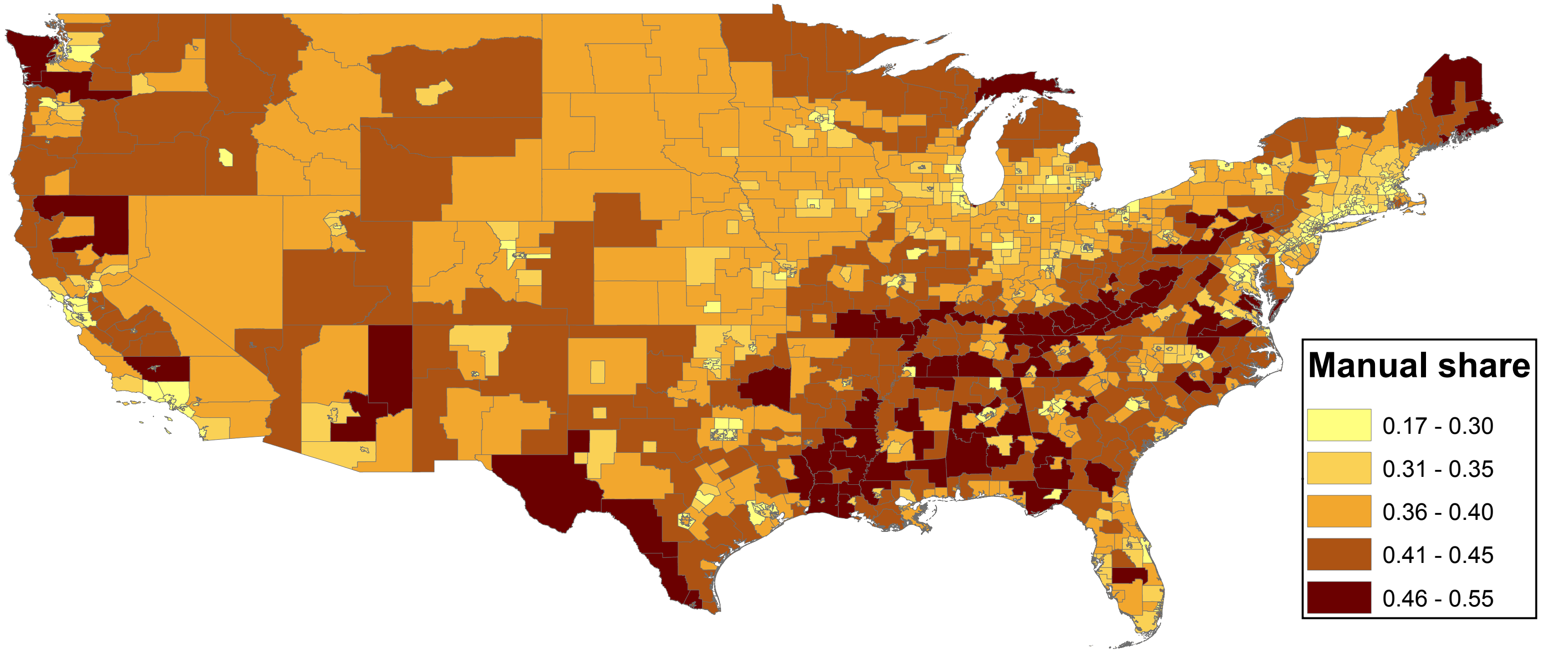
These results help explain how competition between natives and immigrants in certain tasks shapes US immigration policy. It also highlights the way in which new technologies can increase support for nativist politics through changing this competition. Here it seems particularly important that, in contrast to exposure to foreign competition, technology appears to change support for nativist political parties and politicians only through changing views on immigration, but not trade. These results provide important new insights into the mechanism of how technological change and trade shocks have led to the recently documented rise of extremist politics in Western democracies.

Appendix Chapter 3

C Additional Information

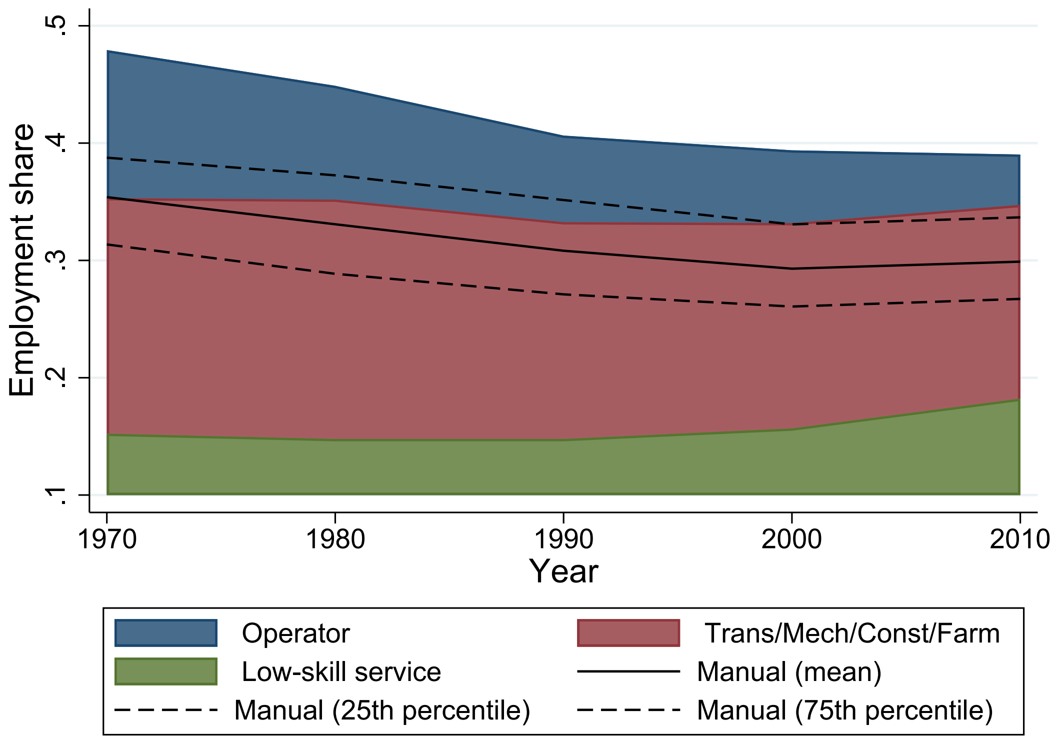
C.1 Figures

Figure C.1: Manual employment share across the US in 1980



Notes: Manual employment share in 1980 across the mainland US. The data is constructed from individual level IPUMS data and depicted for 1980 county groups (the smallest geographical level for which data is available). Alaska and Hawaii not shown but included in the dataset.

Figure C.2: Manual employment share 1970-2010



Notes: The graph depicts a breakdown of the manual employment share across congressional districts. It shows stacked average employment across manual intensive major occupation groups (i) low-skill services, (ii) transportation/mechanical/construction/mining/farm and (iii) machine operators/assemblers (see Autor & Dorn 2013). They are ordered by manual task intensity with low-skill services having the highest manual task content. The graph also depicts manual employment as constructed in Equation 3.17 at the mean, 25th and 75th percentile across congressional districts. It illustrates the increase in manual employment (especially in the most manual intensive occupations) since the 1990s, while also highlighting that occupations routine and manual intensive (i.e. machine operators/assemblers) continued to decline in their importance even after 1990.

C.2 Tables

Table C.1: Immigration bills in US House of Representatives 1973-2014

	Cong	**Date**	**Bill**	**Keyword**	**Direction**	**Skill**	**Yes**	**No**
1	93rd	03.05.1973	HR 392	Employer Sanctions	Contra	Low	305	78
2	93rd	26.09.1973	HR 891	Rodino Bill	Contra	Low	337	31
3	98th	20.06.1984	HR 1510	Simpson-Mazzoli Act	Contra	Low	217	212
4	99th	09.10.1986	HR 3810	Immigration Reform and Control Act (IRCA)	Pro	Low	235	171
5	100th	21.04.1988	HR 4222	Amend Immigration and Nationality Act	Pro	Low	214	203
6	101st	03.10.1990	HR 4300	Immigration Act of 1990 (IMMACT)	Pro	Low	231	193
7	104th	21.03.1996	HR 2202	Immigration Control and Financial Responsibility Act	Contra	Low	333	87
8	105th	25.09.1998	HR 3736	Temporary Access to Skilled Workers and H-1B	Pro	High	288	134
9	109th	10.02.2005	HR 418	Real ID Act	Contra	Low	261	161
10	109th	16.12.2005	HR 4437	Border Protection, Antiterrorism, Illegal Immigration	Contra	Low	240	182
11	109th	14.09.2006	HR 6061	Secure Fence Act	Contra	Low	283	138
12	109th	21.09.2006	HR 6094	Community Protection Act of 2006	Contra	Low	328	95
13	109th	21.09.2006	HR 6095	Immigration Law Enforcement Act	Contra	Low	277	149
14	112th	29.11.2011	HR 3012	Fairness for High-Skilled Immigrants Act	Pro	High	389	15
15	112th	30.11.2012	HR 6429	STEM Jobs Act of 2012	Pro	High	245	140
16	113th	01.08.2014	HR 5272	Prohibit certain actions with regards to illegal aliens	Contra	Low	216	192
17	113th	4.12.2014	HR 5759	Preventing Executive Overreach on Immigration Act	Contra	Low	219	198

Notes: Contested immigration policy bills voted on in US House of Representatives between 1973-2014. Yes (No) comprises Yay (Nay), Paired Yea (Paired Nay) and Announced Yea (Announced Nay) votes. No votes are coded as missing values. Data on voting from Poole & Rosenthal (2000).

Table C.2: Important occupations by task

Number	Manual	Routine	Abstract
1	Truck, delivery, and tractor drivers	Secretaries	Managers and administrators, n.e.c.
2	Primary school teachers	Cashiers	Salespersons, n.e.c.
3	Janitors	Bookkeepers, accounting and auditing clerks	Production supervisors or foremen
4	Waiter/waitress	Cooks, variously defined	Supervisors and proprietors of sales jobs
5	Nursing aides, orderlies, and attendants	General office clerks	Farmers (owners and tenants)
6	Laborers outside construction	Assemblers of electrical equipment	Accountants and auditors
7	Carpenters	Production checkers and inspectors	Child care workers
8	Farm workers	Typists	Secondary school teachers
9	Construction laborers	Welders and metal cutters	Office supervisors
10	Housekeepers, maids, and butlers	Bank tellers	Managers and specialists in marketing, and public relations

Manual & routine task intensive occupations (Top 10): (1) Machine operators, n.e.c.; (2) Textile sewing machine operators; (3) Packers and packagers by hand; (4) Painters, construction and maintenance; (5) Masons, tilers, and carpet installers; (6) Punching and stamping press operatives; (7) Painting machine operators; (8) Vehicle washers and equipment cleaners; (9) Crane, derrick, winch, and hoist operators; (10) Packers, fillers, and wrappers

Manual & abstract task intensive occupations: (1) Kindergarten and earlier school teachers; (2) Locomotive operators (engineers and firemen); (3) Foresters and conservation scientists

Notes: The table presents the ten most important occupations in terms of employment in 1980 for each task. An occupation is recorded as intensive in a certain task when it ranks in the top 33% of wage share paid for this task across all occupation. Most occupations are either coded as manual, routine or abstract task intensive. The bottom of the table presents the occupations that are coded to be intensive in more than one task.

Table C.3: Descriptive statistics manual wage premium

Top 5 industry shares in 1950	
Construction	.073
Educational services	.042
Federal public administration	.039
Retail trade: Eating and drinking places	.034
Personal services: Private households	.032
Top 5 changes in manual wage premium	
Retail trade: Shoe stores	.443
Accounting, auditing, and bookkeeping services	.361
Personal services: Misc personal services	.353
Retail trade: Liquor stores	.189
Retail trade: Household appliance and radio stores	.128
Bottom 5 changes in manual wage premium	
Misc business services	-.312
Misc professional and related	-.313
Manufacturing: Footwear, except rubber	-.333
Manufacturing: Drugs and medicines	-.375
Manufacturing: Office and store machines	-.506

Notes: The table presents the 5 industries with the highest employment share in 1950 as well as the 5 industries with the strongest increase and decrease in the manual wage premium between 1950 and 2010.

Table C.4: Data sources of control variables

Variable	Data sources
log(family income)	Manson et al. (2019)
Poverty	Manson et al. (2019)
Republican	Poole & Rosenthal (2000)
Foreign-born	Manson et al. (2019)
Hispanic	Manson et al. (2019)
African-American	Manson et al. (2019)
Unemployment rate	Manson et al. (2019)
Age 65+	Manson et al. (2019)
College	Manson et al. (2019)
Union membership	Hirsch et al. (2001)
Rural	Manson et al. (2019)
Transport	Manson et al. (2019)
Retail	Manson et al. (2019)
Manufacturing	Manson et al. (2019)
Construction	Manson et al. (2019)
Agriculture	Manson et al. (2019)
DW-1 nominate	Poole & Rosenthal (2000)
DW-2 nominate	Poole & Rosenthal (2000)
Democrat voteshare	Federal Election Commission (1970-2014)
China-US IM	United States Census Bureau (1991); UN Comtrade (1991-2010)
China-US IM-EX	United States Census Bureau (1991); UN Comtrade (1991-2010)

Notes: This table presents information on the data sources of variables used as controls which have not been discussed in detail in Section 3.3.

Table C.5: Summary Statistics

	Mean	Std. dev.	Min	Max	Valid obs.
Pro migration vote	0.38	0.49	0.00	1.00	5,755
Manual share	0.31	0.06	0.14	0.51	5,755
Historical manual share	0.42	0.03	0.32	0.59	5,719
Manual premium	-0.02	0.02	-0.11	0.04	5,719
Manual premium (25%)	-0.02	0.02	-0.10	0.04	5,719
Manual premium (40%)	-0.00	0.02	-0.07	0.06	5,719
Manual employment	-0.08	0.03	-0.21	0.01	5,719
Δ Routine task (35-55)	-0.04	0.03	-0.12	0.09	5,719
log(family income)	10.43	0.61	8.80	11.66	5,755
Poverty	0.16	0.11	0.02	0.69	5,755
Republican	0.49	0.50	0.00	1.00	5,755
Foreign-born	0.09	0.10	0.00	0.59	5,755
Hispanic	0.09	0.14	0.00	0.87	5,755
African-American	0.12	0.14	0.00	0.92	5,755
Unemployment rate	0.07	0.03	0.02	0.24	5,755
Age 65+	0.12	0.03	0.02	0.31	5,755
College	0.20	0.10	0.04	0.69	5,755
Union membership	0.18	0.09	0.03	0.42	5,755
Rural	0.23	0.21	0.00	0.87	5,755
Transport	0.05	0.02	0.02	0.12	5,755
Retail	0.14	0.03	0.07	0.23	5,755
Manufacturing	0.18	0.09	0.02	0.53	5,755
Construction	0.06	0.02	0.01	0.17	5,755
Agriculture	0.03	0.04	0.00	0.29	5,755
DW-1 nominate	0.07	0.46	-0.74	1.23	5,755
DW-2 nominate	0.07	0.39	-1.51	1.24	5,755
Democrat voteshare	0.52	0.25	0.00	1.00	5,620
China-US IM	1.04	6.32	0.00	287.26	5,755
China-US IM-EX	0.92	5.67	-1.97	252.25	5,755

Notes: This table reports the summary statistics for the main variables used in the paper for the dataset covering votes in the house of representatives on low-skill immigration policy. Summary statistics for the trade dataset are different due to the different number of votes in the house of representatives across periods.

Table C.6: Linear estimation of baseline results

Dependent variable: Vote on low-skill immigration policy

Panel A: OLS results for Table 3.1

	(1)	(2)
Manual share	-0.173	-0.958***
	(0.127)	(0.189)
Controls	No	Yes
Observations	5719	5719

Panel B: 2SLS results for Table 3.2

	(1)	(2)
Manual share	-2.409***	-2.437***
	(0.297)	(0.550)
Controls	No	Yes
Observations	5719	5719

Panel C: OLS results for Table 3.3

	(1)	(2)
Manual premium	-4.722***	-1.912***
	(0.937)	(0.741)
Controls	No	Yes
Observations	5719	5719

Notes: Corresponding results using OLS and 2SLS for baseline estimates presented in Table 3.1, Table 3.2 and Table 3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Votes on trade liberalization

	Bill (Cong.)	**Description**	**Date**	**Direction**	**Yes-share**
1	H.R. 10710 (93th)	Trade Act 1974	11.12.1973	Pro	.659
2	H.R. 4537 (96th)	Approval Tokyo Agreements	11.07.1979	Pro	.983
3	H.R. 4848 (100th)	Omnibus T&C Act	13.07.1988	Anti	.107
4	H.R. 5090 (100th)	Approval CUSFTA	09.08.1988	Pro	.902
5	H.Res. 101 (102nd)	Disapproving extension fast track	23.05.1991	Anti	.546
6	H.R.1876 (103rd)	Extension fast track	22.06.1993	Pro	.701
7	H.R.3450 (103rd)	Approval NAFTA	17.11.1993	Pro	.539
8	H.R.5110 (103rd)	Approval Uruguay Agreements	29.11.1994	Pro	.665
9	H.R.2621 (105rd)	Approval fast track	25.09.1998	Pro	.426
10	H.R. 3009 (107th)	Approval fast track	27.07.2002	Pro	.504
11	H.R. 2738 (108th)	US-Chile FTA	24.07.2003	Pro	.634
12	H.R. 2739 (108th)	US-Singapore FTA	24.07.2003	Pro	.637
13	H.R. 4759 (108th)	US-Australia FTA	14.07.2004	Pro	.742
14	H.R. 4842 (108th)	US-Morocco FTA	22.07.2004	Pro	.765
15	H.R. 3045 (109th)	CAFTA	28.07.2005	Pro	.502
16	H.R. 3078 (112th)	US-Colombia FTA	12.10.2011	Pro	.611
17	H.R. 3080 (112th)	US-Korea FTA	12.10.2011	Pro	.648

Notes: The table reports 17 votes on trade policy collected from Poole & Rosenthal (2000) for the time period of interest that are used in Table 3.10 for the placebo check. The table reports the number (congress), description, date and direction of the vote as well as the share of votes in favour of liberalizing trade policy.

C.3 Robustness checks

This section of the Appendix presents the robustness checks for the manual task share. Table C.8 accounts for other economic factors. In particular, it highlights that there is considerable difference between the effect of tasks performed in the labour market with the education level as well as with the broad industrial sectors an individual is employed in. Table C.9 controls for a set of additional political factors including letting the effect of party affiliation vary by decade, democratic vote share and DW-nominate scores. The coefficient for the manual task share remains negative across all specifications. I do not include the specification using representative fixed effects as the instrumentation strategy relies on the initial manual task share in 1950 interacted with time fixed effects so that including representative fixed effects captures nearly all variation apart from that which occurs due to redistricting while the representative is in office. Finally, Table C.10 accounts for the impact of increased US trade with China and highlights.

Table C.8: Robustness checks II - Other economic factors

Dependent variable:	Vote on low-skill immigration policy			
	(1)	(2)	(3)	(4)
Manual share	-2.009**	-3.333***	-6.193***	-2.421**
	(0.941)	(0.841)	(1.054)	(1.128)
College	0.852**			
	(0.356)			
Union membership		-0.0677		
		(0.348)		
Rural			0.543***	
			(0.129)	
Transport				-1.119
				(0.834)
Retail				0.839
				(0.739)
Manufacturing				-0.827***
				(0.308)
Construction				-0.232
				(1.024)
Agriculture				0.663
				(0.694)
Controls	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719

Notes: Presented estimates extend on column 6 of Table 3.2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Robustness checks II - Other political factors

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)
Manual share	-1.861***	-2.629***	-2.626***
	(0.679)	(0.725)	(0.742)
Republican (93rd-97th)	-0.024		
	(0.037)		
Republican (98th-102nd)	-0.236***		
	(0.023)		
Republican (103rd-107th)	-0.432***		
	(0.067)		
Republican (108th-112th)	-0.651***		
	(0.041)		
Republican (113th-117th)	-1.044***		
	(0.060)		
Democrat voteshare		0.052	
		(0.041)	
DW-1 nominate			-0.729***
			(0.054)
DW-2 nominate			-0.084***
			(0.029)
Controls	Yes	Yes	Yes
Observations	5719	5578	5719

Notes: Presented estimates extend on column 6 of Table 3.2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: Robustness checks II - China trade shock

Dependent variable: Vote on low-skill immigration policy	(1)	(2)
Manual share	-3.349***	-3.356***
	(0.822)	(0.822)
China-US IM	-0.006**	
	(0.003)	
China-US IM-EX		-0.005**
		(0.003)
Controls	Yes	Yes
Observations	5719	5719

Notes:Presented estimates extend on column 6 of Table 3.2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Data appendix

C.4 Task content measures for occupations

I use the measures for manual, routine and abstract tasks inputs preformed for each census occupation code from Autor & Dorn (2013). These three task aggregates are based on the following variables in the Dictionary of Occupational Titles [US Department of Labor 1977]: (i) the manual tasks performed is based on "eye-hand-foot coordination" of an occupation; (ii) the routine task is an average of the variables, "set limits, tolerances, and standards" and "finger dexterity"; (iii) the abstract task measure is the average of "direction control and planning" and "GED Math". In the Dictionary of Occupational Titles an occupation consists of multiple tasks that are performed at a varying degree of intensity. Detailed information on the tasks measures can be found in the Appendices of Autor et al. (2003) and Autor & Dorn (2013). To account for automation altering the immigrants task composition and leading to an increased share of low-skill immigrants, as documented by Basso et al. (2017), I construct my task share measures using exclusively citizens –US born and naturalized– over the age of 25 and living outside of group quarters.

C.5 Converting data across geographic areas

I convert data from the respective census geographical areas, denoted by subscript c, to congressional districts, denoted by d, by using population (pop_c) and area-share ($area_c$) of the census district as weights:[27]

$$Var_d = \frac{\sum area_c * pop_c * Var_c}{\sum area_c * pop_c}$$

As the congressional districts are redefined based on the census three years later, I merge for example data from the 1980 census to the time period 1983-1992 (98th-102nd congress). This is illustrated in Figure C.3. In the cases where data is readily available from Manson et al. (2019) at the congressional district level, I use this data. This is the case for the majority of the control variables.

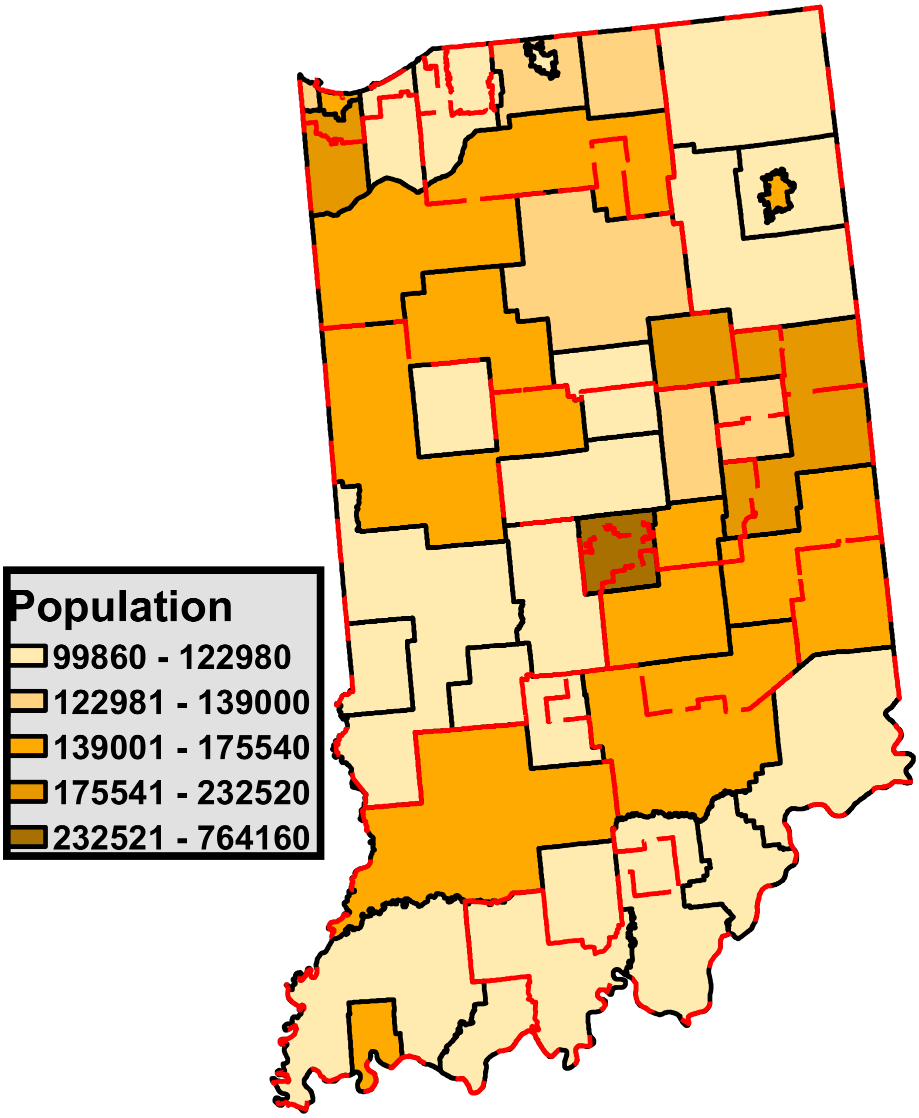
C.6 China trade shock

The measure of exposure to Chinese trade is constructed as follows:

$$IP_{n,t} = \sum_{i=1}^{I} \frac{L_{n,91,i}}{L_{n,91}} \frac{TR_{t,i}^{CHN}}{L_{91,i}}$$

[27] Congressional district shapefiles are obtained form Lewis et al. (2013), while the remaining shapefile's geographical areas required are obtained from Ruggles et al. (2019) for areas used in IPUMS-USA and Manson et al. (2019) for counties.

Figure C.3: Matching across geographic areas



Notes: Map illustrating the conversion of data from 1980 county groups to 98th-102nd congressional districts for the state of Indiana using the overlapping area and county population. Source: IPUMS data [Ruggles et al. 2019]

where for each US industry i, $TR_{t,i}^{CHN}$ is the amount of trade with China (in 2007$) in years 1991,2000 and 2010 (either defined as Imports only or as Imports minus Exports). I use 1991 as the initial year as it is the first one for which the necessary disaggregated bilateral trade data is available. For 1970 and 1980 I set $TR_{t,i}^{CHN}$ equal to zero.[28] Trade is than adjusted by total US employment in industry. Finally, the industry specific measure

[28]This assumption seems plausible as China only accounted for less than 1% of total US trade with China (being mostly balanced) (Wang 2013). This likely relates to Congress conferring contingent Most Favored Nation status to China only on January the 24, 1980. Compared to this trade with China accounted for 14.3% of total US trade in 2010.

of trade penetration is weighted by the share of industry employment in total employment of a district. Data collected from United States Census Bureau (1991) and UN Comtrade (1991-2010).

Bibliography

Acemoglu, D. (2002), 'Technical change, inequality, and the labor market', *Journal of economic literature* **40**(1), 7–72.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H. & Price, B. (2016), 'Import competition and the great US employment sag of the 2000s', *Journal of Labor Economics* **34**(S1), S141–S198.

Acemoglu, D., Cantoni, D., Johnson, S. & Robinson, J. A. (2011), 'The consequences of radical reform: The French Revolution', *American Economic Review* **101**(7), 3286–3307.

Acemoglu, D., Johnson, S. & Robinson, J. A. (2001), 'The colonial origins of comparative development: An empirical investigation', *American economic review* **91**(5), 1369–1401.

Adao, R., Kolesár, M. & Morales, E. (2019), 'Shift-share designs: Theory and inference', *The Quarterly Journal of Economics* **134**(4), 1949–2010.

Alesina, A. & Giuliano, P. (2015), 'Culture and institutions', *Journal of Economic Literature* **53**(4), 898–944.

Allen, T., Dobbin, C. & Morten, M. (2018), Border walls, Technical report, National Bureau of Economic Research.

Arthi, V., Lampe, M., Nair, A. R. & O'Rourke, K. H. (2020), The impact of interwar protection: Evidence from india, Technical report, National Bureau of Economic Research.

Atack, J., Bateman, F. & Margo, R. A. (2004), 'Skill intensity and rising wage dispersion in nineteenth-century american manufacturing', *The Journal of Economic History* **64**(1), 172–192.

Atkin, D., Chaudhry, A., Chaudry, S., Khandelwal, A. K. & Verhoogen, E. (2017), 'Organizational barriers to technology adoption: Evidence from soccer-ball producers in pakistan', *The Quarterly Journal of Economics* **132**(3), 1101–1164.

Autor, D. & Dorn, D. (2013), 'The growth of low-skill service jobs and the polarization of the US labor market', *The American Economic Review* **103**(5), 1553–1597.

Autor, D., Dorn, D. & Hanson, G. (2013*a*), 'The China syndrome: Local labor market effects of import competition in the US', *American Economic Review* **103**(6), 2121–68.

Autor, D., Dorn, D. & Hanson, G. (2013*b*), 'The geography of trade and technology shocks in the United States', *American Economic Review* **103**(3), 220–25.

Autor, D., Dorn, D., Hanson, G. & Majlesi, K. (2020), 'Importing political polarization? The electoral consequences of rising trade exposure', *American Economic Review* **110**(10), 3139–83.

Autor, D., Levy, F. & Murnane, R. (2003), 'The skill content of recent technological change: An empirical exploration', *The Quarterly Journal of Economics* **118**(4), 1279–1333.

Bagchi, A. K. (2000), *Private investment in India, 1900-1939*, Vol. 5, Taylor & Francis.

Bardhan, P. (1971), 'On optimum subsidy to a learning industry: An aspect of the theory of infant-industry protection', *International Economic Review* **12**(1), 54–70.

Basso, G., Peri, G. & Rahman, A. (2017), Computerization and immigration: Theory and evidence from the United States, Technical report, National Bureau of Economic Research.

Beaudry, P., Doms, M. & Lewis, E. (2010), 'Should the personal computer be considered a technological revolution? Evidence from US metropolitan areas', *Journal of Political Economy* **118**(5), 988–1036.

Beaudry, P. & Green, D. (2005), 'Changes in US wages, 1976–2000: Ongoing skill bias or major technological change?', *Journal of Labor Economics* **23**(3), 609–648.

Becker, S. O. & Woessmann, L. (2009), 'Was Weber wrong? A human capital theory of Protestant economic history', *The Quarterly Journal of Economics* **124**(2), 531–596.

Bernard, A. B. & Jones, C. I. (1996), 'Technology and convergence', *The Economic Journal* **106**(437), 1037–1044.

BFS (2019), 'Cantonal gross domestic product (GDP) per capita'.
URL: bfs.admin.ch/bfs/en/home/statistics/nationalaccounts.html, Accessed: 22.06.2020.

Bhavnani, R. R. & Jha, S. (2018), 'Forging a non-violent mass movement: Economic shocks and organizational innovations in India's struggle for democracy'.

Bleakley, H. & Lin, J. (2012), 'Portage and path dependence', *The Quarterly Journal of Economics* **127**(2), 587–644.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D. & Roberts, J. (2013), 'Does management matter? evidence from india', *The Quarterly Journal of Economics* **128**(1), 1–51.

Bolt, J., Inklaar, R., de Jong, H. & Luiten van Zanden, J. (2018*a*), Rebasing 'Maddison': New income comparisons and the shape of long-run economic development, Technical report, Maddison Project Database, version 2018.

Bolt, J., Inklaar, R., de Jong, H. & Luiten van Zanden, J. (2018*b*), Rebasing 'Maddison': New income comparisons and the shape of long-run economic development, Technical report, Maddison Project Database, version 2018.

Bonfatti, R. (2017), 'The sustainability of empire in a global perspective: The role of international trade patterns', *Journal of International Economics* **108**, 137–156.

Bonfatti, R. & Brey, B. (2020), 'Trade disruption, industrialisation, and the setting sun of British colonial rule in India', *CESifo Working Paper* (8461).

Borjas, G. (2003), 'The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market', *The Quarterly Journal of Economics* **118**(4), 1335–1374.

Borjas, G. (2006), 'Native internal migration and the labor market impact of immigration', *Journal of Human Resources* **41**(2), 221–258.

Borjas, G. J. & Monras, J. (2017), 'The labour market consequences of refugee supply shocks', *Economic Policy* **32**(91), 361–413.

Borusyak, K., Hull, P. & Jaravel, X. (2018), Quasi-experimental shift-share research designs, Technical report, National Bureau of Economic Research.

Bossard, W. (1916), *Die Wasserkräfte der Schweiz*, Department des Inneren, Abteilung für Wasserwirtschaft.

Boucekkine, R., de la Croix, D. & Licandro, O. (2008), *Vintage capital*, Palgrave-McMillan, pp. 628–631.

Brey, B. (2020*a*), 'The long-run gains from the early adoption of electricity', *Job Market Paper* .

Brey, B. (2020*b*), 'The effect of recent technological change on US immigration policy: Evidence from Congressional roll call votes'.

Brezis, E. S. & Krugman, P. R. (1997), 'Technology and the life cycle of cities', *Journal of Economic Growth* **2**(4), 369–383.

Broadberry, S. N. (1998), 'How did the United States and Germany overtake Britain? A sectoral analysis of comparative productivity levels, 1870-1990', *Journal of Economic History* pp. 375–407.

Bundesamt für Statistik (1860-2011), *Eidgenössische Volkszählungen, Betriebszählungen, und Statistiken der Unternehmensstruktur*, Departement des Innern.

Burstein, A., Hanson, G., Tian, L. & Vogel, J. (2020), 'Tradability and the labor-market impact of immigration: Theory and evidence from the United States', *Econometrica* **88**(3), 1071–1112.

Card, D. (1990), 'The impact of the Mariel boatlift on the Miami labor market', *ILR Review* **43**(2), 245–257.

Card, D. (2009), 'Immigration and inequality', *American Economic Review* **99**(2), 1–21.

Census Commissioner (1911, 1921), *Census of India*, Calcutta: Superintendent government printing, India.

Census Registrar General (2011), *Census of India*, Directorate of Census Operations.

Census Superintendent (1951), *Census of India*, Government Central Press.

Chandler, C. & Tsai, Y. (2001), 'Social factors influencing immigration attitudes: An analysis of data from the General Social Survey', *The Social Science Journal* **38**(2), 177–188.

Chandra, S., Kuljanin, G. & Wray, J. (2012), 'Mortality from the influenza pandemic of 1918–1919: The case of India', *Demography* **49**(3), 857–865.

Chaudhuri, K. N. (1983), Foreign trade and balance of payments (1757-1947), *in* D. Kumar & M. Desai, eds, 'The Cambridge Economic History of India', Vol. 2, Cambridge University Press.

Che, Y., Lu, Y., Pierce, J., Schott, P. & Tao, Z. (2016), Does trade liberalization with China influence US elections?, Technical report, National Bureau of Economic Research.

Clingingsmith, D. & Williamson, J. G. (2008), 'Deindustrialization in 18th and 19th century India: Mughal decline, climate shocks and British industrial ascent', *Explorations in Economic History* **45**(3), 209–234.

Colantone, I. & Stanig, P. (2017), 'The trade origins of economic nationalism: Import competition and voting behavior in Western Europe', *American Journal of Political Science* .

Colantone, I. & Stanig, P. (2019), 'The surge of economic nationalism in Western Europe', *Journal of Economic Perspectives* **33**(4), 128–51.

Comin, D. & Hobijn, B. (2010), 'An exploration of technology diffusion', *American Economic Review* **100**(5), 2031–59.

Comin, D. & Mestieri, M. (2018), 'If technology has arrived everywhere, why has income diverged?', *American Economic Journal: Macroeconomics* **10**(3), 137–78.

Conconi, P., Facchini, G., Steinhardt, M. & Zanardi, M. (2020), 'The political economy of trade and migration: Evidence from the US Congress', *Economics & Politics* **32**(2), 250–278.

Conley, T. G. (2008), *Spatial Econometrics*, Palgrave Macmillan UK, London, pp. 6159–6165.

Customs and Excise Department (1911-1924), *Annual statement of the trade of the United Kingdom with foreign countries and British possessions*, His Majesty's Stationery Office, London.

David, P. A. (1990), 'The dynamo and the computer: an historical perspective on the modern productivity paradox', *The American Economic Review* **80**(2), 355–361.

David, S. (2003), *The Indian Mutiny: 1857*, Penguin UK.

Davis, D. R. & Weinstein, D. E. (2002), 'Bones, bombs, and break points: the geography of economic activity', *American Economic Review* **92**(5), 1269–1289.

De Faria, F. A., Davis, A., Severnini, E. & Jaramillo, P. (2017), 'The local socio-economic impacts of large hydropower plant development in a developing country', *Energy Economics* **67**, 533–544.

De Pleijt, A., Nuvolari, A. & Weisdorf, J. (2020), 'Human capital formation during the first industrial revolution: evidence from the use of steam engines', *Journal of the European Economic Association* **18**(2), 829–889.

De Rassenfosse, G., Kozak, J. & Seliger, F. (2019), 'Geocoding of worldwide patent data', *Scientific data* **6**(1), 1–15.

Dedinger, B. & Girard, P. (2017), 'Exploring trade globalization in the long run: The RICardo project', *Historical Methods: A Journal of Quantitative and Interdisciplinary History* **50**(1), 30–48.
URL: *http://ricardo.medialab.sciences-po.fr*

Dell, M. (2010), 'The persistent effects of Peru's mining mita', *Econometrica* **78**(6), 1863–1903.

Dell, M. & Olken, B. A. (2020), 'The development effects of the extractive colonial economy: The dutch cultivation system in java', *The Review of Economic Studies* **87**(1), 164–203.

Department des Inneren (1891-1920), *Statistisches Jahrbuch der der Schweiz*, Buckdruckerei Stämpfli & Cie.,Bern.

Department of Industry (1897-1948), *Annual report on the working of the Indian Factories Act in British India*, Superintendent government printing.

Department of Statistics (1911-1921), *Annual statement of the sea-borne trade of British India with the British Empire and foreign countries*, Govenor-General in Council, India.

Dinkelman, T. (2011), 'The effects of rural electrification on employment: New evidence from South Africa', *American Economic Review* **101**(7), 3078–3108.

Donaldson, D. (2018), 'Railroads of the Raj: Estimating the impact of transportation infrastructure', *American Economic Review* **108**(4-5), 899–934.

Downs, A. (1957), 'An economic theory of political action in a democracy', *Journal of Political Economy* **65**(2), 135–150.

Du Boff, R. B. (1967), 'The introduction of electric power in american manufacturing', *The Economic History Review* **20**(3), 509–518.

Dustmann, C. & Preston, I. (2007), 'Racial and economic factors in attitudes to immigration', *The BE Journal of Economic Analysis & Policy* **7**(1).

Dustmann, C., Schönberg, U. & Stuhler, J. (2016), 'The impact of immigration: Why do studies reach such different results?', *The Journal of Economic Perspectives* **30**(4), 31–56.

Eaton, J. & Kortum, S. (2002), 'Technology, geography, and trade', *Econometrica* **70**(5), 1741–1779.

Eidgenössische Amt für Wasserwirtschaft (1928-2018), *Statistik der Wasserkraftanlagen der Schweiz*, Eidgenössisches Amt des Innern.

Emery, C. E. (1896), 'The relations of electricity to steam and water-power', *Journal of the Franklin Institute* **142**(3), 165–186.

Espenshade, T. & Hempstead, K. (1996), 'Contemporary American attitudes toward US immigration', *International Migration Review* pp. 535–570.

European Environment Agency (2004), 'Elevation map of Europe 1 km x 1 km'.
URL: eea.europa.eu/dataandmaps/data/digitalelevationmodelofeurope, Accessed: 01.08.2019.

Facchini, G. & Mayda, A. (2008), 'From individual attitudes towards migrants to migration policy outcomes: Theory and evidence', *Economic Policy* **23**(56), 652–713.

Facchini, G. & Mayda, A. (2009), 'Does the welfare state affect individual attitudes toward immigrants? Evidence across countries', *The Review of Economics and Statistics* **91**(2), 295–314.

Facchini, G. & Steinhardt, M. (2011), 'What drives US immigration policy? Evidence from congressional roll call votes', *Journal of Public Economics* **95**(7), 734–743.

Federal Election Commission (1970-2014), 'Election results for the U.S. president, the U.S. senate and the U.S. house of representatives', Public Disclosure Division, Office of Communications.
URL: https : //transition.fec.gov/pubrec/electionresults.shtml (last access: December 19, 2018).

Feenstra, R. C. & Hanson, G. H. (1999), 'The impact of outsourcing and high-technology capital on wages: estimates for the united states, 1979–1990', *The Quarterly Journal of Economics* **114**(3), 907–940.

Feigenbaum, J. & Hall, A. (2015), 'How legislators respond to localized economic shocks: Evidence from Chinese import competition', *The Journal of Politics* **77**(4), 1012–1030.

Fetzer, J. (2006), 'Why did House members vote for HR 4437?', *International Migration Review* **40**(3), 698–706.

Fisher, G. H. (1986), 'A short note on the long history of chemistry education', *The Science Teacher* **53**(4), 35–37.

Foster, A. D. & Rosenzweig, M. R. (1995), 'Learning by doing and learning from others: Human capital and technical change in agriculture', *Journal of political Economy* **103**(6), 1176–1209.

Franck, R. & Galor, O. (2019), 'Flowers of evil? industrialization and long run development', *Journal of Monetary Economics* .

Frey, C., Berger, T. & Chen, C. (2018), 'Political machinery: Did robots swing the 2016 US presidential election?', *Oxford Review of Economic Policy* **34**(3), 418–442.

Fuchs, S. (2018), 'The spoils of war: Trade shocks during WWI and Spain's regional development', *mimeo* .

Gaggl, P., Gray, R., Marinescu, I. E. & Morin, M. (2019), 'Does electricity drive structural transformation? evidence from the united states'.

Gallego, A., Kurer, T. & Schöll, N. (2018), Not so disruptive after all: How workplace digitalization affects political preferences, Technical report, Barcelona GSE Working Paper Series.

Galor, O. (2011), *Unified growth theory*, Princeton University Press.

Galor, O. & Moav, O. (2006), 'Das human-kapital: A theory of the demise of the class structure', *The Review of Economic Studies* **73**(1), 85–117.

Gimpel, J. & Edwards, J. (1999), *The congressional politics of immigration reform*, Allyn & Bacon.

Giorcelli, M. (2019), 'The long-term effects of management and technology transfers', *American Economic Review* **109**(1), 121–52.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N. & Topalova, P. (2010), 'Imported intermediate inputs and domestic product growth: Evidence from India', *The Quarterly Journal of Economics* **125**(4), 1727–1767.

Goldberg, P., Khandelwal, A., Pavcnik, N. & Topalova, P. (2009), 'Trade liberalization and new imported inputs', *American Economic Review* **99**(2), 494–500.

Goldin, C. (1994), The political economy of immigration restriction in the United States, 1890 to 1921, *in* 'The regulated economy: A historical approach to political economy', University of Chicago Press, pp. 223–258.

Goldin, C. & Katz, L. F. (1998), 'The origins of technology-skill complementarity', *The Quarterly journal of economics* **113**(3), 693–732.

Goldin, C. & Katz, L. F. (2001), 'The legacy of us educational leadership: Notes on distribution and economic growth in the 20th century', *American Economic Review* **91**(2), 18–23.

Goldin, C. & Sokoloff, K. (1982), 'Women, children, and industrialization in the early republic: Evidence from the manufacturing censuses', *The Journal of Economic History* **42**(4), 741–774.

Goldsmith-Pinkham, P., Sorkin, I. & Swift, H. (2018), Bartik instruments: What, when, why, and how, Technical report, National Bureau of Economic Research.

Goldstein, J. & Peters, M. (2014), 'Nativism or economic threat: Attitudes toward immigrants during the Great Recession', *International Interactions* **40**(3), 376–401.

Gollin, D., Hansen, C. W. & Wingender, A. (2018), Two blades of grass: The impact of the green revolution, Technical report, National Bureau of Economic Research.

Gollin, D., Lagakos, D. & Waugh, M. E. (2014), 'The agricultural productivity gap', *The Quarterly Journal of Economics* **129**(2), 939–993.

Gonon, P. (1997), 'Schule im spannungsfeld zwischen arbeit, elementarer bildung und beruf', *Geschichte der Erziehung und Schule in der Schweiz im* **19**, 57–88.

Gonzalez, J. & Kamdar, N. (2000), 'Do not give me your tired, your poor! Determinants of legislator voting on immigration issues', *Eastern Economic Journal* **26**(2), 127–143.

Goos, M., Manning, A. & Salomons, A. (2014), 'Explaining job polarization: Routine-biased technological change and offshoring', *The American Economic Review* **104**(8), 2509–2526.

Grob, C. (1887-1914), *Jahrbuch des Unterrichtswesens in der Schweiz*, Orell Füssli & Cie., Zürich.

Grossman, G. M. & Rossi-Hansberg, E. (2008), 'Trading tasks: A simple theory of offshoring', *American Economic Review* **98**(5), 1978–97.

Gupta, B. & Roy, T. (2017), From artisanal production to machine tools - Industrialization in India over the long run, *in* K. H. O'Rourke & J. G. Williamson, eds, 'The Spread of Modern Industry to the Periphery Since 1871', Oxford University Press.

Halbeisen, P., Müller, M. & Veyrassat, B. (2017), *Wirtschaftsgeschichte der Schweiz im 20. Jahrhundert*, Schwabe AG.

Hall, B. H. & Rosenberg, N. (2010), *Handbook of the Economics of Innovation*, Vol. 1, Elsevier.

Hanson, G., Scheve, K. & Slaughter, M. (2007), 'Public finance and individual preferences over globalization strategies', *Economics & Politics* **19**(1), 1–33.

Hare, C. & Poole, K. T. (2014), 'The polarization of contemporary American politics', *Polity* **46**(3), 411–429.

Hatton, T. & Williamson, J. (2005), *Global migration and the world economy*, MIT Press, Cambridge, Massachusetts.

Haubert, J. & Fussell, E. (2006), 'Explaining pro-immigrant sentiment in the US: Social class, cosmopolitanism, and perceptions of immigrants', *International Migration Review* **40**(3), 489–507.

Hausmann, R. & Rodrik, D. (2003), 'Economic development as self-discovery', *Journal of Development Economics* **72**(2), 603–633.

Hirsch, B., Macpherson, D. & Vroman, W. (2001), 'Estimates of union density by state', *Monthly Labor Review* **124**(7), 51–55.

HLS (2020), Historisches Lexikon der Schweiz, Schweizerische Akademie der Geistes- und Sozialwissenschaften, Bern.
URL: hls − dhs − dss.ch, Accessed: 05.10.2020.

Homburg, E., Travis, A. S. & Schröter, H. G. (1998), *The chemical industry in Europe, 1850–1914: Industrial growth, pollution, and professionalization*, Vol. 17, Springer Science & Business Media.

Hsiang, S. M. (2010), 'Temperatures and cyclones strongly associated with economic production in the caribbean and central america', *Proceedings of the National Academy of sciences* **107**(35), 15367–15372.

HSSO (2012), 'Population Income of Cantons in current Swiss Francs 1890-2001'.
URL: hsso.ch/2012/q/19, Accessed: 06.06.2020.

Hunter, L. C. & Bryant, L. (1979-1991), *A History of Industrial Power in the US, 1780-1930*, Vol. I-III, Charlottesville: The University Press of Virginia & Cambridge: MIT Press.

India Office (1937), *Return showing the results of elections in India 1937*, Her Majesty's Stationery Office.

Indian Delimitation Committee (1936), *Report of the Indian Delimitation Committee*, Manager of Publications.

Indian National Congress (1922), *Civil Disobedience Enquiry Committee Report, 1922*, Tagore.

Jaeger, D. A., Ruist, J. & Stuhler, J. (2018), Shift-share instruments and the impact of immigration, Technical report, National Bureau of Economic Research.

Jovanovic, B. & Rousseau, P. L. (2005), General purpose technologies, *in* 'Handbook of Economic Growth', Vol. 1, Elsevier, pp. 1181–1224.

Juhász, R. (2018), 'Temporary protection and technology adoption: Evidence from the Napoleonic blockade', *American Economic Review* **108**(11), 3339–76.

Juhász, R., Squicciarini, M. & Voigtländer, N. (2019), 'Technology adoption and productivity growth during the industrial revolution: Evidence from france', *Available at SSRN 3507694* .

Kammerer, P., Müller, M., Tanner, J. & Woitek, U. (2012), 'Historical statistics of Switzerland online'.
URL: fsw.uzh.ch/histstat/, Accessed: 13.09.2019.

Kapur, K. N. (1949), *The Factories Act 1948 & The Payment of Wages Act*, Premier Publishing Co., Fountain-Dehli.

Katz, L. F. & Margo, R. A. (2014), Technical change and the relative demand for skilled labor: The united states in historical perspective, *in* 'Human capital in history: The American record', University of Chicago Press, pp. 15–57.

Katz, L. & Murphy, K. (1992), 'Changes in relative wages, 1963–1987: Supply and demand factors', *The Quarterly Journal of Economics* **107**(1), 35–78.

Kelly, M. (2020*a*), 'Direct standard errors for regressions with spatially autocorrelated residuals'.

Kelly, M. (2020*b*), 'Understanding persistence'.

Kelso, N. V. & Patterson, T. (2009), 'Natural earth vector', *Cartographic Perspectives* (64), 45–50.

Kemp, M. C. (1960), 'The Mill-Bastable infant-industry dogma', *Journal of Political Economy* **68**(1), 65–67.

Kitchens, C. (2014), 'The role of publicly provided electricity in economic development: the experience of the Tennessee Valley Authority, 1929–1955', *The Journal of Economic History* **74**(2), 389–419.

Kitchens, C. & Fishback, P. (2015), 'Flip the switch: The impact of the rural electrification administration 1935–1940', *The Journal of Economic History* **75**(4), 1161–1195.

Kohli, A. (2004), *State-directed development: Political power and industrialization in the global periphery*, Cambridge University Press.

Krishna, G. (1966), 'The development of the Indian National Congress as a mass organization, 1918-1923', *The Journal of Asian Studies* **25**(3), 413–430.

Krueger, A. (1993), 'How computers have changed the wage structure: Evidence from microdata, 1984–1989', *The Quarterly Journal of Economics* **108**(1), 33–60.

Krugman, P. (1991), 'History and industry location: the case of the manufacturing belt', *The American Economic Review* **81**(2), 80–83.

Kulke, H. & Rothermund, D. (2016), *A history of India*, Routledge.

Kuznets, S. (1957), 'Quantitative aspects of the economic growth of nations: Ii. industrial distribution of national product and labor force', *Economic development and cultural change* **5**(S4), 1–111.

Kuznets, S. (1973), 'Modern economic growth: findings and reflections', *The American economic review* **63**(3), 247–258.

Landes, D. S. (1969), *The unbound Prometheus: Technological change and development in Western Europe from 1750 to the present*, Cambridge University Press.

Lee, K., Miguel, E. & Wolfram, C. (2020), 'Does household electrification supercharge economic development?', *Journal of Economic Perspectives* **34**(1), 122–44.

Lehmann, S. H. & O'Rourke, K. H. (2011), 'The structure of protection and growth in the late nineteenth century', *Review of Economics and Statistics* **93**(2), 606–616.

Leknes, S. & Modalsli, J. (2020), 'Who benefited from industrialization? the local effects of hydropower technology adoption in norway', *The Journal of Economic History* **80**(1), 207–245.

Lewis, E. (2011), 'Immigration, skill mix, and capital skill complementarity', *The Quarterly Journal of Economics* **126**(2), 1029–1069.

Lewis, E. & Peri, G. (2015), Immigration and the economy of cities and regions, *in* 'Handbook of Regional and Urban Economics', Vol. 5, Elsevier, pp. 625–685.

Lewis, J., DeVine, B., Pitcher, L. & Martis, K. (2013), 'Digital Boundary Definitions of United States Congressional Districts, 1789-2012.'.
URL: `http : //cdmaps.polisci.ucla.edu` (last access: Febuary 16, 2017).

Lewis, J. & Severnini, E. (2019), 'Short-and long-run impacts of rural electrification: evidence from the historical rollout of the us power grid', *Journal of Development Economics* p. 102412.

Lipscomb, M., Mobarak, A. M. & Barham, T. (2013), 'Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil', *American Economic Journal: Applied Economics* **5**(2), 200–231.

Litman, S. (1926), 'The effects of the World War on trade', *The annals of the American Academy of Political and Social Science* **127**(1), 23–29.

Liu, C. (2020), 'The effects of World War I on the Chinese textile industry: Was the world's trouble China's opportunity?', *The Journal of Economic History* pp. 1–40.

Lockwood, D. (2012), *The Indian bourgeoisie: A political history of the Indian capitalist class in the early twentieth century*, Vol. 5, IB Tauris.

Lucas, R. E. (1988), 'On the mechanics of economic development', *Journal of Monetary Economics* **22**(1), 3–42.

Lunge, G. (1901), *Zur Geschichte der Entstehung und Entwicklung der chemischen Industrien in der Schweiz*, Schweizerische Gesellschaft für Chemische Industrie.

Mägli, U. (1989), *Geschichte der gewerblichen und kaufmännischen Berufsbildung im Kanton Zürich: von 1830 bis zur Gegenwart*, Sauerländer.

Mansfield, E. (1961), 'Technical change and the rate of imitation', *Econometrica: Journal of the Econometric Society* pp. 741–766.

Manson, S., Schroeder, J., Van Riper, D. & Ruggles, S. (2019), 'IPUMS National Historical Geographic Information System: Version 14.0 [Database].', Minneapolis, MN. **URL:** `http://doi.org/10.18128/D050.V14.0` (last access: Novermber 25, 2019).

Markovits, C. (2002), *Indian business and nationalist politics, 1931-1939: The indigenous capitalist class and the rise of the Congress Party*, Cambridge University Press.

Mayda, A. (2006), 'Who is against immigration? A cross-country investigation of individual attitudes toward immigrants', *The Review of Economics and Statistics* **88**(3), 510–530.

Mayhew, D. R. (1974), *Congress: The electoral connection*, Yale University Press.

Melitz, M. J. (2005), 'When and how should infant industries be protected?', *Journal of International Economics* **66**(1), 177–196.

Mincer, J. A. (1974), Age and experience profiles of earnings, *in* 'Schooling, experience, and earnings', NBER, pp. 64–82.

Mitchener, K. J. & Weidenmier, M. (2008), 'Trade and empire', *The Economic Journal* **118**(533), 1805–1834.

Mokyr, J. (1992), *The lever of riches: Technological creativity and economic progress*, Oxford University Press.

Mokyr, J. (2010), The contribution of economic history to the study of innovation and technical change: 1750–1914, *in* 'Handbook of the Economics of Innovation', Vol. 1, Elsevier, pp. 11–50.

Molinder, J., Karlsson, T. & Enflo, K. (2019), More Power to the People: Electricity Adoption, Technological Change and Social Conflict, Lund Papers in Economic History 206, Lund University, Department of Economic History.

Moneke, N. (2019), Can big push infrastructure unlock development? evidence from ethiopia, Technical report, Mimeo.

Moore, R. (1983), 'Jinnah and the Pakistan demand', *Modern Asian Studies* **17**(4), 529–561.

Morris, M. D. (1983), The growth of large-scale industry to 1947, *in* D. Kumar & M. Desai, eds, 'The Cambridge Economic History of India', Vol. 2, Cambridge University Press.

Neuman, S. & Ziderman, A. (1991), 'Vocational schooling, occupational matching, and labor market earnings in Israel', *Journal of Human Resources* pp. 256–281.

NobelPrize.org (2020), 'Paul Müller - Biographical'.
URL: nobelprize.org/prizes/medicine/1948/muller/, Accessed: 20.03.2020.

Nye, D. (1992), 'Electrifying america: Social meanings of a new technology'.

Olson, D., Dinerstein, E., Wikramanayake, E. et al. (2001), 'Terrestrial ecoregions of the world', *BioScience* **51**(11), 933–938.

O'Rourke, K. H. & Sinnott, R. (2006), 'The determinants of individual attitudes towards immigration', *European journal of political economy* **22**(4), 838–861.

O'Rourke, K. H. & Williamson, J. G. (2017), *The spread of modern industry to the periphery since 1871*, Oxford University Press.

Ottaviano, G. I. & Peri, G. (2012), 'Rethinking the effect of immigration on wages', *Journal of the European economic association* **10**(1), 152–197.

Pandey, D. (1978), 'Congress-Muslim League relations 1937–39: The parting of the ways', *Modern Asian Studies* **12**(4), 629–654.

Phillips, A. W. (1958), 'The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861–1957', *economica* **25**(100), 283–299.

Pierce, J. & Schott, P. (2016), 'The surprisingly swift decline of US manufacturing employment', *American Economic Review* **106**(7), 1632–62.

Poole, K. & Rosenthal, H. (2000), *Congress: A political-economic history of roll call voting*, Oxford University Press.
URL: http : //voteview.com/ (last access: Febuary 16, 2017).

Poole, K. T. & Rosenthal, H. (1984), 'The polarization of American politics', *The Journal of Politics* **46**(4), 1061–1079.

Prideaux, W. (1917), *A guide to the Indian Factories Act*, Thacker, Spink & Co.

Ramankutty, N., Evan, A., Monfreda, C. & Foley, J. (2010), 'Global agricultural lands: Croplands, 2000', *NASA SEDAC, Palisades* **10**.

Romer, P. M. (1990), 'Endogenous technological change', *Journal of political Economy* **98**(5, Part 2), S71–S102.

Rosenberg, N. (1972), 'Factors affecting the diffusion of technology', *Explorations in economic history* **10**(1), 3.

Roth, H. (1920), ‘Elektrizitätsversorgung der Schweiz’, *Naturwissenschaften* **8**(14), 271–277.

Rothermund, D. (1992), *India in the Great Depression, 1929-1939*, Vol. 6, Manohar Publications.

Roy, T. (2002), ‘Economic history and modern India: redefining the link’, *Journal of Economic Perspectives* **16**(3), 109–130.

Rud, J. P. (2012), ‘Electricity provision and industrial development: Evidence from india’, *Journal of development Economics* **97**(2), 352–367.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E. & Sobek, M. (2019), ‘IPUMS USA: Version 9.0 [dataset]’, Minneapolis, MN.
URL: `https : //doi.org/10.18128/D010.V9.0` (last access: Novermber 25, 2019).

SBB (2020), ‘Open Data - working together for an attractive public transport’.
URL: `data.sbb.ch/pages/home/`, Accessed: 02.03.2020.

Scheve, K. & Slaughter, M. (2001), ‘Labor market competition and individual preferences over immigration policy’, *The Review of Economics and Statistics* **83**(1), 133–145.

Schröder, U., Hemund, C. & Weingartner, R. (2012), ‘Erhebung des kleinwasserkraftpotentials der schweiz’.

Sivasubramonian, S. (1997), ‘Revised estimates of the national income of India, 1900-1901 to 1946-47’, *The Indian Economic & Social History Review* **34**(2), 113–168.

Snyder Jr, J. & Groseclose, T. (2000), ‘Estimating party influence in congressional roll-call voting’, *American Journal of Political Science* pp. 193–211.

Squicciarini, M. P. & Voigtländer, N. (2015), ‘Human capital and industrialization: Evidence from the age of enlightenment’, *The Quarterly Journal of Economics* **130**(4), 1825–1883.

Statistischen Bureau (1880-1910), *Pädagogische Prüfung bei der Rekrutierung*, Eidg. Departement des Innern.

Stiel, W. (1933), *Elektrobetrieb in der Textilindustrie. Textile Electrification. A treatise on the application of electricity in textile factories.*, G. Routledge & Sons. Authorized translation by AF Rodger, etc.

Swissvotes (2019), ‘Swissvotes - the Database on the Swiss Popular Votes.’. Annee Politique Suisse, University of Bern
URL: `swissvotes.ch` , Accessed: 13.09.2019.

Tena-Junguito, A. (2010), ‘Bairoch revisited: Tariff structure and growth in the late nineteenth century’, *European Review of Economic History* **14**(1), 111–143.

Tomlinson, B. R. (2013), *The economy of modern India: From 1860 to the twenty-first century*, Vol. 3, Cambridge University Press.

Topalova, P. & Khandelwal, A. (2011), ‘Trade liberalization and firm productivity: The case of India’, *Review of Economics and Statistics* **93**(3), 995–1009.

Turner, C. (1923), The Indian Factories Act, 1911 as amended by the Indian Factories Amendment Act, 1922, Technical report, Bombay (Presidency). Laws.

UN Comtrade (1991-2010), 'UN Comtrade Database', United Nations, Trade Statistics Branch.
URL: https : //www.census.gov/data/datasets/1991/econ/cbp/1991 − cpb.html (last access: June 19, 2018).

United States Census Bureau (1991), 'County Business Patterns'.
URL: https : //www.census.gov/data/datasets/1991/econ/cbp/1991 − cpb.html (last access: June 19, 2018).

US Department of Commerce (1912), *Central electric light and power stations and street and electric railways*, Washington Goverment Printing Office.

US Department of Labor (1977), *Dictionary of occupational titles*, number 4th ed, Washington, DC: US Government Printing Office.

Vaidyanathan, A. (1983), The Indian economy since independence (1947-70), *in* D. Kumar & M. Desai, eds, 'The Cambridge Economic History of India', Vol. 2, Cambridge University Press.

Van de Walle, D., Ravallion, M., Mendiratta, V. & Koolwal, G. (2017), 'Long-term gains from electrification in rural India', *The World Bank Economic Review* **31**(2), 385–411.

Vanden Eynde, O. (2016), 'Military service and human capital accumulation: Evidence from colonial Punjab', *Journal of Human Resources* **51**(4), 1003–1035.

Wang, D. (2013), 'US-China trade: 1971-2012: Insights into the US-China relationship', *The Asia-Pacific Journal* **11**(24).

Weingartner, R. (2016), 'Wasserkraft: Zwischen roten Zahlen und grünen Ansprüchen. Bericht zum Seminar Wasserwirtschaft 2015 an der Uni Bern'.

Wettstein, E. (1987), *Die Entwicklung der Berufsbildung in der Schweiz*, Sauerländer Aarau.

Wolcott, S. (1991), 'British myopia and the collapse of Indian textile demand', *The Journal of Economic History* **51**(2), 367–384.

Wolcott, S. (1994), 'The perils of lifetime employment systems: Productivity advance in the Indian and Japanese textile industries, 1920–1938', *The Journal of Economic History* **54**(2), 307–324.

Wolcott, S. & Clark, G. (1999), 'Why nations fail: Managerial decisions and performance in Indian cotton textiles, 1890–1938', *The Journal of Economic History* **59**(2), 397–423.