The Role of “Warm-glow Giving” in Mitigating Climate Change and Promoting Sustainable Economic Growth

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To my parents
You gave me faith in myself because
you have always had faith in me.
I am the person I am because of you.

Abstract

This dissertation studies how the incentives behind the new direction of the international climate change negotiations since 2015 can be modelled by combining the two theories of *warm-glow giving* and endogenous growth. Linking these two theories in this context for the first time confirms that a country's environmental commitments and economic growth are not mutually exclusive. This dissertation provides a framework on which future International Environmental Agreements (IEAs) can be based in order to avoid an environmental disaster.

The first chapter explores how the voluntary premium that people are paying for sustainable energy can be explained by *warm-glow giving* theory and the escalating global concern about environmental degradation. An endogenous growth model with a *warm-glow giving* extension (WGPM) demonstrates a less expensive clean energy transition rather than a model relying exclusively on carbon taxes and clean R&D subsidies. However, *warm-glow* alone cannot explain the changes in climate change negotiations seen in the Paris Agreement and the emissions growth limit established. The second chapter demonstrates how this can be achieved by extending the WGPM to include nonhomothetic preferences.

As part of the solution for environmental degradation, chapter three will show how WGPM provides a decision-making tool for firms and policymakers in their cost-benefit analysis of emission reduction. This chapter, therefore, focuses on empirically validating WGPM through the design of a VEC model and demonstrates how the essential carbon tax value can be accurately captured and forecast by WGPM in the short term using data for the European Community economy.

Finally, chapter four supports our theoretical framework to the extent that it looks at how past IEAs until Paris failed in reducing emissions worldwide. A GVAR model is built based on 90% of global GDP, the total number of IEAs subscribed between 1995 and 2015, and, significantly, both inputs and outputs for industries. The model exposes how past IEA commitments on emissions targets were realised through some OECD countries 'off-shoring' to others.

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Declaration

The papers described in chapters 1 and 2 are co-authored with Omar Licandro (University of Nottingham). We preciously circulated them as working papers for the Centre for Finance, Credit and Macroeconomics (CFCM) of the University of Nottingham.

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Introduction

The 1990 UN Framework Convention on Climate Change (UNFCCC) declared climate change as a man-made degradation of the environment and identified emissions from fossil fuels as the leading cause. In the last thirty years, a dramatic rise in the accumulation of emissions in the atmosphere (64% between 1990 and 2018) has resulted in global mean temperature increasing in an "unprecedented" manner in 1,000 years [NASA, 2018]. In addition to threatening life on the planet, these changes are also threatening economies through reduction in productivity, limited options for growth and high economic costs for both present and future generations. Acknowledging, therefore, that the world was facing an environmental disaster, the convention concluded that achieving a worldwide agreement to reduce emissions was of paramount importance.

Following the 1990 climate change declaration and despite 33 international climate change conventions over 25 years, it proved impossible to reduce worldwide emissions. The world economy has been dependent on fossil fuels to generate energy since industrialisation began. In addition, to encourage growth in developing regions and sustain the living standards in the developed world, global energy demand has increased dramatically since 1970 and will continue to do so for the next 20 years at least[1]. It was not until 2015, under the umbrella of the Paris Agreement, that significant progress was made because, for the first time, 196 countries agreed to share responsibility and seek to limit the increase in the global average temperature below 2°C by 2050 [2] by searching for their own mechanisms to decarbonise their economies.

Paris opened a new chapter in climate change negotiations and evidenced the changes in society's culture and values occurring around that time. The *warm-glow giving* theory postulated by [Andreoni, 1990] could have been behind these changes, and as a result, raised people's awareness about environmental degradation and demand for more attention to be paid to "non economic aspects" which, as [Yergin, 2020] has pointed out, can

[1] By 2040, in eighteen years, global GDP is set to double and energy demand to increase by about 30%[BP, 2018]

[2] Limit established for the Intergovernmental Panel on Climate Change (IPCC) as the maximum increase in the temperature that the planet can afford before facing an environmental disaster such as species extinctions, dramatic increase in sea level and so on.

be one of the greatest motivators for energy transition. However, proving that connection requires an approach that quantifies the impacts of this greater sense of responsibility on sustainable growth and industrial configuration worldwide. Until now, and as far as we are aware, literature has paid little attention to this topic.

The literature on the economics of climate change, which analyses the impacts of economic activity on the environment, usually focuses on strategies to internalise the real cost of environmental degradation by levying taxes that discourage the use of non-renewable energy and providing subsidies for sustainable energy innovation. The largest part of this literature has been based on the Integrated Assessment Models (IAMs), a framework that brings together knowledge from economic and physical science to find the optimal policy. A second approach, linked with economic growth theory and less detailed climate variables, analyses policy options to promote innovation in less energy intensive and clean technologies. The third approach, using empirical methods, has focused primarily on the impacts of environmental policies on the confirguration of the sectors in an economy and trade.

Despite this massive advance in the literature, further theoretical assumptions and different empirical techniques are required to fully understand the impacts on economic growth across sectors of the past IEAs and to model the incentives that made possible the Paris Agreement and the common goal of limiting emissions by 2050. Acknowledging this gap, we are interested in responding to four questions: (I) if people are experiencing a *warm-glow* when they are voluntarily paying more for sustainable energy, what are the policies that countries have to undertake to avoid an environmental disaster? (II) could a growth model with *warm-glow* preferences be extended to include nonhomothetic preferences and fully explain the success of the Paris Agreement in achieving every country's commitment that will avoid an environmental disaster? (III) did the adoption of the IEAs before Paris reduce the level of dirtiness of its sectoral outputs in a region? or on the contrary, (IV) did they amplify the importance of the "off-shoring" effect?.

This dissertation proposes two new ways to respond to these important questions: firstly, it searches for an alternative and voluntarily channel to correct environmental externalities by giving individuals a more active role in combating climate change and not waiting passively for governmental intervention. Secondly, this study looks back at the history of the IEAs and shifts the attention from their impacts on manufacturing industries exclusively, towards impacts across industries, across regions and the interrelationships among them. In order to do that, this dissertation is divided into five chapters in adition to this introduction. In the first chapter we focus particularly on the fact that people are taking actions to tackle climate change and make compatible the economic growth and the sustainability of the planet. This escalating public concern about environmental degradation and the premium that people are voluntarily paying for sustainable energy support the design of a model which links the two theories of *warm-glow giving* and economic growth with directed technical change. The model suggests a way to reach greater clean energy innovation over dirty rather than a model relying exclusively on carbon taxes, also called social cost of carbon or carbon price, and clean R&D subsidies.

The second chapter extends this approach to fully model the Paris Agreement. This extension shows that the individual's attitude linked to "impure altruism" (*warm-glow giving*) [Andreoni, 1990] cannot explain alone the 196-commitment achieved because the countrys' available resources limit this. Therefore, adding heterogeneity in the income elasticity of demand across consumption goods, known as nonhomothetic preferences, allows us to understand *warm-glow* theory also as a reflection of the people's responsiveness to income growth and explain why the wealthier countries could voluntarily do more, and collectively stop the advance of climate change before the world faces an environmental disaster.

Exploring the relationship between environmental policies and growth with empirical methods, chapter 3 builds on the theoretical framework developed in the first two chapters. We prove in this chapter the accuracy of WGPM by building a Vector Error Correction Model (VECM) to forecast the carbon price in the European Community. In so doing, this chapter proves a tool to analyse future carbon price scenarios, which is crucial for firms and policymakers in their decision-making process related to their emissions reduction goals in the short-term.

Finally, the chapter 4 validates our theoretical framework by demonstrating how IEAs before Paris failed in limiting emissions growth worldwide. Using the input-output tables for seven regions that cover 90% of the global GDP, a GVAR model is built. This determines the impacts of the IEAs adopted worldwide on growth across industries over the twenty years before Paris. Disaggregating these impacts into two kinds: impacts on technology changes (technology intervention) and impacts on input-output ratio growth (input intervention); the study analyses to what extent, in each region, the IEAs reduced or not the level of dirtiness, known as the amount of emissions generated per unit of output, in the economic sectors or if the agreements stimulated the presence of the "off-shoring effect".

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1 | "Warm-glow" Preferences and Sustainable Growth

1.1 Introduction

Global energy demand has dramatically increased since 1970 to encourage growth in developing regions and sustain the living standards in the developed world, and it will continue to do so for the next 20 years at least[1]. Since industrialisation began, the world economy has been dependent on fossil fuels to meet that energy demand, and by doing so, they have been responsible for an excessive amount of carbon dioxide (CO2) and other greenhouse gases (GHGs) accumulated in the atmosphere, leaving us, as a result, with the climate change phenomenon. This creates high economic costs for present and future generations because it reduces productivity and limits options for economic growth, specifically in regions that are still in the early stages of development.

The actions required to tackle the environmental degradation are challenging to the extent that they will achieve benefits in the very distant future but they involves redistribution of current resources and sacrifices in current social welfare. In other words, society must decide how balance the welfare of the present generation and future ones, taking into account the right of future generations to enjoy an environment similar to the one every-

[1] By 2040, in eighteen years, global GDP is set to double and energy demand to increase by about 30%[BP, 2018]

one is enjoying now, society's ethical obligation to preserve the planet, and the fact that future generations might have more financial resources to deal with the possibility of a worse climate.

Another difficult issue in combating climate change is its inherent characteristic of being a public good. Therefore, traditional economic theory has established that people do not recognise the impact of some of their actions on other people, and governments have to intervene to correct market failures. However, as [Falkner, 2016] explains, in the last decade, around the world, local community groups have spring up to advance voluntary carbon emissions reductions; multinational corporations have increasingly invested in low-carbon business opportunities and adopted corporate social responsibility approaches with an explicit focus on climate change; institutional investors have begun to demand greater transparency on climate risks in business operations; and subnational authorities (cities and municipal governing bodies) have taken it upon themselves to create climate mitigation pledges and policies.

This awareness of the necessity of making compatible the economic growth and the sustainability of the planet has been changing domestic policies and stimulating the global coordination interest for finding definitive environmental solutions in each country. In 2015, as a result of those different forces, Paris Agreement emerged as a more decisive accord to abate climate change because the dynamic of the negotiations switched. Countries have to make public their pledges, and those are going to be internationally compared and reviewed every five years; then, global ambition can be increased through a process of "naming and shaming".

One of the theoretical explanation about why the Paris agreement might work is found in the behavioural forces encouraging the public concern about environmental degradation previously stated. According to [Andreoni, 1990] one of these forces might be "Impure Altruism", some individuals are donating to privately provide public goods to receive a "warm-glow" for many factors other than altruism. Moreover, individuals knows that their individuals actions are negligible in the solution of the problem, but they are still persisting, because they want to satisfy social and psychological objectives by taking actions considered virtuous [Feddersen and Sandroni, 2009].

The literature of the economics of climate change analyses the impacts of economic activity on the environment. It usually proposes strategies to internalise the real cost of environmental degradation, by levying taxes that discourage the production of carbon energy, and by providing a subsidy for clean energy innovation. The largest part of this literature has been based on the Integrated Assessment Models (IAMs), a framework that brings together knowledge from economic and physical science to find the optimal policy to be implemented. A second approach, linked with economic growth theory and less detailed climate variables, analyses policy options to promote innovation in cleaner energy sources.

In this sense, the aim of this chapter is to model how public concern about climate degradation may contribute to transitioning towards sustainable energy with less governmental distortions (taxes and subsidies). In order to do that, an endogenous economic growth model with environmental constraint developed by [Acemoglu et al., 2012], will be extended. This extension reflects the *warm-glow* received by the individual when unilaterally decides to consume clean over dirty energy. Hence, this study is the first one to search for an alternative and voluntary channel to correct environmental externalities by giving individuals a more active role in combating climate change and not wait passively for governmental intervention.

This chapter is organised as follows: section 1.2, reviews the literature of the economics of climate change and empirical evidence of the willingness to pay for sustainable energy; section 1.3 describes the model, sections 1.4, 1.5 and 1.6, explains the decentralised equilibrium, the central planner solution of the model, and the implementation of the optimal policy respectively; description of the numerical exercises are in sections 1.7 and 1.8. Finally section 1.9 presents the main conclusion.

1.2 Energy Transition, Economic Growth and Climate Change Impacts

The literature of economics of climate change concentrates on estimating: impacts of economic activity on the environment, reduction in social welfare because of climate change, and cost of abatement polices. [Nordhaus, 1991] was the first attempt to explain and measure the economic impacts of climate change over welfare in an integrated model and to advise about optimal policies. However, the most recognised IAM was developed by [Nordhaus, 1993] and called Dynamic Integrated Climate and Economy Model (DICE). DICE extended the Ramsey Model to include detailed climate constraints and in so doing, permits the estimation of the social cost of carbon, conventionally termed as carbon tax.

ENTICE [Popp, 2004] and MIND [Edenhofer et al., 2005] were the first IAMs to consider the endogenous technical change. ENTICE was based on empirical evidence in the US, where changes in the relative prices among energy sources were related to innovation in the energy industry. MIND segregated the energy sector and concluded, first, that endogenous rather than exogenous technological change substantially reduced abatement costs, and, second, mitigation policies were required to encourage the transition to the only use of renewable energy.

[Acemoglu et al., 2012] introduced directed technical change and environmental constraints into a growth model, which simplifies mathematically the treatment of the environment. The term “directed” refers to a way to endogenise the direction and bias of new technical change, and, in this model these changes are driven by public policies. This paper concludes that in the long-term, with zero intervention, advancement in dirty innovation causes dirty input production and drives the economy to an environmental disaster. However, if an optimal policy (carbon tax and clean R&D subsidy) is implemented, advancement in the clean sector takes place and an environmental disaster will be avoided.

[Acemoglu et al., 2014] extended their previous work to evaluate how global coordination is necessary to avoid an environmental disaster in the economy of two countries, the North and the South, which produce the same final good using clean and dirty inputs. The model assumes that the North practices innovation in both sectors and is more technically advanced, and the South evolves through imitation of the technology in the North. The paper concludes that under free trade, a global central planner must impose differentiated carbon taxes and clean R&D subsidies in both countries to avoid an environmental disaster.

[Hémous, 2016] built on [Acemoglu et al., 2014] in the following two ways; by differentiating between highly polluting and non-polluting tradable sectors, and by including the possibility of innovation in the South. He demonstrates that a more complex policy (carbon tax, clean R&D subsidy and trade tax) must be imposed in the North to prevent an environmental disaster. [Manson and Rémi Morin, 2018] returned to the seminal approach and proposed a neoclassical growth model where utility is a function of three variables: consumption, level of pollution, and capacity of renewable resources to produce energy. This approach introduces the concept of sustainability (societal well-being must never decline) and links it to the need to eliminate the consumption of non-renewable polluting resources.

During the last twenty years, this literature has also been interested in defining why different societies are increasing their willingness to pay for environmental conservation. For example, [Perfecto et al., 2005] established a theoretical approach for the success of environmental certification that depends on consumers willing to pay premium prices for a product that conserves biodiversity. From an empirical point of view, two works link to our hypothesis; the first one is [Arnot et al., 2006] which concludes that in the US, ethical attributes may be the primary influence on coffee purchasing behaviour for most consumers of fair trade coffee. The second, [Carlson, 2009] concludes that if fair trade coffee costs more than the non-fair trade coffee, most of this extra cost will be covered by the consumers, and could mean that "moral consumers" would be a solution to negative externalities and there would be no need for "Pigovian taxes".

There is literature which addresses contingent evaluation studies in different countries and regions to find specific evidence about the willingness to pay for sustainable energy. [Murakami et al., 2015] found that awareness of global environmental problems combined with knowledge of what is required to reduce GHGs emissions move people to pay for sustainable electricity in the US and Japan. In addition, [Ivanova, 2013] discovered that consumers in Australia expressed willingness to pay for renewable energy, and [Soon and Ahmad, 2015] meta-analysis showed that most EU consumers are willing to pay for green energy. [Lee et al., 2017] demonstrated that people in South Korea are willing to pay higher prices for their monthly electricity bills, especially when they have young children and an awareness of global environmental problems. Finally, there is evidence of willingness to pay for sustainable energy in developing countries such as China, Crete and Slovenia ([Xie and Zhao, 2018],[Zografakis et al., 2010] and [Zorić and Hrovatin, 2012] correspondingly).

1.3 Two-sector Growth Model with *Warm-glow* Preferences

The proposed approach is an extension of growth model with directed technical change and environmental constraint developed by [Acemoglu et al., 2012] in an infinite-horizon discrete time. The main extension is a modification in the utility function which reflects the *warm-glow* individuals receive when they choose to improve the environment by consuming the clean energy option.

As was established by [Acemoglu et al., 2012] and [Acemoglu, 2008] the key factors of a growth model with directed technical change are the *market size* and the *price* effects. The market size effect drives innovation towards the sector with higher allocation of labour meanwhile the price effect will do towards the sector which has higher prices. In that sense, if the theory proposes in this study is true, prices will be the channel across which the *warm-glow* operates to stimulate clean energy innovation with low (or without) governmental intervention. However, whichever the effect dominates their magnitudes depend on two factors: (i) elasticity of substitution between two sectors; and (ii) the relative levels of development of the technologies of the two sectors.

The main implication of the analysis is that, if we assume the world as single economy, the foundations of the Paris Agreement will be reflecting in the *warm-glow* parameter ϕ to the extent that average individual is giving more value to clean over dirty energy consumption in her utility. This new approach might alter the inevitable result of environmental disaster obtained in [Acemoglu et al., 2012] and [Acemoglu et al., 2014] under decentralised equilibrium and it also shows that governmental intervention via carbon taxes and clean R&D research subsidies to avoid that disaster could be lower or suppressed.

1.3.1 Households and Homothetic Preferences

It is assumed that there is a unit mass of homogeneous workers, each of them endowed with one unit of labour, a unit mass of homogeneous scientists, each of them endowed with one unit of research services, and a unit mass of homogeneous potential entrepreneurs. There is also a unit mass of identical households grouping each a worker, a scientist and an entrepreneur.

Preferences of the representative household are represented by

$$u_t = \sum_{t=0}^{\infty} \beta^t \frac{(C_t E_t)^{1-\theta}}{1-\theta}, \tag{1.1}$$

where C_t is consumption as defined below and E_t is the quality of the environment; $\beta = \frac{1}{1+\rho}$ is the subjective discount factor and $\theta > 1$ is the inverse of the inter-temporal elasticity of substitution.

Finally, it considers that final consumption C_t is a CES utility function representing household preferences on both clean c_{ct} and dirty c_{dt} final consumption according to:

$$C_t = \left((1+\phi)c_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + c_{dt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1.2}$$

The elasticity of substitution between clean and dirty consumption is $\varepsilon > 0$. *Warm-glow* is modelled here through the parameter ϕ, $\phi \geq 0$. We interpret the case $\phi = 0$ as the situation where people only care about the direct utility of consuming the clean good, ϕ, measuring any addition to utility related to the fact that they feel a *warm-glow* by helping to reduce pollution.

At any period t, the representative household chooses c_{ct} and c_{dt} to maximise consumption (1.2) subject to the budget constraint:

$$p_{ct}c_{ct} + p_{dt}c_{dt} = w_t + \pi_{ct} + \pi_{dt} \tag{1.3}$$

The price of both energy sources p_{ct} and p_{ct}, wages w_t, and profits earned by scientists and entrepreneurs, π_{ct} and π_{dt}, are all taken as given. The labour supply is assumed to be infinitely inelastic, as well as the supply of scientists and entrepreneurs. Scientists may direct their effort to the clean or the dirty sectors. Their sectorial choice is studied in section 1.3.3.2.

1.3.2 Environment

$$E_{t+1} = \max\{\ \min\{\bar{E}, -\xi c_{dt} + (1+\delta)E_t\}, 0\} \tag{1.4}$$

where $\xi > 0$ measures the environmental degradation caused by producing the dirty consumption good; δ is a natural environmental regeneration rate. When E_t crosses zero, emissions are sufficiently large to cause an environmental disaster with the economy reaching a “point of no return”.

Notice that sustainability requires that $c_{dt} < \frac{(1+\delta)\bar{E}}{\xi}$, a necessary but not sufficient condition. Sustainable growth then requires dirty production to be bounded.

1.3.3 Production and Innovation Possibilities Frontier

There are two types of producers: final and intermediate goods producers. A unit mass of identical firms produce the clean consumption good and another unit mass of identical firms produce the dirty consumption good. Both operate under perfect competition and use sector specific intermediate goods as the sole production input. Intermediate producers operate under monopolistic competition and use labour as the sole production factor.

1.3.3.1 Clean and Dirty Sectors

Firms in the clean and dirty sectors use a continuum of intermediate inputs x_{jit}, for j $\in \{c,d\}$ and i $\in$ (0, 1), to produce the clean and dirty consumption goods, respectively. The CES production function for j $\in c,d$, is

$$c_{jt} = \left(\int_0^1 \left(A_{jit} x_{jit}\right)^{\alpha} di \right)^{\frac{1}{\alpha}} \tag{1.5}$$

With parameter $\alpha \in$ (0, 1); in each sector (clean or dirty) the elasticity of substitution among intermediate good is $\frac{1}{1-\alpha}$.

1.3.3.2 Innovation

Innovation drives growth by improving the quality A_{jit}, $j \in \{c, d\}$ and $i \in (0, 1)$, of differentiating intermediate inputs in both sectors. At the beginning of period *t*, as in [Acemoglu et al., 2012], scientists decide in which sector they will *direct* their research, with s_{ct} optimally doing research in the clean sector and s_{dt} in the dirty sector; s_{ct} + s_{dt} = 1. Then, scientists are randomly allocated to one of the intermediate inputs in the sector; they research this sector, and if successful, monopoly rights to produce that variety are assigned to them. They operate this variety as entrepreneurs. Monopoly rights of the remaining intermediate inputs, for both $j \in \{c, d\}$, are randomly assigned to potential entrepreneurs.

Each scientist has a probability $\eta_j \in$ (0, 1), $j \in \{c, d\}$, of being successful on improving the quality of the particular intermediate input she was assigned to. When a scientist is lucky, the quality of the intermediate input increases at the rate $\gamma > 0$. Consequently, the quality of intermediate input *i* in sector *j*, $j \in \{c, d\}$, follows the process:

$$A_{jit} = \begin{cases} (1+\gamma)A_{jit-1} & \text{with probability} \quad \eta_j \\ A_{jit-1} & \text{with probability} \quad 1-\eta_j \end{cases} \tag{1.6}$$

which allows us to set that the average qualities in each sector *j* evolves like:

$$A_{jt} = (1+\gamma\eta_j s_{jt})A_{jt-1}, \tag{1.7}$$

having defined the relationship between A_{jit} and A_{jt} such as:

$$A_{jt} = \int_0^1 A_{jit} di \tag{1.8}$$

1.3.4 Labour Market Clearing

The labour market clearing condition reads:

$$\int_0^1 x_{cit} di + \int_0^1 x_{dit} di = 1 \tag{1.9}$$

1.4 Decentralised Equilibrium

1.4.1 Households' Problem

At any period *t*, the representative household chooses the consumption basket $\{c_{ct}, c_{dt}\}$ that minimises the cost of generating utility C_t, by solving

$$\min_{\{c_{ct}, c_{dt}\}} p_{ct}c_{ct} + p_{dt}c_{dt} + \lambda_t \left(C_t^{\frac{\varepsilon-1}{\varepsilon}} - (1+\phi)c_{ct}^{\frac{\varepsilon-1}{\varepsilon}} - c_{dt}^{\frac{\varepsilon-1}{\varepsilon}} \right),$$

where λ_t represents the marginal value of c_t i.e., the Lagrangian multiplier associated to constraint (1.2). Combining the first order conditions for both c_{ct} and c_{dt} it can be easily shown that:

$$\frac{p_{ct}}{p_{dt}} = (1+\phi)\left(\frac{c_{dt}}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \tag{1.10}$$

Households are willing to pay more for clean goods, the larger the *warm-glow* parameter ϕ is. As it will become clear later, households face no inter-temporal trade-off, then there is no Euler equation associated to the representative household problem.

Finally, the price of the total consumption, P_1, is set to be equal to 1 and defined such as

$$P_t = \left((1+\phi)^{\varepsilon} p_{ct}^{1-\varepsilon} + (1+\tau_t)^{1-\varepsilon} p_{dt}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}, \tag{1.11}$$

1.4.2 Production

1.4.2.1 Consumption Goods

The representative firm producing good j, $j \in \{c,d\}$, solves the following problem

$$\underset{\{x_{jit}\}}{Max} \quad p_{jt}c_{jt} - \int_0^1 p_{jit}x_{jit} \text{ di}$$

subject to technology (1.5) and taking prices as given, where p_{jit} represents the price of intermediate input *i* in the production of good *j*, $j \in \{c,d\}$. The optimal (inverse) demand function of intermediate input *i* in sector *j* is:

$$\frac{p_{jit}}{p_{jt}} = \left(\frac{c_{jt}}{x_{jit}}\right)^{1-\alpha} A_{jit}^{\alpha} \tag{1.12}$$

Conditional on prices, clean and dirty firms optimally buy more of better quality intermediate inputs.

1.4.2.2 Intermediate Inputs

Intermediate firm *i* requires an entrepreneur to be operative, and produces one unit of output per unit of labour. Subject to the demand function (1.12), the firm producing intermediate input *i* for sector *j* solves the following problem:

$$\pi_{jit} = \underset{\{p_{jit},x_{jit}\}}{Max} \quad p_{jit}x_{jit} - x_{jit}$$

Monopolistically competitive profits π_{jit} are appropriated by the entrepreneur. Labour is adopted as numeraire, then wages are normalised to one. As a consequence, firms optimally charge a constant markup $\frac{1}{\alpha}$ to a constant marginal cost:

$$p_{jit} = \frac{1}{\alpha} \tag{1.13}$$

The same for all intermediate firms and time invariant. After substituting the optimal price rule (1.13) into the demand function (1.12), production is shown to be demand driven:

$$x_{jit} = \left(\alpha p_{jt}\right)^{\frac{1}{1-\alpha}} c_{jt} A_{jit}^{\frac{\alpha}{1-\alpha}} \tag{1.14}$$

being larger for firms producing higher quality A_{jit}.

After substituting (1.14) into the intermediate input producer problem in both sectors, profits become:

$$\pi_{jit} = \nu p_{jt}^{\frac{1}{1-\alpha}} c_{jt} A_{jit}^{\frac{\alpha}{1-\alpha}} \quad \text{with} \quad \nu = (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}} \tag{1.15}$$

After substituting (1.14) into (1.5), for $j \in \{c,d\}$, the price of clean and dirty goods, $j \in \{c,d\}$, becomes:

$$p_{jt} = \frac{1}{\alpha A_{jt}}, \tag{1.16}$$

where we use the symmetry between A_{jit} and A_{jt} established above in (1.8). Notice then that the ratio of prices (clean vs dirty) is equal to the inverse of the ratio of average productivities.

$$\frac{p_{ct}}{p_{dt}} = \frac{A_{dt}}{A_{ct}} \tag{1.17}$$

Since one unit of labour is required to produce one unit of intermediate goods. Substituting back (1.14) into (1.9), the clearing labour market conditions becomes:

$$\frac{c_{ct}}{A_{ct}} + \frac{c_{dt}}{A_{dt}} = 1 \tag{1.18}$$

Combining (1.5) and (1.17) with (1.18), clean and dirty consumption become

$$c_{ct} = \frac{(1+\phi)^{\varepsilon} A_{ct} A_{dt}^{1-\varepsilon}}{\left((1+\phi)^{\varepsilon} A_{dt}^{1-\varepsilon} + A_{ct}^{1-\varepsilon}\right)} \quad \text{and} \quad c_{dt} = \frac{A_{dt} A_{ct}^{1-\varepsilon}}{\left((1+\phi)^{\varepsilon} A_{dt}^{1-\varepsilon} + A_{ct}^{1-\varepsilon}\right)} \tag{1.19}$$

Defining $a_t = \frac{A_{dt}}{A_{ct}}$ and $r_t = \frac{c_{dt}}{c_{ct}}$, the relative clean consumption can be expressed as:

$$r_t = \frac{a_t^{\varepsilon}}{(1+\phi)^{\varepsilon}} \tag{1.20}$$

The larger the *warm-glow* parameter is, the most labour is allocated to the production of the clean good. Moreover, the elasticity of the relative demand of dirty to clean goods with respect to the relative productivity of dirty to clean technologies is equal to the elasticity of substitution of these two technologies as clearly emerges from equation (1.2).

Total profits $\pi_{ct} + \pi_{dt}$ are redistributed to households as the return to entrepreneurial activities, for $j \in \{c, d\}$,

$$\pi_{jt} = \int_0^1 \pi_{jit} di = \nu p_{jt}^{\frac{1}{1-\alpha}} c_{jt} A_{jt} \tag{1.21}$$

Recall that an entrepreneur is a scientists who was granted with a patent to produce the variety of intermediate inputs that she improved. Going one step back, each scientist, in order to decide the sector in which she will direct her research, compares expected returns on both sectors. So, given that π_{jt}^s are profits conditional on being successful and η_j the probability of being successful, then the unconditional expected profits of a scientist are:

$$\eta_j \pi_{jt}^s = \Pi_{jt} = \eta_j \left(\frac{1-\alpha}{\alpha}\right) p_{jt}^{\frac{1}{1-\alpha}} c_{jt} (1+\gamma)^{\frac{\alpha}{1-\alpha}} A_{jt-1}^{\frac{\alpha}{1-\alpha}} \tag{1.22}$$

The ratio of expected profits in the clean vs dirty sector reads, after using both expression in (1.5) and (1.10),

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{1-\alpha}} \frac{c_{ct}}{c_{dt}} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\frac{\alpha}{1-\alpha}} \tag{1.23}$$

$$\frac{\Pi_{ct}}{\Pi_{dt}} = (1+\phi)^{\varepsilon} \underbrace{\frac{\eta_c}{\eta_d} \left(\frac{(1+\gamma\eta_c s_{ct})}{(1+\gamma\eta_d(1-s_{ct}))} \right)^{\frac{(1-\alpha)\varepsilon-1}{1-\alpha}}}_{=\frac{1}{\Gamma(s_{ct})}} \left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{\frac{-\varphi}{1-\alpha}} \tag{1.24}$$

where $\varphi = (1-\alpha)(1-\varepsilon)$

Corner solutions: There are two possible corner solutions associated with the allocation of scientists. The economy will assign all scientists to the clean sector if

$$\left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{\frac{-\varphi}{1-\alpha}} > (1+\phi)^{-\varepsilon} \quad \Gamma(s_{ct}=1)$$

and all scientists to the dirty sector if

$$\left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{\frac{-\varphi}{1-\alpha}} < (1+\phi)^{-\varepsilon} \quad \Gamma(s_{ct}=0)$$

Notice that if clean and dirty consumption are gross substitutes and at the initial time any of these two inequalities hold, it will hold forever. In this case, the economy will never reach the interior solution. However, if they are complements and one of these two inequalities hold initially, the economy will likely converge on a finite time to the interior solution. We discuss this issue below when analysing the behaviour of the interior solution.

Interior solution: From equation (1.23) and using the definition of r_t and a_t, a scientist will be indifferent between performing research in any of the two sectors if and only if

$$r_t = \hat{\eta} \left(\frac{a_t}{a_{t-1}^{\alpha}} \right)^{\frac{1}{1-\alpha}} \quad \text{where} \quad \hat{\eta} = \frac{\eta_c}{\eta_d} \tag{1.25}$$

By combining (1.25), (1.10) and (1.17), the dynamics of innovation can be studied by solving the following difference equation on a_t, for $t \geq 1$ and $a_0 > 0$:

$$a_t = \left(\frac{\left(\hat{\eta}(1+\phi)^{\varepsilon}\right)^{1-\alpha}}{a_{t-1}^{\alpha}} \right)^{\frac{1}{(1-\alpha)(\varepsilon-1)}} \tag{1.26}$$

For a past relative productivity a_{t-1}, equation (1.26) shows the equilibrium current productivity that makes scientists indifferent between working for the dirty or clean technologies. The concavity of this relation critically depends on the elasticity of substitution between dirty and clean consumption in households' preferences (1.5). When dirty and clean consumption goods are substitute, and initially the dirty technology is more efficient that a the stationary equilibrium, technical change is directed more towards the clean technology reducing its relative price, which induce substitution in consumption. The corresponding increase in clean consumption supports then a reallocation of production labour towards the clean sector.

The dynamics of a_t in (1.26) has a unique stationary interior solution:

$$a^* = \left((1+\phi)^{\varepsilon}\hat{\eta}\right)^{\frac{1-\alpha}{-\varphi}} \tag{1.27}$$

The stationary interior solution a^* is stable if dirty and clean goods are complements, but unstable if they are gross substitutes. In the later case, depending on initial conditions the economy converges to one of the corner stationary equilibria.

The interior solution monotonically converges to a^* if clean and dirty consumption are gross complements, i.e., if $\varepsilon \in (0,\ 1)$. Consequently, complementarity makes the equilibrium non-sustainable, since in a growing economy both clean and dirty consumption will grow. If the economy was initially in a corner solution, it will converge to the interior solution, then to the interior steady-state. *Warm-glow* will no solve the unsustainability problem, but by reducing a_t it will make the economy to survive for longer time before reaching the "point of no return".

Since at the balanced growth path (BGP) the quality of both goods increases at the same rate, the allocation of scientists to the clean and dirty sectors must be constant and equal to:

$$s_c^* = \frac{\eta_d}{\eta_d + \eta_c} \quad \text{and} \quad s_d^* = \frac{\eta_c}{\eta_d + \eta_c}$$

Differences in R&D technologies needs to be compensated by a larger use of scientists in the less productive sector. Complementarity in consumption rationalise such a long-term equilibrium.

Notice that

$$a_t = \left(\frac{1+\gamma\eta_d s_d}{1+\gamma\eta_c s_c}\right)^{\frac{1}{1-\alpha}} \left(\frac{\hat{\eta}(1+\phi)^{\varepsilon}}{a_{t-1}}\right),^{\frac{1}{\varepsilon}}$$

makes a_t to be bounded in the interval

$$(1+\gamma\eta_d)^{\frac{1}{1-\alpha}} \left(\frac{\hat{\eta}(1+\phi)^{\varepsilon}}{a_{t-1}}\right)^{\frac{1}{\varepsilon}}, \left(\frac{1}{1+\gamma\eta_c}\right)^{\frac{1}{1-\alpha}} \left(\frac{\hat{\eta}(1+\phi)^{\varepsilon}}{a_{t-1}}\right)^{\frac{1}{\varepsilon}}$$

In the case of substitutability, since $\varepsilon > 1$, for any interior initial condition $a_0 < a^*$ the equilibrium monotonically decreases until reaching the corner solution with $s_{ct} = 1$. At this stage A_{dt} becomes constant and a_t converges to $a_t = 0$; equilibrium being sustainable. Unsustainability occurs if initially the relative productivity of the dirty sector is too high, with $a_0 > a^*$. In this case, a_t converges to infinity. *Warm-glow* may solve the problem by increasing a_t and making that the initial conditions enter the sustainable zone -i.e., $a_0 < a^*$.

1.5 Central Planner Solution

In this section is assumed that a central planner implements a solution, which is called optimal policy, to correct all imperfections found in the market. In order to do so, she will maximise the household's utility (1.1) subject to constraints (1.2), (1.4), (1.5), (1.7), (1.9) and market clearing for scientists (See detailed solution in appendix A).

We represent the shadow price of total consumption, clean consumption, dirty consumption, and quality of the environment by λ_{1t}, λ_{2t}, λ_{3t} and λ_{6t} respectively. Then, from the first order conditions (FOCs) with respect to (wrt) these variables, we get:

$$\hat{p}_{ct} = (1+\phi)\left(\frac{C_t}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \quad \text{and} \quad \hat{p}_{dt} = \left(\frac{C_t}{c_{dt}}\right)^{\frac{1}{\varepsilon}} - \frac{\lambda_{6t+1}\xi}{\lambda_{1t}}, \tag{1.28}$$

where we have divided the clean and dirty consumption shadow prices by λ_{1t} to express them in terms of total consumption and denote them by $\hat{p}_{ct}$ and $\hat{p}_{dt}$. As seen in the second expression in (1.29), the marginal utility of the dirty energy consumption is not exactly equal to its price, appearing a wedge between these two terms. Following [Acemoglu et al., 2012] this wedge is referred to as the carbon tax (τ_t) that the central planner establishes to internalise the externality that dirty energy consumption is causing to the environment:

$$\underbrace{\frac{\lambda_{6t+1}\xi}{\lambda_{1t}\hat{p}_{dt}}}_{\tau_t} = 1 \qquad \Longrightarrow \qquad (1+\tau_t)\hat{p}_{dt} = \left(\frac{C_t}{c_{dt}}\right)^{\frac{1}{\varepsilon}} \tag{1.29}$$

Taking the ratio between both prices gives:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = (1+\phi)(1+\tau_t)\left(\frac{c_{dt}}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \tag{1.30}$$

In turn, the FOCs wrt x_{cit} and x_{dit} are:

$$\lambda_{2t} c_{ct}^{1-\alpha} A_{cit}^{\alpha} x_{cit}^{\alpha-1} = \lambda_{7t} \quad \text{and} \quad \lambda_{3t}\alpha c_{dt}^{1-\alpha} A_{dit}^{\alpha} x_{dit}^{\alpha-1} = \lambda_{7t} \tag{1.31}$$

The central planner also eliminates any positive profits in the economy, so production of machines will be equal to one taking place under perfect competition. If one unit of labour is required to produce one unit of machine *i* and in this economy wages are the numeraire, then this cost is equal to one. After dividing by λ_{1t} the machine shadow price *i* in clean and dirty sectors, λ_{7t}, the isoelastic inverse demand for machine *i* in each sector is:

$$x_{cit} = \hat{p}_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{cit}^{\frac{\alpha}{1-\alpha}} \quad \text{and} \quad x_{dit} = \hat{p}_{dt}^{\frac{1}{1-\alpha}} c_{dt} A_{dit}^{\frac{\alpha}{1-\alpha}} \tag{1.32}$$

As in the decentralised equilibrium, we substitute expressions in (1.32) back into equation (1.5) to find:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = \frac{A_{dt}}{A_{ct}} \tag{1.17}$$

On the other hand, we take the FOCs wrt A_{cit}, A_{dit}, s_{ct} and s_{dt}, dividing them by λ_{1t}, and after some iterations and substitutions, it gives[2]:

$$\frac{\eta_c(1+\gamma\eta_d(1-s_{ct}))}{\eta_d(1+\gamma\eta_c s_{ct})} \underbrace{\frac{\sum_{v=1}^{\infty} \lambda_{1,t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}}{\sum_{v=1}^{\infty} \lambda_{t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}}}_{Q_t} \tag{1.33}$$

The central planner corrects the myopia of the monopolists in their innovation decisions by determining the allocations of scientists as a function of the discounted value of the entire flow of additional revenues generated by their innovation in both sectors (knowledge externality in the innovation possibilities frontier). The central planner, however, does recognise that innovation in the dirty sector generates environmental degradation, so she must allocate scientists to the sector with the higher social gain from innovation, in this case, the clean sector. In so doing, the social optimum implies that scientists will be allocated to the clean R&D whenever (1.33) will be greater than 1.

In addition, when we compare (1.33) with the relative profits obtained under the decentralised equilibrium (see equation (1.24)), in the central planner solution there is an extra term which we denote Q_t. This term reflects the adjustments that must be made to implement the optimal policy, which are materialised as a carbon tax and a clean R&D subsidy.

[2] Here λ_{4t} is the shadow price of clean innovation and λ_{5t} is the shadow price of dirty one

1.6 Implementation of the Optimal Policy

As it was established in the decentralised equilibrium, depending on the value that the *warm-glow* parameter takes, this could be insufficient to avoid an environmental disaster. If the dirty energy technology started with an advantage over clean energy no matter if both inputs are gross complements or substitutes, *warm-glow* delay the disaster over time.

According to the central planner solution, if both inputs are substitutes, a carbon tax and a clean R&D subsidy will complement the job done by *warm-glow* giving the final push to drive all innovation to the clean sector; as a result, an environmental disaster will be avoided. Furthermore, the intervention might be temporary because profits from innovation in the clean sector will be higher than profits from innovation in the dirty.

Considering τ_t as the carbon tax, the budget constraint to be faced by households will be:

$$p_{ct}c_{ct} + (1+\tau_t)p_{dt}c_{dt} = w_t + \pi_{ct} + \pi_{dt}, \tag{1.34}$$

and the relative price of clean energy consumption will be:

$$\frac{p_{ct}}{p_{dt}} = (1+\phi)(1+\tau_t)\left(\frac{c_{dt}}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \tag{1.35}$$

which implies that the definitions of clean and dirty consumption have changed:

$$c_{ct} = \frac{(1+\phi)^{\varepsilon}(1+\tau_t)^{\varepsilon}a_t^{1-\varepsilon}A_{ct}}{(1+\phi)^{\varepsilon}(1+\tau_t)^{\varepsilon}a_t^{1-\varepsilon}+1} \qquad c_{dt} = \frac{A_{dt}}{(1+\phi)^{\varepsilon}(1+\tau_t)^{\varepsilon}a_t^{1-\varepsilon}+1} \tag{1.36}$$

Under this new setup, the unconditional expected profits of a scientist in the clean sector changes and becomes:

$$\Pi_{ct} = (1+q_t)\eta_c\left(\frac{1-\alpha}{\alpha}\right)p_{ct}^{\frac{1}{1-\alpha}}c_{ct}(1+\gamma)^{\frac{\alpha}{1-\alpha}}A_{ct-1}^{\frac{\alpha}{1-\alpha}} \tag{1.37}$$

Where $(1+q_t)$ is the subsidy that will be necessary to drive innovation towards the clean sector. In dirty sector, the unconditional expected profits of a scientist does not change, therefore the ratio of expected profits in the clean vs dirty sector reads:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = (1+q_t)(1+\phi)^{\varepsilon}(1+\tau_t)^{\varepsilon} \underbrace{\frac{\eta_c}{\eta_d}\left(\frac{(1+\gamma\eta_c s_{ct})}{(1+\gamma\eta_d(1-s_{ct}))}\right)^{\frac{(1-\alpha)\varepsilon-1}{1-\alpha}}}_{=\frac{1}{\Gamma(s_{ct})}} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\frac{-\varphi}{1-\alpha}} \tag{1.38}$$

If both inputs are complements, both policy tools will adjust correspondingly to reach an interior solution and (1.38) will be equal to 1 no matter the starting point of the economy. However, assuming substitutability between both goods, policy tools must guarantee that (1.38) is greater than one until the economy completes its transition to clean consumption. In addition, as seen in (1.38), the carbon tax can be taken as a complement for the *warm-glow* parameter, and the right subsidy q_t could be defined as:

$$\frac{\Gamma(s_{ct}=0)}{(1+\tau_t)^{\varepsilon}(1+\phi)^{\varepsilon}} \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\varphi}{1-\alpha}} - 1 \leq q_t \tag{1.39}$$

1.7 Numerical Simulation

In this part two quantitative exercises of the model discussed are explained. The first exercise aims to show under which range of values the *warm-glow* parameter, ϕ, could avoid or delay environmental disaster under the decentralised equilibrium by transitioning towards sustainable energy. The second exercise aims to determine the size of governmental intervention required when the optimal policy is implemented, taking into account the presence of the *warm-glow* parameter. So, the model is simulated assuming that at time zero there is not carbon tax and clean R&D subsidy and the model will define the future paths for these two instruments that are going to avoid an environmental disaster and make the energy transition in a defined period of time.

1.7.1 Parameter Values

In both exercises, each period corresponds to five years, which means that the model is calibrated over 400 years. This horizon is common in models where environmental degradation is studied due to the long time that the environment takes to react to a certain level of accumulated emissions. The utility function used in both exercises is identical to one described in the model section. The share of machines is set $\alpha = 1/3$ and the probability of successful innovation per year is $\eta_j = 0.002 \in$ {c,d}.

As in [Acemoglu et al., 2012], the initial levels of technology for both sectors are set to match the implied values of world renewable and fossil fuels energy consumption at a certain year (2018). Specifically, dirty consumption is fixed as 11.272 million tonnes of oil equivalent (Mtoe) and clean consumption as 2.004 Mtoe [BP, 2018]. As it was mentioned in the description of the model, one of its key parameters is the elasticity of substitution between the two goods (ε), but because by definition, under complementarity case ($\varepsilon < 1$) environmental degradation is not possible to avoid, the simulation focuses particularly on the two levels of substitutability following [Acemoglu et al., 2012]: (i) low substitutability, $\varepsilon = 3$; and (iii) high substitutability, $\varepsilon = 10$. However, we give more attention to the case when $\varepsilon = 3$ because it is closer to the current level of substitution between fossil fuels and non-fossil fuels found in the recent empirical literature as [Greaker et al., 2018] point out.

With regard to *warm-glow* parameter, it is obtained from [Ma et al., 2015] where they performer a meta-regression analysis to determine the people's willingness to pay for a premium in their electricity bills when energy comes from renewable sources. The paper works on 29 different studies carried out in an equal number of countries to determine that the premium on average was 14% over the value of kilowatt/hour paid per households to a maximum of 160% per households. Therefore, the *warm-glow* parameter is calibrated by using three different scenarios: 14%, 70% and 160%.

Following [Acemoglu et al., 2012], they define a general function $\Phi(\Delta)$ as the cost of environmental degradation where Δ denotes the temperature increase relative to the pre-industrial level ($\Phi(\Delta) < 0$). In order to specify $\Phi(\Delta)$ as:

$$\Phi(\Delta) = \frac{(\Delta_{disaster} - \Delta(S))^{\lambda} - \lambda \Delta_{disaster}^{\lambda-1}(\Delta_{disaster} - \Delta(S))}{(1-\lambda)\Delta_{disaster}^{\lambda}} \tag{1.40}$$

$\lambda = 0.1443$ is fixed to match this function with Nordhaus's damage function over the range of temperature increases up to 3°C. It is also set the CO2-concentration at time t, C_{CO2t}, with respect to the disaster level, S, such as $S = C_{CO_{2,disaster}} - max(C_{CO2t}, 278)$, which has the following relationship with the temperature increase in the atmosphere, Δ, measured in parts per million (ppm):

$$\Delta = 3 * log_2(S/278) \tag{1.41}$$

The pre-industrial level of CO2-concentration is 278 ppm and $C_{_{CO2-disaster}}$ denotes the concentration level associated with the disaster temperature increase, which is set to 6°C as in [Acemoglu et al., 2012]. The constant regeneration rate of atmosphere, δ, is assumed equal to 0.005 per year and the rate at which dirty production reduces the quality of the environment, ξ, equals to 0.0015.

Regarding the values of discount rate, this study does not take part in the discussion about the fairness value to be assumed (Nordhaus's research, Sterm's research, etc) and the results are evaluated using two different cases used in [Acemoglu et al., 2012]: $\rho = 0,001$ and $\rho = 0.015$.

1.8 Results

This section is divided into two parts. The first part describes the calibration of the model under decentralised equilibrium and, the second part shows the calibration of the implementation of the optimal policy. In both cases, we illustrate the path follows for the main variables for each value of the *warm-glow* parameter: increases in the temperature, percentage of scientists allocated in the clean sector and, when it applies, the paths for the carbon tax and the clean R&D subsides.

1.8.1 Decentralised Equilibrium

The first case to be described is when the model assumes substitutability between both inputs, which can be equal to 3 or 10. Figure 1.1 shows the path follows for the increases in the temperature and the allocation of scientists linked to it. Starting with the temperature, the figure suggests a way in which a decentralised economy can detour its progression towards an environmental disaster. This occurs only when the *warm-glow* parameter is over 0.7, indicating that no intervention is possible if people are sufficiently aware of the damage their consumption patterns are infringing on the planet when they are not sustainable.

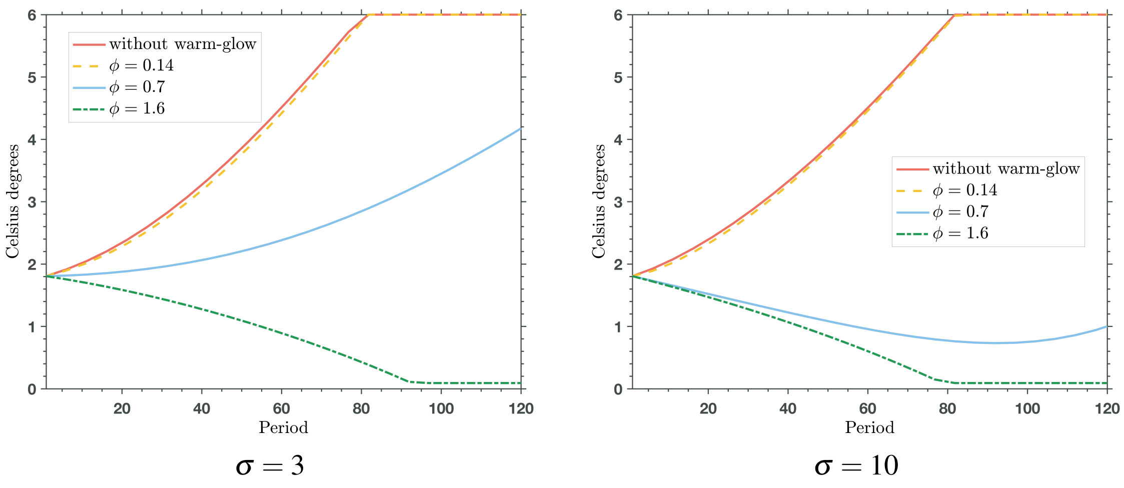
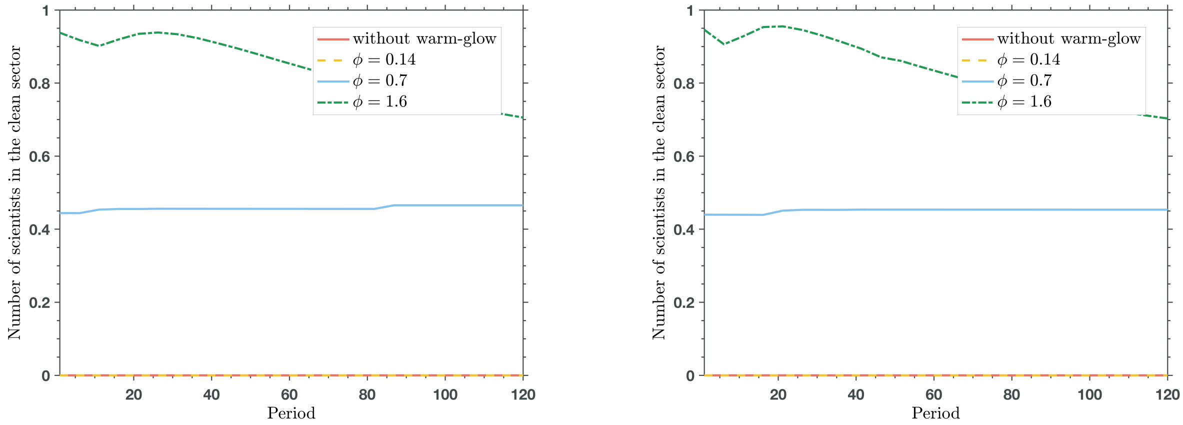


Figure 1.1: Decentralised Equilibrium: Increase in Temperature over Pre-industrial Era

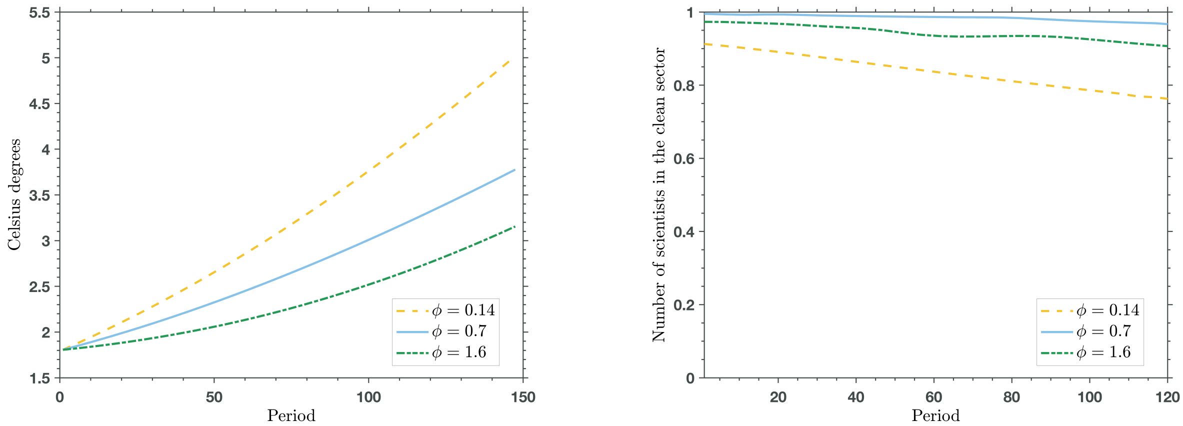
Aligned with the previous results, figure 1.2 illustrates that most scientists are allocated to the clean energy sector when the value of *warm-glow* parameter is 0.7 or 1.6.



$\sigma = 3$ $\sigma = 10$

Figure 1.2: Decentralised Equilibrium: Scientists Allocation in Clean Sector

The following graphs illustrate the model's results assuming complementarity among both inputs ($\varepsilon < 1$). As explained above, in his case, the model always achieves a steady-state and allocates scientists in both sectors as observed in figure 1.3. However, the moment when this equilibrium is reached could be very distant in the future (more than 150 years) as it can be seen in figures 1.3 and 1.4. At time zero, there is a technological gap between both sectors therefore the economy assigns more scientists to clean R&D, but once the gap is closed, scientists will be assigned to both sectors.



Temperature Increase Scientist Allocation

Figure 1.3: Complementary Case ($\varepsilon = 0.8$)

It is proven that under this complementarity case, the *warm-glow* parameter will not avoid an environmental disaster; but as figure 1.4 reports, what *warm-glow* is actually doing is to reduce the ratio between the technology of the two sectors, a_t, and postpone an environmental disaster.

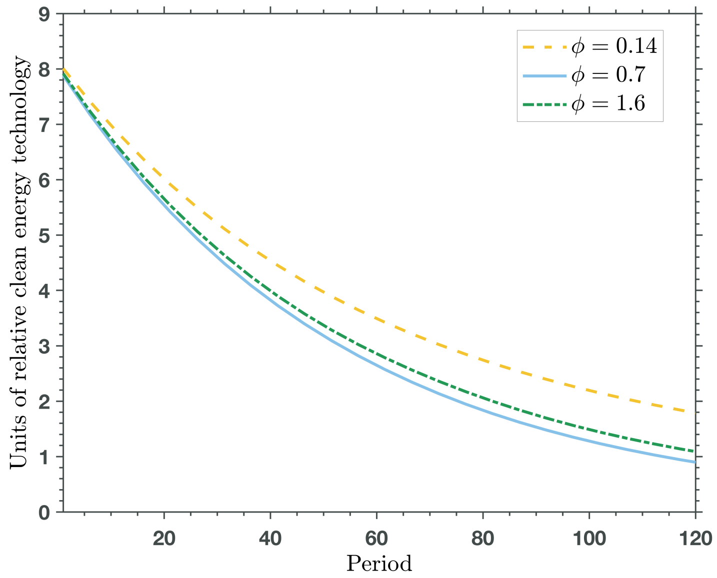
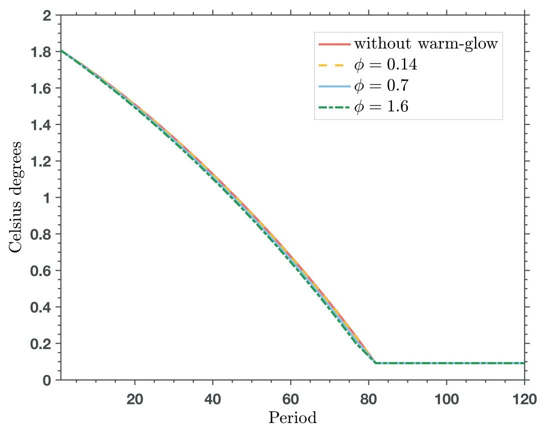


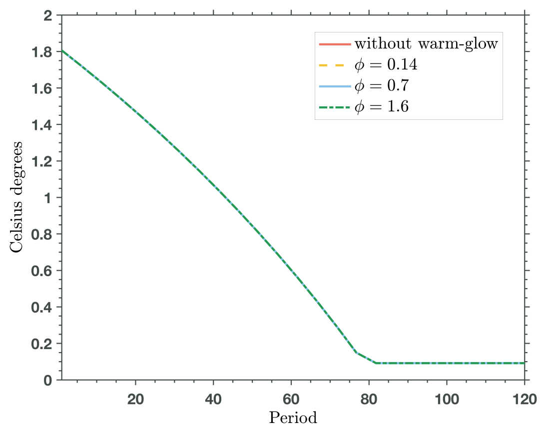
Figure 1.4: Complementary Case: Relative Clean Technology

1.8.2 Optimal Policy

The implementation of the optimal policy consists of a tax on dirty consumption goods and and a subsidy to clean R&D. In figure 1.5 illustrates the changes in the temperature with respect to the pre-industrial era for $\varepsilon = 3$ and $\varepsilon = 10$. As it was expected, under both levels of substitutability, an environmental disaster is avoided, but when $\varepsilon = 3$, the larger the *warm-glow* parameter, the earlier the increase in the temperature reverses.



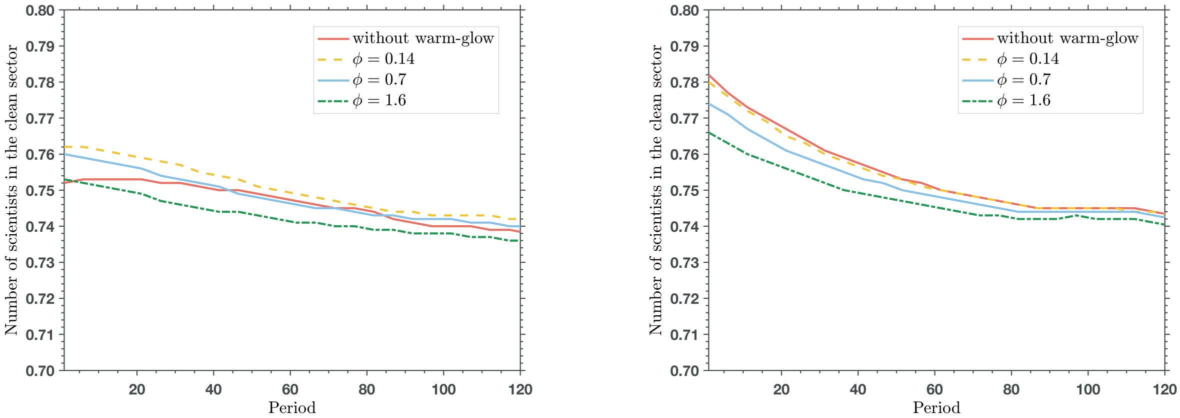
$\sigma = 3$



$\sigma = 10$

Figure 1.5: Optimal policy: Increase in the Temperature over the Pre-industrial Era

Figure 1.6 shows the allocation of scientists to the clean sector. Although most of the scientist are allocated in the clean sector from the beginning, it is interesting that for the first 60 years, if the *warm-glow* parameter is higher than 0.14, paradoxically there is a slightly decrease in the number of scientists allocated in the clean sector. Nevertheless, the allocation is never less than 70% for both values of ε and the selected allocation avoid the disaster.



$\sigma = 3$ $\sigma = 10$

Figure 1.6: Optimal policy: Scientist Allocation in Clean Sector

Figures 1.7 and 1.8 show the optimal combination of carbon taxes and clean R&D subsidies. It can be seen in those figures that the required value of both reduce when a *warm-glow* parameter is included. Starting with carbon tax, figure 1.7 illustrates the carbon tax required for both the *warm-glow* and ε parameters. Similar to the findings highlighted in [Acemoglu et al., 2012], the carbon tax in these two figures does not reduce to zero during the period analysed.

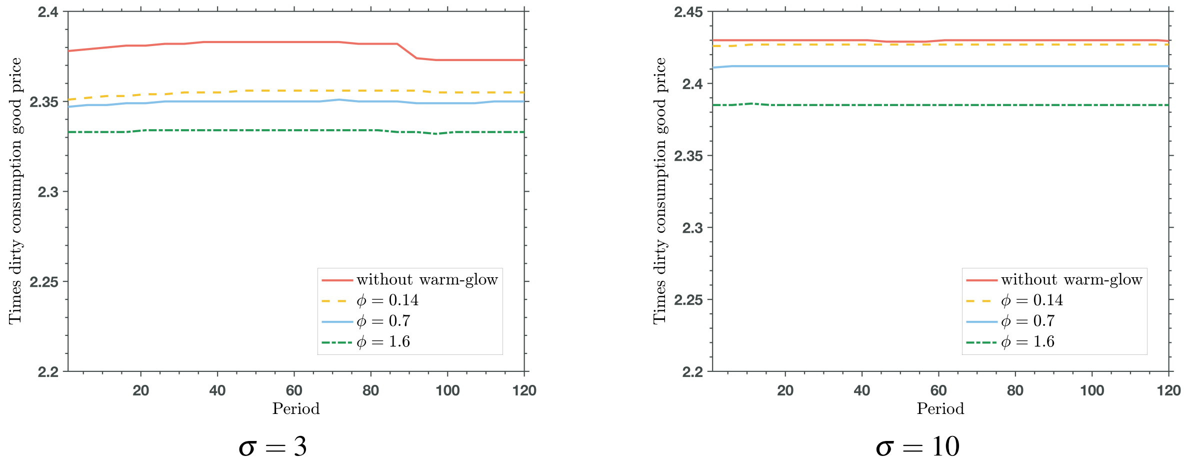


Figure 1.7: Optimal Policy: Carbon Tax

In turn, figure 1.8 illustrates the behaviour of the clean R&D subsidy. The value of this instrument remains stable overall the simulated period and across scenarios. Moreover, the range of values for this tool is similar to carbon tax and follows its dynamic: high values of the *warm-glow* parameter generally drives towards low values of the subsidy.

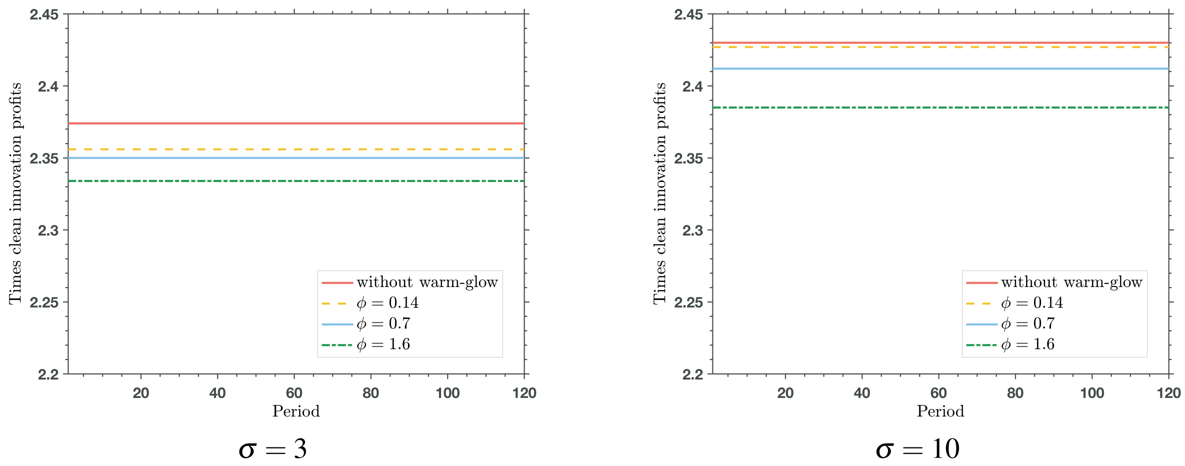


Figure 1.8: Optimal Policy: Clean R&D Subsidy

The results for both tools are in line with the findings in [Greaker et al., 2018], the required tax and subsidy exceed 100% of the dirty consumption price and clean profit of innovation, respectively. These findings give us a flavour of the magnitude of the solution needed across countries to meet the net-zero emissions objectives.

1.9 Conclusion

Climate change is one of the most challenging and universal problems that the global society has been facing in the last three decades. Being in particular, the results of the spectacular use of fossil fuels to leverage the economic growth experimented by a group of countries that today have the wealthiest economies. The problem is and will be getting worse if it considers that most global economies are still in low and middle levels of development, and they will keep increasing the global energy demand to make their way toward the developed status.

It is possible to say that problem lies more in the quality of energy that the world is consuming rather than the quantity. If the energy comes from sustainable sources, society can consume as much energy as it wishes. Therefore, there is no more suitable way to pursue that status than investing in innovation, making global society less dependent on non-renewable sources without sacrificing economic growth and well-being.

[Nordhaus, 1991] and [Nordhaus, 1993] started the study of the link between economic growth and climate change formally, and the topic has been getting more and more attention over the years that today there are a vast majority of studies that look for a better way to conciliate economic growth and sustainability of the planet. In particular, in this study, we work on an extension of the growth model developed by [Acemoglu et al., 2012]. We develop and simulate a theoretical framework that brings together two different theories: economic growth and *warm-glow* giving, to determine if an individual receives a *warm-glow* for their unilateral decision of consuming more renewable energy than non-renewable one, it will make the avoidance of an environmental disaster possible reducing or eliminated in some cases governmental intervention.

The decentralised equilibrium shows that an environmental disaster can only be tackled, regardless of substitutability between clean and dirty inputs, when *warm-glow* is higher than 0.7. As we demonstrated above, under the complementarity scenario by definition, the economy will always consume both inputs, so environmental degradation keeps occurring because dirty consumption must always be present. However, the presence of *warm-glow* delays the disaster over time. The numerical simulation confirms that the higher the *warm-glow* parameter, the further the time horizon in which the disaster occurs. This result is not entirely disappointing when it considers that what the *warm-glow* could do is to buy us time while technology advances enough to make possible the complete transition towards sustainable energy.

The implementation of the optimal policy enables the economy to avoid the environmental disaster under all levels of *warm-glow*, results that are not always present in [Acemoglu et al., 2012]. Supporting our theory, higher levels of *warm-glow* reduce the values of intervention (carbon tax and clean R&D subsidy) than otherwise take place if that *warm-glow* would not be present. Nevertheless, the size of the tax and subsidy found by the model is significant, revealing that countries worldwide urgently need to embrace drastic measures to mitigate climate change because any delay makes policies more expensive as the problem gets unsustainable.

This study presents an alternative perspective to analyse the policies that could be undertaken if climate change is to be stopped. This perspective calls governments to explore more unconventional channels to transition faster toward sustainable lifestyles, for instance, the public concern about the impact of the alarming environmental degradation and the evidence of people's willingness to take action about it.

2 | Modelling the Paris Agreement

2.1 Introduction

There is no doubt that the battle against climate change has to be fought unitedly by the world as a whole and investing now in energy with planet benefits for both current and future generations, is of paramount importance. Reaching an agreement on how to share this massive investment, however, is proving problematic. In positive terms, the wealthiest part of the world should pay more, but the historical and ongoing causal relationship between economic growth and environmental damage complicates responsibility and, thus, any agreement.

It was not until 2015, under the umbrella of the Paris Agreement, that significant progress was made towards a viable commitment. By introducing the setting of emissions targets through mutual agreement rather than imposition, both attendance and national contributions increased. In addition, as [Yergin, 2020] put it, there is a “before and after Paris world” as around this time society’s culture and values about environmental degradation were changing increasing demand, especially in developed countries, for attention to be paid to “non economic aspects”. The wealthiest member countries volunteered to pay more, and all members agreed to do more. As a result, Paris achieved a seminal 196-country commitment to limit temperature rises to less than 2 or $1.5°$C.

Although, *warm-glow giving* [Andreoni, 1990] explains why countries want to participate and commit, "impure Altruism", alone, cannot explain the relationship between a country's income and volunteered emissions target. This can be explained, however, by applying the concept of *income elasticity of the demand* (IED) in the theory of consumer behaviour, where IED for clean consumption goods would be higher than dirty, and demand for the former increases as a country gets richer. It is necessary, therefore, in order to theoretically justify the Paris Agreement, to bring together *warm-glow giving theory* and the heterogeneity in IED across goods.

This justification enables the economic growth model present in chapter 1 to be extended by assuming nonhomothetic preferences and linking the *warm-glow* parameter with the commitment value for each member country. Once extended, this model demonstrates how the Paris Agreement can stop the advance of climate change before the world faces an environmental disaster.

The structure of the chapter is as follows after this introduction, section 2.2 lists the key references for this study; section 2.3 describes the main structure of the model; sections 2.4 and 2.5 present the descentralised equilibrium and central planner solution respectively; section 2.6 illustrates the optimal policy implementation, section 2.7 reports the results of the numerical simulation of the model and finally, section 2.9 summarises the conclusions.

2.2 Nonhomothetic Preferences, Technical Change and Environmental Awareness

The theory of consumer behaviour uses the income elasticity of demand for goods to classify them into three different categories. An *inferior* good implies that the quantity demanded proportionally decreases when income increases ($\phi < 0$); a good classified as *necessity* refers to ones in which the quantity demanded is less sensitive to income changes, for instance, food ($\phi < 1$). Finally, opposed to those categories as mentioned earlier, for *luxury* goods the quantity demanded increases with income ($\phi > 1$)

[Frank and Cartwright, 2010].

The demand-side literature of structural change relied on this heterogeneity in the IED across goods, known as nonhomothetic preferences, to explain the constant reallocation of employment and capital in an economy when it walks through the development curve. Dividing an economy broadly into three sectors, agriculture, manufacturing and services, these demand-side theories postulate that the income growth is accompanied by reducing the importance[1] of the agricultural sector, the temporary increases in the manufacturing sector's (humped shape), and the subsequent ever-growing importance of services. So, adopting these postulates can explain why huge improvements in technologies have licensed the use of more sustainable energy in the advanced world in the last three decades.

[Buera and Kaboski, 2009] and [Dennis and İşcan, 2009] propose an approach which integrates the assumption of sector-biased technological progress and nonhomothetic preferences to explain the dynamic observed in the US economy over the twentieth century. They confirm that nonhomothetic preferences alone do a good job in explaining the increases over time in the expenditure shares of sector with higher income elasticities when the economy is getting richer. [Herrendorf et al., 2014] departing from the stylised facts of the structural transformation in OECD countries over 30 years, build a multi-sectoral growth using generalised Stone-Geary preferences as the best tool to understand the reallocation of activity across sectors by allowing individuals' demand to react to changes in income and relative prices.

Recognising that the nonhomothetic preferences used in the literature until that moment could have some shortcomings to the extent that the heterogeneity in the income elasticity vanishes over time, [Boppart, 2014] proposes a model that focuses on nonhomothetic preferences called non-Gorman preferences which avoid that vanish and is

[1] Importance is understood here as the expenditure share of each sector

suitable to rationalise the shifts observed in the sectoral composition of the US economy over 1986–2011. Finally, going a little further, [Comin et al., 2021] based on empirical evidence from data for OECD countries and India, postulate a particular kind of preferences denominated as nonhomothetic Constant Elasticity of Substitution (CES) preferences, which guarantee the differences in the income elasticity of demands for goods remains at all levels of income. This approach has more explanatory power of the demand channel as an engine of structural change in the long run. The study in this chapter adopts their approach to model preferences.

2.3 Two-sector Growth Model with *Warm-glow* Nonhomothetic Preferences

We present a different extension of the growth model with directed technical change and environmental constraint ([Acemoglu et al., 2012]), where we am assuming the presence of nonhomothetic preferences following [Comin et al., 2021].

Keeping in mind the assumption of people's desire to do something privately for the environment (warm-glow giving), we propose to include the nonhomothetic preferences assumption in the model to reflect that if a country is increasing its income, apart from enabling people to consume more goods non considered as necessities, government will have more resources to provide a public structure that facilitates people to adopt more sustainable lifestyle choices such as consuming cleaner energy. Furthermore, we highlight that these preferences are also convenient because they accommodate the fact that a permanent increase in a country's income makes the income elasticises between goods remain different and not vanish over time [Comin et al., 2021].

2.3.1 Household and Nonhomothetic Preferences

It assumes that there is a unit mass of homogeneous workers, each of them endowed with one unit of labour, a unit mass of homogeneous scientists, each of them endowed with one unit of research services, and a unit mass of homogeneous potential entrepreneurs. There is also a unit mass of identical households grouping each a worker, a scientist and an entrepreneur.

Preferences of the Representative Household are:

$$u_t = \sum_{t=0}^{\infty} \beta^t \frac{(C_t E_t)^{1-\theta}}{1-\theta} \tag{2.1}$$

Where C_t is consumption as defined below and E_t is the quality of the environment. The subjective discount factor is $\beta \in (0,1)$, and $\theta > 0$ is the inverse of the inter temporal elasticity of substitution. The utility function u_t is increasing both in *C* and *E*, twice differentiable, jointly concave in (*C*, *S*), and follows Inada-type conditions such as:

$$\lim_{C \to 0} \frac{\partial u(C_t E_t)}{\partial C_t} = +\infty \qquad \lim_{S \to 0} \frac{\partial u(C_t E_t)}{\partial S_t} = +\infty \qquad \lim_{S \to 0} \partial u(C_t E_t) = -\infty \tag{2.2}$$

At any period t, households consume two different type of highly substitutable goods, a clean and a dirty good, the later negatively affecting the environment as described in section 2.3.5. Their consumption is denoted by c_{ct} and c_{dt}, respectively. Time t consumption utility C_t is implicitly defined by the nonhomothetic utility function:

$$C_t = \left(C_t^{\frac{\phi}{\sigma}} c_{ct}^{\frac{\sigma-1}{\sigma}} + c_{dt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2.3}$$

Where σ is the elasticity of substitution between clean and dirty consumption.[2] Parameter ϕ, $\phi \in (0, \sigma - 1)$, measures the degree of *warm-glow* and C being monotonically

[2] Following [Acemoglu et al., 2012], we assume clean and dirty goods are gross substitutable in preferences ($\sigma > 1$), otherwise an environmental catastrophe becomes unavoidable

increasing and quasi-concave in c_c and c_d (See appendix B for more details of consumption function)

When $\phi > 0$, as income grows, households consume more of the clean and dirty goods, raising C_t and giving more and more weight to clean consumption. Wealthier societies will then care more about environmental protection reducing the relative consumption of dirty goods[3].

Household budget is defined by

$$p_{ct}c_{ct} + p_{dt}c_{dt} = w_t + \pi_{ct} + \pi_{dt} \tag{2.4}$$

Where p_{jt} is the price of good j, $j \in (c,d)$, w_t are the wage rates of production workers, ℓ_t is the labour supply of production workers and equal to 1, and π_{jt} represents the profits earned by households in each sector. As will become clear later, households have no access to any asset, behaving as a hand-to-mouth consumer, monopoly rights lasting one period.

2.3.2 Clean and Dirty Sectors

There are two sectors: A clean sector producing a clean consumption good that has a neutral effect on the environment, and a dirty sector producing a dirty and good negatively affects the environment. In addition, in each sector there are a unit mass of perfectly competitive, identical final firms using sector-specific intermediate inputs to produce a sector-specific final consumption good.

Final firms use a continuum of intermediate inputs x_{jit}, for j $\in \{c,d\}$ and $i \in$ (0, 1), to

[3] Preferences in (2.3), belong to the family of non-homothetic preferences suggested by [Comin et al., 2021] to study structural transformation.

produce the clean and dirty consumption goods, respectively, by the mean of technology

$$c_{jt} = \left(\int\limits_0^1 \left(A_{jit} x_{jit} \right)^{\alpha} di \right)^{\frac{1}{\alpha}}, \tag{2.5}$$

with parameter $\alpha \in (0, 1)$; in both sectors (clean or dirty) the elasticity of substitution among intermediate good is $\frac{1}{1-\alpha} > 1$. The quality of intermediate good i in sector j, denoted by A_{jit}.

There is a unit mass of monopolistically competitive intermediate firms, each producing a specific differentiated intermediate input x_{jit}, $i \in (0, 1)$, in sector j, $j \in \{c, d\}$. They produce one unit of output per unit of labour.

2.3.3 Labour Market Clearing

The labour market clearing condition reads:

$$\int_0^1 x_{cit} di + \int_0^1 x_{dit} di = 1 \tag{2.6}$$

2.3.4 Innovation

Innovation drives growth by improving the quality A_{jit}, $j \in \{c, d\}$ and $i \in (0, 1)$, of differentiating intermediate inputs in both sectors (see equation (2.5)). At the beginning of period t, as in [Acemoglu et al., 2012] and [Acemoglu et al., 2014], scientists decide in which sector they will *direct* their research, with s_{ct} optimally doing research in the clean sector and s_{dt} in the dirty sector; $s_{ct} + s_{dt} = 1$. Then, scientists are randomly allocated to one of the intermediate inputs in the sector; they do research in this sector and if successful, monopoly rights are assigned to them. They operate this variety as entrepreneurs. Monopoly rights of the remaining intermediate inputs, for both $j \in \{c, d\}$, are randomly assigned to potential entrepreneurs.

Each scientist has a probability $\eta_j \in$ (0, 1), $j \in \{c,d\}$, of being successful on improving the quality of the particular intermediate input she was assigned to. When a scientist is successful, the quality of the intermediate input increases at the rate $\gamma > 0$. Consequently, the quality of intermediate input *i* in sector *j*, $j \in \{c,d\}$, follows the process:

$$A_{jit} = \begin{cases} (1+\gamma)A_{jit-1} & \text{with probability} \quad \eta_j \\ A_{jit-1} & \text{with probability} \quad 1-\eta_j \end{cases}$$

which means that the average productivity in each sector evolves over time according to the difference equation[4]

$$A_{jt} = (1+\gamma\eta_j s_{jt})A_{jt-1} \tag{2.7}$$

when we define that the average productivity in sector *j* such as:

$$A_{jt} = \left(\int_0^1 A_{jit}di\right) \tag{2.8}$$

2.3.5 Environment

$$E_{t+1} = \max\{\ \min\{\bar{E}, -\xi c_{dt} + (1+\delta)E_t\}, 0\} \tag{2.9}$$

where $\xi > 0$, measures the environmental degradation caused by producing the dirty consumption good; δ is a natural environmental regeneration rate. When E_t crosses zero, emissions are sufficiently large to cause an environmental disaster with the economy reaching a "point of no return".

[4] Working on the process followed by quality of intermediate input *i* in sector *j*

$$A_{jit} = \eta_j * (1+\gamma)A_{jit-1} + (1-\eta_j)A_{jit-1}$$
$$A_{jit} = \eta_j\gamma A_{jit-1} + A_{jit-1}$$

Given the symmetry between A_{jit-1} and A_{jt-1}, the number of the intermediates goods add up to 1 and the total of scientists in sector *j* is denoted by s_{jt}, the average technology in sector *j* will be given by $A_{jt} = (1+\gamma\eta_j s_{jt})A_{jt-1}$

Notice that sustainability requires that $c_{dt} < \frac{(1+\delta)\bar{E}}{\xi}$, a necessary but not sufficient condition. Sustainable growth then requires dirty production to be bounded.

2.4 Decentralised Equilibrium

2.4.1 Households Problem

At any period t, the representative household chooses the consumption basket $\{c_{ct}, c_{dt}\}$ that minimises the cost of generating utility c_t, by solving

$$\min_{\{c_{ct}, c_{dt}\}} p_{ct}c_{ct} + p_{dt}c_{dt} + \lambda_t \left(C_t^{\frac{\sigma-1}{\sigma}} - C_t^{\frac{\phi}{\sigma}} c_{ct}^{\frac{\sigma-1}{\sigma}} - c_{dt}^{\frac{\sigma-1}{\sigma}} \right),$$

where λ_t represents the marginal value of C_t i.e., the Lagrangian multiplier associated to constraint (2.5).

From the first order conditions for c_{jt}, $j \in \{c,d\}$, after substituting λ_t out, we get the nonhomothetic **Hicksian Demand** functions

$$c_{ct} = \left(\frac{p_{ct}}{P_t}\right)^{-\sigma} C_t^{1+\phi} \quad \text{and} \quad c_{dt} = \left(\frac{p_{dt}}{P_t}\right)^{-\sigma} C_t, \quad \text{where} \quad P_t = \left(C_t^{\phi} p_{ct}^{1-\sigma} + p_{dt}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{2.10}$$

with the following relationship between relative clean consumption and relative clean price:

$$\frac{c_{ct}}{c_{dt}} = \left(\frac{p_{ct}}{p_{dt}}\right)^{-\sigma} C_t^{\phi} \tag{2.11}$$

2.4.2 Production

2.4.2.1 Final Goods Producers

The representative firm producing the final consumption good *j*, $j \in \{c, d\}$, solves the following problem

$$\max_{\{x_{jit}\}} \quad p_{jt}c_{jt} - \int_0^1 p_{jit}x_{jit}di, \tag{2.12}$$

subject to technology (2.5) and taking prices as given. The optimal (inverse) demand function of intermediate input *i* in sector *j* is given by

$$\frac{p_{jit}}{p_{jt}} = \left(\frac{c_{jt}}{x_{jit}}\right)^{1-\alpha} A_{jit}^{\alpha}. \tag{2.13}$$

Final firms make zero profits.

2.4.2.2 Intermediate Inputs

There is a unit mass of monopolistically competitive intermediate firms, each producing a specific differentiated intermediate input *i*, $i \in (0, 1)$, in each sector *j*, $j \in \{c, d\}$. Intermediate firm *i* requires an entrepreneur to be operative, and produces one unit of output per unit of labour.

Subject to the demand function (2.13), the firm producing intermediate input *i* for sector *j* solves the following problem

$$\pi_{jit} = \underset{\{p_{jit}, x_{jit}\}}{Max} \quad p_{jit}x_{jit} - x_{jit} \tag{2.14}$$

which implies that the entrepreneurs appropriates the monopolistically competitive profits π_{jit}. Labour is adopted as numeraire, then wages are normalised to one. By solving the previously mentioned problem, entrepreneur optimally charge a constant markup $\frac{1}{\alpha}$ to a constant marginal cost:

$$p_{jit} = \frac{1}{\alpha} \tag{2.15}$$

The same for all intermediate firms and time invariant. After substituting the optimal price rule (2.15) into the demand function (2.13), production is shown to be demand driven:

$$x_{jit} = \left(\alpha p_{jt}\right)^{\frac{1}{1-\alpha}} c_{jt} A_{jit}^{\frac{\alpha}{1-\alpha}} \tag{2.16}$$

being larger for firms producing higher quality A_{jit}.

After substituting (2.16) into (2.14), for $j \in \{c,d\}$, profits become

$$\pi_{jit} = \nu p_{jt}^{\frac{1}{1-\alpha}} c_{jt} A_{jit}^{\frac{\alpha}{1-\alpha}}, \quad \text{with} \quad \nu = (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}$$

After substituting (2.16) into (2.5), for $j \in \{c,d\}$, the price of clean and dirty goods, $j \in \{c,d\}$, becomes:

$$p_{jt} = \frac{1}{\alpha A_{jt}} \tag{2.17}$$

where we are using the symmetry between A_{jt} and A_{jit}. Notice then that the ratio of prices (clean vs dirty) is equal to the inverse of the ratio of average productivities.

$$\frac{p_{ct}}{p_{dt}} = \frac{A_{dt}}{A_{ct}} \tag{2.18}$$

Total profits $\pi_{ct} + \pi_{dt}$ are redistributed to households as the return to entrepreneurial activities, for $j \in \{c,d\}$,

$$\pi_{jt} = \int_0^1 \pi_{jit} di = \nu p_{jt}^{\frac{1}{1-\alpha}} c_{jt} A_{jt}^{\frac{\alpha}{1-\alpha}} \tag{2.19}$$

Since one unit of labour is required to produce one unit of intermediate goods. It reads:

$$\frac{c_{ct}}{A_{ct}} + \frac{c_{dt}}{A_{dt}} = 1 \tag{2.20}$$

which results from substituting (2.17) into (2.16) and then into (2.6).

Combining (2.18) and (2.11) with (2.20), and defining $a_t = \frac{A_{dt}}{A_{ct}}$, clean and dirty consumption become

$$c_{ct} = \frac{A_{ct} C_t^{\phi} a_t^{1-\sigma}}{\left(C_t^{\phi} a_t^{1-\sigma} + 1\right)} \quad \text{and} \quad c_{dt} = \frac{A_{dt}}{\left(C_t^{\phi} a_{ct}^{1-\sigma} + 1\right)} \tag{2.21}$$

We can also define demand for clean and dirty consumption goods in terms of technology substituting (2.17) into (2.10) to have:

$$c_{ct} = \left(\frac{A_{ct}}{A_t}\right)^{\sigma} C_t^{1+\phi} \quad \text{and} \quad c_{dt} = \left(\frac{A_{dt}}{P_t}\right)^{\sigma} C_t, \tag{2.22}$$

and combining (2.22) and (2.20) gives:

$$A_t = \left(A_t^{\phi} A_{ct}^{\sigma-1} + A_{dt}^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{2.23}$$

Defining $r_t = \frac{c_{dt}}{c_{ct}}$, then, the relative clean consumption can be expressed as:

$$r_t = \frac{a_t^{\sigma}}{A_t^{\phi}} \tag{2.24}$$

The larger the *warm-glow* parameter is, the most labour is allocated to the production of the clean good. Moreover, the elasticity of the relative clean demand with respect to the relative clean productivity is equal to the elasticity of substitution of these two goods as clearly emerges from equation (2.3).

2.4.3 Innovation

A scientist, in order to decide the sector in which she will direct her research, compares expected returns on both sectors. So, given that π_{jt} are profits conditional on being successful and η_j the probability of being successful, then using (2.14) the unconditional expected profits of a scientist are:

$$\eta_j \pi_{jt}^s = \Pi_{jt} = \eta_j \left(\frac{1-\alpha}{\alpha} \right) p_{jt}^{\frac{1}{1-\alpha}} c_{jt} (1+\gamma)^{\frac{\alpha}{1-\alpha}} A_{jt-1}^{\frac{\alpha}{1-\alpha}} \tag{2.25}$$

Then, a scientist will be indifferent between performing research in any of the two sectors if and only if

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left(\frac{(1+\gamma\eta_c s_{ct})}{(1+\gamma\eta_d(1-s_{ct}))} \right)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} \left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{\frac{-\varphi}{1-\alpha}} \tag{2.26}$$

where $\varphi = (1-\alpha)(1-\varepsilon)$ and we are using the assumption of $s_{ct} + s_{dt} = 1$.

Notice that if clean and dirty consumption are gross substitutes and at the initial time we assume that dirty technology is most advanced than clean technology, scientists are going to allocate themselves to the dirty sector in the next period, and the next and so forth. As a result of that dynamic, the equilibrium condition described in (2.26) could not be achieved and, an environmental disaster not be avoided. In other words, depending on which sector is more advanced, one of the following two conditions will hold forever:

$$\frac{\eta_c}{\eta_d} \left(\frac{1}{(1+\gamma\eta_d)} \right)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} < \left(\frac{A_{dt-1}}{A_{ct-1}} \right)^{\frac{-\varphi}{1-\alpha}} \quad \text{if} \quad s_{ct} = 0 \quad \text{or} \tag{2.27}$$

$$\frac{\eta_c}{\eta_d} (1+\gamma\eta_c)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} > \left(\frac{A_{dt-1}}{A_{ct-1}} \right)^{\frac{-\varphi}{1-\alpha}} \quad \text{if} \quad s_{ct} = 1 \tag{2.28}$$

However, suppose they are complements, and one of these two inequalities hold initially. In that case, the economy will likely converge on a finite time to the equilibrium described by the equality (2.26), and again and environmental disaster will not be avoided because, by definition, the economic growth requires the production of both inputs to grow.

2.5 Central Planner Solution

In this section is assumed that a central planner implements a solution, which will call optimal policy, to correct all imperfections found in the market. In doing so, she maximises the household's utility (2.1) subject to constraints (2.3), (2.5), (2.6), (2.7), (2.9), and market clearing for scientists (See more details of the solution in appendix B section B.2).

Denoting the shadow price of total consumption, dirty consumption and clean consumption by λ_{1t}, λ_{2t} and λ_{3t} respectively, from the FOC's with respect to c_{ct} and c_{dt} we have:

$$\hat{p}_{ct} = \left(\frac{\sigma - 1}{\sigma}\right)\left(\frac{C_t^{\phi}}{c_{ct}}\right)^{\frac{1}{\sigma}} \tag{2.29}$$

$$\hat{p}_{dt} = \left(\frac{\sigma - 1}{\sigma}\right)\frac{1}{(1+\tau_t)c_{dt}^{\frac{1}{\sigma}}} \tag{2.30}$$

Where it can be seen that $\hat{p}_{dt}$ is not only equal to the marginal utility of the dirty energy consumption, as in decentralised equilibrium, and this wedge between these terms, following [Acemoglu et al., 2012], is referred to as the carbon tax (τ_t) that the central planner establishes to internalise the externality that dirty energy consumption is causing to the environment[5].

Taking the ratio between (2.29) and (2.30) gives:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = (1+\tau_t)\left(\frac{c_{dt}}{c_{ct}}\right)^{\frac{1}{\sigma}} C_t^{\frac{\phi}{\sigma}} \tag{2.31}$$

It is known that a central planner eliminates any positive profits in the economy, so production of machines will take place under perfect competition. From the FOC's with

[5] λ_{6t} is the shadow price of the quality of the environment

respect to x_{ijt}, $i \in$ {c,d} are:

$$x_{cit} = \hat{p}_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{cit}^{\frac{\alpha}{1-\alpha}} \tag{2.32}$$

$$x_{dit} = \hat{p}_{dt}^{\frac{1}{1-\alpha}} c_{dt} A_{dit}^{\frac{\alpha}{1-\alpha}} \tag{2.33}$$

As before, equations (2.32) and (2.33) can be used in the market clearing condition for labour to find:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = \left(\frac{A_{dt}}{A_{ct}}\right) \tag{2.18}$$

Once we compute the FOC's wrt A_{cit}, A_{dit}, s_{ct} and s_{dt}, we can get:

$$\frac{\eta_c(1+\gamma\eta_d(1-s_{ct}))}{\eta_d(1+\gamma\eta_c s_{ct})} \underbrace{\frac{\sum_{v=1}^{\infty} \lambda_{1t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}^{\frac{\alpha}{1-\alpha}}}{\sum_{v=1}^{\infty} \lambda_{1t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}^{\frac{\alpha}{1-\alpha}}}}_{Q_t} \tag{2.34}$$

Where we are using the assumption of $s_{dt} = 1 - s_{ct}$.

If we recall equation (2.26) from the decentralised equilibrium equation, which can be written as:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left(\frac{(1+\gamma\eta_c s_{ct})}{(1+\gamma\eta_d(1-s_{ct}))}\right)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\frac{-\varphi}{1-\alpha}} \tag{2.26}$$

It is not difficult to see how the central planner intervenes to correct the myopia of the monopolists in their innovation decisions by determining the allocations of scientists as a function of the discounted value of the entire flow of additional revenues generated by their innovation in both sectors (knowledge externality in the innovation possibilities frontier). However, the central planner does recognise that innovation in the dirty sector generates environmental degradation, then she must allocate scientists to the sector with the higher social gain from innovation. The social optimum implies that scientists will be allocated to the clean sector whenever (2.34) will be greater than 1.

2.6 Implementation of the Optimal Policy

As it was established in the decentralised equilibrium, the *warm-glow* is insufficient to avoid an environmental disaster. If the dirty technology started with an advantage over clean no matter if both inputs are gross complements or substitutes, *warm-glow* could delay the disaster over time but not avoid it.

According to the analysis of optimal policy, if both inputs are sufficiently substitutable, a carbon tax on dirty consumption and subsidy to the clean R&D will drive all innovation to that sector (clean sector) and an environmental disaster will be avoided. Furthermore, the intervention might be temporary, because profits from innovation in clean are going to be higher than profits from innovation in the dirty sector.

Considering τ_t as the carbon tax on the price of dirty consumption, the budget constraint to be faced by households become:

$$p_{ct}c_{ct} + (1+\tau_t)p_{dt}c_{dt} = w_t + \pi_{ct} + \pi_{dt} \tag{2.35}$$

Given this new budget constraint, relative price of clean energy consumption is now given by:

$$\frac{p_{ct}}{p_{dt}} = (1+\tau_t)\left(\frac{c_{dt}}{c_{ct}}\right)^{\frac{1}{\sigma}} C_t^{\frac{\phi}{\sigma}} \tag{2.36}$$

The problem to be solved for the producers of final goods does not change. However, under this extended setup, the unconditional expected profits of a scientist in clean sector changes and becomes:

$$\Pi_{ct} = \eta_c(1+q_t)\mu p_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{ct-1}^{\frac{\alpha}{1-\alpha}} \quad \text{where} \quad \mu = \left((1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}\right)(1+\gamma)^{\frac{\alpha}{1-\alpha}} \tag{2.37}$$

Where $(1+q_t)$ is the subsidy that will be necessary to drive innovation towards the clean sector, in the dirty sector, the unconditional expected profits of a scientist remains the same, therefore, the relative unconditional expected profits of innovating in clean sector becomes:

$$\Pi_t = \frac{\eta_c}{\eta_d}(1+\tau_t)^{\sigma}(1+q_t)A_t^{\phi}\left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d(1-s_{ct})}\right)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\frac{-\varphi}{1-\alpha}}$$

Regardless the definition of clean and dirty consumption, they take into account the carbon tax:

$$c_{ct} = \frac{A_{ct}C_t^{\phi}(1+\tau_t)^{\sigma}a_t^{1-\sigma}}{\left((1+\tau_t)^{\sigma}C_t^{\phi}a_t^{1-\sigma}+1\right)} \qquad c_{dt} = \frac{A_{dt}}{\left((1+\tau_t)^{\sigma}C_t^{\phi}a_t^{1-\sigma}+1\right)} \tag{2.38}$$

Recall that at the beginning the dirty sector is more advanced than the clean, thus, the following inequality would hold forever:

$$\frac{\eta_c}{\eta_d}\left(\frac{1}{(1+\gamma\eta_d)}\right)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} < \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\varphi}{1-\alpha}} \quad \text{if} \quad s_{ct}=0 \quad \text{or} \tag{2.27}$$

Nevertheless, the implementation of the optimal policy must guarantee that:

$$(1+q_t)(1+\tau_t)^{\sigma}\frac{\eta_c}{\eta_d}(1+\gamma\eta_c)^{\frac{\sigma(1-\alpha)-1}{1-\alpha}} A_t^{\phi} > \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\varphi}{1-\alpha}} \quad \text{when} \quad s_{ct}=1 \tag{2.39}$$

therefore, the environmental disaster will be avoided in finite time if both inputs are substitutes.

2.7 Numerical Simulation

This section presents the numerical analysis that builds on the model discussed above and its solution under decentralised equilibrium and the implementation of optimal policy. We follow [Acemoglu et al., 2012], [Greaker et al., 2018] and [Comin et al., 2021] to calibrate the main parameters.

Starting with the estimation of the *warm-glow* parameter, we use equation (2.16) by using the information available for countries that adopted the Paris Agreement. So, taking the logarithm in both sides of equation (2.16) gives:

$$Ln(c_{ci}) = -\sigma Ln\left(\frac{p_{ci}}{P_i}\right) + (1+\phi)Ln(C_i)$$

which has the econometric formulation:

$$Y_{C_{ci}} = \beta_0 + \beta_1 P_{ci} + \beta_2 X_{C_i} + \mu_i \quad i \in \{1,2,...96\}; \tag{2.40}$$

where $Y_{C_{ci}}$ represents the demand for sustainable energy that is planned to be met for each country by 2030, and P_{ci}, is the price of the cleanest energy source for which there is an international market index, in this case, Natural gas (NBP natural gas index, traded on the International Petroleum Exchange [Bloomberg, 2021])[6]. To control for the difference across countries, we work with the Purchasing Power Parities (PPP) data available in [OECD, 2021b] and with dummy variables which distinguish if a country is or not a member of the OECD. Finally, we use the country real GDP as a proxy of the total consumption which is represents by X_{C_i}. All variables are fixed to 2012, the year established as a baseline in the Paris Agreement goals.

Table 2.1: Estimation of *warm-glow* parameter

Parameters	Coefficient	95% Confidence interval
β_0	-24.84^{***}	$(-28.00, -21.67)$
β_1 (OECD)	-0.06^{**}	$(-0.16, -0.05)$
β_1 (non OECD)	-0.09^{***}	$(-0.17, -0.01)$
β_2	1.10^{***}	$(0.97, -1.23)$

96 observation

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

6 There is not yet an international index considered as a fair reference of the market price for the non fossil fuels basket, therefore we follow [Zhao et al., 2018] and assume the consumption of natural gas as a proxy for the clean consumption

Based on table (2.1), we simulate the model assuming three different values of the *warm-glow* parameter which are equivalent to the mean, lower and upper bounds of the confidence interval for β_2.

In this exercise, as it was set in chapter 1, each period corresponds to five years, which means that the model is calibrated over 400 years. Horizon is commonly established in the literature due to the atmosphere's reaction to changes in emissions takes a long time. The utility function used in the simulations is identical to one described in the model section. The share of machines is set $\alpha = 1/3$ and the probability of successful innovation per year is $\eta = 0.002$.

The initial levels of technology for both sectors are set to match the implied values of world renewable and fossil energy consumption at a certain year (2018): dirty consumption was fixed as 11.272 million tonnes of oil equivalent (Mtoe) and clean consumption as 2.004 (Mtoe) [BP, 2018].

The environmental degradation parameters and the definition of enviromental quality are set following [Acemoglu et al., 2012]. They define a function for the cost of environmental degradation $\Phi(\Delta)$, such as:

$$\Phi(\Delta(S_t)) \equiv \frac{(\Delta_{disaster} - \Delta(S_t))^{\lambda} - \lambda \Delta_{disaster}^{\lambda-1}(\Delta_{disaster} - \Delta(S_t))}{(1-\lambda)\Delta_{disaster}^{\lambda}}$$

where Δ denotes the temperature increase given the atmospheric concentration in CO2 at time *t* relative to the pre-industrial levels measured in parts per million (ppm):

$$\Delta = 3 * log_2(S_t/278),$$

where 278 ppm is the pre-industrial level of CO2-concentration, $S_t = C_{CO2,disaster} - \max\{C_{CO2t}, 278\}$, denoting $C_{CO2,disaster}$ the concentration level associated with the disaster temperature increase, which it sets to disaster = 6 degrees. For purpose of numerical simulation, we substitute $\Phi(\Delta(S_t))$ for the quality of the environment E_t in the utility function, which also holds the assumption made in (2.2)

The constant regeneration rate (δ) of atmosphere is assumed equal to 0.005 per year and the rate at which dirty production reduces the quality of the environment (ξ) regeneration rate equals to 0.0015.

For the values of the discount rate, this study does not take account of the fair value to be assumed (Nordhaus's research, Sterm's research, etc) and the results are evaluated using two different cases as in [Acemoglu et al., 2012]: $\rho = 0{,}001$ and $\rho = 0.015$.

As explained in the model's description, the value of the elasticity of substitution between the two goods (σ) is crucial for the results. Following [Acemoglu et al., 2012] , we use two different values for σ, 3 and 10, but focus my attention mainly on the results for $\sigma = 3$ because it is closer to the current level of substitution found in the empirical literature [Greaker et al., 2018].

2.8 Results

This section has two parts. The first explains the results under the decentralised equilibrium, and the other illustrates the implementation of the optimal policy. In both cases, we plot the paths followed for the main variables: increase in the temperature, percentage of scientists allocated in the clean sector, and when it applies, carbon tax and R&D subsidy.

2.8.1 Decentralised Equilibrium

Figure 2.1 reveals that an environmental disaster cannot be avoided no matter the level of substitutability assumed. However, it can be seen that the presence of *warm-glow* always delays the disaster over time. The higher the *warm-glow* parameter, the later the disaster occurs. In addition, the figure also elucidates that high values of substitutability ($\sigma = 10$), the effect of *warm-glow* is small.

For both values of σ, the allocation of scientists never switches to clean research; therefore, plotting those results is needless.

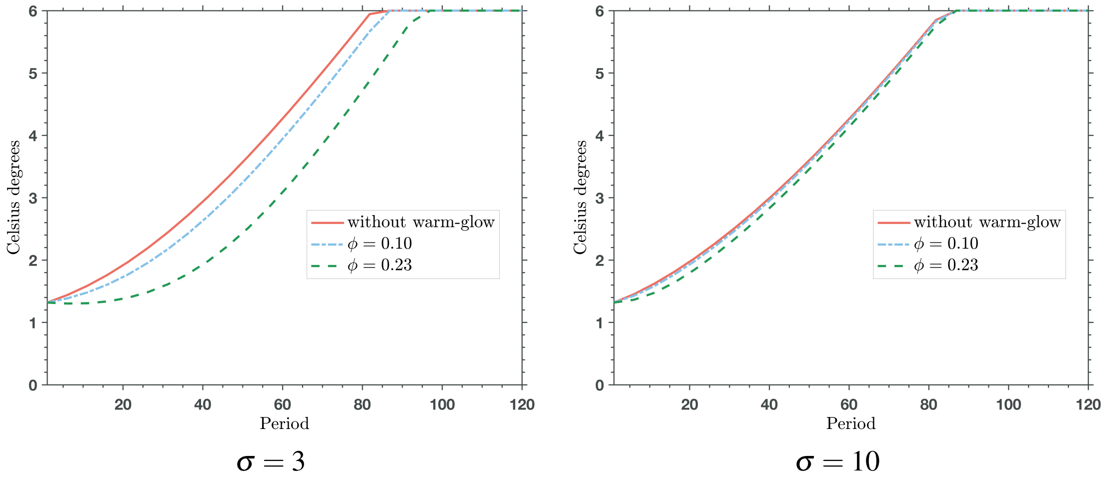
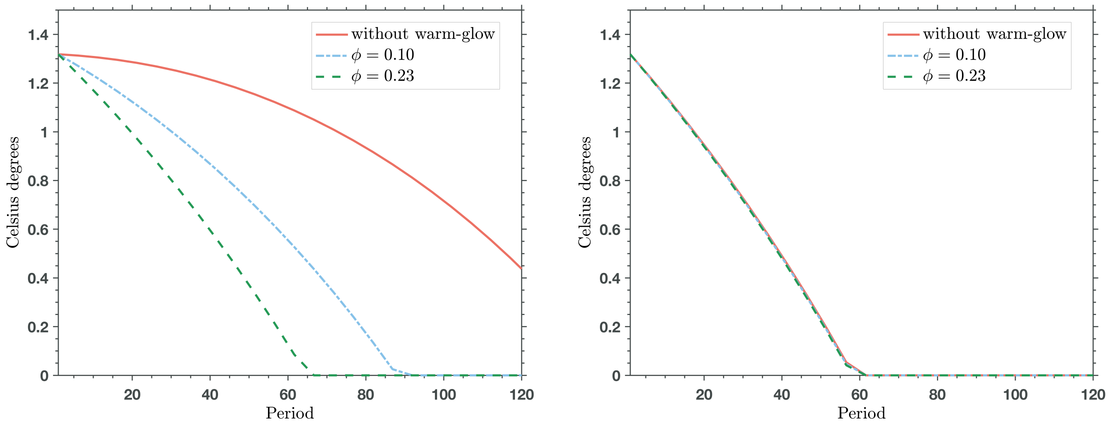


Figure 2.1: Decentralised Equilibrium: Increase in the Average Earth Temperature over Pre-industrial Era Levels

2.8.2 Optimal Policy

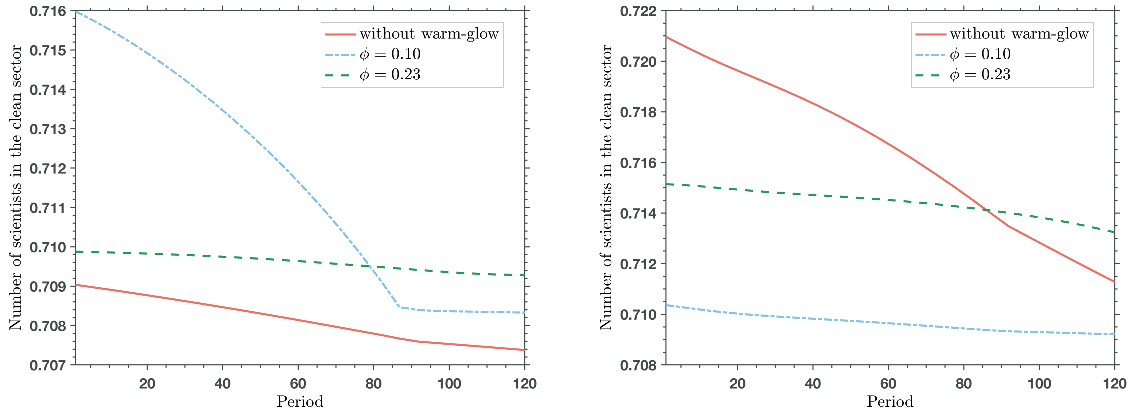
The implementation of the optimal policy avoids an environmental disaster across values of the *warm-glow* parameter and levels of substitutability. Starting with the increases in the temperature, as shown in figure 2.2, the presence of the *warm-glow* parameter makes the temperature return to its pre-industrial levels quicker when $\sigma = 3$, but has no remarkable effect on temperature dynamics when $\sigma = 10$. However, compared to results presented in [Acemoglu et al., 2012], when $\sigma = 3$, this model can always avoid an environmental disaster.



$\sigma = 3$ $\sigma = 10$

Figure 2.2: Optimal Policy: Increase in the Average Earth Temperature over Pre-industrial Era Levels

In terms of the allocation of scientists, as seen in both figures in 2.3, the complete switch of all research activities towards the clean sector does not occur over the period simulated, although most scientists (greater than 70%) are directed to clean innovation, in particular, when *warm-glow* is present and $\sigma = 10$. This finding might suggest that achieving the complete transition towards sustainable energy is still challenging worldwide.



$\sigma = 3$ $\sigma = 10$

Figure 2.3: Optimal Policy: Scientist Allocation in Clean R&D

Figures in 2.4 show the share of clean consumption in the total consumption. As seen, the higher the *warm-glow* parameter, the larger the share of clean consumption. Although the transition is quicker when $\sigma = 10$ and is not immediate, it takes place before period 100.

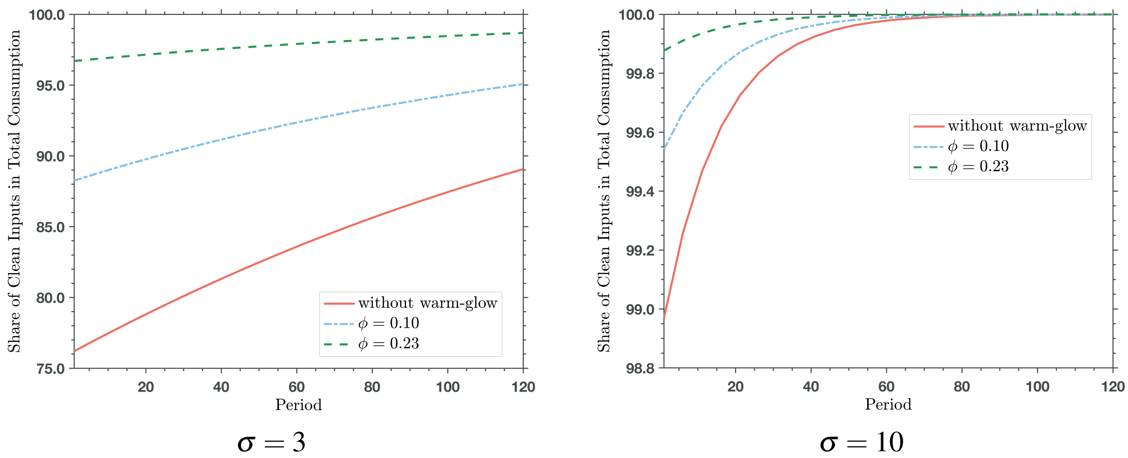
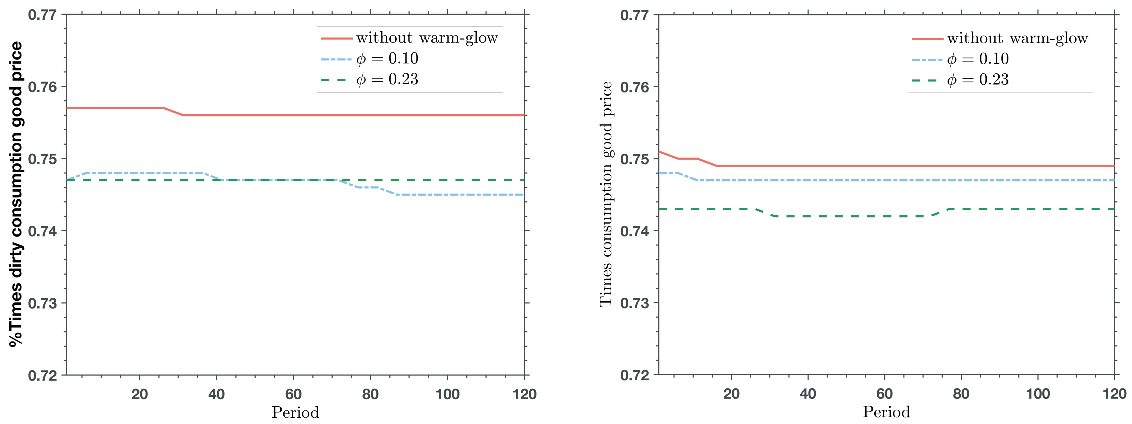


Figure 2.4: Optimal Policy: Share of Clean Inputs in Total Consumption

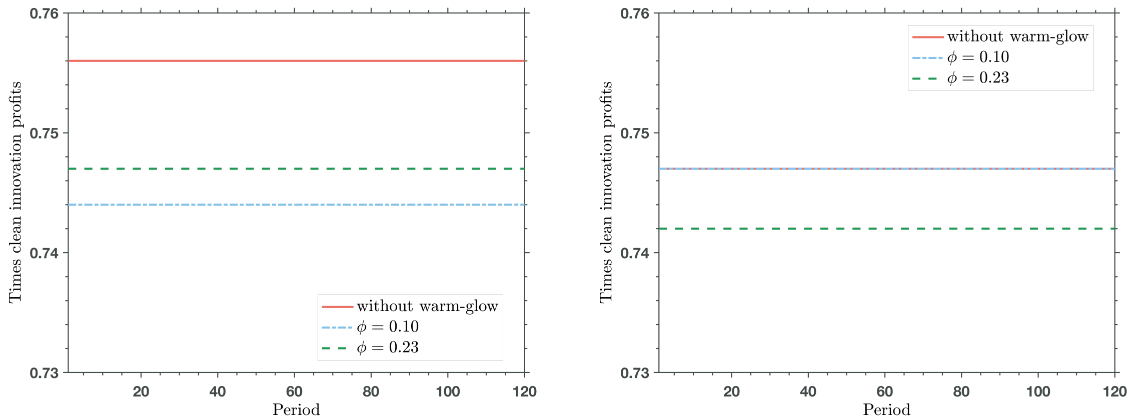
Figures 2.5 and 2.6 show the optimal combination of carbon tax and clean R&D subsidy. In those figures, it can be seen that to keep emissions down enough, the required size for both instruments is much lower than the ones found in chapter 1, [Acemoglu et al., 2012] and [Greaker et al., 2018]. It can also be seen in figure 2.5 that there is a linear relationship between the *warm-glow* parameter and the cabon tax, the added value of the *warm-glow* is generally proportional to the reduction in the value of this instrument. Regarding the R&D subsidy, figure 2.6 illustrates, in turn, a nonlinear relationship between the *warm-glow* parameter and the subsidy, larger values for *warm-glow* do not always result in lower sizes of the subsidy.

In the light of the overall results, although the low impact of *warm-glow* in reducing, significantly, the size of the tax and the subsidy in most cases, this extension avoids an environmental disaster under all scenarios. Results that are not always present in [Acemoglu et al., 2012]. This model is also confirming the alternative channel proposed in chapter 1 to tackle climate change, and how this could make a difference in the effectiveness of the policies and the support the current strategies in place, as written into the Paris and its sequel, the Glasgow Pact.



$\sigma = 3$ $\sigma = 10$

Figure 2.5: Optimal Policy: Carbon Tax



$\sigma = 3$ $\sigma = 10$

Figure 2.6: Optimal Policy: Clean R&D Subsidy

2.9 Conclusion

In this chapter, following the approach proposed in [Comin et al., 2021], we extend the endogenous economic growth model built in chapter 1 by assuming nonhomothetic preferences and linking the countries' emission targets to *warm-glow giving* theory, in order to model the Paris Agreement fully.

Assuming the world as a whole economy, we solve and calibrate the model under the decentralised equilibrium and optimal policy structures. By so doing, we find that the *warm-glow* parameter has more limited effects compared to the WGPM under decentralised equilibrium, but concerning policy intervention, this model requires lower policy intervention (lower values required for taxes and subsidies).

Further disentangling the results, in the case of the decentralised equilibrium, although an environmental disaster cannot be avoided, the *warm-glow* parameter delays the disaster when the degree of substitutability between inputs is low ($\sigma = 3$). This result makes sense considering that the literature has proved that the range of substitutability is between 1.5 and 3 worldwide. In addition, [Yergin, 2020] points out that the world energy sector is still not prepared to depend on renewable sources entirely. On the one hand, that status is still unaffordable for a large part of the world, and on the other hand, the world has not found a solution yet to deal with the intermittent nature of renewable sources such as wind speed or sunlight hours, for instance.

The model only quantitatively accounts for the global clean energy transition process when the optimal policy is implemented. As was expected, the policy causes less distortion when the *warm-glow* parameter is included: the higher the *warm-glow* parameter, the lower the values of the tax and subsidies required to avoid the disaster.

In summary, the approach proposed in this chapter offers a different angle to analyse the motivations of the new state in the climate change negotiations, where it is indisputable that public opinion is playing a definitive role around the world. The model suggests that governments find more effective strategies to achieve the environmental goals by exploring ways to make people more conscious about the level of degradation that society is inflicting on the environment with current and permanent threatening life consequences for all.

3 | Understanding the Dynamics of Carbon Pricing in the EU

3.1 Introduction

The urgency of addressing climate change motivates governments around the world to deal with the extreme difficulties of assigning responsibilities to each other to find the ultimate solution to climate change, and individuals to choose more sustainable life styles. Crucially the production side of economies must incorporate efficiently the cost of emissions reduction inside their activities.

From the production viewpoint, there is a wide discrepancy in the amount of emissions firms generate when they carry out their activities. These differences are not only related to the specific activities (energy and non-energy intensive) but also to the state of technology possessed by a particular firm in a particular economic sector. Therefore, any policy that seeks to reduce emissions generated when producing services and goods will have diverse impacts across the economy, and because of that, these policies also have to balance the cost-benefit among economic actors.

From a theoretical perspective, one of the best ways to set a fair value on the damage done by utilising non-renewable inputs is establishing a "carbon price" for each unit of emissions generated, as was proposed in the first and second chapter of this thesis and the literature cited in them. The right carbon price should be tailored to each country's conditions (differences in institutions and infrastructures) in order to avoid an over or undercharge that could jeopardise sustainable and inclusive growth.

In terms of the implementation, there are two ways to achieve the right carbon price: one is to fix a tax that takes the emissions to the optimal level that the theory recommends. The other is to limit the overall emissions of all actors in the economy, allowing them to trade their own emissions rights. In the presence of inevitable market failures, the last format commonly known as a "cap-and-trade" system, offers an opportunity for the governments and the market to work cooperatively. While the market fixes a fair carbon price, the government only needs to step in when it detects the presence of distorted incentives or behavioural biases which prevent carbon prices alone from succeeding.

The European Community (EUC) adopted in 2005 a cap-and-trade scheme which currently has targeted the reduction of EUC carbon dioxide emissions by 55% from 1990 levels by 2030 (Paris Agreement pledges). This scheme is officially known as the EU-Emissions Trading System (EU ETS) and has claimed that, while following the theory, it facilitates all economic units to face the same "carbon price", guarantees emissions reduction where it costs the least to do so, and finally provides a signal to firms of the right moment for making sustainable energy transition. In addition, EU ETS offers a suitable way for governments to track the compliance of countries' emissions paths closely.

The EU ETS is currently the largest and most well-established cap-and-trade system globally, and given the overall good results obtained from it, the scheme has attracted the attention of other regions to control their emissions. This mechanism has proved not only that it provides the right incentives without spending more than necessary but also, that it works adequately with minimum information required (emissions amount per actor) [Blanchard et al., 2021]. In that respect, and as far as we know, no study uses a theoretical economic growth model with *warm-glow* preferences to forecast the carbon price in the EUC.

This chapter embarks on that task and works with the theoretical structure proposed in chapter 1 to empirically validate its carbon price definition by using data from the EU-ETS and EUC economy. In so doing, we offer an alternative tool to understand the dynamics of this price and generate future scenarios of its movements in the short-term. The approach that we propose is crucial for firms and policymakers in their decision-making process related to emissions goals, considering that, since 2015, firms and politicians have felt the pressure imposed by the public for being perceived as actors with sustainable profiles.

The structure of the chapter is as follows: in the next section the literature references used are illustrated, section 3.3 presents the model used to perform the forecasting exercises, section 3.5 reports the results and finally, section 3.6 summarises the main conclusions.

3.2 Environmental Policy Implementation and Forecasting Techniques

Environmental policies could be classified into two major types: command-and-control standards or marked-based instruments. The first kind refers to policies that propose uniform standards for relevant operators to achieve domestic climate change commitments. As [Stavins, 2008] points out, among these policies, is included efficiency standards for appliances, vehicle fuel economy standards, renewable portfolio standards for electricity generators, etc. The second kind, market-based instruments, are policies that intervene directly on the market prices and quantities, such as carbon taxes, subsidies for sustainable innovation and consumption, and cap-and-trade systems.

Although both kinds of policies have been used in the last three decades, the ones which advocate for market-based instruments have proved to be more cost-efficient in achieving the environmental goals established in countries where these policies have taken place. However, as [Goulder and Parry, 2020] argue, these kinds of instruments still have some limitations in terms of minimising general equilibrium costs or achieving household equity given the market failures that are impossible to remove in most contexts.

In their work, [Hahn and Stavins, 2011] approach that link between market failures and environmental policies. They explain how a cap-and-trade system, under certain conditions, is an application of the "Coase theorem"[1], because, disregarding the initial allocation of tradable rights, the market equilibrium is cost-effective. They analyse in particular four applications of the cap-and-trade system in the US, and offer indirect (circumstantial) and direct (statistical) evidence that independent property was held without compromising the achievement of the environmental goals: The reduction content of lead in gasoline (1973), the Montreal Protocol (1987) to limit emissions that damaged Earth's stratospheric ozone layer, the cap-and-trade system for regulating emissions of SO_2, the primary precursor of acid rain (1990), and the Regional Clean Air Incentives Market (RECLAIM) which pursued the reduction of NOx and SO2 emissions in the Los Angeles area.

Focusing on the US economy as well, [Stavins, 2008] proposes an upstream, economy-wide CO_2 cap-and-trade as the best instrument to reduce CO_2 emissions, after comparing this policy with standards-based counterparts under a theoretical and empirical point of view. The assessment of the policy is undertaken using the Emissions Prediction and Policy Analysis (EPPA) model of the Massachusetts Institute of Technology's Joint Program on the Science and Policy of Global Change. They conclude that a medium-term cap-and-trade system (at least 25 years) provides certainty on emissions levels, price signals and hence incentives for firms to invest in the development of sustainable tech-

[1] The "Coase theorem" stipulates that the bilateral negotiation between the generator and the recipient of an externality will lead to the same efficient outcome regardless of the initial assignment of property rights, in the absence of transaction costs, income effects, and third party impacts [Hahn and Stavins, 2011]

nologies, thereby lowering the future costs of achieving emission reductions. He also adds that it is convenient from a climate change global goals point of view because it is straightforward to harmonise with other countries' climate policies.

In terms of the forecasting carbon price literature, although most of the current studies have been based on conventional econometric models, for instance, multiple linear regression, GARCH, nonparametric models, there is an increasing part of the literature that is working with unconventional methods such as artificial intelligence (AI) models, artificial neural networks (ANNs), and least squares support vector regression (LSSVR). In particular, [Zhu and Wei, 2013] proposes a novel hybrid methodology that exploits the strength of the ARIMA and LSSVM models in forecasting carbon prices. They use the ARIMA model to capture linear patterns hidden in carbon prices, whilst the LSSVM is used to capture nonlinear patterns existing in those prices. They conclude that their hybrid methodology can outperform the results obtained from a single ARIMA or least squares support vector machine (LSSVM) alone.

In a similar line of thought, [Zhu et al., 2017] uses empirical mode decomposition (EMD) as an input for LSSVR model to forecast carbon prices. Their results show that when their model is compared with more conventional ARIMA models, it can obtain better statistical and trading performances and has more precise prediction results. [Zhao et al., 2018] in turn presents a real-time forecasting procedure that utilises multiple factors with different sampling frequencies to predict the weekly carbon price; models which are usually used in financial market studies. They compared their results against autoregressive (AR), moving average (MA) and threshold autoregressive conditional heteroskedasticity (TGARCH) models and demonstrate its robustness in forecasting carbon prices.

3.3 *Warm-glow* Growth Model and Forecasting

This section is divided into two parts. The first describes the variables and equations from WGPM which are combined to write the econometric expression of the carbon price. The second explains the link between the carbon price equation and the Vector Correction Error Model (VECM) used to estimate that expression.

3.3.1 Theoretical Framework

The model considers an economy where composite consumption of the representative household, C_t, is produced using only two different consumption goods: clean or renewable, c_{ct}, and dirty or non-renewable, c_{dt}. $\frac{p_{ct}}{P_t}$ and $\frac{p_{dt}}{P_t}$ denote the real prices[2] of both consumption goods, which are defined as follows respectively:

$$\frac{p_{ct}}{P_t} = (1+\phi)\left(\frac{C_t}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \tag{1.24}$$

$$\frac{p_{dt}}{P_t} = \frac{1}{(1+\tau_t)}\left(\frac{C_t}{c_{dt}}\right)^{\frac{1}{\varepsilon}} \tag{1.25}$$

Where ϕ is the *warm-glow* parameter, ε represents the elasticity of substitution between both inputs. In addition, the central planner solution to internalise the externality of environmental degradation generated by dirty consumption is to include in its price a carbon tax, τ_t. In doing so, the tax must fix the quantity of dirty consumption at the level in which the representative household's welfare is maximised.

[2] In the solution of the model in chapter 1 it is assumed that the price of a unit of composite consumption $P_t = \left((1+\phi)^{\varepsilon} p_{ct}^{1-\varepsilon} + (1+\tau_t)^{1-\varepsilon} p_{dt}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ is equal to 1

Recalling the relation between relative price and relative technology

$$\frac{p_{ct}}{p_{dt}} = \left(\frac{A_{dt}}{A_{ct}}\right) \tag{1.11}$$

We combine these equations with (1.24) and (1.25), and take the logarithm of both sides of the resulted expression to get:

$$log(1+\tau_t) = log\left(\frac{1}{1+\phi}\right) + \left(\frac{1}{\varepsilon}\right) log\left(\frac{c_{ct}}{c_{dt}}\right) + log\left(\frac{A_{dt}}{A_{ct}}\right), \tag{3.1}$$

which has the following econometric specification:

$$\tau_t - \beta_0 - \beta_1 x_t - \beta_2 a_t = \xi_t \tag{3.2}$$

when I define $x_t = log\left(\frac{c_{ct}}{c_{dt}}\right)$, $a_t = log\left(\frac{A_{dt}}{A_{ct}}\right)$, and assume that $\tau_t \approx log(1+\tau_t)$ due to $\tau_t < 1$.

Equation 3.2 establishes that deviations of the carbon tax from the the long-term equilibrium will be temporary by assuming that ξ_t is a stationary disturbance term. With reference to coefficient assumptions, the theory suggests that $\beta_1 > 0$ and $\beta_2 = 1$, which implies that any increase either in relative clean consumption or relative technology increases carbon tax.

3.3.2 Cointegration and Vector Error Correction Model (VECM)

According to [Enders, 2008], if a linear combination of a group of nonstationary variables is stationary, the variables are said to be cointegrated, and the time paths of the variables involved are influenced by any deviation from long-term equilibrium. So, a Vector Error Correction Model (VEC) is the common tool to be used to represent non only the long-term dynamics but also the short-term ones among variables simultaneously. With that in mind, once variables included in equation 3.2 are confirmed to be not stationary

(Dickey-Fuller unit root test), that their first differences are stationary, and that they are cointegrated (Johansen test), it is possible to build the following VECM:

$$\Delta\tau_t - \beta_\tau - \alpha_1\left(\tau_{t-1} - \Phi_{12}x_{t-1} - \Phi_{13}a_{t-1}\right) - \sum_{j=1}^{p-1}\Gamma_{11,j}\Delta\tau_{t-j} - \sum_{j=1}^{p-1}\Gamma_{12,j}\Delta x_{t-j} - \sum_{j=1}^{p-1}\Gamma_{13,j}\Delta a_{t-j} = \mu_{\tau,t} \tag{3.3}$$

$$\Delta x_t - \beta_x - \alpha_2\left(\tau_{t-1} - \Phi_{22}x_{t-1} - \Phi_{23}a_{t-1}\right) - \sum_{j=1}^{p-1}\Gamma_{21,j}\Delta\tau_{t-j} - \sum_{j=1}^{p-1}\Gamma_{22,j}\Delta x_{t-j} - \sum_{j=1}^{p-1}\Gamma_{23,j}\Delta a_{t-j} = \mu_{x,t} \tag{3.4}$$

$$\Delta a_t - \beta_a - \alpha_3\left(\tau_{t-1} - \Phi_{32}x_{t-1} - \Phi_{33}a_{t-1}\right) - \sum_{j=1}^{p-1}\Gamma_{31,j}\Delta\tau_{t-j} - \sum_{j=1}^{p-1}\Gamma_{32,j}\Delta x_{t-j} - \sum_{j=1}^{p-1}\Gamma_{33,j}\Delta a_{t-j} = \mu_{a,t} \tag{3.5}$$

where we denote the white-noise disturbances as $\mu_{\tau,t}$, $\mu_{x,t}$ and $\mu_{a,t}$, the "speed of adjustment" parameters as α_1, α_2 and α_3, which tells us the size of the response of each variable to the previous period's deviation from the long-term equilibrium. Finally, the number of lags included in each equation for each variable p . From (3.3), (3.4) and (3.5), we can represent the error correction terms as:

$$\begin{aligned}
\xi_{\tau,t} &= \tau_{t-1} - \Phi_{12}x_{t-1} - \Phi_{13}a_{t-1} \\
\xi_{x,t} &= \tau_{t-1} - \Phi_{22}x_{t-1} - \Phi_{23}a_{t-1} \\
\xi_{a,t} &= \tau_{t-1} - \Phi_{32}x_{t-1} - \Phi_{33}a_{t-1}
\end{aligned}$$

and stacking the three equations (equations 3.3, 3.4 and 3.5), we can write the VECM in matrix notation:

$$\Delta\mathbf{Y}_t = \beta + \mathbf{A}(\mathbf{B}'\mathbf{Y}_{t-1} + \mathbf{C}_0) + \sum_{j=1}^{p-1}\Lambda_j\Delta\mathbf{Y}_{t-j} + \varepsilon_t \quad \text{where} \quad \mathbf{Y}_t' = [\tau_t \quad x_t \quad a_t], \tag{3.6}$$

where $\mathbf{A}(\mathbf{B}'\mathbf{Y}_{t-1} + \mathbf{C}_0)$ is the error-correction term, $\mathbf{AB}'$ is in turn the cointegrating matrix, and the rank (r) of $\mathbf{AB}'$ matrix is equal to the number of cointegrating vectors. Finally, $\sum_{j=1}^{p-1} \Lambda_j \Delta \mathbf{Y}_{t-j}$ represents the short-term dynamics.

3.4 Data

3.4.1 European Trading System (ETS)

The European Community established an emissions trading system (ETS), a cap-and-trade system, to pursue the environmental goals set under the Kyoto Protocol, and it has been the critical tool for the EUC to achieve the Paris Agreement goals (2015) and the Glasgow climate pact (2021) for 2050. ETS is currently the oldest well- established cap-and-trade system globally to limit emissions generation inside the EUC in a cost-effective and economically efficient manner.

Introduced in 2005, the ETS relies on auctions and free allocations to assign rights to emit GHGs equal to 1 tonne of CO_2 equivalent (tCO2e), called European Union Allowance (EUA). The cap level determines the number of allowances available in the whole system. Currently, the system gathers installations and aircraft operators responsible for about 50% of the GHGs generated for the EUC. Figures represent about 11,000 power plants and factories in the 27 EU member states plus Iceland, Liechtenstein, Croatia, and Norway [3].

The ETS has had four phases: (I) from 2005-2007, “pilot phase”; (II) from 2008 to 2012 set a goal of generating 6.5% lower emissions over the period compared to 2005; (III) from 2013 to 2020, looked for reducing the emissions by 1.74% per year; and (IV) from 2021-2030, current phase, seeks to reduce emissions by 2.2% per year which means

[3] The emissions which are counted in the ETS are coming from power stations, energy-intensive industries such as oil refineries, steelworks, and producers of iron, aluminium, cement, paper, glass and civil aviation

that the EUC would reduce its emissions by 55% by 2030 compared to 1990.

In this chapter, we work with the monthly average of settlement prices for the first month of the EUA futures contracts traded in the European Climate Exchange (ECX) from June 1st, 2008, to December 31st, 2020 [Bloomberg, 2021]. However, considering that 3.2 defines the carbon price as a percentage of the dirty consumption good price, we re-express EUA as a percentage of oil and coal prices, which are sources accounting for about 60% of the European energy mix. Following [Xie and Zhao, 2018], for oil and coal prices, we use the monthly average of Brent futures settlement price ($USD\$/barrel$) for oil and the European ARA port power coal price ($USD\$/ton$) for coal for the first-month contract in both cases [Bloomberg, 2021]. The calculation is as follows:

$$\tau_t = \frac{EUA_t}{p_{it}}, \quad i \in \{oil, coal\}$$

3.4.2 Relative Clean Energy Consumption

The relative clean consumption is defined as the ratio between consumption of clean and dirty goods. In the *warm-glow* growth model, we calibrate each variable by using the total world consumption of fossil and non-fossil fuels. However, for the European Community detailed and specific data for the period required was not available, so performing interpolation in each case was needed. To do that, we use the annual energy consumption by source (fossil and non-fossil fuels) available in [Eurostat, 2021], the monthly average of each source price and the monthly average of a group of economic indicators [4]. The data was built for the period 2008M6-2020M12.

In line with the calculations to express EUAs as a percentage, we work with oil and coal consumption to indicate dirty consumption. For the clean case, because there is not an

[4] In particular, we use four indexes: Dow Jones Euro Stoxx 50, which is Europe's leading stock index for futures contracts, the European Commission Sentiment Indicator, the Stoxx Europe 600 index and the unemployment rate for European Union [Bloomberg, 2021]

international index considered as a fair reference of the market price for the non-fossil fuels basket, we follow [Zhao et al., 2018] and assume the consumption of natural gas as a proxy for clean consumption[5]. This assumption is shared by the International Energy Agency (IEA) position, which categorises natural gas as the least carbon-intensive fossil fuel, and as a bridge between the dirtiest sources (oil and coal) towards more sustainable energy. In addition, according to [Dechezleprêtre and Sato, 2017], firms have found the fuel switching to natural gas a potentially attractive emission reduction strategy, and the increasing European Community consumption of natural gas since the ETS began serves as evidence.

3.4.3 Technology

Advances in clean and dirty technology is assumed in this chapter as the reduction in emissions generated for production purposes. In other words, improvements in dirty technology imply producing the same amount of output using fewer inputs, therefore emitting less per unit of GDP. Relative technology is measured in this chapter as the amount of emissions generated per dollar of European Community GDP in real terms. Data available in [Eurostat, 2021].

3.5 Results

In this section, we report the results of the VEC models estimations specified in (3.6) for both measures of carbon price (oil and coal). In addition, we present the estimates of simple ARIMA models for both carbon price versions. The purpose of adding ARIMA results to this analysis is to illustrate how the theory-based VEC models reproduce more accurately the dynamics of the carbon price and produce better forecastings.

[5] Consumption measured in joules per equivalent ton of natural gas, and the price reference for natural gas is the NBP natural gas index, which is traded on the International Petroleum Exchange [Bloomberg, 2021]

This section is divided into four parts. The first part describes the VEC's estimation, the second part, for comparison purposes, illustrates the structure of the ARIMA models used and their respective results. The third part presents the analysis of the Impulse-Response Functions (IRFs) from both models. Finally, the fourth part shows and analyses the forecastings obtained over different time horizons (1, 3, 6 and 12 months ahead).

3.5.1 Vector Error Correction Model

Tables 3.1 and 3.2 report the VEC's estimates for oil and coal-based carbon price. Following [Enders, 2008], to choose the lag length for each case, we start with five lags [6], drop variables with t-statistic lower than 1 in absolute terms, and test the significance of the model by using the likelihood ratio test (LRT). Specifically for the coefficient of the relative technology, a_t, we also test the null hypothesis that its coefficient is significantly equal to 1 as the theory suggested (see equation 3.1).

In both tables, the signs of the coefficients in the error correction term is as expected. An increase in relative clean consumption or improvements in relative technology will increase the carbon price, reflecting that more stringent measures in emissions generation increase the demand for EUAs from agents who are not ready to meet the new requirements. In addition, both models include a statistically significant drift term outside the cointegrating relationship, capturing the effects of a sustained tendency for the variables to increase (or decrease).

Regarding the individual results, in table 3.2, the negative sign of the carbon price coefficient could be explained by the fact that during the initial phases of the ETS, there was a price intervention when the value was "too low" as [Climat, 2012] suggests. It can also be seen in table 3.2 that leaving aside the error correction terms, relative clean

[6] Initial lag length results from $T^{1/3}$, where T=151

consumption is determined as a constant. In contrast, the relative technology is given only for relative clean consumption growth lagged one period. This last part might make sense when it is considered that most of the short-term technology changes are directly related to consumption patterns.

Table 3.1: Reduced Form Error Correction Model Specification
(Oil-based Carbon Price)

	Equation		
	$\Delta\tau_t$	Δx_t	Δa_t
Constant	0.067^{**}	0.010^{*}	0.999^{***}
	(0.027)	(0.058)	(0.258)
$\hat{\xi}_{\tau,t}$	0.003^{**}		
	(0.001)		
$\hat{\xi}_{x,t}$		0.005^{*}	
		(0.003)	
$\hat{\xi}_{a,t}$			0.052^{***}
			(0.013)
Δx_{t-1}	0.070^{*}		
	(0.036)		
Δa_{t-1}	0.010		
	(0.008)		
$\Delta\tau_{t-2}$	-0.350^{***}	0.164	0.883
	(0.076)	(0.169)	(0.773)
Δx_{t-2}	0.074^{**}	-0.170^{**}	
	(0.037)	(0.081)	
Δa_{t-2}	-0.017		
	(0.018)		

Error corrections terms given by

$\hat{\xi}_{\tau,t} = \tau_{t-1} - 3.314x_{t-1} - 1.538a_{t-1} - 8.599$

$\hat{\xi}_{x,t} = x_{t-1} - 0.302\tau_{t-1} + 0.464a_{t-1} - 2.595$

$\hat{\xi}_{a,t} = a_{t-1} - 0.650\tau_{t-1} + 2.155x_{t-1} - 5.590$

Speed of adjustment is the coefficients of the error correction term $\hat{\xi}_{i,t}$, $i \in \{\tau, a, x\}$

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: Reduced Form Error Correction Model Specification
(Coal-based Carbon Price)

	Equation		
	$\Delta\tau_t$	Δx_t	Δa_t
Constant	-0.172^{*}	0.818^{***}	0.617^{**}
	(0.095)	(0.139)	(0.250)
$\hat{\xi}_{\tau,t}$	-0.010^{*}		
	(0.006)		
$\hat{\xi}_{x,t}$		0.047^{***}	
		(0.008)	
$\hat{\xi}_{a,t}$			0.036^{**}
			(0.015)
$\Delta\tau_{t-1}$	-0.180^{**}		
	(0.080)		
Δx_{t-1}	-0.112^{**}		0.201
	(0.047)		(0.132)

Error corrections terms given by

$$\hat{\xi}_{\tau,t} = \tau_{t-1} - 2.076x_{t-1} - 0.783a_{t-1} + 4.956$$

$$\hat{\xi}_{x,t} = x_{t-1} - 0.4817\tau_{t-1} + 0.377a_{t-1} - 2.387$$

$$\hat{\xi}_{a,t} = a_{t-1} - 1.278\tau_{t-1} + 2.653x_{t-1} - 6.332$$

Speed of adjustment is the coefficients of the error correction term $\hat{\xi}_{i,t}$, $i \in \{\tau, a, x\}$
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2 ARIMA Models

Table 3.3 presents the results for the ARIMA models estimated for oil and coal-based carbon prices, and in both cases, the variables are in logarithms. In addition, given that the Auto Correlation Functions (ACFs) for both are highly persistent (non-stationary), we take the first difference of the series, which makes them stable according to their ACFs and Partial Auto correlation Functions (PACFs). Finally, to choose the appropriate lag length for the ARIMA processes, we use the Akaike Information Criterion (AIC).

Table 3.3: ARIMA Models

	ARIMA(2,1,2)†			ARIMA(3,1,2)‡		
Regressor	Coefficient	Std Err	t-Ratio	Coefficient	Std Err	t-Ratio
τ_{t-1}	0.875	0.347	2.526^{**}	1.014	0.119	8.511^{***}
τ_{t-2}	-0.317	0.201	-1.581	-0.620	0.111	-5.611^{***}
τ_{t-3}				-0.236	0.072	-3.276^{***}
ε_{t-1}	-1.079	0.345	-3.130^{***}	-1.274	0.106	-12.038^{***}
ε_{t-2}	0.472	0.203	2.323^{**}	0.901	0.105	8.595^{***}

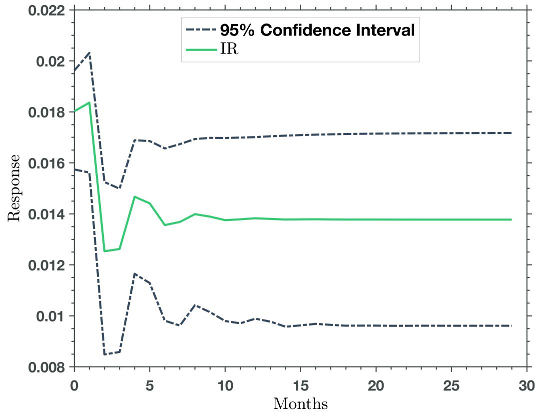
Oil based carbon price †; Coal based carbon price ‡
148 observation used for estimation period 2008M6-2020M12
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

3.5.3 Impulse-Response Functions

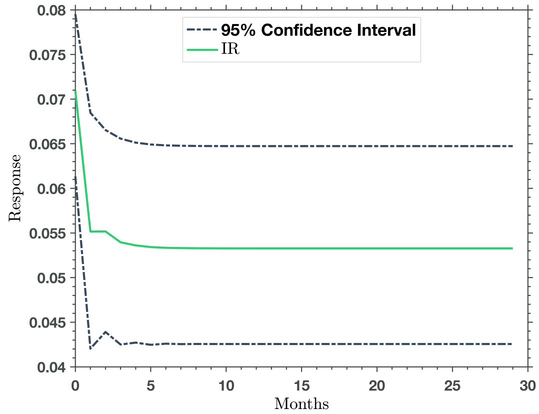
Understanding the impulse response functions as the representation of the effects of a given shock in t on the future evolution of a variable, in this section we trace the time path of various shocks affecting carbon price, relative clean consumption and relative technology variables. We emphasise the comparison between effects of carbon price shocks when they are modelled through the VEC and ARIMA specifications. In appendix C section C.2, we present the IRFs for the three targeted variables when relative clean consumption and relative technology are shocked.

Following [Pesaran and Shin, 1998] we perform a generalised shock impulse response analysis which helps to avoid making assumptions about the order in which a shock on a variable propagates across the other variables in the system (orthogonalization of shocks). Starting with the IRFs from VEC models, figures in 3.1 show the behaviour of the variables in response to a carbon price shock. Regarding the oil-based case, from the figures it is not difficult to see that relative clean consumption is the variable which quickly eliminates the shock while the carbon price and relative technology take more than 50 periods (months) to stabilise. We have to bear in mind, however, that by definition in VECM, the analysis of the final response have to consider together all variable reactions.

IRFs Carbon Price

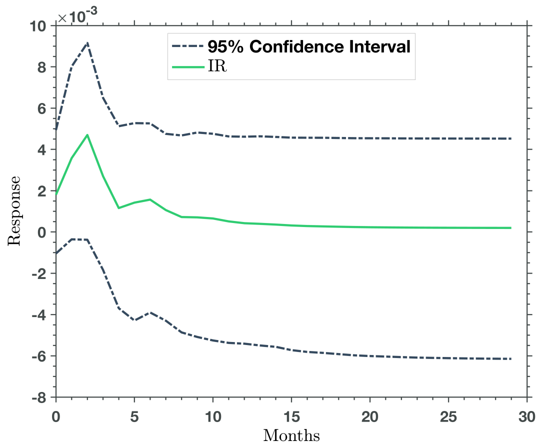


(a) Oil-based

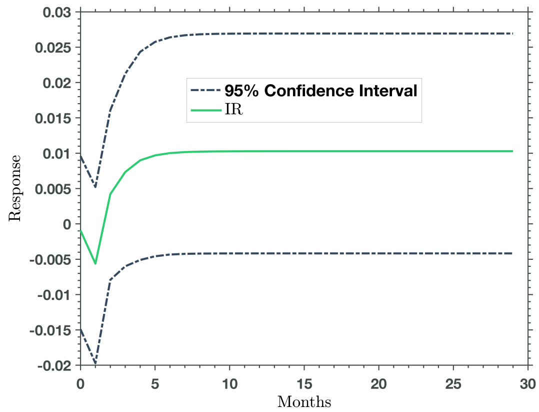


(b) Coal-based

IRFs Relative Clean Consumption

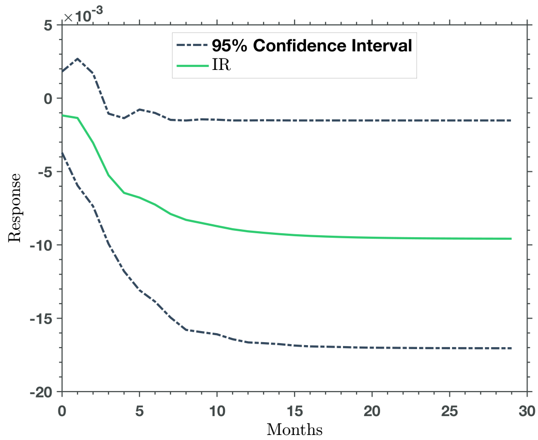


(c) Ratio Clean - Oil-base dirty Consumption

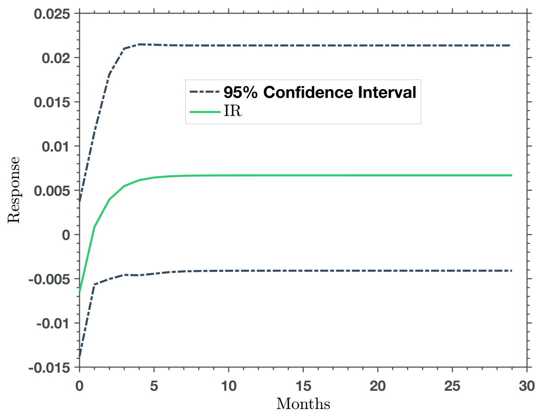


(d) Ratio Clean - Coal-base Dirty Consumption

IRFs of Relative Technology



(e) Ratio Clean - Oil-base Dirty Technology

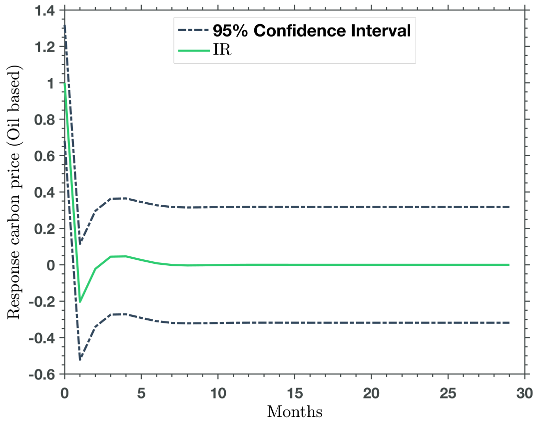


(f) Ratio Clean - Coal-base Dirty Technology

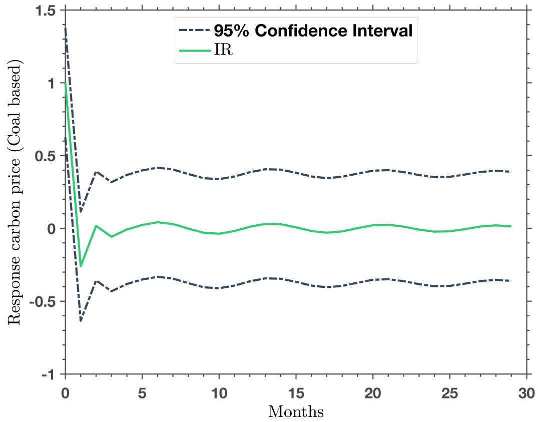
Figure 3.1: Responses when Carbon Price is Shocked

Figures 3.1b, 3.1d and 3.1f illustrate the dynamics of the three variables resulting from a coal-based carbon price shock. Interestingly, the reaction to the shock was steadier than the previous case.

The IRFs related to both ARIMA models are illustrated in figures 3.2a and 3.2b. In both cases, the variable reverts to zero in about thirty periods (months).



(a) Oil-based Carbon Price Shock



(b) Coal-based Carbon Price Shock

Figure 3.2: ARIMA models: Impulse-Response Functions

3.5.4 Forecasting Analysis

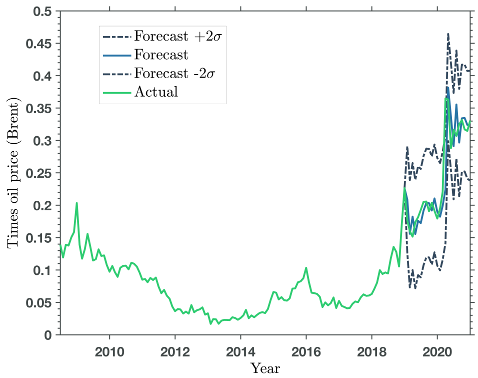
This section reports the forecasts obtained from the models in recursive and density forecasting specifications. Performing both exercises allows us to have a complete analysis of the future possible dynamics of the variables. We can focus not only on their future expected values, but also on all the future values that these targeted variables can take by summarising the information of their estimated forecast distributions. We work on four different time horizons: one, three, six and twelve months ahead. For comparison purposes, finally, we describes recursive forecastings obtained from the VEC and ARIMA models.

We split the total sample into two parts: the in-sample part, which covers the period from June 30th 2008 to December 31st 2018 and is used to estimate the model, and the out-of-sample predictive data, from January 1st 2019 to December 31st 2020, which is used to evaluate the forecasting.

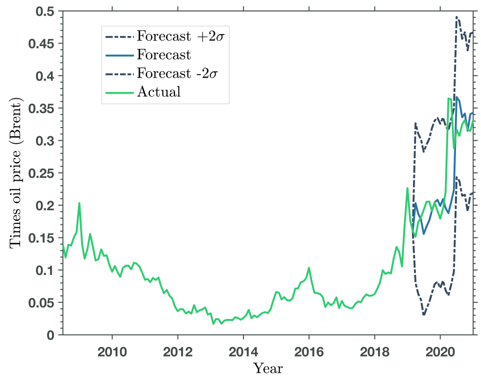
3.5.4.1 Recursive Forecasting

Figures in 3.3 and 3.4 show the out-of-sample prediction results for oil-based and coal-based carbon price variables. Both VEC models are generally good to forecast the carbon price over the different horizons. However, based on the results of the Diebold-Mariano test statistic and the Root Mean Square Error (RMSE) for each case (See appendix C section C.3 to see more details), the oil-based carbon price is the model with the best ability to predict the price's dynamic.

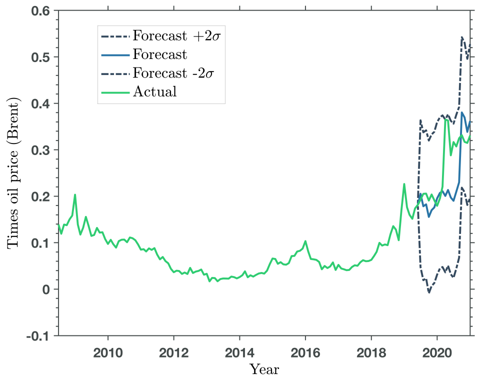
In addition, it is clear that compared with the VEC models, the forecastings of the both ARIMA are incapable of capturing the actual values of carbon price inside the confidence intervals across horizons, however the size of the intervals remains stable in all cases. In that respect, it is not strange that the ARIMA models have larger forecast errors than VEC. (See figures in 3.3, 3.4, 3.5 and 3.6)



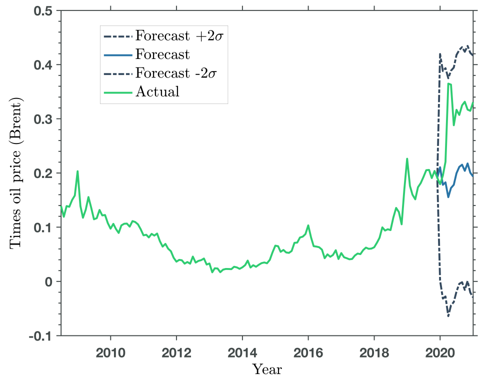
(a) 1-month ahead



(b) 3-month ahead

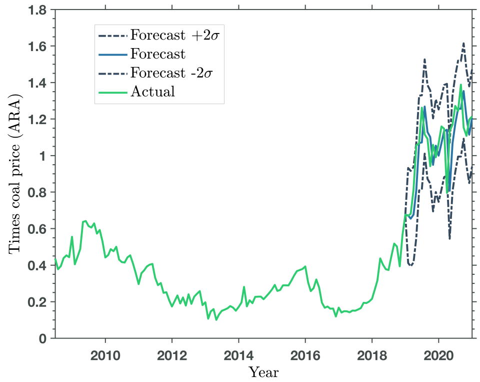


(c) 6-month ahead

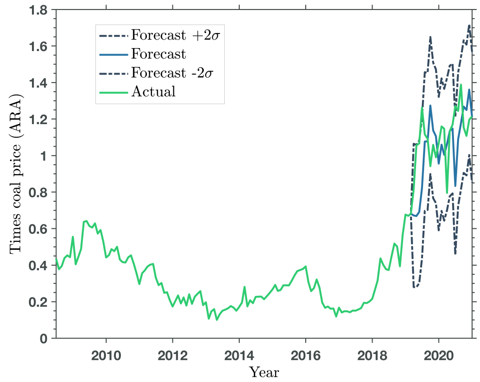


(d) 12-month ahead

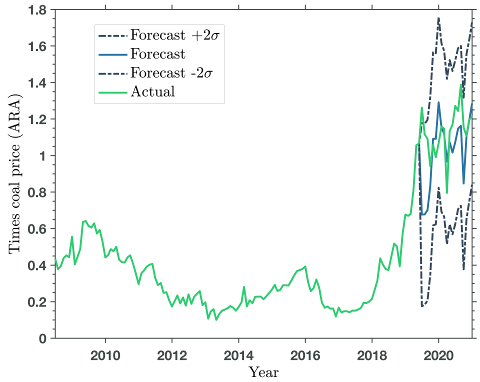
Figure 3.3: Recursive forecasting: Oil-based Carbon Price



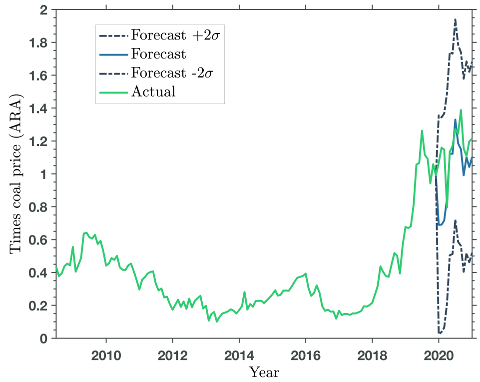
(a) 1-month



(b) 3-months ahead

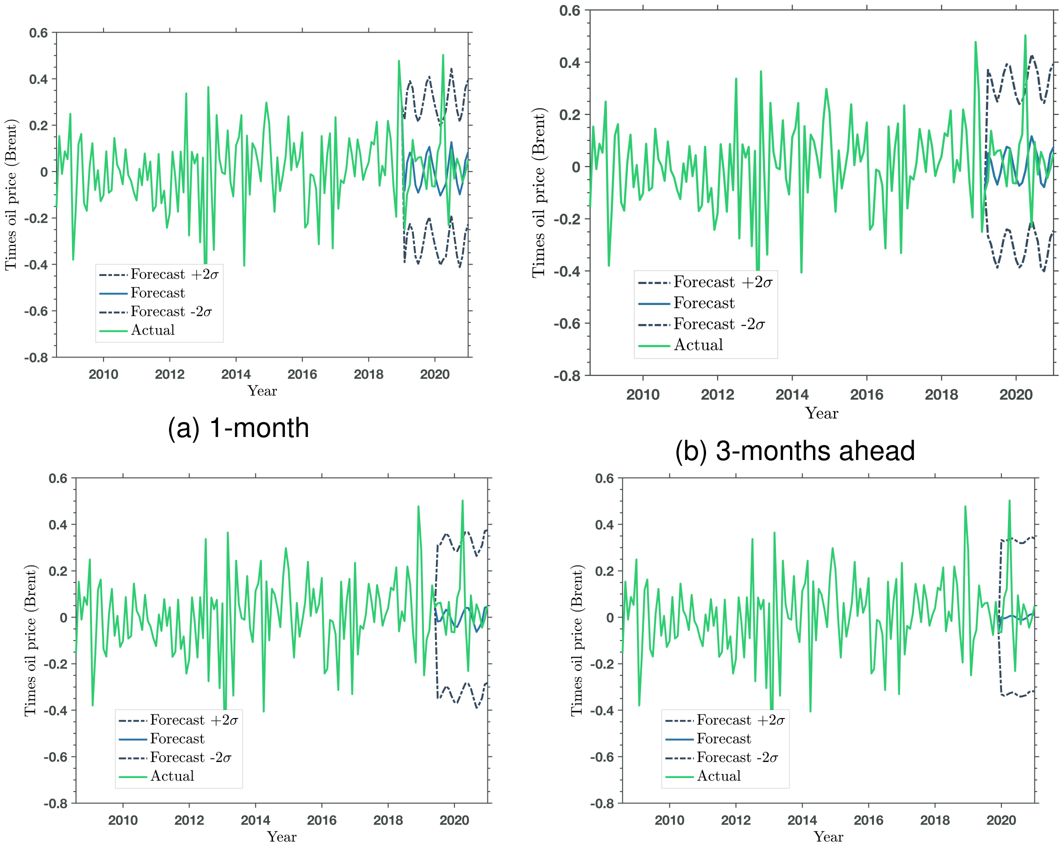


(c) 6-months ahead



(d) 12-months ahead

Figure 3.4: Recursive forecasting: Coal-based Carbon Price



(a) 1-month

(b) 3-months ahead

(c) 6-months ahead

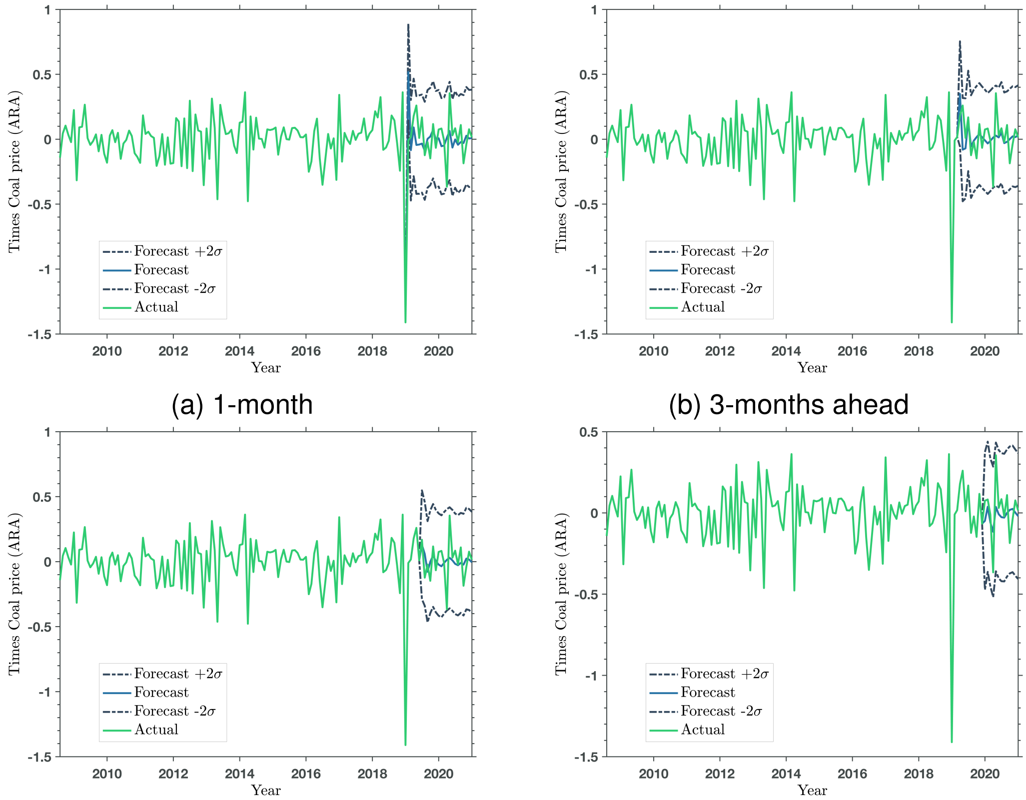
(d) 12-months ahead

Figure 3.5: Recursive forecasting: ARIMA Model of Oil-based Carbon Price

Further comparing the forecasting of both VEC models, it can be found that the most accurate predictions are related to 1-month and 3-months ahead. As seen in figures 3.3a, 3.3b, 3.4a and 3.4b, under these horizons the models prove to have more adaptability to changes in the carbon price change patterns, which is a key input for system participants in their decisions to cover the emissions from current projects or to hedge against future price increases. On the contrary, results for both six and twelve cases are generally under predicting the real values of the variables.

The recursive forecasting for the the other two variables, relative clean consumption and relative technology, are detailed in appendix C section C.3.

3.5.4.1.1 Density Forecasting



(a) 1-month

(b) 3-months ahead

(c) 6-months ahead

(d) 12-months ahead

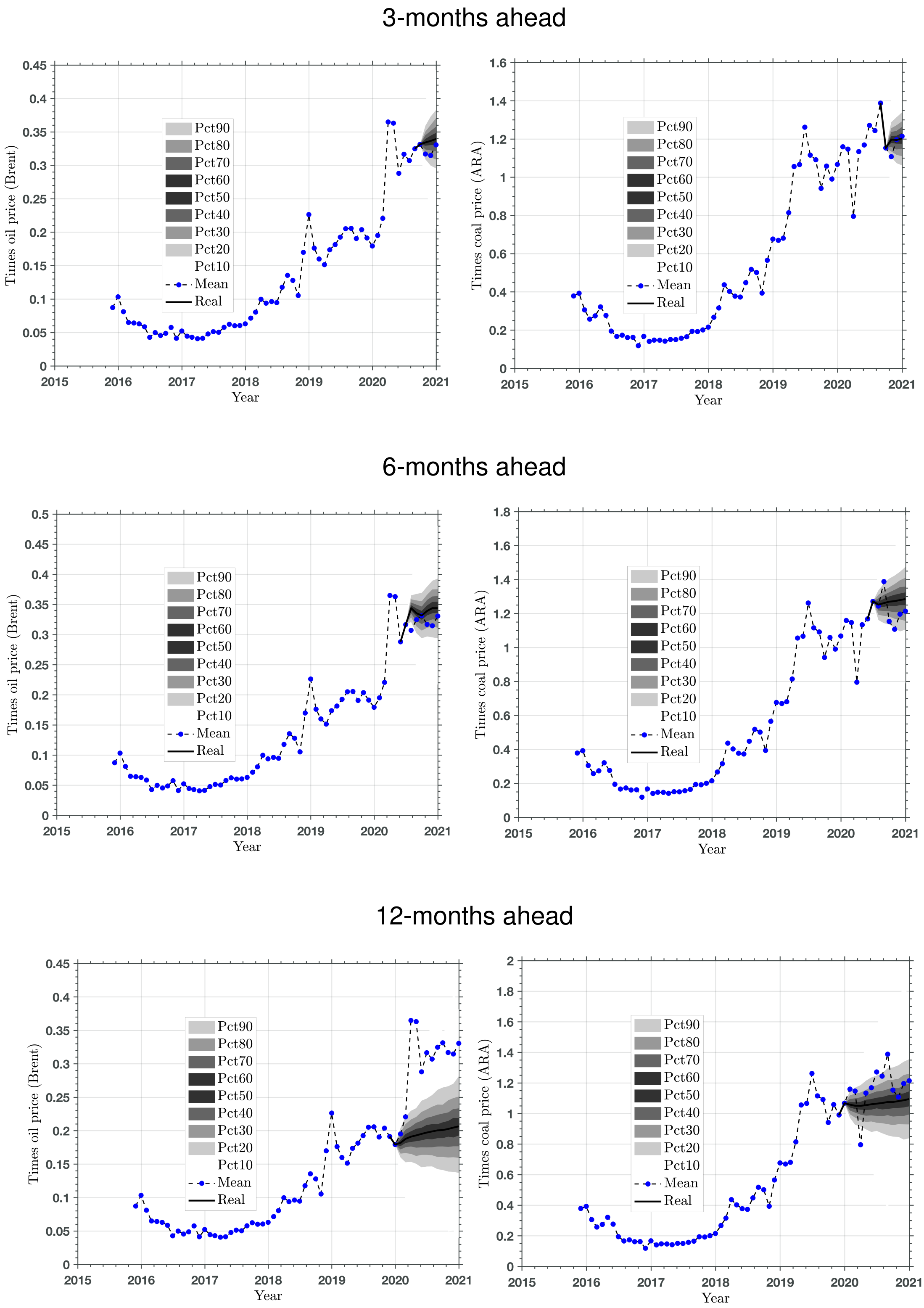
Figure 3.6: Recursive forecasting: ARIMA Model of Coal-based Carbon Price

Although the recursive forecasting exercises prove the accuracy of both VEC models, it is well known that point forecasts are not the most appropriate tool in some cases for the decision-making process; that is the reason why measuring the level of uncertainty of future outcomes for targeted variables is more relevant. This measure is called density forecasting and focuses on determining the probability that a variable takes a value between a specific range within a particular time horizon. This measure also offers the opportunity of calculating the probability that in h-periods ahead, the series under study will be lower than a threshold b.

Graphs in figure 3.7 illustrates the predictions for carbon price of both VEC models. The left panel shows the results for the oil-based carbon price, and the right panel, in turn, for the coal-based carbon price across selected horizons. Making the comparison between both cases, up to 6 months ahead, the oil-based carbon price model generates better forecasts. The coal-based model, nevertheless, achieves the best prediction performance in the 12-months ahead.

In summary, based on the above results, it can be concluded that the VEC models proposed in this study have significant advantages in capturing and predicting the dynamics of the carbon price when this variables is measured as a percentage of oil price and coal price. The results are also more relevant if we take into account that in 2020, the world economy experienced the worst part of the covid-shock, making it particularly difficult to forecast the dynamics of economic variables.

The density forecasting graphs for the other two variables, relative clean consumption and relative technology, are presented in appendix C section C.4. Overall, as in the carbon price case, the best results are obtained with the oil-based carbon price model; for both variables, however, the forecasting density consistently captures the actual values of the variables across all horizons.



(a) Oil-based Carbon Price (b) Coal-based Carbon Price

Figure 3.7: Density Forecasting

3.6 Conclusion

In 2005 the European Community introduced a "cap-and-trade" system to control the emissions generation inside the community and manage the Kyoto protocol targets. This scheme was called EU-Emissions Trading System (EU ETS) and currently it is the critical tool for the community to achieve the Paris Agreement goals of reducing emissions by 55% in 2030 versus 1990 levels.

In economics and climate change literature, a "cap-and-trade" approach is recognised as one of the most cost-efficient environmental policies. It is a way to implement the central planner solution when an externality, like the environmental degradation by consuming non-renewable resources, is present. Fixing a cap for emissions equal to the optimal level but letting the market set the price, the system becomes a fair way to control the emissions across the economic sectors.

In this chapter, we use the general equilibrium growth model with *warm-glow* preferences built in chapter 1 to write a VECM that predicts and evaluates the carbon price in the European Community. In so doing, the study empirically validates the theoretical structure previously mentioned. Furthermore, this model might be useful for firms and policymakers in their decision-making process (risk-management) related to choosing the abatement channels such as switching to cleaner inputs, investing in abatement capital, reducing the overall scale of production and so on.

Regarding the data and procedures, first at all, the carbon price is measured by taking the European Emissions Allowances (EUA) as a percentage of the oil and coal prices for 2008M6-2020M12 period, the most important non-renewable sources in the EUC energy mix. Second, the results are presented as recursive forecasting and density forecasting. In particular, we use the former to compare the results obtained from VEC models with simple ARIMA models.

In that respect, based on Diebold-Mariano test statistic and the RMSE, we find that using the theory-based VEC models there is an improvement in fitting and prediction accuracy compared to ARIMA models results. In addition, focusing only on the VEC models, the oil-based approach does a better job in forecasting the dynamics of the carbon price, the relative clean consumption and the relative technology over the period analysed. Interestingly, both models generate good results considering that the last part of the series covers the worst time of the Covid-shock effects on the European Community economy.

Acknowledging that the measures of the relative clean consumption and relative technology variables used in this study could be improved when more data is available, the chapter has proven to be an theoretical-effective tool to predict and it could be used to evaluate the dynamics of carbon price in other different regions, given the increasing attractiveness of cap-and-trade system worldwide currently [Goulder and Parry, 2020].

4 | Growth and Pollution

4.1 Introduction

In 1990 climate change was declared by the scientific community (UNFCCC) as a man-made degradation of the environment mainly due to the carbon dioxide emissions generated by the use of fossil fuels for the growth and development purposes of the wealthiest regions. Although the warning made by scientists did not stop emissions growth, it did trigger a global consensus about the importance of the phenomenon and the fact that it has to be tackled by coordinated actions across countries because climate change is not a territorial problem.

Under the umbrella of the United Nations and until 2015 when the Paris Agreement modified the strategy of climate change negotiations, there were different scenarios in which the world community tried to find the right path to mitigate climate change and the three main actions were: the establishment of the Framework Convention on Climate Change (UNFCCC) (1992) in Rio de Janeiro, the Kyoto protocol (1997) and the Copenhagen Climate Change Conference (2009).

From the beginning, the target of all these agreements was to oblige the wealthiest countries to reduce the emissions they were generating and encourage them to find ways to deal with the consequences of the greenhouse gases they had put into the atmosphere. However, most of the efforts were in vain or at least not enough to tackle the environmental degradation because few countries successfully met their goals, and sadly other countries outside of the agreements became more polluting as their growth took off.

Figure 4.1 illustrates the world map of energy consumption and emissions generation in 2015. Evident in this figure is the considerable concentration of both consumption and emissions in the OECD and China[1], creating more pressure on these economies to reduce their emissions by finding more sustainable energy sources, and future pressure on the rest of the world to avoid substantial additional environmental degradation as a result of its economic development process:

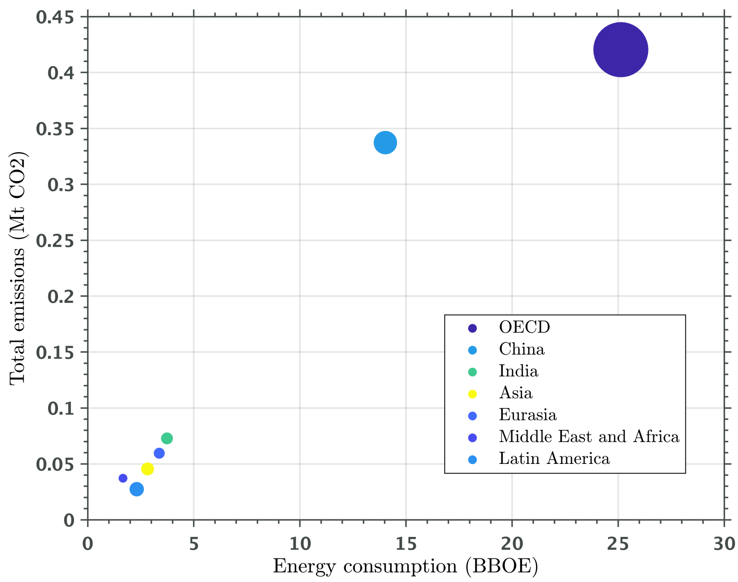


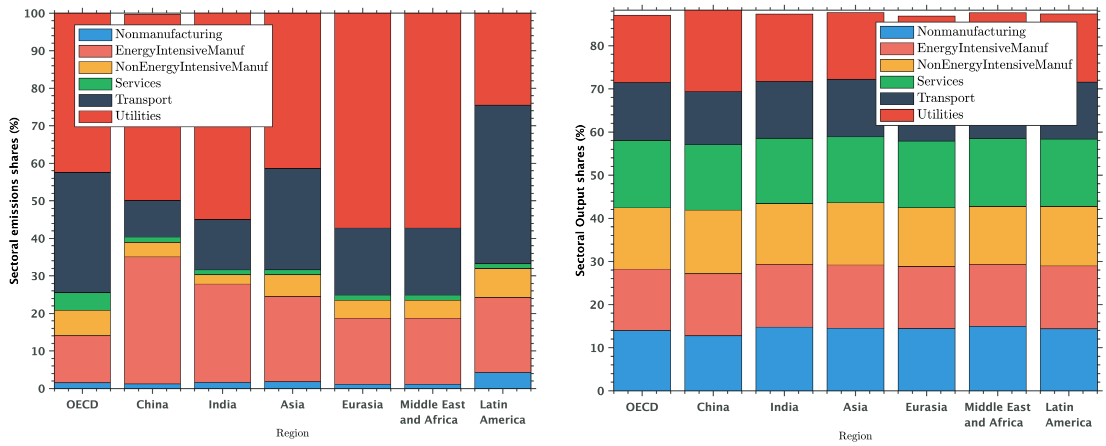
Figure 4.1: Energy use and emissions generation by region. Source: oecd.org

Undoubtedly, stopping climate change demands changes in society's culture and values worldwide. Modifications must be materialised by redefining the consumption patterns and structure of the economic sectors in a country. Therefore, examining the reconfiguration occurred within an economy and among economies due to domestic and international environmental policies is a way to assess climate awareness in terms of worldwide production structure before Paris.

Figure 4.2a presents the industrial emissions in 2015. In summary, the most polluting

[1] The size of the bubble in figure 4.1 is representing the weight of the region in the global GDP

sectors are utilities and transport across regions. In line with this pattern, figure 4.2b shows that the utilities, transport and energy-intensive manufacturing sectors also make up 50% of the total output across regions. So, determining how much both emissions and output growth evolved between 1995 and 2015 is crucial in understanding the international environmental policies' real impact on the global economy.



(a) Industrial Emissions Shares

(b) Industrial Output Shares

Figure 4.2: Regional Emissions and Output Shares

Given these facts, in this chapter, we will focus on determining the effects of the International Environmental Agreements (IEAs) on sectoral demands for dirty (energy intensive industries) and clean (non energy intensive industries) inputs in most of the global economies. In particular, we support our theoretical framework by offering evidence about how the adoption of the IEAs across countries only reduced the level of dirtiness (emissions generation capacity) of sectoral outputs in the OECD over 1995-2015 period and amplified the importance of "off-shoring" effect in China and India.

To conduct our study, we work with the annual input-output tables (IOTs) over the period between 1995 and 2015 for 62 countries grouped into 7 regions: the OECD, China, India, Asia, Eurasia, Middle East & Africa, and Latin America; 46 economic industries grouped into 6 main industries according to their energy intensity level. In addition, we use sectoral emissions and the number of IEAs adopted by region over those 21 years. To our knowledge, this is the first study which works with the regional IOTs that cover more than 90% of the world gross domestic product (GDP) to analyse the impacts of the IEAs.

The chapter is organised as follows: section 4.2, presents the literature related to economic impacts of environmental policies; section 4.3, describes the modelling framework; section 4.4, explains the data used in the study; section 4.5, presents the main results, and section 4.6 details the conclusions.

4.2 Emissions, Economic Growth and Climate Change Policy

The literature on the link between environmental policies and economic growth could be divided into two branches: (i) the Pollution Heaven Hypothesis, postulating that stringent policies incentivise reallocation of production towards regions with more flexible pollution laws and lower costs; (ii) the Porter Hypothesis, which in turn sees that net reduction in costs and the fostering of efficiency and innovation in an economy might be a result of stringent environmental policies because they incentivise firms to be more competitive internationally [Dechezleprêtre and Sato, 2017].

[Tobey, 1990] addressed one of the primary empirical works on the link between environmental policies and economic growth. He tests the hypothesis that a stringent environmental policy has altered the international trade of commodities produced by dirty industries, creating pollution havens in countries with less severe environmental policies. He uses the cross-section Heckscher-Ohlin-Vanek (HOV) model of international trade but he does not find support for that hypothesis. Two key conclusions extracted from this study marked much of the subsequent research: first, the hypothesis was difficult to analyse at that moment because environmental policies were not as severe as they are currently; and second, the impact of such policies are better studied over time not under cross-section models.

[Lucas et al., 1992], following the previous work but focusing more on the manufacturing sectors, examines the relationship between the variation in manufacturing production structure and toxic emissions in a panel of 80 countries over the period 1960-1988. He concluded that pollution exhibited an inverse **U**-shape relationship with economic development: pollution is believed to first rise faster than output at low levels of income, then to rise more slowly than output after some critical income level. However, he does not find strong evidence of investments being diverted to pollution intensive activities off-shore. [Hettige et al., 1992], on the contrary, working on two extreme cases: OECD and Less Developed Countries (LDCs), find that more stringent environmental policies displaced energy-intensive industries towards the LDCs under study.

Moving away a little from the link between manufacturing sectors and environmental policies only, [Grossman and Krueger, 1995] study the relationship among four environmental indicators and the level of a country's per capita income, and controversially find no strong evidence that environmental quality deteriorates "steadily" with economic growth using a panel data of 42 countries over the period 1977-1988. In turn, interested in the relationship between environmental regulations and trade, [Levinson and Taylor, 2008] work with data from Canada, the US and Mexico from 1977-1986 and again, they do not find evidence in favour of the pollution heaven effect, notwithstanding the public's strong belief in its unarguable presence.

Taking advantage of more available data, [Broner et al., 2012] show evidence that the adoption of environmental policies have created different trade patterns across countries. Those countries with less strict environmental policies possess a more comparative advantage [in] polluting industries over the period 1980-2010 in a sample of 102 countries. More recently, [Ederington et al., 2018] use a very extensive database (35 years, 163 countries and 13 major multilateral environmental protocols and subsequent amendments) and a gravitational regression approach to test the hypothesis of competitive loss in the manufacturing sectors in a country which ratifies an IEA. They conclude that in the short-term the effect of IEA membership on dirty industries exports is negative but small. However, in the long-term that effect disappears and a significant compositional shift in exports away from dirty and towards clean industries is found when more IEAs are ratified.

4.3 Modelling International Environmental Agreements

The empirical work is based on simple time series representations of sectoral outputs and inputs which are used to quantify the impact of successive IEAs in the different industries in each region. The modelling is split into two stages to identify two separate potential effects from IEAs: a *technology intervention* in which IEAs encourage firms to adapt production methods to move away from using emission-producing inputs; and an *input intervention* effect in which the IEAs cause firms to improve production methods to obtain the same outputs with fewer inputs (or, equivalently, more output for the same inputs). Both effects linked to the fundamental point of the Porter hypothesis previously discussed.

The modelling accommodates the important interactions between industries, through industry-to-industry inputs and outputs across regions and distinguishes the local and global effects of the IEAs on sectoral inputs and outputs. These are then translated to measure the local and global effects on emissions via the emissions vector.

4.3.1 Two-country and Two-industry Model

For the sake of a clear exposition of the model described in the chapter, we first introduce in this section a simpler version of that model which enables me to present its core structure and to generate the intuition about the short and long term impacts of IEAs (hereafter intervention) on the configuration of economic industries within a region and among regions, taking into account the intermediate input supply interdependencies.

4.3.1.1 Theoretical Framework

We assume in this section that the world economy is constituted by two different regions ($n = 2$): a developed region (n=1) and a developing one (n=2). In these economies, there are only two industries ($R = 2$). One is an energy-intensive industry which means it is highly polluting, while the other is a non energy intensive industry, which is assumed to have more sustainable production methods. This specification allows me to have $S = n \times R = 4$ sectors in total.

Denoting sectors by $s = 1,..,S$, the production function of each sector *s* has a simple Leontief form such as [2]:

$$Y_{st} = A_{st}\ell_{st}^{\alpha_1}k_{st}^{\alpha_2}M_{\circ s,t}^{1-\alpha_1-\alpha_2}$$

Where the output is denoted by Y_{st}, the level of technology by A_{st}, labour by ℓ_{st}, capital by k_{st} and the total intermediate inputs are represented by $M_{\circ s,t}$. With that in mind, if it is assumed that labour and capital are tied in fixed proportions with intermediate inputs, we can define $M_{\circ s,t}^{\alpha_3} = \ell_{s,t}^{\alpha_1}k_{s,t}^{\alpha_2}$ and $\theta = (1 - \alpha_1 - \alpha_2 + \alpha_3)$, then the output of sector *s* can be expressed in this way [3]:

$$Y_{s,t} = A_{s,t}M_{\circ s,t}^{\theta} \tag{4.1}$$

Defining lower case as the notation for the logarithm of any variable, equation (4.1) becomes:

$$y_{s,t} = a_{s,t} + \theta m_{\circ s,t} \tag{4.2}$$

[2] It assumes that in each production function α_1, α_2 and α_3 are sector-specific; in that sense, they would have an *s* in their subscripts, however, tidier notation demands for omitting this extra letter.

[3] The production function takes the simple Leontief form, and in doing so, the output is tied in fixed proportion with intermediate inputs. It also assumes that the supply side determines output levels on its own and independently of the demand for output. Furthermore, the demand-output relationship shows how relative prices have to change to make sure demand and supply for sectoral outputs are equal. As a result, it is possible to take the relative prices and the demand relationship out of the model.

Technology, $a_{s,t}$, is defined as a simple unit root process affected by the intervention, z_t, as the following expression details:

$$a_{st} = \rho_s a_{s,t-1} + g_s + \lambda_s z_{s,t} + \varepsilon_{s,t} \tag{4.3}$$

Where g_s is the annual growth rate of sectoral productivity and λ_s is the size of the technological intervention effect. More precisely, λ_s shows whether the adoption of IEAs has encouraged (positive value) firms to improve their production techniques to get the same output with more sustainable production methods, in other words with, less pollution. On the contrary, a negative value of λ_s indicates that the adoption is slowing down sectoral growth: firms cannot maintain the same level of production but generating less pollution as agreements demand.

Replacing equation (4.3) into equation (4.2) and assuming that $\rho = 1$ is possible to calculate the growth of $Y_{s,t}$ as follows [4]:

$$\Delta y_{s,t} = g_s + \theta_s \Delta m_{\circ s,t} + \lambda_s z_{s,t} + \mu_{s,t} \tag{4.4}$$

Equation (4.4) for each sector can be stacked to have the following global system:

$$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \\ \Delta y_{4t} \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \end{bmatrix} + \begin{bmatrix} \theta_1 & 0 & 0 & 0 \\ 0 & \theta_2 & 0 & 0 \\ 0 & 0 & \theta_3 & 0 \\ 0 & 0 & 0 & \theta_4 \end{bmatrix} \begin{bmatrix} \Delta m_{\circ 1t} \\ \Delta m_{\circ 2t} \\ \Delta m_{\circ 3t} \\ \Delta m_{\circ 4t} \end{bmatrix} + \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & \lambda_3 & 0 \\ 0 & 0 & 0 & \lambda_4 \end{bmatrix} \begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \\ z_{4t} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \\ \mu_{4t} \end{bmatrix} \tag{4.5}$$

System (4.5) helps to see the phenomenon that we call *off-shoring effect*, which means that the adoption of IEAs for regions that have stringent environmental policies shift the production of dirty inputs towards regions where environmental policies are not strong. In the present case, as we have assumed that region 1 is a developed region and region

[4] $\rho = 1$ implies a_t is non-stationary but its first difference is stationary

2 is a developing one, then a negative θ_1 and a positive θ_3 would reflect the presence of this phenomenon.

4.3.1.2 Data Structure

An Input-Output Table (IOT) is a structure where sectors and regions are correlated to each other accommodating complicated dynamics and interdependent responses among them. This table also displays how sectoral outputs and other economic variables are organised: [5]:

Table 4.1: Input-Output Table

	Recipient					
	Sector 1	Sector 2	sector 3	Sector 4	**RE**	**Output**
Sector 1	$M_{1,1}$	$M_{1,2}$	$M_{1,3}$	$M_{1,4}$	RE_1	Y_1
Sector 2	$M_{2,1}$	$M_{2,2}$	$M_{2,3}$	$M_{2,4}$	RE_2	Y_2
Sector 3	$M_{3,1}$	$M_{3,2}$	$M_{3,3}$	$M_{3,4}$	RE_3	Y_3
Sector 4	$M_{4,1}$	$M_{4,2}$	$M_{4,3}$	$M_{4,4}$	RE_4	Y_4
$\sum_{p=1}^{4}$**Intermediate inputs**	$M_{\circ 1,t}$	$M_{\circ 2,t}$	$M_{\circ 3,t}$	$M_{\circ 4,t}$		
VA+Taxes-Subsidies	VTS_1	VTS_2	VTS_3	VTS_4		
Output	Y_1	Y_2	Y_3	Y_4		

Recalling from equation (4.1) that the total intermediate inputs are represented by $M_{\circ s,t}$ which is equivalent to the summation showed in the fifth row of table (4.1). In particular, any $M_{pq,t}$ is denoting inputs from sector p to sector q at time t, where p and q $\in (1,2,3,4)$. The IOTs give the information required to compute the Input-Output Coefficients (IOCs):

$$B_{pq,t} = \left\{ \frac{M_{pq,t}}{Y_{q,t}} \right\},$$

which represents how many units of sector p are required to produce one unit of output of sector *q*. Additionally, IOTs give me permission to differentiate for each sector the intermediate inputs supplied domestically from those coming from outsourcing.

[5] RE stands for Rest of the Economy and VA for Value Added

We collect all IOCs into a 4-by-4 matrix $\mathbf{B}_t$ and all sectoral outputs into a 4-by-1 vector $\mathbf{Y}_t$ such as:

$$\mathbf{B}_t = \begin{bmatrix} B_{1,1} & B_{1,2} & B_{1,3} & B_{1,4} \\ B_{2,1} & B_{2,2} & B_{2,3} & B_{2,4} \\ B_{3,1} & B_{3,2} & B_{3,3} & B_{3,4} \\ B_{4,1} & B_{4,2} & B_{4,3} & B_{4,4} \end{bmatrix} \quad \text{and} \quad \mathbf{Y}_t = \begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \end{bmatrix}$$

Then, we define $\mathbf{M}'_{\circ,t}$ as a 1-by-4 vector which represents the fifth row in table (4.1). Putting all these definitions together results in the following system:

$$\begin{bmatrix} M_{\circ 1,t} & M_{\circ 2,t} & M_{\circ,3t} & M_{\circ 4,t} \end{bmatrix} = \begin{bmatrix} Y_{1,t} & Y_{2,t} & Y_{3,t} & Y_{4,t} \end{bmatrix} \times \begin{pmatrix} B_{1,1} & B_{1,2} & B_{1,3} & B_{1,4} \\ B_{2,1} & B_{2,2} & B_{2,3} & B_{2,4} \\ B_{3,1} & B_{3,2} & B_{3,3} & B_{3,4} \\ B_{4,1} & B_{4,2} & B_{4,3} & B_{4,4} \end{pmatrix} \tag{4.6}$$

4.3.1.3 Modelling Strategy

System (4.6) can be written in matrix notation as $\mathbf{M}_{\circ t} = \mathbf{B}'_t \times \mathbf{Y}_t$, which enables to express the growth of $\mathbf{M}_{\circ,t}$ (which is also represented by $\Delta\mathbf{m}_{\circ,t}$) as the growth of its constituent parts, with weights reflecting the relative importance of composition and growth changes in the different sectors:

$$\Delta\mathbf{m}_{\circ,\mathbf{t}} = \bar{\mathbf{M}}_{\circ}\Delta\mathbf{B}'_{\mathbf{t}}\mathbf{Y} + \bar{\mathbf{M}}_{\circ}\mathbf{B}'\Delta\mathbf{Y}_{\mathbf{t}} \tag{4.7}$$

In equation (4.7) I define $\bar{\mathbf{M}}_{\circ,\mathbf{t}} = \textbf{diag}(\mathbf{M}_{\circ,\mathbf{t}})^{-1}$ and denote $\Delta\mathbf{M}_{\circ,\mathbf{t}}$, $\Delta\mathbf{Y}_t$ and $\Delta\mathbf{B}_t$ as the first difference of $\mathbf{Y}_t$, $\mathbf{M}_{\circ,\mathbf{t}}$ and $\mathbf{B}_t$, respectively. We also fix the weights in the middle of the sample at year 2005 as $\bar{\mathbf{M}}_{\circ t} = \bar{\mathbf{M}}_{\circ}$, $\mathbf{B}_t = \mathbf{B}$ and $\mathbf{Y}_t = \mathbf{Y}$.[6]

[6] Fixing matrices $\bar{\mathbf{M}}_{\circ}$, $\mathbf{B}$ and $\mathbf{Y}$ at year 2005 over the whole sample is a mathematical strategy that we re using to facilitate the computation of the long term effects without affecting the results considerably.

Using equation (4.7) into equation (4.5) makes explicit the fact that in the long term, each sectoral output depends, through their material inputs, on outputs from all other sectors. The system also shows how the outputs of each sector interact with each other over time and how any intervention (technology or input intervention) in any sector would have implications in every other sector:

$$\Delta \mathbf{y}_t = \psi_0 + \psi_1(\ell)\left(\bar{\mathbf{M}}_\circ \Delta \mathbf{B}_\mathbf{t}' \mathbf{Y}\right) + \psi_2(\ell)\mathbf{z}_t + \varepsilon_t \tag{4.8}$$

Where $\psi(\ell) = (\mathbf{I}_4 - \theta \bar{\mathbf{M}}_\circ \mathbf{B}' \bar{\mathbf{Y}}_\mathbf{t}^{-\mathbf{1}})^{-1}$, $\psi_0 = \psi(\ell)\mathbf{g}$, $\psi_1(\ell) = \psi(\ell)\theta$ and $\psi_2(\ell) = \psi(\ell)\lambda$. The third term in equation (4.8) represents the impact on each sector output of all interventions in all regions interacting each other:

$$\begin{bmatrix} \psi_{2,11}(\ell) & \psi_{2,12}(\ell) & \psi_{2,13}(\ell) & \psi_{2,14}(\ell) \\ \psi_{2,21}(\ell) & \psi_{2,22}(\ell) & \psi_{2,23}(\ell) & \psi_{2,24}(\ell) \\ \psi_{2,31}(\ell) & \psi_{2,32}(\ell) & \psi_{2,33}(\ell) & \psi_{2,34}(\ell) \\ \psi_{2,41}(\ell) & \psi_{2,42}(\ell) & \psi_{2,43}(\ell) & \psi_{2,44}(\ell) \end{bmatrix} z_t$$

For the sake of simplicity, it assumes here that intervention z_t is a scalar, which means that the number of agreements adopted for each region at time *t* is the same. Adding across the first row of $\psi_2(\ell)$, for instance, results in the long-term impact of a new intervention in region 1 and 2 on output of sector 1. On the other hand, adding across the first column of $\psi_2(\ell)$ gives the impact of a new intervention in region 1 on all other 4 sectoral outputs, through the inputs that they supply to sector 1. Thus, $\psi_2(\ell)$ collects the *global technology intervention* effect across all different sectors.

Additionally, to consider the whole impact of intervention on sectoral output growths, it is necessary to incorporate into equation (4.8) the impact of intervention on IOCs too. In order to do that, we come back to $\mathbf{B}_t$ matrix, and define its growth rate as follows:

$$\Delta \mathbf{b}_t = \mu + \delta_\mathbf{1} \mathbf{D}_t z_t + \nu_t \tag{4.9}$$

Where $\mathbf{D}_t$ is a 4-by-4 matrix of sectoral dummies variables:

$$\mathbf{D}_t = \begin{bmatrix} \mathbf{D}_{11} & \mathbf{D}_{12} & \mathbf{D}_{13} & \mathbf{D}_{14} \\ \mathbf{D}_{21} & \mathbf{D}_{22} & \mathbf{D}_{23} & \mathbf{D}_{24} \\ \mathbf{D}_{31} & \mathbf{D}_{32} & \mathbf{D}_{33} & \mathbf{D}_{34} \\ \mathbf{D}_{41} & \mathbf{D}_{42} & \mathbf{D}_{43} & \mathbf{D}_{44} \end{bmatrix}$$

Where $\mathbf{D}_{pq} = 1$ for sector *p* inputs coming into sector *q*, $\forall\ p, q \in (1, 2, ...4)$. δ_1 is a 4-by-4 matrix which contains the size of *input intervention effects*. In particular, these effects show how intervention in region *n* impacts resources efficiency in sector *s*. A positive impact implies negative coefficients because they would be reflecting that intervention pushes firms to use fewer inputs per unit of output produced. In particular, considering that two sectors out of 4 are highly polluting ones (sector 1 and 3), the input intervention effect on the IOCs has to be larger for polluting sectors than for less polluting ones. Moreover, from comparing the sizes of input intervention effects among regions, in the developing region, this effect has to be larger than in the developed region because the production techniques in the developing regions are usually less advanced.

Regarding the definition of $\Delta\mathbf{b}_t$, we declare that:

$$\Delta\mathbf{b}_t = \bar{\mathbf{B}}_t \odot \Delta\mathbf{B_t} \tag{4.10}$$

Where $\bar{\mathbf{B}}_t$ is the inverse of $\mathbf{B}_t$ matrix and $\odot$ denotes the element-wise product between both matrices in right hand side of equation (4.10). With that definitions in mind, we can use the following redefinition technique,

$$\mathbf{B_t} \odot \Delta\mathbf{b}_t = \mathbf{B_t} \odot \bar{\mathbf{B}}_\mathbf{t} \odot \Delta\mathbf{B_t} \quad \Longrightarrow \quad \mathbf{B_t} \odot \Delta\mathbf{b}_t = \Delta\mathbf{B_t}, \tag{4.11}$$

into equation (4.8) to unravel further the system and get:

$$\Delta\mathbf{y_t} = \psi_0(\ell) + +\psi_1(\ell)(\mathbf{B} \odot \delta_1 \mathbf{D}_t z_t)'\mathbf{Y} + \psi_4(\ell) z_t + \psi_5(\ell)\mathbf{w}_t + \xi_t \tag{4.12}$$

Being $\psi_0 = \psi_0(\ell) + \psi_1(\ell)(\mathbf{B} \odot \mu)'\mathbf{Y}$ and $\eta_t = \xi_t + \psi_1(\ell)(\mathbf{B} \odot \nu_t)'\mathbf{Y}$, I can set $z_t = 1$ and establish that $\psi_1(\ell)(\mathbf{B} \odot \delta_1 \mathbf{D}_t)'\mathbf{Y}$ represents the effect of an additional intervention in each region on sectoral output through intermediate inputs. In other words, this expression is the *global input intervention* effect on output growth while $\psi_4(\ell)$ is the *global technology intervention* effects on output growth.

Detailing the structure of expression $\psi_1(\ell) \times (\mathbf{B} \odot \delta_1 \mathbf{D}_t)'\mathbf{Y}$ gives a better idea about the *global input intervention* effects:

$$\begin{bmatrix} \psi_{1,11}(\ell) & \psi_{1,12}(\ell) & \psi_{1,13}(\ell) & \psi_{1,14}(\ell) \\ \psi_{1,21}(\ell) & \psi_{1,22}(\ell) & \psi_{1,23}(\ell) & \psi_{1,24}(\ell) \\ \psi_{1,31}(\ell) & \psi_{1,32}(\ell) & \psi_{1,33}(\ell) & \psi_{1,34}(\ell) \\ \psi_{1,41}(\ell) & \psi_{1,42}(\ell) & \psi_{1,43}(\ell) & \psi_{1,44}(\ell) \end{bmatrix} \times \begin{bmatrix} \left(\frac{\delta_{1,11}}{B_{11,t}} + \frac{\delta_{1,21}}{B_{21,t}} + \frac{\delta_{1,31}}{B_{31,t}} + \frac{\delta_{1,41}}{B_{41,t}}\right) y_1 \\ \\ \left(\frac{\delta_{1,12}}{B_{12,t}} + \frac{\delta_{1,22}}{B_{22,t}} + \frac{\delta_{1,32}}{B_{32,t}} + \frac{\delta_{1,42}}{B_{42,t}}\right) y_2 \\ \\ \left(\frac{\delta_{1,13}}{B_{13,t}} + \frac{\delta_{1,23}}{B_{23,t}} + \frac{\delta_{1,33}}{B_{33,t}} + \frac{\delta_{1,43}}{B_{43,t}}\right) y_3 \\ \\ \left(\frac{\delta_{1,14}}{B_{14,t}} + \frac{\delta_{1,24}}{B_{24,t}} + \frac{\delta_{1,34}}{B_{34,t}} + \frac{\delta_{1,44}}{B_{44,t}}\right) y_4 \end{bmatrix} \tag{4.13}$$

Taking for instance, the sumproduct between the first row of $\psi_1(\ell)$ and the column-vector results in the aggregation of the *global input intervention* effects on output growth of sector 1 when a new agreement is adopted by all regions. Regarding the second term in equation (4.12), its structure is the same one described in (4.13).

4.3.2 The Global Model

The global model was estimated based on the annual input-output tables (IOTs) for the period 1995-2015[7] and for each of the 62 countries which I group into seven regions: the OECD, China, India, Asia, Eurasia, Middle East & Africa, and Latin America (See

[7] 2015 is the latest year for which IOTs are available

countries' list in appendix D table D.1). In terms of the economic industries (46) detailed in the IOTs, we group them into six industries according to their energy intensity level: non manufacturing, energy-intensive manufacturing, non energy-intensive manufacturing, services, transport and utilities (See list in appendix D table D.2). Finally, with regards to the emissions, we use the annual sectoral emissions per region, and the number of IEAs subscribed annually by region over the same period 1995-2015 (See table D.3).

4.3.2.1 Data Definitions and Notations

This study relates output in $n = 7$ regions and $R = 6$ industries, making $S = n \times R = 42$ sectors in total. Sectors are denoted by $s = 1,..,S$[8]. The data employed includes:

1. Output from sector $s = 1,...,42$ for $t = 1995,...,2015$, denoted by Y_{st}. Here and throughout the rest of the text, lower cases are used to denote logarithms so $y_{st} = \log(Y_{st})$. The (log) outputs from every sector in time t can be arranged in a 1-by-42 vector $\mathbf{y}_t' = (y_{1t}, y_{1t}, ...,y_{42t})$ as we had in the illustrative example above.

2. IOTs, over the same time frame, describe the inputs from sector p to sector q at time t and they collected in a 42-by-42 matrix denoted as $\mathbf{M}_t = \{M_{pq,t}\}$ for $p = 1,..,42$ and $q = 1,...,42$. Working down column q of $\mathbf{M}_t$ it finds the inputs from each sector p into output of sector q (plus other sector variables) so that:

$$\sum_{p=1}^{42} M_{pq,t} + \text{value added + taxes - subsidies in sector q at time t } = Y_{q,t}$$

   It can also define the input-output coefficients (IOCs) matrix $\mathbf{B}_t = \{B_{pq,t}\} = \{\frac{M_{pq,t}}{Y_{q,t}}\}$ which shows, as before, the quantity required of inputs from sector p to produce 1

[8] We define $R = 1$ for non-manufacturing, $R = 2$ for energy intensive manufacturing,..., and $R = 6$ for utilities, while $n = 1$ for OECD, $n = 2$ for China,.., and $n = 7$ for Latin America; thus $s = 1,2,..,6$ is non-manufacturing in OECD, energy intensive manufacturing in OECD,..., utilities in OECD respectively, while $s = 36,37,..,42$ is non-manufacturing in Latin America, energy intensive manufacturing in Latin America,..., utilities in Latin America

unit of output of sector q.

3. The number of agreements adopted by a region at time t is denoted by z_{st} where $s \in s = 1,...,42$, taking into account that interventions for the 6 sectors belonging to a region are all the same. We collect interventions in a 42-by-1 vector, $\mathbf{z}_t$, which we call "intervention vector".

4. A set of "emission factors", e_s for $s = 1,..,42$ shows the emissions created by the production of one unit of sector *s* output. So, we use those factors to built a "emissions vector" $\mathbf{e} = (\mathbf{e_1}, \mathbf{e_2}, ..., \mathbf{e_S})'$.

5. The growth in the level of globalisation by region is represented by w_{st}. We collect all variables in a vector $\mathbf{w}_t = (w_1, w_2, ..., w_S)'$. To measure the level of globalisation by a region we use data of the total of their imports and exports as a percentage of regional GDP.

4.3.2.2 Theoretical Structure

Recall from section (4.3.1) that sectoral growth is defined by:

$$\Delta y_{st} = \Delta a_{st} + \theta_s \Delta m_{\circ s,t} \tag{4.14}$$

However, in this case, technological growth is defined by a more complicated expression such as:

$$\Delta a_{s,t} = \rho_s \Delta a_{s,t-1} + (1-\rho_s) g_s + (1-\rho_s) \lambda_s z_{st} + (1-\rho_s) \beta_s w_{st} + \varepsilon_{st} \tag{4.15}$$

Where g_s is the annual growth rate of productivity, λ_s captures the size of the technological effect due to intervention, and w_{st} measures the evolution in the level of globalisation experimented by each region. In particular, we are including (w_{st}) to make evident some efficiencies that are taking place irrespective of the intervention.

Substituting (4.15) into (4.14), sectoral growth becomes:

$$\Delta y_{st} = \phi_{0,s} + \phi_{1,s}\Delta y_{s,t-1} + \phi_{2,s}\Delta m_{\circ s,t} + \phi_{3,s}\Delta m_{\circ s,t-1} + \phi_{4,s} z_{st} + \phi_{5,s} w_{s,t} + \varepsilon_{st} \tag{4.16}$$

Equation (4.16) differs from its equivalent in the illustrative example because it includes the lags of the dependent and independent variables. This inclusion allows the accommodation of slow adjustments to changes in economic conditions. Along these lines, $\phi_{4,s}$ represents now, the elasticity that capture the *direct technology effect* of intervention on sector *s*.

Stacking equation (4.16) across sectors results in the following global system:

$$\Delta \mathbf{y}_t = \phi_0 + \phi_1 \Delta \mathbf{y}_{t-1} + \phi_2 \Delta \mathbf{m}_{\circ t} + \phi_3 \Delta \mathbf{m}_{\circ, t-1} + \phi_4 \mathbf{z}_t + \phi_5 \mathbf{w}_t + \varepsilon_t \tag{4.17}$$

In system (4.17), ϕ_4 is a 42-by-42 matrix which collects the *accumulated technology intervention* effects across sectors.

4.3.2.3 Modelling Strategy

The total intermediate inputs growth, $\Delta \mathbf{m}_{\circ t}$, can be approximated by:

$$\Delta \mathbf{m}_{\circ,\mathbf{t}} = \bar{\mathbf{M}}_\circ \Delta \mathbf{B}_\mathbf{t}' \mathbf{Y} + \bar{\mathbf{M}}_\circ \mathbf{B}' \Delta \mathbf{Y}_\mathbf{t} \tag{4.18}$$

Where $\bar{\mathbf{M}}_\circ$, $\mathbf{Y}$ and $\mathbf{B}$ are fixed at year 2005 as before, so substituting equation (4.18) into system (4.17) gives:

$$\Delta \mathbf{y}_\mathbf{t} = \psi_0(\ell) + \psi_1(\ell)\Delta \mathbf{B}_\mathbf{t}' \mathbf{Y} + \psi_3(\ell)\Delta \mathbf{B}_{\mathbf{t-1}}' \mathbf{Y} + \psi_4(\ell)\mathbf{z}_t + \psi_5(\ell)\mathbf{w}_t + \psi(\ell)\varepsilon_t \tag{4.19}$$

Where, once we define $\psi(\ell) = \left(\mathbf{I} - \phi_1(\ell) - \phi_2 \bar{\mathbf{M}}_\circ \mathbf{B}' \bar{\mathbf{Y}}^{-\mathbf{1}} - \phi_3(\ell) \bar{\mathbf{M}}_\circ \mathbf{B}' \bar{\mathbf{Y}}^{-\mathbf{1}}\right)^{-1}$, I can have $\psi_0 = \psi(\ell)\phi_0$, $\psi_1(\ell) = \psi(\ell)\phi_2 \bar{\mathbf{M}}_\circ$, $\psi_3(\ell) = \psi(\ell)\phi_3 \bar{\mathbf{M}}_\circ$, $\psi_4(\ell) = \psi(\ell)\phi_4$ and $\psi_5(\ell) = \psi(\ell)\phi_5$.

The system (4.19) makes explicit the interdependencies among sectors over time and how intervention in any one region would have implications in every other region. The system also differentiates the simple and accumulated impact of domestic and foreign supplies on sectoral output growth. The long-run effects described in equation (4.17) can be easily set as $\ell = 1$. The elasticities in the matrix $\psi_4(1)$ show the *long-run* and *direct* effects on output in each sector, completing the full description of the *technology effect* generated by the interventions.

Equation (4.9) defines that the variations in the IOCs across sectors depend on the intervention in each region, however the global model includes also the world trade variable, $w_{pq,t}$, to control for the efficiencies gained by the improvement in the supply chain, so the panel setting of the model is as follows:

$$\Delta b_{pq,t} = \mu_{pq} + \delta_{1,pq} z_{pq,t} + \delta_{2,pq} w_{pq,t} + v_{pq,t} \tag{4.20}$$

Where $\Delta b_{pq,t}$ represents the growth in the input-output coefficient of inputs supplied by sector *p* to sector *q*, $\forall$ *p and q* $\in$ (1,2...,42); and $z_{pq,t}$ is the intervention variable, which reflects the number of agreements adopted by each region.

Regarding the estimation procedure; we estimate 42 different panels with sectoral fixed effects, which assume that the impact of the intervention on the IOCs is not the same across sectors. Stacking the $\Delta b_{pq,t}$ across *p* at each sector *q* at a time allows us to have the following compact representation of the individual equations in (4.20):

$$\Delta \mathbf{b}_{q,t} = \mu_q + \delta_{\mathbf{1},\mathbf{q}} \mathbf{D}_{q,t} z_{q,t} + \delta_{\mathbf{2},\mathbf{q}} \mathbf{w}_{q,t} + v_{q,t} \quad \textit{where} \quad q \quad \in (1, 2, ..., 42) \tag{4.21}$$

Where μ_q is the 42-by-1 vector gathering the unobserved fixed effects, μ_{pq}; $z_{q,t}$ is an scalar that contains the number of agreements adopted by the region sector *q* belongs to; $\mathbf{D}_{p,t}$ contains the sectoral dummies variables, which enable to have differentiation in the impact of intervention on each sector; $\mathbf{w}_{q,t}$ contain the stacked $w_{pq,t}$ and $\delta_{\mathbf{1},\mathbf{q}}$, $\delta_{\mathbf{2},\mathbf{q}}$ and $\delta_{\mathbf{3},\mathbf{q}}$ contain the parameters.

Going one step further and stacking the 42 panels enables to have the following global system for IOCs such as:

$$\Delta\mathbf{b}_t = \mu + \delta_1 \mathbf{D}_t \tilde{\mathbf{z}}_t + \delta_2 \tilde{\mathbf{w}}_t + \nu_t \tag{4.22}$$

$\Delta\mathbf{b}_t$ is a 42-by-42 matrix of the individual IOCs; μ is a 42-by-42 matrix which contains the unobserved fixed effects; $\tilde{\mathbf{z}}_t$ is a 42-by-42 matrix of the regional interventions on its main diagonal; $\tilde{\mathbf{w}}_t$ is another 42-by-42 matrix composed by the regional world trade measures on its main diagonal; and δ_1 and δ_2 contain the parameters.

Substituting back equation (4.22) in equation (4.19) gives:

$$\begin{aligned}\Delta\mathbf{y_t} = \psi_0 &+ \psi_1(\ell)(\mathbf{B}\odot\delta_1\mathbf{D}_t\tilde{\mathbf{z}}_t)'\mathbf{Y} \\ &+ \psi_3(\ell)(\mathbf{B}\odot\delta_1\mathbf{D}_t\tilde{\mathbf{z}}_{t-1})'\mathbf{Y} \\ &+ \psi_1(\ell)(\mathbf{B}\odot\delta_2\tilde{\mathbf{w}}_t)'\mathbf{Y} + \psi_2(\ell)(\mathbf{B}\odot\delta_3\tilde{\mathbf{w}}_{t-1})'\mathbf{Y} + \psi_4(\ell)\mathbf{z}_t + \psi_5(\ell)\mathbf{w}_t + \xi_t\end{aligned} \tag{4.23}$$

Where we gather the constant terms to set $\psi_0 = \psi_0(\ell) + (\psi_1(\ell)(\mathbf{B}\odot\mu)' + \psi_3(\ell)(\mathbf{B}\odot\mu)')\,\mathbf{Y}$ and the error terms to have $\xi_t = \left(\psi_1(\ell)(\mathbf{B}\odot\nu_t)' + \psi_3(\ell)(\mathbf{B}\odot\nu_{t-1})'\right)\mathbf{Y} + \psi(\ell)\varepsilon_t$.

The model described in (4.23) captures the accumulated *technology intervention* and *input intervention* effects on sectoral output growths. Second and third terms collect the *indirect accumulated input intervention effects* of an additional agreement in each region, and summing up across columns or rows, the effect on regions or industries are recovered. In the same line, $\psi_4(\ell)$ is the *direct accumulated technology intervention effects*. As in the previous case, aggregation across its columns or rows gives the effects on regions or industries.

Following the same logic of the illustrative example from section (4.3.1), the positive sign for $\psi_4(\ell)$ implies that *technology intervention effect* encourages firms in all sectors to use fewer dirty inputs to produce the same quantity, while $\psi_1(\ell)$ and $\psi_3(\ell)$ with a negative sign reflect that the *input intervention effect* pushes firms to improve their input management to use fewer inputs per unit of output produced. In summary, $\psi_1(\ell)$, $\psi_3(\ell)$ and $\psi_4(\ell)$ matrices show the total impact on all sectors of the adoption of an additional agreement in any region taking account of the interactions among sectors.

4.3.2.4 Emissions Evolution

At the beginning of this chapter we established that the most important goal is to quantify in terms of sectoral emissions the impact of the adoptions of IEAs across the seven regions under study. Having said that, we define $\Delta\hat{y}_{s,zt}$ as the part of the growth caused by intervention in sector *s*, and fix emissions factors (emissions generated by a US dollar of output produced in sector *s*), θ_s, at the year 2005 being $s \in (1,2,...,42)$. Then, if we collect we can have an estimation of the sectoral emissions over the period under study such as:

$$\hat{e}_{st} = \theta_s \times (1+\Delta\hat{y}_{s,zt})\hat{y}_{s,t} \quad \text{where } s \in (1,2,...,42) \text{ and } t \in (2,...,21) \tag{4.24}$$

4.4 Data

4.4.1 Regional and Industrial Classification

This study works with the data called Industry and Service Statistic (MEI) available in [OECD, 2020], which includes the input-output tables from 1995 to 2015 divided into two different databases: Input-Output tables (IOTs) Rev 3 from 1995 to 2011 and Input-Output tables (IOTs) Rev 4 from 2005 to 2015. Both data have different industrial disaggregation levels, which requires a strategy to concatenate all the data. These data are also available for 62 countries, which we grouped into 7 regions: countries belonging to the Organisation for Economic Co-operation and Development (oecd- 36 countries), China, India, non-oecd Asian (9 countries), non-oecd Eurasian (5 countries), non-oecd

Middle East & African (5 countries) and non-oecd Latin American countries (5 countries). Although the groups do not cover the whole world economies, they account for about 90% of the world GDP and enables the study of global patterns among them, taking into account their level of development but without losing sight of the main interactions.

Given that the concern of this chapter is the classification of industries according to their energy intensity levels, we follow the classification made by the U.S Energy Information Administration (EIA) which ranks an economy in 5 sectors: non manufacturing, energy-intensive manufacturing, non energy-intensive manufacturing, services and transport. However, we made a variation in the services industry taking out the utilities sub-industry due to the level of emissions generated by that sector differing considerably from its peers.

For more details about the countries and industries considered in this study, see appendix D tables D.2 and D.1.

4.4.2 International Environmental Agreements (EIA)

We work with part of the exhaustive database of 3,750 international environmental agreements adopted by almost all countries around the world built by [Mitchell, 2020]. This data is part of the International Environmental Agreements (IEA) Database Project of the University of Oregon, and considers all kinds of agreements: protocol, conventions and treaties and their corresponding amendments subscribed at the multinational and binational level.

In this study, we include only the agreements related to climate change and emissions generations between 1995 and 2015. As a result, our sample is reduced to 34 agreements adopted by each country listed in the seven groups. A completed list of the agreements is in the appendix D table D.3. We also weigh the annual commitments made by regions once they sign up for an IEA, using the yearly Environmental Policy Stringency Index (EPS) per region. This index is a country-specific and internationally comparable measure of environmental policy stringency computed and published by [OECD, 2021a].

4.4.3 Emissions Generation and International Trade

The Kyoto protocol, the first formal international agreement for combating climate change classified the following gases as having a global warming potential: Carbon dioxide (CO2), Methane (CH4), Nitrous oxide(N2O), Hydrofluorocarbons (HFCs), Perfluorocarbons (PFCs), Sulfur hexafluoride (SF6) and Nitrogen trifluoride (NF3). However, given that CO2 is the main greenhouse-gas (GHG) emitted by human activities and counts for about 80% of the total of those emissions, it is common practice to publish the CO2 emissions when it comes to revealing the GHGs generated by industries and countries. In this study we focus on the carbon emissions by country and by industry published by International Energy Agency (IEA) [EIA, 2021].

Even though this chapter is not specifically focused on trade, the interaction among different regions and different industries over time requires that trade evolution must be taken into account, especially if it is recognised that the presence of some effects such as the "off-shoring effect", takes place depending on how globalised some regions are. In that respect, we use the trade international data by country published by the World Bank and available in [Bank, 2021], in particular with the Merchandise trade index, which measures the total of exports and imports of goods relative to GDP per region.

4.5 Results

4.5.1 Technology Intervention Effect

We estimate equation (4.16) for each sector (42), however, given the volume of results to be presented, we follow the strategy used by [Janke et al., 2020] of grouping the sectoral estimation results per region. By doing so, we can analyse the main interactions within a region and compare them with any other region. The average (unweighted) estimations per region are[9]:

OECD:
$$\Delta \mathbf{y}_{st} = \underset{(0.004)}{0.007} + \underset{(0.050)}{0.820}\Delta \mathbf{m}_{\circ st} \underset{(0.0002)}{-0.0002}\mathbf{z}_{st} - \underset{(0.045)}{0.132}\mathbf{w}_{st} + \varepsilon_{st}$$

China:
$$\Delta \mathbf{y}_{st} = \underset{(0.006)}{0.030} + \underset{(0.080)}{0.713}\Delta \mathbf{m}_{\circ st} \underset{(0.015)}{+0.031}\mathbf{z}_{st} - \underset{(0.060)}{0.030}\mathbf{w}_{st} + \varepsilon_{st}$$

India:
$$\Delta \mathbf{y}_{st} = \underset{(0.012)}{0.043} + \underset{(0.077)}{0.585}\Delta \mathbf{m}_{\circ st} \underset{(0.042)}{-0.120}\mathbf{z}_{st} + \varepsilon_{st}$$

Asia:
$$\Delta \mathbf{y}_{st} = \underset{(0.006)}{0.010} - \underset{(0.037)}{0.065}\Delta \mathbf{y}_{st-1} \underset{(0.043)}{+0.923}\Delta \mathbf{m}_{\circ st} - \underset{(0.060)}{0.060}\mathbf{w}_{st} + \varepsilon_{st}$$

Eurasia:
$$\Delta \mathbf{y}_{st} = \underset{(0.021)}{0.032} + \underset{(0.090)}{0.930}\Delta \mathbf{m}_{\circ st} \underset{(0.002)}{-0.043}\mathbf{z}_{st} - \underset{(0.180)}{0.280}\mathbf{w}_{st} + \varepsilon_{st}$$

Middle East & Africa:
$$\Delta \mathbf{y}_{st} = \underset{(0.005)}{0.005} + \underset{(0.080)}{0.140}\Delta \mathbf{y}_{st-1} \underset{(0.090)}{+0.880}\Delta \mathbf{m}_{\circ st} - \underset{(0.008)}{0.110}\mathbf{z}_{st} + \varepsilon_{st}$$

Latin America:
$$\Delta \mathbf{y}_{st} = \underset{(0.010)}{0.020} + \underset{(0.040)}{0.050}\Delta \mathbf{y}_{st-1} \underset{(0.060)}{+0.900}\Delta \mathbf{m}_{\circ st} - \underset{(0.100)}{0.131}\mathbf{w}_{st} + \varepsilon_{st}$$

Those estimations were done independently using OLS, and we perform a specification

[9] The standard deviation in parentheses

search over each regression to remove non well-determined coefficients and improve the precision of the estimations[10]. In particular, following [Janke et al., 2020] we eliminate the variables where the t-statistic is less than 1 in absolute terms and test the joint insignificance of excluded variables by using an LRT. In addition, the fact that in all estimations the coefficients of the total intermediate input and trade variables are significant and white errors are present gives confidence in the quality of the estimations.

The details of the 42 estimations are presented in appendix D, section D.4, however, we reflect on particular findings. Firstly, India is highlighted as the region with the largest negative technology intervention effect, which is surprising considering the argument in the literature that stringent environmental policies in some advanced economies have relocated dirty sectors towards developing regions with less environmental policies and lower production costs. Secondly, the technology intervention effect in the OECD, the region which has adopted more agreements throughout the analysis, is negative although low. This finding could support the position of one part of the OECD members who decided not to keep their commitments or withdraw their participation in some of those agreements before 2015; the Kyoto protocol, for instance. They argued that their obligations might stop economic growth because the decrease in the production levels in the dirty sectors is not offset by higher growth in other sectors.

Thirdly, the positive intervention effect in China contrasts with the fact that this country has raised many discussions concerning its participation in different IEAs. China was reluctant to be part of these agreements, letting their emissions more than triple in the last 30 years from 2.42 Gtc to 9.84 Gtc in 2018[11] [EIA, 2021]. In light of its more committed behaviour, the results suggest that China's mild adoption of IEAs, ironically, has had a positive impact on its economy.

[10] This is also why some equations do not include the whole group of variables considered in the theoretical part.

[11] Gtc: gigatons of carbon

Finally, the results comparison between the OECD and China might suggest the presence of the "off-shoring effect" of IEAs, taking into account that the positive impact of agreements in China is across its economy, including, of course, an intensely polluting sector such as transport.

4.5.2 Input Intervention Effect

Following the strategy used in the previous section, we present the average estimation for equation (4.22) per region:

OECD: $$\Delta \mathbf{b}_t = \underset{(0.01)}{0.028} - \underset{(0.000)}{0.002}\mathbf{z}_{s,t} + \underset{(0.23)}{1.100}\mathbf{w}_{s,t} + v_{s,t}$$

China: $$\Delta \mathbf{b}_t = \underset{(0.001)}{-0.001} + \underset{(0.029)}{0.077}\mathbf{z}_{s,t} + \underset{(0.22)}{0.313}\mathbf{w}_{s,t} + v_{s,t}$$

India : $$\Delta \mathbf{b}_t = \underset{(0.024)}{-0.034} - \underset{(0.100)}{0.105}\mathbf{z}_{s,t} + \underset{(0.4)}{0.422}\mathbf{w}_{s,t} + v_{s,t}$$

Asia: $$\Delta \mathbf{b}_t = \underset{(0.004)}{0.014} - \underset{(0.002)}{0.002}\mathbf{z}_{s,t} + \underset{(0.27)}{0.660}\mathbf{w}_{s,t} + v_{s,t}$$

Eurasia: $$\Delta \mathbf{b}_t = \underset{(0.000)}{-0.041} + \underset{(0.001)}{0.001}\mathbf{z}_{s,t} + \underset{(0.22)}{0.490}\mathbf{w}_{s,t} + v_{s,t}$$

Middle East & Africa: $$\Delta \mathbf{b}_t = \underset{(0.005)}{0.018} + \underset{(0.008)}{0.010}\mathbf{z}_{s,t} + \underset{(0.19)}{0.491}\mathbf{w}_{s,t} + v_{s,t}$$

Latin America: $$\Delta \mathbf{b}_t = \underset{(0.002)}{0.015} + \underset{(0.019)}{0.022}\mathbf{z}_{s,t} + \underset{(0.21)}{0.690}\mathbf{w}_{s,t} + v_{s,t}$$

For more details about sectoral estimations see appendix D section D.5.

By definition, a negative sign of intervention variable in the input equations indicates that the intervention encouraged a sector to be more efficient in their ratio of inputs consumed by a unit of output produced. Thus, the efficiency gains could be related either to using fewer units of input or inputs that could be more profitable and contain fewer pollutants. Regarding the size of the technology intervention and input interventions effects, on average, the former tends to be larger than the latter.

Although the results presented above give a sense of the impact of *input intervention* on IOC growths, I highlight some of the results obtained. Firstly, the intervention coefficient is significant across all regions, but sadly, most are positive, suggesting that more inputs have been used to produce one unit of output on average. Secondly, India stands out again, showing the negative and larger input intervention effect among all regions. Thirdly, it is interesting that the trade variable coefficient, although significant, has had a negative impact on IOCs across regions.

We unravel the results per region a little because we want to emphasise two findings from the OECD and China. First, most of the efficiency losses found in the OECD are related to inputs supplied by China. In contrast, the efficiency gains are associated with Latin American and the Middle East & African outsourcing. Considering that most of the fossil fuels consumed by the OECD come from the Middle East & Africa, the last result might suggest that the region worked to reduce the ratio of dirty inputs per unit of output of its economy. On the other hand, it is disappointing to find the efficiency losses in China are linked to Eurasia supplies, the region from which China obtains a good portion (10% approx.) of its energy sources (fossil fuels).

4.5.3 Global Interactions and Long-term Effects of Intervention

Results for system (4.19) imply the analysis of big matrices (42-by-42), so for the sake of clarity, we define a group of summary measures by region and by industry to obtain an overview of the main findings. These measures work by adding up across all the rows and/or columns of $\psi_4(1)$ and/or $\psi_1(1)$, with and without emissions weights, or adding subsets of rows and columns to see the impact of intervention on different regions and/or industries:

$$\eta_u = \frac{1}{\tau_u} \sum_{p=\tau_l}^{\tau_u} \psi_{jp}, \qquad \text{and} \qquad \eta_w = \frac{\sum_{p=\tau_l}^{\tau_u} e_p \, \psi_{jp}}{\sum_{p=\tau_l}^{\tau_u} e_p} \qquad j \in \{1,4\} \tag{4.25}$$

Where the *u* subscript denotes an unweighted average of the elasticities and the *w* subscript denotes a weighted average with weights reflecting the sector emissions. Finally, $\{\tau_l, \tau_u\}$ is the range of sectors under analysis.

To compute the weighted summary measures, we take the volume of emissions generated for each industry in each region in 2005 published by the International Energy Agency. We chose emissions generation at year 2005 to match with the year in which we fixed weights in equation (4.18):

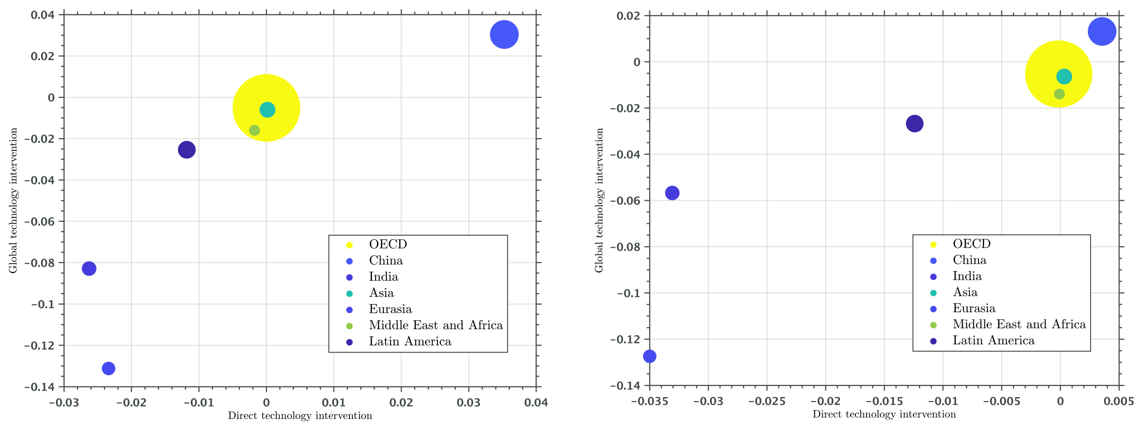
Table 4.2: Industrial emissions generation 2005 (Mt CO_2)

	OECD	China	India	Asia	Eurasia	Middle East & Africa	Latin America	Total by Industry
Non-manufacturing	189	87	24	22	19	6	28	**375**
Energy intensive manufacturing	2,068	2,008	243	273	253	188	158	**5,191**
Non-energy intensive manufacturing	187	167	28	8	7	6	13	**416**
Services	560	97	10	15	26	7	9	**724**
Transport	3,563	440	115	224	247	136	209	**4,934**
Utilities	5,225	2,538	561	324	962	366	83	**10,059**
Total by Region	**11,792**	**5,337**	**981**	**866**	**1,514**	**709**	**500**	**21,699**

4.5.3.1 Global Technology Intervention

The values of the summary measures for the technology intervention matrices are illustrated in the following figures, where we differentiate them by region and industry. Either the elasticities are or are not weighted by emissions.

From figures 4.3a and 4.3b it can be concluded that while IEAs adopted around the world positively impacted sectoral output growths in China, while in the OECD, the effects were offsetting each other, and as a result the region was almost unaffected by the



(a) Unweighted Effects

(b) Weighted Effects

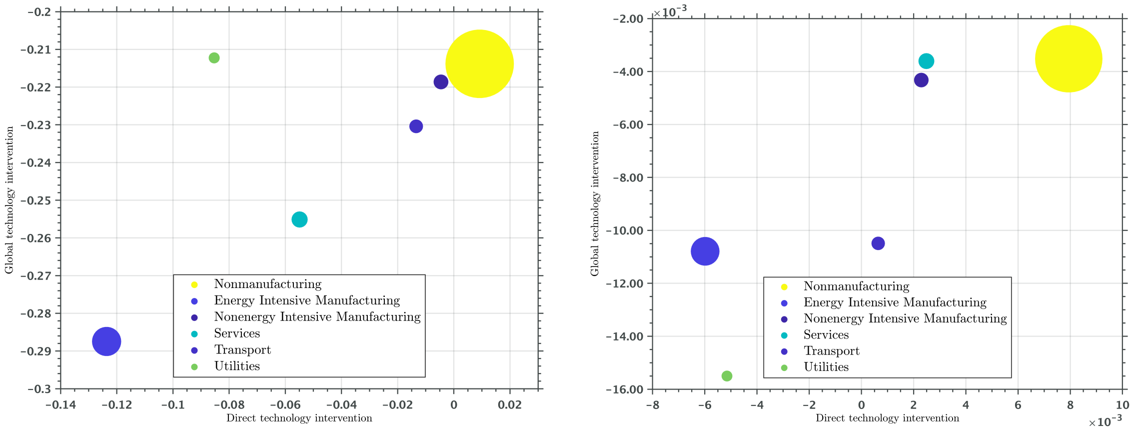
Figure 4.3: Technology Intervention Effects by Region

agreements. Although, Latin America, the third economy in the group in terms of GDP shares, was negatively affected by the IEAs, it is important to mention that this region was the least polluting in the group over the period under study.

Further unravelling the results, in the OECD, the sector with the largest *global technology intervention* effect is energy-intensive manufacturing, which is one of the industries with the highest levels of emissions generated per unit of output produced. In China, the *global technology intervention* effects in the nonmanufacturing, services and transport sectors are large and negative compared to other sectors, which is again disappointing, considering that together these sectors generate together approximately 12% of the total Chinese emissions.

India, which in terms of emissions is the third most polluting region, the *global technology intervention* effect on the nonenergy-intensive manufacturing sector is the largest one within the country, which suggests that the impact on the emissions is almost negligible because this industry generates at most 1% of Indian emissions on average.

In reference to the size of the *global technology intervention* effects at industry level, figures 4.4a and 4.4b evidence that these effects are lower than the regional version described above. In addition, as expected, the most polluting industries, energy-intensive manufacturing and utilities, were the ones more negatively affected by intervention.

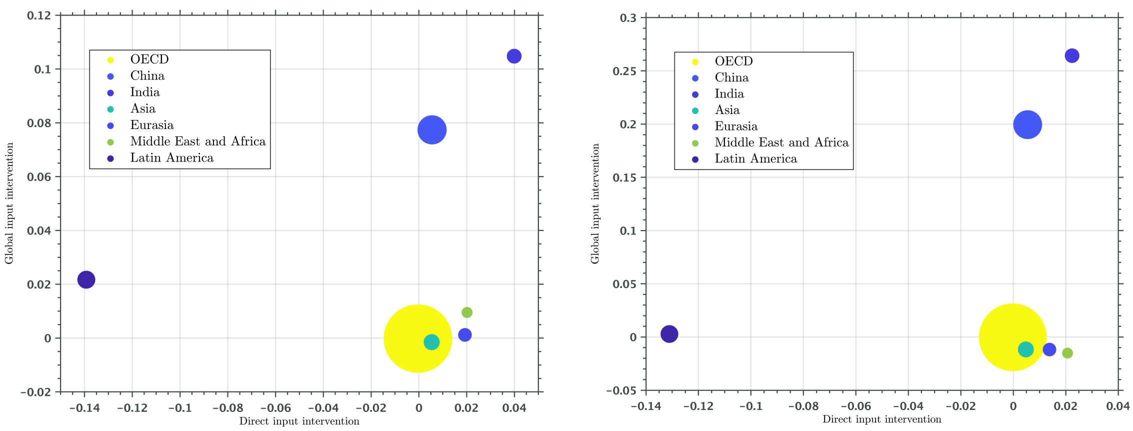


(a) Unweighted Effects (b) Weighted Effects

Figure 4.4: Technology Intervention Effects by Industry

4.5.3.2 Global Input Intervention

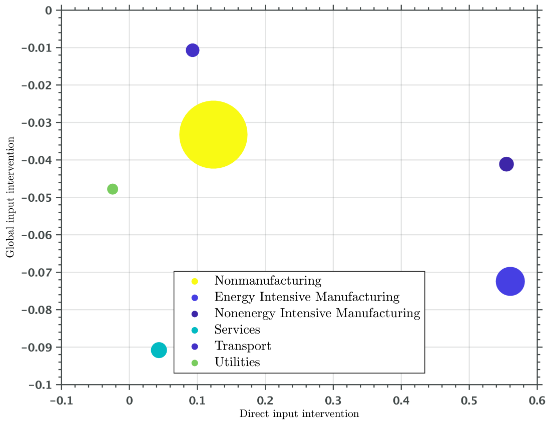
Figures 4.5a and 4.5b show the summary measures for direct and global *input intervention* effects across regions with or without sectoral emissions used as weights. The key results summarised are: (I) The effects in the OECD although negative, are very low; (II) China's results are mainly driven by the large efficiency gains in nonmanufacturing and services sectors; (III) India is the region with the efficiency losses in almost all its sectors; and (IV) results for Latin America classified it as the outsider, located always in the bottom left corner with negative direct effect but almost negligible global effects on growth.



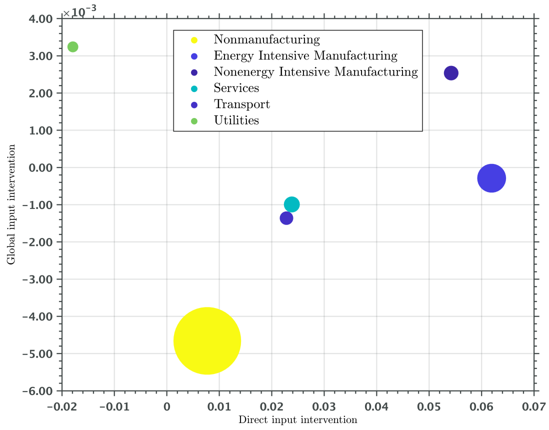
(a) Unweighted Effects (b) Weighted Effects

Figure 4.5: Input Intervention Effects by Region

Finally, figures 4.6a and 4.6b present the map for the direct and global *input intervention* effects across industries. All in all, it is possible to assert that almost all industries experienced efficiency gains. However, the downside of these findings is that larger gains did not precisely occur in the more polluting industries: utilities and energy-intensive manufacturing.



(a) Unweighted Effects



(b) Weighted Effects

Figure 4.6: Input Intervention Effects by Industry

4.5.4 Sectoral Emissions Evolution

Using equation (4.24), the following figures show the estimated sectoral growth caused by the direct and global effects of intervention but expressed in emissions generated.

Highlighting the main findings in the OECD: firstly, it is positive that emissions from most industries were reduced overall; secondly, the utility industry experienced negative growth most of the time under study, contrasting with the fact that this industry typically consumes fossil fuels to generate electricity and the price of these commodities was low for most of the years in the sample.

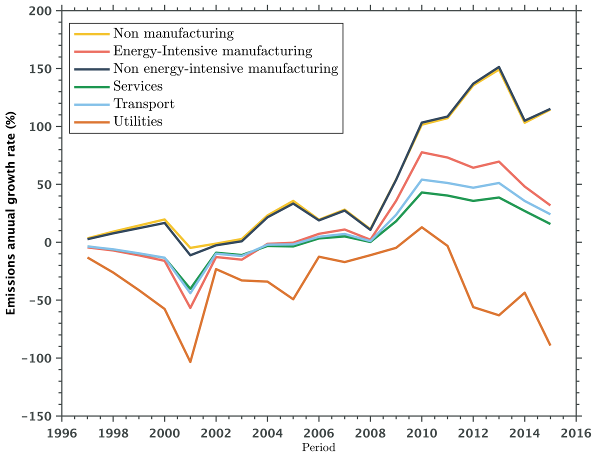
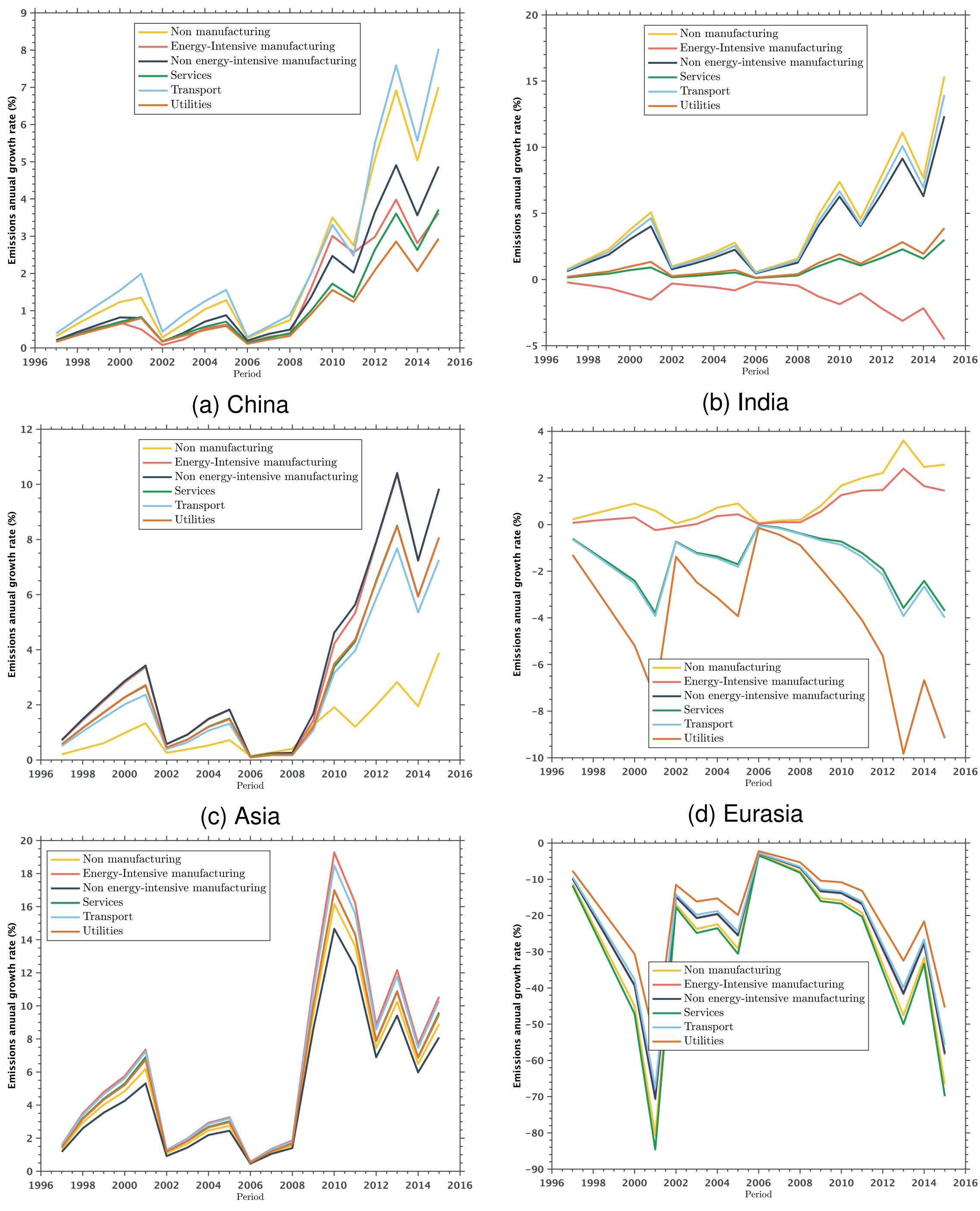


Figure 4.7: Emission Generation due to Intervention-OECD

Figure 4.8a illustrates that agreements have no impact on the emissions by sector at all in China; they increased over the whole period. The results confirm the impact of China's reluctance to have any serious commitments in terms of IEAs, before 2015. The picture in India (figure 4.8b) is disappointing too; only the utilities industry experienced emissions annual growth below 2%. Results for these two countries are not surprising; it is well known that the economic growth experienced by both has been leveraged mainly by fossil fuels.

Finally, analysing the results for the smallest economies, Asia does not surprise with its ever growing emissions due to its developing economic status, while Eurasia does with its emissions decreasing overall. This is contrary to expectations, considering that this region includes Russia's economy which highly depends on fossil fuels. Another interesting finding is that Latin America is the unique region where emissions, on average, decreased over the whole period. Figure 4.8f spots that the more considerable decrease in emissions occurred close to the economic crisis experienced by the global economy in the last 30 years.



(a) China
(b) India
(c) Asia
(d) Eurasia
(e) Middle East & Africa
(f) Latin America

Figure 4.8: Emission Generation due to Intervention

4.6 Conclusion

Since 1990 when the world started to see the threat that climate change represents for all, a series of agreements were negotiated to mitigate the phenomenon. In general, the philosophy of those agreements was to reduce the level of emissions generated worldwide to a level that the scientific community has approved as manageable before facing an environmental disaster. To do that, they focused on forcing countries, especially the richest ones, to invest in technology that generates sustainable energy sources and better production processes. In addition, those improvements had to be disseminated across regions as a unique way to impact the evolution of climate change.

It is indisputable that these agreements did not fulfil their goals, and emissions kept increasing at alarming levels. However, their recurring appearance almost yearly shows that the world walked along a learning curve in climate change negotiations until achieving the Paris Agreement, which is expected to limit emissions growth worldwide. As a result, it is right to say that the IEAs were not completely useless because, bit by bit, they triggered technology improvements and reconfiguration of the economic sectors around the world over the last 30 years.

This chapter looks for evidence of how IEAs have altered production methods and input demands across world regions. In order to do that, we propose a GVAR model to identify the direct and long-term global effects of the intervention on sectoral output growths throughout technology and input demands. We also compute these effects in terms of sectoral emissions generation and look for evidence of the ”off-shoring” effect among regions. This model was estimated using data from the Input-Output Tables and IEAs adopted for seven regions over the 1995-2015 period: the OECD, China, India, Asia, Eurasia, Middle East& Africa and Latin America.

We found evidence that the direct technology intervention effect was significant in five regions, but positive and considerably larger for China. These findings support the presence of the ”off-shoring” effect in China and explain why the OECD countries withdrew their membership to some agreements in the last two decades. Although the direct input intervention effect was significant across all regions, the efficiency gains were only found in the OECD, India, and Asia.

The computation of the effects at the industrial level served as a robust check, confirming that across industries, there is more evidence in favour of input intervention than technology intervention on growth.

The global effects, as expected, magnified in almost all cases the direct effects. In particular, it was found that China is the region that was positively more affected by all agreements adopted around the world. The input and technology effects offset each other in the OECD, and the region was mildly affected by the agreements in the long term. Regarding the results for the smaller regions, it was also interesting that almost all of them did not experience efficiency gains in demand for inputs coming from China and the Middle East & Africa. The reason could be that these regions are low-cost suppliers. For instance, in terms of commodities, the Middle East & Africa offers the best quality and good availability of fossil fuels given the market prices, which discourage to some extent massive improvements in production methods.

Finally, when all these results are translated into emissions generated per unit of output produced, the model replicates the real data by showing that emissions generated in the developed region were reducing over the sample period. The estimation results also show that some industries in the smaller regions, such as Eurasia and Latin America, followed the same trend. In addition, the estimations prove, not surprisingly, that emissions in China and India increased across industries and for most of the period analysed.

All in all, it is possible to say that international environmental agreements, despite their significant shortcomings, impacted the economic sectors around the world. Most importantly, they made evident to the world that climate change must be dealt with cooperatively; otherwise, phenomena such as the ”off-shoring effect will be aggravated and the emissions generation will not stop growing as the economic growth in developing regions take off.

Summary and Conclusions

The inherent characteristic of the environment being a public good has proved to be the most difficult issue in combating climate change, because people do not usually recognise the impact of some of their actions on other people, and at the same time, nobody wants to do more than others when it is known that the benefits of any mitigation action is both non-excludable and non-rivalrous. However, the life threatening condition of climate change has encouraged cooperation attempts between countries and international organisations through IEAs to limit enviromental degradation since 1990, but, for 20 years, these have generally failed, and climate change continues to advance alarmingly.

In 2015, the Paris Agreement emerged as a more decisive accord to abate climate change because it gathered, for the first time in history, almost all countries around the world, the private sector, ONGs, and the general public. This action raised questions about the incentives behind this milestone and whether they can be enough to guarantee success in emissions reduction, and therefore, avoid an environmental disaster. It also questions if all IEAs, before Paris, generated sufficient reconfiguration of the global economy in terms of migration away from carbon-intensive industries. This study presents a theoretical and empirical framework that look at those questions.

The link between the endogenous economic growth with directed technical change theory developed by [Acemoglu et al., 2012] and the *warm-glow giving* theory developed by [Andreoni, 1990] is the foundation of the aproach presented in chapter 1 and 2. In particular, chapter 1 explores the idea that changes in society's culture and values are pushing people around the world to willingly pay more for sustainable goods than for unsustainable because the former kind is not threatening the planet. The model proves that substitutability between clean and dirty inputs is indispensable to avoid an environmental disaster under whatever economic structure, decentralised equilibrium or central planner solution; otherwise, the full transition towards clean energy would be impossible. Furthermore, under a decentralised equilibrium, the model proves that an environmental disaster is only avoided if the *warm-glow* parameter is big enough (170% the price of the dirty consumption). The implementation of the optimal policy, in turn, always puts in place a carbon tax and clean R&D subsidy to avoid the disaster; nevertheless, *warm-glow* guarantees that the size of both instruments is smaller than the case when this parameter is absent.

Chapter 2 extends the model by recognising that although *warm-glow giving* explains why countries want to participate and commit, "impure altruism" cannot explain alone the relationship between a country's income and volunteered emissions target established in the Paris Agreement. Therefore, we bring the concept of the income elasticity of demand to understand why nations respond differently according to their income levels. In so doing, the model demonstrates that transition towards clean energy is only possible when the optimal policy is implemented. As it happened in the previous chapter, the *warm-glow* parameter reduces the size of the distortion caused by the required taxes and clean subsidies.

In chapter three, based on the carbon tax definition from WGPM, we build a Vector Error Correction Model to forecast the carbon price in the European Community. This economy established a "cap-and-trade" system to put in place a carbon price as the optimal policy dictates, becoming the only region with the largest and well-established system of that kind. The predictions are presented as recursive forecasting and density forecasting. We conclude, using recursive forecasting, that the theory-based VEC models outperformed the simple ARIMA approaches in predicting the carbon price movements over short periods (1, 3, 6 and 12 months ahead). In addition, density forecasting allows using the models in a broader context because firms and policymakers can see them as a new and accurate input for their carbon price risk-management analysis.

In chapter four, we turn the attention towards the historical dynamic of the IEAs to support our theoretical framework and determine the impacts of the agreement's adoption on the growth and configuration of the economic sectors across global regions over 1995-2015. Using the input-output tables for seven regions (90% of the world GDP), we build a GVAR model that quantitatively accounts for these impacts, considering the interrelationship among regions and industries. On the one hand, the chapter concludes that China is the big winner because it benefited from IEAs adopted across countries in terms of sectoral growth, but it was also the economy with the most considerable emissions growth. On the other hand, it proves that IEAs incentivised the OECD members to move towards clean-energy or less-fossil-fuel-intensive sectors, and in doing so, they curbed their emissions growth overall. In terms of technological changes, the agreements, however, did not have statistically significant impacts on sectoral growth in this region.

In summary, this research offers a new angle to analyse the current and past effects of the environmental agreements on the global economy and understand that, although the cost of transition toward a more sustainable lifestyle is high, the *status quo* is becoming unaffordable for the planet. We need to put in place actions that urgently leave behind the use of carbon-intensive energy, and as we demonstrated in this work, pushing clean technology is the perfect way out. More precisely, we want to call for more attention to be paid to the power of public opinion in achieving a limit to the advance of climate change. Governments might find more effective strategies to achieve the environmental goals by exploring ways to make people more conscious about the level of degradation that society's consumption patterns are inflicting on the environment with current and permanent threatening life consequences for all. In so doing, the demand for more sustainable goods and services will take off.

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A | Central Planner Solution for the WGPM

The central planner solves the following problem:

$$Max \quad \sum_{t=0}^{\infty} \beta^t \frac{\left(C_t E_t\right)^{1-\theta}}{1-\theta} \quad subject \quad to:$$

$$C_t = \left((1+\phi) c_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + c_{dt}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

$$c_{ct} = \left(\int_0^1 \left(A_{cit} x_{cit}\right)^{\alpha} di \right)^{\frac{1}{\alpha}} \quad \text{and} \quad c_{dt} = \left(\int_0^1 \left(A_{dit} x_{dit}\right)^{\alpha} di \right)^{\frac{1}{\alpha}}$$

$$A_{ct} = (1+\gamma\eta_c s_{ct}) A_{ct-1} \quad \text{and} \quad A_{dt} = (1+\gamma\eta_d s_{dt}) A_{dt-1}$$

$$E_t = max\Big\{ min\{\bar{E}, -\xi c_{dt-1} + (1+\delta) E_{t-1}\}, 0 \Big\}$$

$$\int_0^1 x_{cit} di + \int_0^1 x_{dit} di = 1 \quad \text{and} \quad s_{ct} + s_{dt} = 1$$

The shadow price of total consumption, dirty consumption, clean consumption, and the quality of the environment are represented by λ_{1t}, λ_{2t}, λ_{3t}, and λ_{6t} respectively, FOCs wrt these variables are:

$$\left(C_t^{-\theta} E_t^{1-\theta} \right) = \lambda_{1t} \tag{A.1}$$

$$\lambda_{1t} \left(\frac{C_t}{c_{dt}} \right)^{\frac{1}{\varepsilon}} - \lambda_{6t+1} \xi = \lambda_{3t} \tag{A.2}$$

$$\lambda_{1t}(1+\phi)\left(\frac{C_t}{c_{ct}}\right)^{\frac{1}{\varepsilon}} = \lambda_{2t} \tag{A.3}$$

$$\left(C_t^{1-\theta}E_t^{-\theta} + \lambda_{6t+1}(1+\delta)\right) = \lambda_{6t} \tag{A.4}$$

If we divide each shadow price by λ_{1t}, it turns out that they are defined in terms of total consumption. To start with, we call the ratios for dirty and clean consumption such as $\hat{p}_{ct}$ and $\hat{p}_{dt}$ and have:

$$\frac{\lambda_{2t}}{\lambda_{1t}} = \hat{p}_{ct} = (1+\phi)\left(\frac{C_t}{c_{ct}}\right)^{\frac{1}{\varepsilon}} \quad \text{and} \quad \frac{\lambda_{3t}}{\lambda_{1t}} = \hat{p}_{dt} = \left(\frac{C_t}{c_{dt}}\right)^{\frac{1}{\varepsilon}} - \frac{\lambda_{6t+1}\xi}{\lambda_{1t}} \tag{A.5}$$

According to [Acemoglu et al., 2012] in the central planner solution, the difference between the marginal utility of the dirty energy consumption and its price is referred to as the carbon tax (τ_t). Therefore, this price can be re expressed such as:

$$\underbrace{\frac{\lambda_{6t+1}\xi}{\lambda_{1t}\hat{p}_{dt}}}_{\tau_t} = 1 \qquad \Longrightarrow \qquad (1+\tau_t)\hat{p}_{dt} = \left(\frac{C_t}{c_{dt}}\right)^{\frac{1}{\varepsilon}} \tag{1.29}$$

Taking the ratio between clean and dirty consumption prices gives:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = (1+\phi)(1+\tau_t)\left[\frac{c_{dt}}{c_{ct}}\right]^{\frac{1}{\varepsilon}} \tag{1.30}$$

The FOCs wrt A_{cit} and A_{dit}, after dividing by λ_{1t} are[1] :

$$\lambda_{1t}\hat{p}_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{ct}^{\frac{2\alpha-1}{1-\alpha}} + \lambda_{4t+1}(1+\gamma\eta_c s_{ct+1}) = \lambda_{4t} \tag{A.6}$$

$$\lambda_{1t} c_{dt}\hat{p}_{dt}^{\frac{1}{1-\alpha}} A_{dt}^{\frac{2\alpha-1}{1-\alpha}} + \lambda_{5t+1}(1+\gamma\eta_c s_{dt+1}) = \lambda_{5t} \tag{A.7}$$

and after doing some iterations, they become:

$$\frac{\sum_{v=0}^{\infty}\lambda_{1,t+v}\hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}^{\frac{\alpha}{1-\alpha}}}{A_{ct}} = \lambda_{4t} \tag{A.8}$$

$$\frac{\sum_{v=0}^{\infty}\lambda_{1,t+v}\hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}^{\frac{\alpha}{1-\alpha}}}{A_{dt}} = \lambda_{5t} \tag{A.9}$$

[1] Here λ_{4t} is the shadow price of clean innovation and λ_{5t} is the shadow price of dirty one

Defining the shadow price of the price of machine *i* in sector *j* by λ_{7t}, FOCs wrt x_{cit} and x_{dit} are:

$$\lambda_{2t} c_{ct}^{1-\alpha} A_{cit}^{\alpha} x_{cit}^{\alpha-1} = \lambda_{7t} \tag{A.10}$$

$$\lambda_{3t} \alpha c_{dt}^{1-\alpha} A_{dit}^{\alpha} x_{dit}^{\alpha-1} = \lambda_{7t}, \tag{A.11}$$

and after dividing λ_{7t} by λ_{1t}, the isoelastic inverse demand for machine *i* in each sector is:

$$x_{cit} = \hat{p}_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{cit}^{\frac{\alpha}{1-\alpha}} \quad \text{and} \quad x_{dit} = \hat{p}_{dt}^{\frac{1}{1-\alpha}} c_{dt} A_{dit}^{\frac{\alpha}{1-\alpha}} \tag{1.32}$$

Using expressions in (1.32) into equation (1.5) gives:

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = \frac{A_{dt}}{A_{ct}} \tag{1.17}$$

On the other hand, the FOCs wrt s_{ct} and s_{dt} are:

$$\lambda_{4t} \gamma \eta_c A_{ct-1} = \lambda_{8t} \quad \text{and} \quad \lambda_{5t} \gamma \eta_d A_{dt-1} = \lambda_{8t}, \tag{A.12}$$

which are combined with (A.6), (A.7) and (A.12) to get:

$$\frac{\gamma \eta_c}{(1+\gamma \eta_c s_{ct})} \sum_{v=0}^{\infty} \lambda_{1,t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}^{\frac{\alpha}{1-\alpha}} = \lambda_{8t} \tag{A.13}$$

$$\frac{\gamma \eta_d}{(1+\gamma \eta_d s_{dt})} \sum_{v=0}^{\infty} \lambda_{1,t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}^{\frac{\alpha}{1-\alpha}} = \lambda_{8t} \tag{A.14}$$

Finally, taking the ratio between (A.13) and (A.14), and using $s_{dt} = 1 - s_{ct}$, we get:

$$\frac{\eta_c(1+\gamma \eta_d (1-s_{ct}))}{\eta_d (1+\gamma \eta_c s_{ct})} \underbrace{\frac{\sum_{v=1}^{\infty} \lambda_{1,t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}}{\sum_{v=1}^{\infty} \lambda_{t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}}}_{Q_t} \tag{1.33}$$

B | Detailed Solution for the Nonhomothetic Preferences Model

B.1 Consumption Utility Function

Keeping in mind that the consumption utility function is defined as:

$$C_t = \left(C_t^{\frac{\phi}{\sigma}} c_{ct}^{\frac{\sigma-1}{\sigma}} + c_{dt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2.3}$$

Total derivative of 2.3 with respect to c_{ct} is:

$$\frac{dC_t}{dc_{ct}} = \frac{c_{ct}^{-\frac{1}{\sigma}} C_t^{\frac{\phi+1}{\sigma}}}{1 - \left(\frac{\phi}{\sigma-1}\right) c_{ct}^{-\frac{1}{\sigma}} C_t^{\frac{\phi+1-\sigma}{\sigma}}}, \tag{B.1}$$

and with respect to c_{dt} is:

$$\frac{dC_t}{dc_{dt}} = \frac{c_{dt}^{-\frac{1}{\sigma}} C_t^{\frac{1}{\sigma}}}{1 - \left(\frac{\phi}{\sigma-1}\right) c_{dt}^{-\frac{\sigma-1}{\sigma}} C_t^{\frac{\phi+1-\sigma}{\sigma}}} \tag{B.2}$$

Both expressions need to be positive in order to have well-defined consumption function. In that respect, these derivatives are greater than zero if only if the $\phi < 1$, as it is assumed in the model.

B.2 Central Planner Solution

The central planner solves the following problem:

$$Max \quad \sum_{t=0}^{\infty} \beta^t \frac{(C_t E_t)^{1-\theta}}{1-\theta} \quad subject \quad to:$$

$$C_t = \left(C_t^{\frac{\phi}{\sigma}} c_{ct}^{\frac{\sigma-1}{\sigma}} + c_{dt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$$c_{ct} = \left(\int_0^1 (A_{cit} x_{cit})^{\alpha} di \right)^{\frac{1}{\alpha}} \quad \text{and} \quad c_{dt} = \left(\int_0^1 (A_{dit} x_{dit})^{\alpha} di \right)^{\frac{1}{\alpha}}$$

$$A_{ct} = (1 + \gamma \eta_c s_{ct}) A_{ct-1} \quad \text{and} \quad A_{dt} = (1 + \gamma \eta_d s_{dt}) A_{dt-1}$$

$$E_t = max\Big\{ min\{\bar{E}, -\xi c_{dt-1} + (1+\delta) E_{t-1}\}, 0 \Big\}$$

$$\int_0^1 x_{cit} di + \int_0^1 x_{dit} di = 1 \quad \text{and} \quad s_{ct} + s_{dt} = 1$$

As we did in the previous chapter, λ_{1t}, λ_{2t} and λ_{3t} represent the the shadow price of total consumption, dirty consumption and clean consumption respectively, and the shadow price of machine *i* in sector *j* by λ_{7t}.

If we divide FOC's with respect to c_{ct}, c_{dt} and x_{jit} by λ_{1t}, it turns out that the resulted definitions will be comparable to the ones found in the decentralised equilibrium. To start with, let us define $\hat{p}_{ct} = \frac{\lambda_{2t}}{\lambda_{1t}}$ and $\hat{p}_{dt} \frac{\lambda_{3t}}{\lambda_{1t}}$ to have:

$$\hat{p}_{ct} = \left(\frac{\sigma - 1}{\sigma} \right) \left(\frac{C_t^{\phi}}{c_{ct}} \right)^{\frac{1}{\sigma}} \tag{2.29}$$

$$\hat{p}_{dt} = \left(\frac{\sigma - 1}{\sigma} \right) c_{dt}^{-\frac{1}{\sigma}} - \frac{\lambda_{6t+1} \xi}{\lambda_{1t}} \tag{B.3}$$

Where in (B.3), the difference between the marginal utility of the dirty consumption and its price is equal to the carbon tax (τ_t) [1]:

$$\underbrace{\frac{\lambda_{6t+1} \xi}{\hat{p}_{dt} \lambda_{1t}}}_{\tau_t} \implies (1 + \tau_t) \hat{p}_{dt} = \left(\frac{\sigma - 1}{\sigma} \right) \frac{1}{c_{dt}^{\frac{1}{\sigma}}} \tag{2.30}$$

Taking the ratio between (2.29) and (2.30)

$$\frac{\hat{p}_{ct}}{\hat{p}_{dt}} = (1 + \tau_t) \left(\frac{c_{dt}}{c_{ct}} \right)^{\frac{1}{\sigma}} C_t^{\frac{\phi}{\sigma}} \tag{2.31}$$

[1] λ_{6t} is again the shadow price of the quality of the environment

Recalling that one unit of labour is required to produce one unit of machine *i*, then, dividing the shadow prices of machine *i*[2] in sector *j* ∈ {c,d} by λ_{1t} again, the isoelastic inverse demand for machine x_{ijt}, *i* ∈ (c,d), in each sector is:

$$x_{cit} = \hat{p}_{ct}^{\frac{1}{1-\alpha}} c_{ct} A_{cit}^{\frac{\alpha}{1-\alpha}} \tag{2.32}$$

$$x_{dit} = \hat{p}_{dt}^{\frac{1}{1-\alpha}} c_{dt} A_{dit}^{\frac{\alpha}{1-\alpha}} \tag{2.33}$$

Using the FOC's wrt A_{cit} and A_{dit} and the symmetry between A_{jit} and A_{jt}, $j \in \{c,d\}$ it gives:

$$\lambda_{1t} c_{ct} \hat{p}_{ct}^{\frac{1}{1-\alpha}} A_{ct}^{\frac{2\alpha-1}{1-\alpha}} + \lambda_{4t+1}(1+\gamma\eta_c s_{ct+1}) = \lambda_{4t}$$

$$\lambda_{1t} c_{dt} \hat{p}_{dt}^{\frac{1}{1-\alpha}} A_{dt}^{\frac{2\alpha-1}{1-\alpha}} + \lambda_{5t+1}(1+\gamma\eta_c s_{dt+1}) = \lambda_{5t}$$

and after doing some iterations, they become[3]:

$$\frac{\sum_{v=0}^{\infty} \lambda_{1t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}^{\frac{\alpha}{1-\alpha}}}{A_{ct}} = \lambda_{4t} \tag{B.4}$$

$$\frac{\sum_{v=0}^{\infty} \lambda_{1t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}^{\frac{\alpha}{1-\alpha}}}{A_{dt}} = \lambda_{5t} \tag{B.5}$$

On the other hand, the FOCs wrt scientists allocations in each sector are:

$$\lambda_{4t}\gamma\eta_c A_{ct-1} = \lambda_{8t} \quad \text{and} \quad \lambda_{5t}\gamma\eta_d A_{dt-1} = \lambda_{8t} \tag{B.6}$$

After combining (B.4) and (B.5) with their corresponding expressions in (B.6), we can take the ratio between both results to obtain:

$$\frac{\eta_c(1+\gamma\eta_d(1-s_{ct}))}{\eta_d(1+\gamma\eta_c s_{ct})} \underbrace{\frac{\sum_{v=1}^{\infty} \lambda_{1t+v} \hat{p}_{ct+v}^{\frac{1}{1-\alpha}} c_{ct+v} A_{ct+v}^{\frac{\alpha}{1-\alpha}}}{\sum_{v=1}^{\infty} \lambda_{1t+v} \hat{p}_{dt+v}^{\frac{1}{1-\alpha}} c_{dt+v} A_{dt+v}^{\frac{\alpha}{1-\alpha}}}}_{Q_t} \tag{2.34}$$

Where we are using the assumption of $s_{dt} = 1 - s_{ct}$.

[2] The shadow price of machine *i* in sector *j* is denoted by λ_{7t}

[3] Here λ_{4t} is the shadow price of clean innovation and λ_{5t} is the shadow price of dirty one

C | Estimation Details of the Carbon Price Forecasting Model

C.1 Unit root and Cointegration Tests

C.1.1 Unit Root

The augmented Dickey-Fuller test was performed for carbon price (τ_t^{Oil} and τ_t^{Coal}), relative clean consumption (x^{Oil} and x^{Coal}), and for the relative clean technology. Table C.1 reported the results of the tests, where all statistics are significant. It is also important to mention that if either the time trend or the drift are not included, the tests do not lose their power.

Table C.1: Augmented Dickey-Fuller unit root test

Variable	ADF lag length	ADF statistic
Carbon price		
τ^{Oil}	3	46.0594^{***}
τ^{Coal}	2	49.7382^{***}
Relative clean consumption		
x^{Oil}	3	15.3049^{***}
x^{Coal}	2	49.73812^{***}

148 observation used for estimation period 2008M6-2020M12

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1.2 Johansen Cointegration Test

Following [Enders, 2008], Johansen cointegration test implies to estimate a VECM as described in (3.6), and using the *n* estimated characteristic roots of the matrix AB', $\hat{\lambda}_i$, to built the trace statistics:

$$\lambda_{trace}(r) = -\mathbf{T} \sum_{i=r+1}^{n} ln(1-\hat{\lambda}_i), \qquad \text{where } \mathbf{T} \text{ is the number of usable observations}$$

This statistic tests the null hypothesis that the number of cointegrating vectors is less than or equal to r against a general alternative. Table C.2 the results for the Johansen cointegration tests for both measures of the carbon price.

Table C.2: Johansen Cointegration Test

	Oil-based Carbon Price†			Coal-based Carbon Price‡		
Null	alternative	Trace	C-Value	alternative	Trace	C-Value
r=0	r=1	34.7^{**}	29.8	r=1	43.7^{**}	29.8
$r \leq 1$	$r \geq 2$	13.8^{**}	15.5	$r \geq 2$	14.9^{**}	15.5

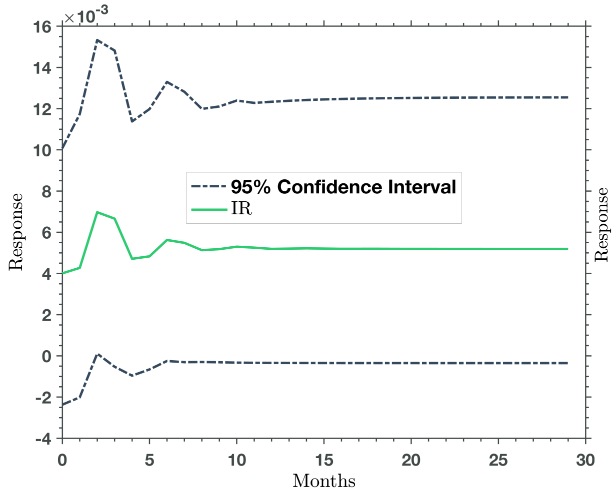
Oil based carbon price †; Coal based carbon price ‡; C-Value: Critical Value

148 observation used for estimation period 2008M6-2020M12

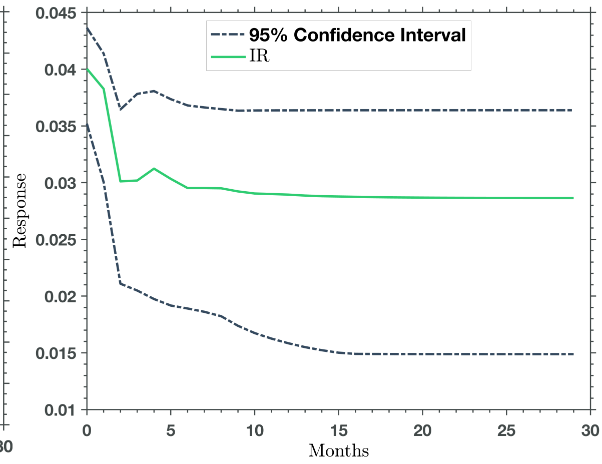
$^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

C.2 Impulse-Response Functions

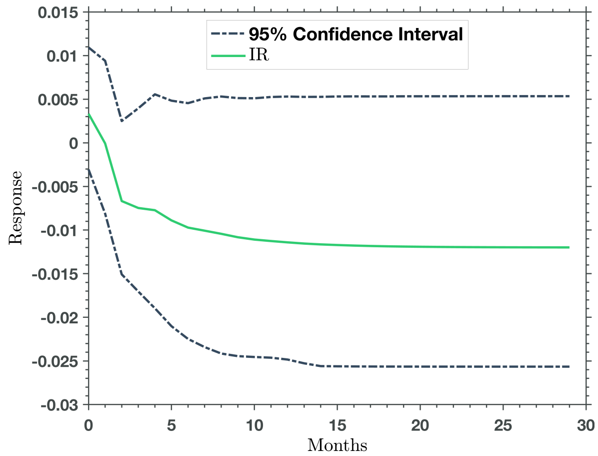
The following graphs illustrates the IRFs from the VEC models for the three variables when relative clean consumption or relative technology variables are shocked.



(a) IRF of carbon price

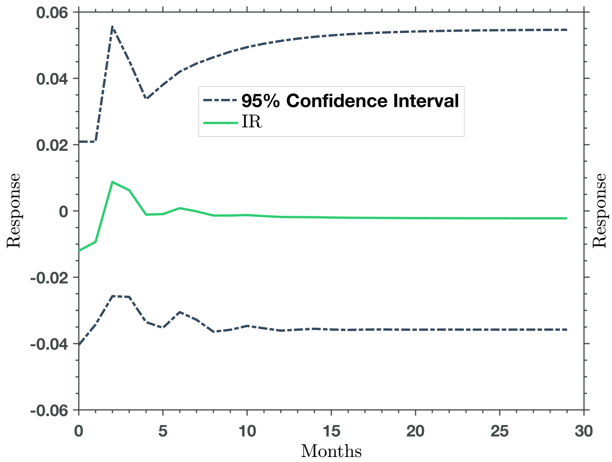


(b) IRF of relative clean consumption

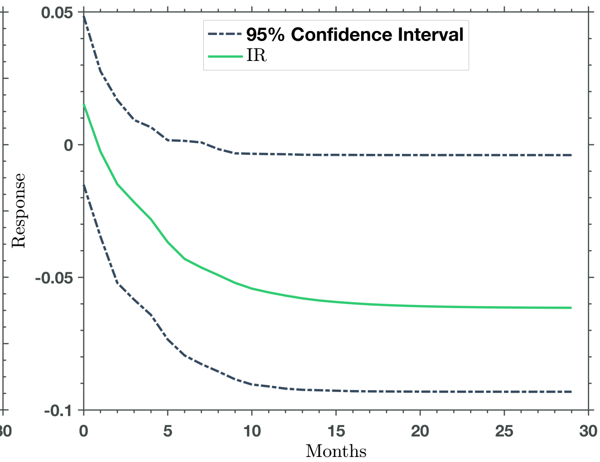


(c) IRF of relative clean technology

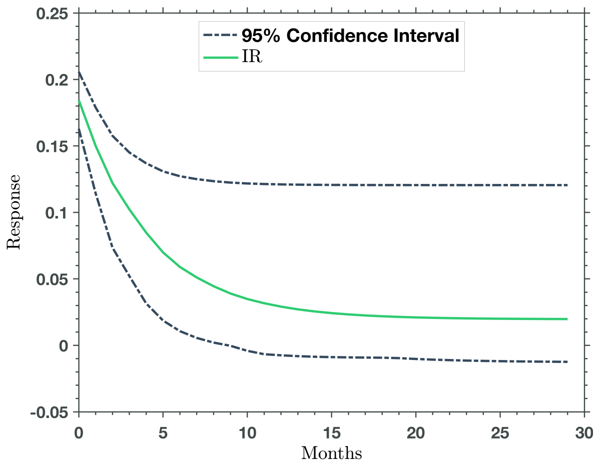
Figure C.1: Oil based carbon price: Responses when relative clean consumption is shocked



(a) IRF of carbon price

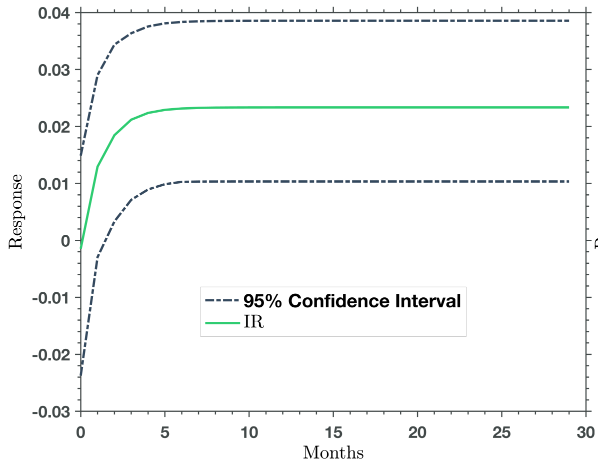


(b) IRF of relative clean consumption

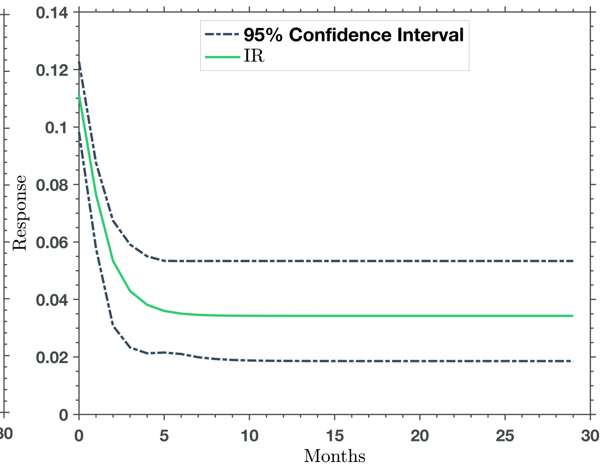


(c) IRF of relative clean technology

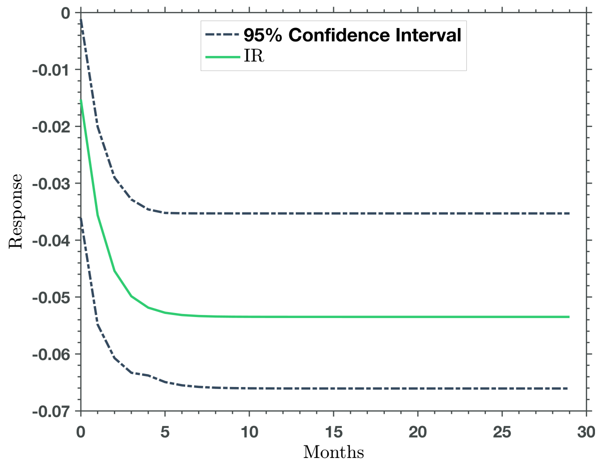
Figure C.2: Oil based carbon price: Responses when relative technology is shocked



(a) IRF of carbon price

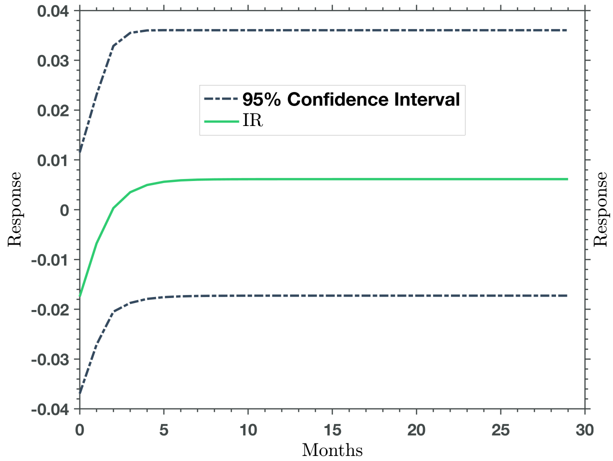


(b) IRF of Relative Clean Consumption

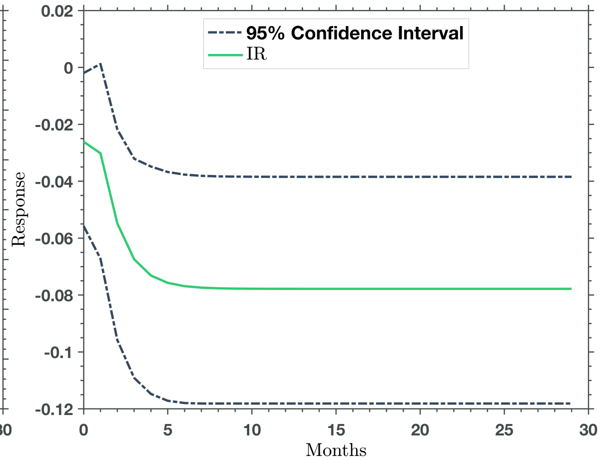


(c) IRF of relative clean technology

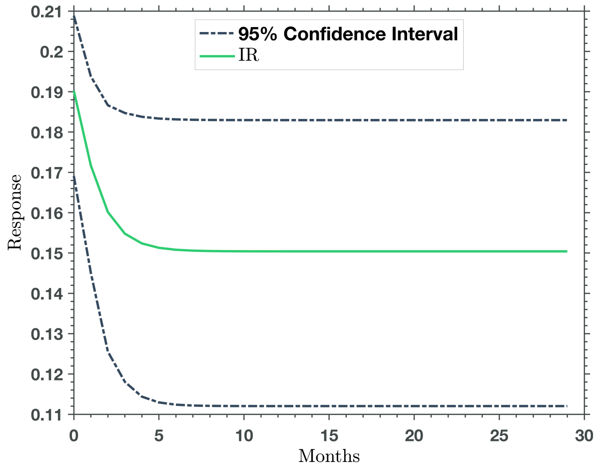
Figure C.3: Coal based carbon price: Responses when relative clean consumption is shocked



(a) IRF of carbon price



(b) IRF of Relative Clean Consumption



(c) IRF of Relative Clean Technology

Figure C.4: Coal-based Carbon Price: Responses when Relative Clean Technology is Shocked

C.3 Recursive Forecasting

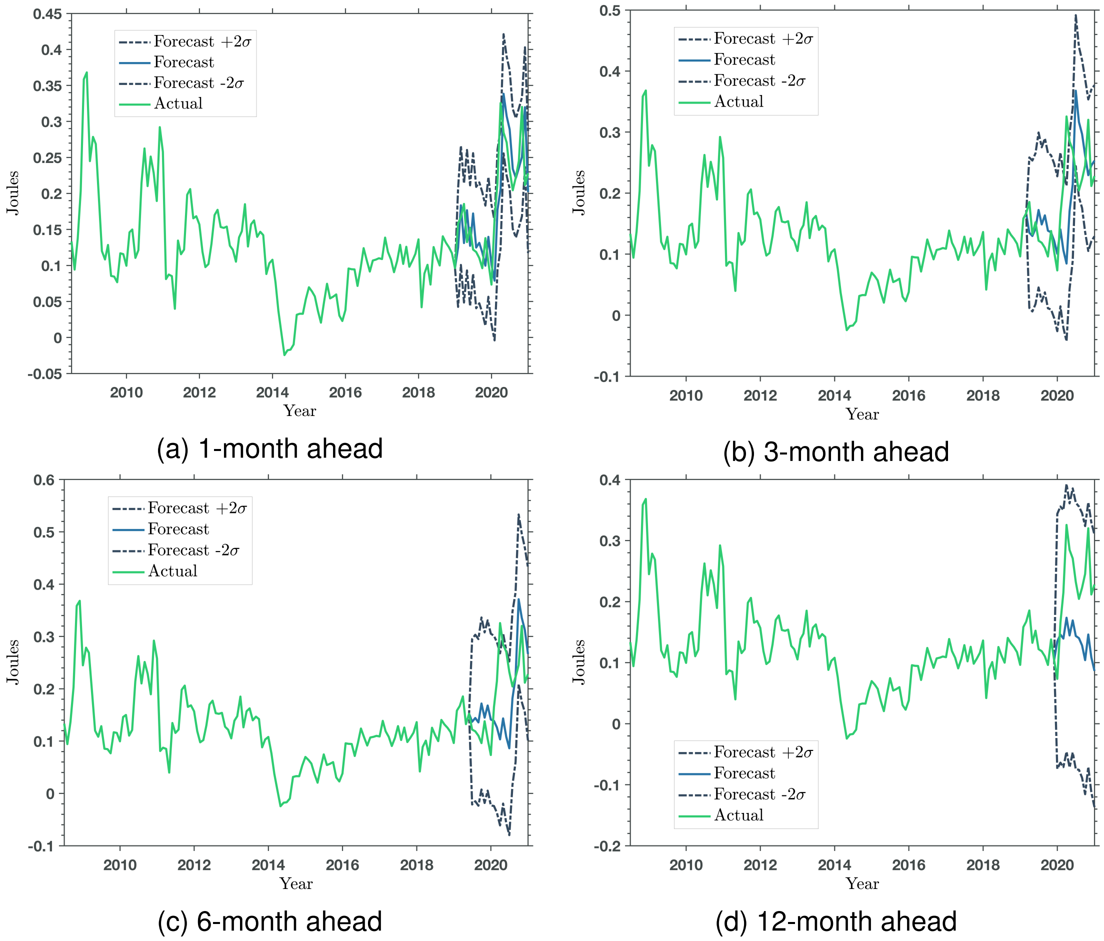
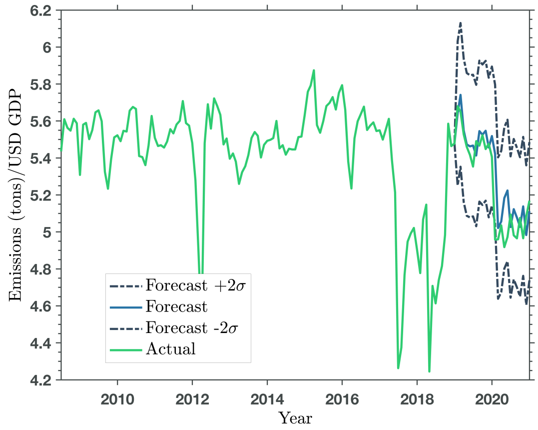
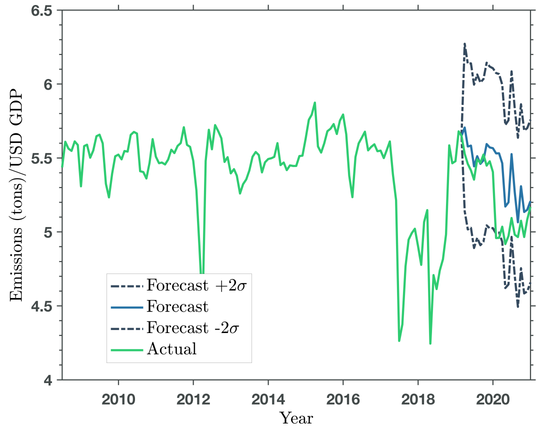


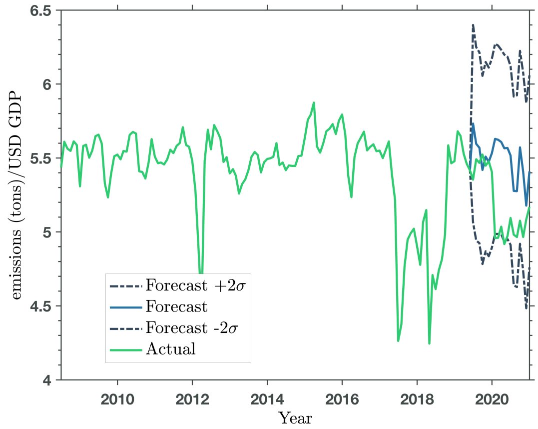
Figure C.5: Recursive forecasting: Relative Clean Consumption (Oil-based Case)



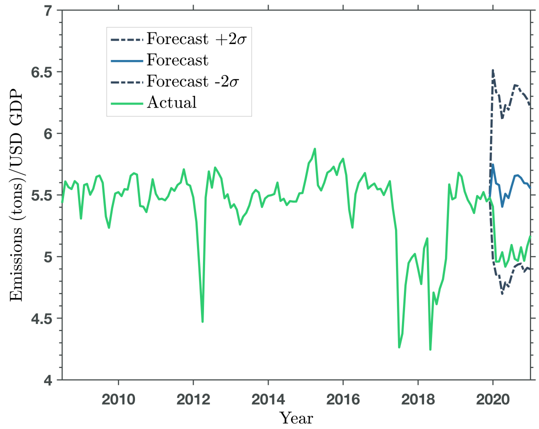
(a) 1-month ahead



(b) 3-month ahead

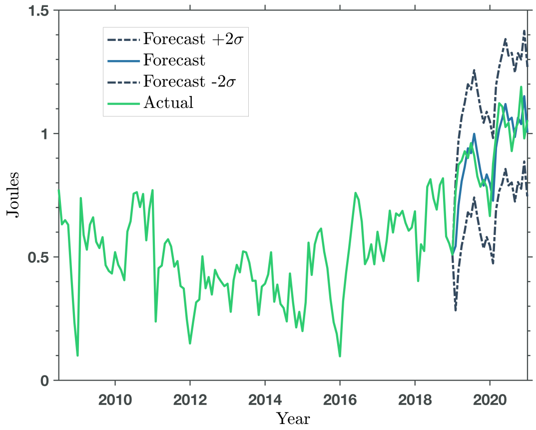


(c) 6-month ahead

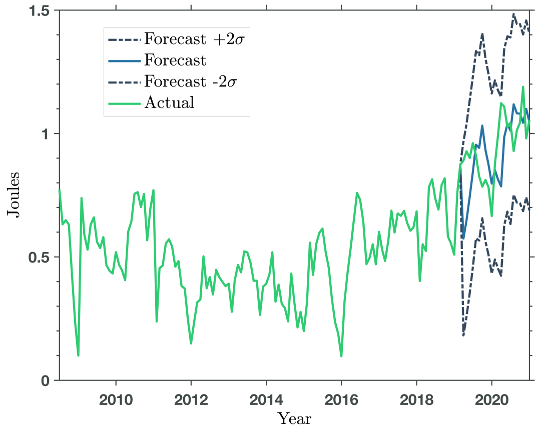


(d) 12-month ahead

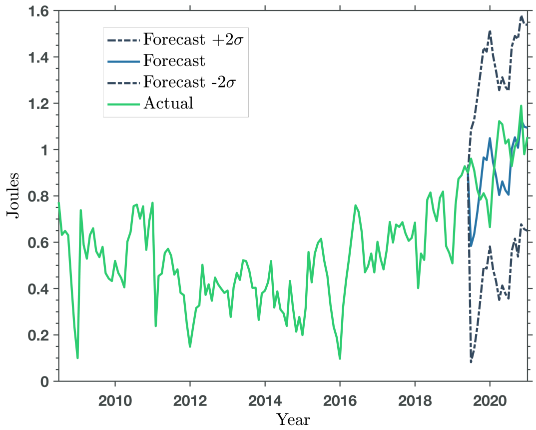
Figure C.6: Recursive forecasting: Relative Technology (Oil-based Case)



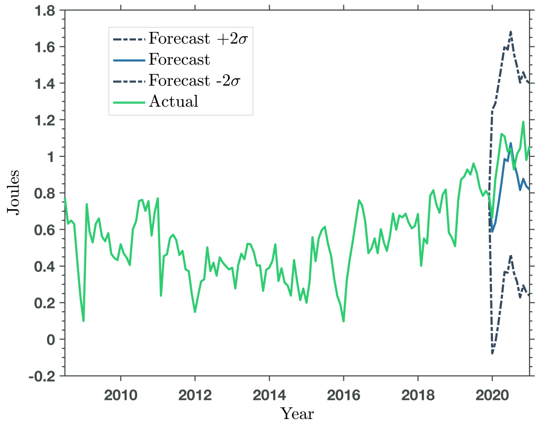
(a) 1-month ahead



(b) 3-month ahead

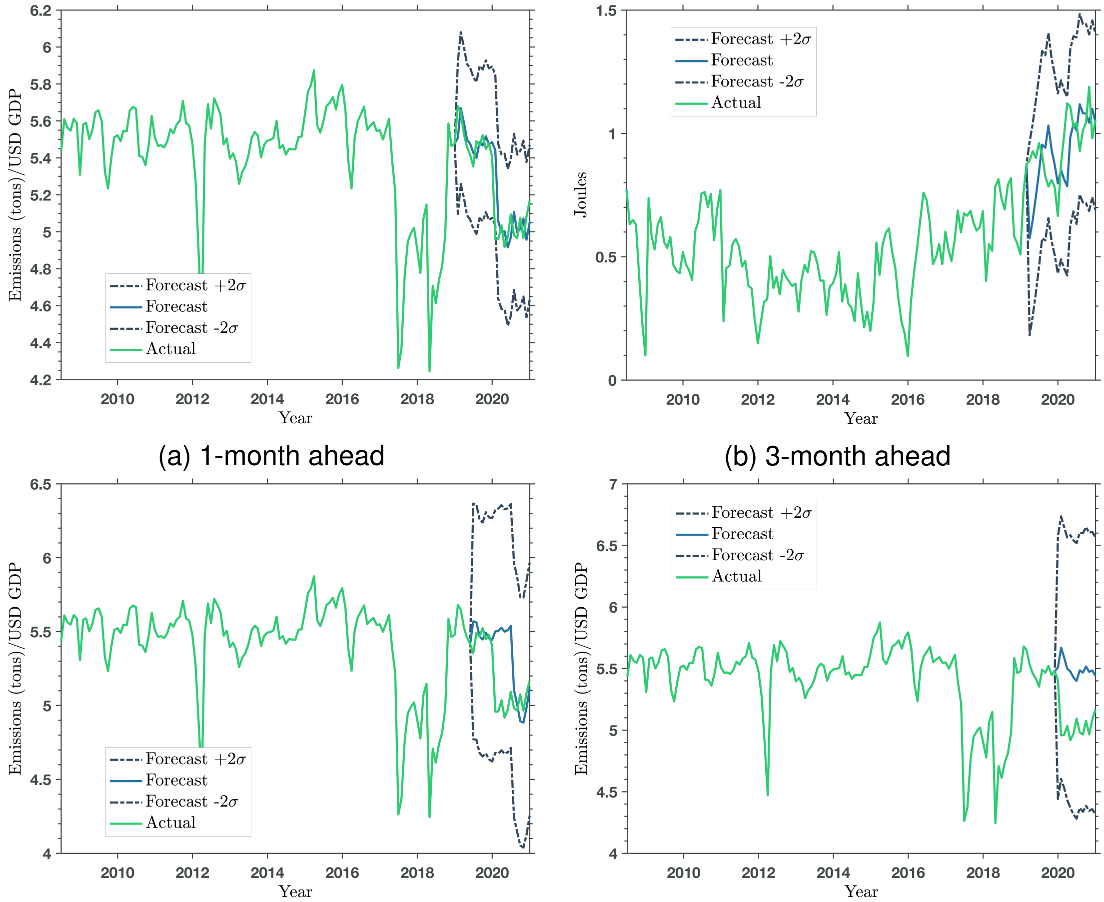


(c) 6-month ahead



(d) 12-month ahead

Figure C.7: Recursive forecasting: Relative Clean Consumption (Coal-based Case)



(a) 1-month ahead

(b) 3-month ahead

(c) 6-month ahead

(d) 12-month ahead

Figure C.8: Recursive forecasting: Relative Technology (Coal-based Case)

Table C.3: Root Square Forecast Error-VECM)

	Oil-based Carbon Price			Coal-based Carbon		
Horizon	τ_t	x_t	a_t	τ_t	x_t	a_t
1-month	0.035	0.050	0.141	0.812	0.737	0.126
3-month	0.057	0.079	0.252	0.216	0.158	0.205
6-month	0.072	0.092	0.391	0.225	0.192	0.299
12-month	0.116	0.109	0.529	0.221	0.181	0.458

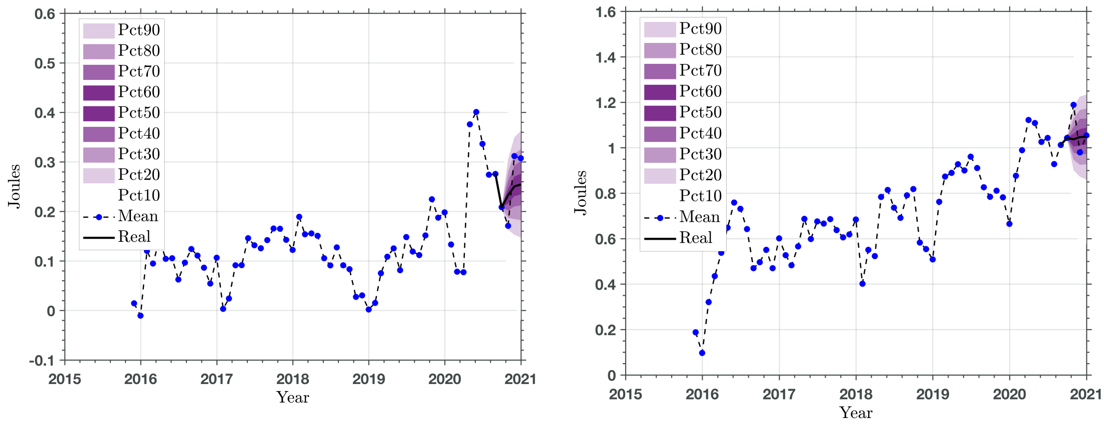
148 observation used for estimation period 2008M6-2020M12

Table C.4: Root Square Forecast Error- ARIMA Models

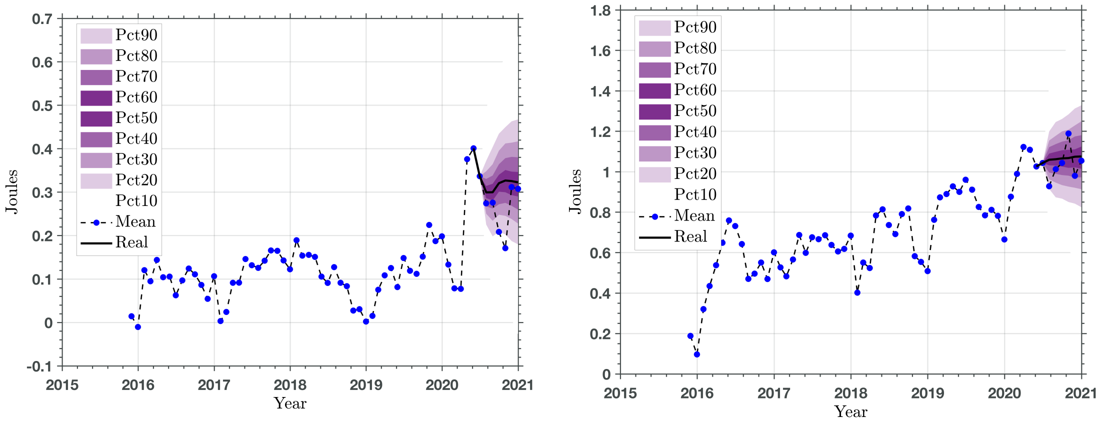
Horizon	Oil-based Carbon Price	Coal-based Carbon Price
1-month	0.165	0.178
3-month	0.151	0.145
6-month	0.127	0.127
12-month	0.118	0.102

148 observation used for estimation period 2008M6-2020M12

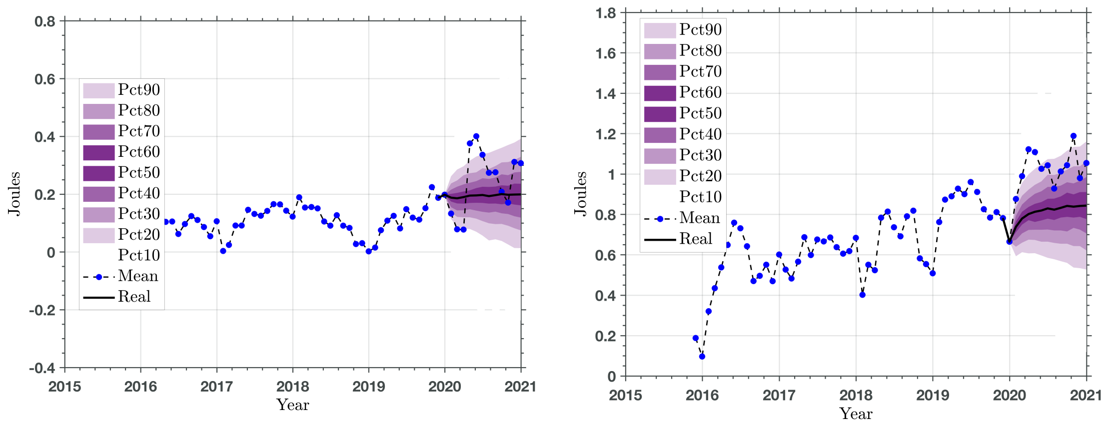
C.4 Density forecasting



3-moths ahead



6-moths ahead

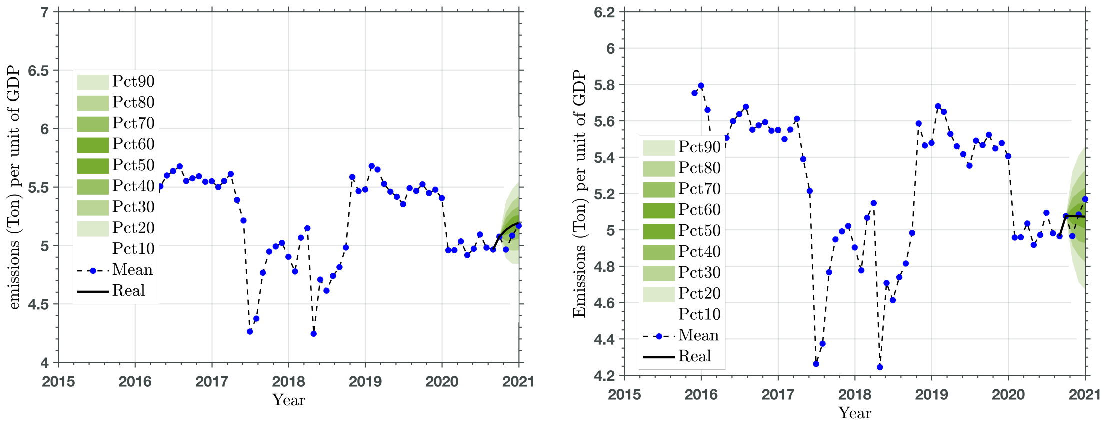


(a) Oil-base Case

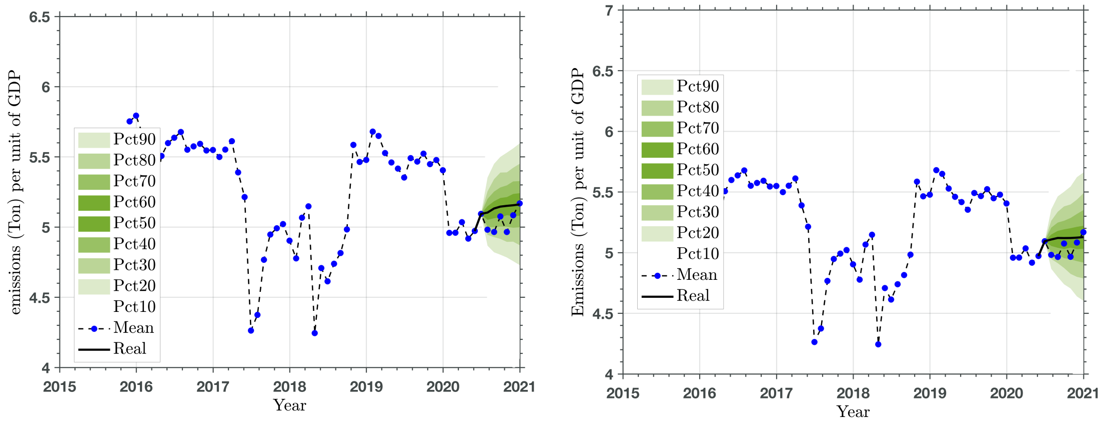
(b) Coal-base Case

12-moths ahead

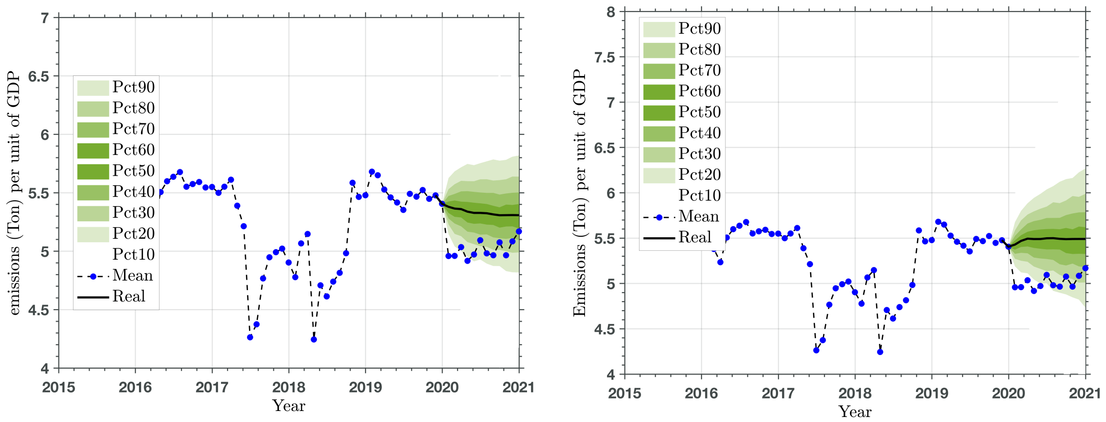
Figure C.9: Density Forecasting Relative Clean Consumption



3-moths ahead



6-moths ahead



(a) Oil-base Case

(b) Coal-base Case

12-moths ahead

Figure C.10: Density Forecasting Relative Technology

D | Complementary Information for GVAR Model

D.1 List of countries

Table D.1: Region member countries

OECD	China	India	Asia	Eurasia	Middle East & Africa	Latin America
Australia	People's Republic of China	India	Brunei	Bulgaria	Cyprus	Argentina
Austria	Chinese Taipei		Cambodia	Croatia	Morocco	Brazil
Belgium			Hong Kong	Malta	Saudi Arabia	Colombia
Canada			Indonesia	Roumania	South Africa	Costa Rica
Chile			Malaysia	Russian Federation	Tunisia	Peru
Czech Republic			Philippines			
Denmark			Singapore			
Estonia			Thailand			
Finland			Vietnam			
France						
Germany						
Greece						
Hungary						
Iceland						
Ireland						
Israel						
Italy						
Japan						
South Korea						
Latvia						
Lithuania						
Luxembourg						
Mexico						
Netherlands						
New Zealand						
Norway						
Poland						
Portugal						
Slovak						
Solvenia						
Spain						
Sweden						
Switzerland						
Turkey						
United Kingdom						
United States						

D.2 Industry classification

Table D.2: Industries by energy intensity level

Nonmanufacturing	Energy-intensive manufacturing	Nonenergy-intensive manufacturing	Services	Transport	Utilities
Agriculture, forestry and fishing	Food products, beverages and tobacco	Textiles, wearing apparel, leather and related products	Mining support service activities	Transportation and storage	Electricity, gas, water supply, sewerage, waste and remediation services
Mining and extraction of energy producing products	Paper products and printing	Wood and of products of wood and cork (except furniture)	Wholesale and retail trade; repair of motor vehicles		
Mining and quarrying of non-energy producing products	Coke and refined petroleum products	Fabricated metal products, except machinery and equipment	Accommodation and food services		
Construction	Chemicals and pharmaceutical products	Computer, electronic and optical products Electrical equipment	Publishing, audiovisual and broadcasting activities		
	Rubber and plastics products	Machinery and equipment n.e.c.	Telecommunications		
	Other non-metallic mineral products	Motor vehicles, trailers and semi-trailers	IT and other information services		
	Manufacture of basic metals	Other manufacturing; machinery repair and installation	Financial and insurance activities		
		Other transport equipment	Real estate activities		
			Other business sector services		
			Public administration and defence; compulsory social security		
			Education		
			Human health and social work		
			Arts, entertainment, recreation and other services		
			Private households with employed persons		

D.3 International Environmental Agreements

Table D.3: List of Agreements

Signature Year	Agreement Name	Lineage
1996	Amendments to the Convention on Long-Range Transboundary Air Pollution Concerning the Control of Nitrogen Oxides or their Transboundary Fluxes (CLTAP)	LRTAP
1997	Amendment to the Montreal Protocol on Substances that Deplete The Ozone Layer	Ozone Protection
1997	Protocol Adopting Regulations for the Prevention of Air Pollution from Ships to the International Convention for the Prevention of Pollution from Ships (PMARPOL)	MARPOL
1997	Protocol to the United Nations Framework Convention on Climate Change (UNFCCC)	Climate Change
1997	Amendment to the UNFCCC	Climate Change
1998	Protocol on Persistent Organic Pollutants to the (CLTAP)	LRTAP
1998	Protocol on Heavy Metals to the Convention on Long-Range Transboundary Air Pollution (CLTAP)	LRTAP
1999	Protocol to abate Acidification, Eutrophication and ground-level Ozone to the (CLTAP)	LRTAP
1999	Amendment to the Montreal Protocol on Substances that Deplete the Ozone Layer	Ozone Protection
2001	Amendment to the UNFCCC	Climate Change
2002	Agreement Establishing the Caribbean Community Climate Change Centre (CCCCC)	Climate Change
2002	Protocol on the Provisional Application of the Agreement establishing the CCCCC	Climate Change
2003	Agreement on a testing ground for Application of the Kyoto Mechanisms on energy projects in the Baltic Sea region	Climate Change
2006	Amendments to the UNFCCC	Climate Change
2008	Amendments to the PMARPOL	MARPOL
2008	Amendments to the PMARPOL	MARPOL
2009	Amendments to the Protocol on Persistent Organic Pollutants to the (CLTAP)	LRTAP
2009	Amendments to Protocol on Persistent Organic Pollutants to the CLTAP	LRTAP
2009	Amendments to the Protocol on Persistent Organic Pollutants to the CLTAP	LRTAP
2009	Amendment to the UNFCCC	Climate Change
2010	Amendments to the PMARPOL	MARPOL
2010	Amendments to the PMARPOL	MARPOL
2011	Amendment to the UNFCCC	Climate Change
2011	Amendments to the PMARPOL	MARPOL
2011	Amendments to the PMARPOL	MARPOL
2012	Amendment to the UNFCCC	Climate Change
2012	Amendments to the PMARPOL	MARPOL
2012	Amendments to the Protocol to abate Acidification, Eutrophication and ground-level Ozone to the CLTAP	LRTAP
2012	Amendments to the Protocol to Abate Acidification, Eutrophication and ground-level Ozone to the CLTAP	LRTAP
2012	Amendments to the Protocol on Heavy Metals to the CLTAP	LRTAP
2012	Amendments to the Protocol on Heavy Metals to the CLTAP	LRTAP
2015	Paris Agreement	Climate Change
2016	Amendments to the PMARPOL	MARPOL
2016	Amendment to the Montreal Protocol on Substances that deplete the Ozone Layer	Ozone Protection

International Convention for the Prevention of Pollution from Ships (MARPOL)
Air pollutant emissions (LRTAP)

D.4 Direct Technology Intervention Effect by Region and by Sector

Table D.4: OECD

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{1,t-1}$						
$\Delta m_{1,t}$	0.942^{***}					
	(33.207)					
$\Delta y_{2,t-1}$						
$\Delta m_{2,t}$		0.840^{***}				
		(16.848)				
$\Delta y_{3,t-1}$			-0.037			
			(-1.347)			
$\Delta m_{3,t}$			0.968^{***}			
			(21.498)			
$\Delta y_{4,t-1}$				-0.040		
				(-1.118)		
$\Delta m_{4,t}$				0.849^{***}		
				(21.255)		
$\Delta y_{5,t-1}$						
$\Delta m_{5,t}$					0.861^{***}	
					(24.251)	
$\Delta y_{6,t-1}$						0.095
						(1.047)
$\Delta m_{6,t}$						0.589^{***}
						(9.686)
z_t			0.000^{*}	-0.000	0.000	-0.000
			(1.788)	(-1.427)	(1.566)	(-1.194)
w_t	0.096^{***}	-0.091^{*}	-0.117^{***}	-0.185^{***}	-0.237^{***}	-0.258^{***}
	(3.124)	(-1.820)	(-3.247)	(-6.129)	(-6.101)	(-3.384)
Constant				0.006^{**}		0.007
				(2.557)		(1.200)
N	20	20	19	19	20	19

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.5: China

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{7,t-1}$						
$\Delta m_{7,t}$	0.888^{***}					
	(11.731)					
$\Delta y_{8,t-1}$		0.043				
		(1.078)				
$\Delta m_{8,t}$		0.952^{***}				
		(22.990)				
$\Delta y_{9,t-1}$						
$\Delta m_{9,t}$			0.843^{***}			
			(14.847)			
$\Delta y_{10,t-1}$				-0.171		
				(-1.437)		
$\Delta m_{10,t}$				0.746^{***}		
				(7.912)		
$\Delta y_{11,t-1}$					-0.197^{*}	
					(-1.934)	
$\Delta m_{11,t}$					0.607^{***}	
					(6.480)	
$\Delta y_{12,t-1}$						0.229
						(1.276)
$\Delta m_{12,t}$						0.240^{*}
						(2.027)
z_t	0.045^{**}			0.034^{***}	0.027^{*}	
	(2.561)			(3.084)	(1.784)	
w_t		0.052		0.097		
	(-1.003)			(1.317)		(1.297)
Constant	-0.008		0.013^{***}			
	(-1.184)		(2.897)			
N	20	19	20	19	19	19

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: India

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{13,t-1}$	0.135					
	(1.241)					
$\Delta m_{13,t}$	0.675^{***}					
	(9.542)					
$\Delta y_{14,t-1}$						
$\Delta m_{14,t}$		0.183^{*}				
		(2.003)				
$\Delta y_{15,t-1}$			0.108			
			(1.679)			
$\Delta m_{15,t}$			0.943^{***}			
			(19.584)			
$\Delta y_{16,t-1}$				-0.086		
				(-0.881)		
$\Delta m_{16,t}$				0.755^{***}		
				(12.915)		
$\Delta y_{17,t-1}$						
$\Delta m_{17,t}$					0.765^{***}	
					(9.723)	
$\Delta y_{18,t-1}$						-0.330^{*}
						(-1.887)
$\Delta m_{18,t}$						0.186^{*}
						(1.861)
w_t	-0.108		-0.125^{**}			-0.215
	(-1.711)		(-2.212)			(-1.708)
z_t		-0.136^{**}	0.046^{*}	-0.067^{**}		
		(-2.226)	(1.845)	(-2.248)		
Constant	0.011^{*}	0.077^{***}		0.041^{***}	0.016^{*}	0.072^{***}
	(1.766)	(4.666)		(3.831)	(1.821)	(4.665)
N	19	20	19	19	20	19

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.7: Asia

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{19,t-1}$	-0.109^{*}					
	(-2.112)					
$\Delta m_{19,t}$	1.125^{***}					
	(25.313)					
$\Delta y_{20,t-1}$						
$\Delta m_{20,t}$		0.976^{***}				
		(64.017)				
$\Delta y_{21,t-1}$			-0.021^{*}			
			(-1.802)			
$\Delta m_{21,t}$			0.995^{***}			
			(75.466)			
$\Delta y_{22,t-1}$						
$\Delta m_{22,t}$				0.945^{***}		
				(48.255)		
$\Delta y_{23,t-1}$						
$\Delta m_{23,t}$					0.948^{***}	
					(14.229)	
$\Delta y_{24,t-1}$						
$\Delta m_{24,t}$						0.550^{***}
						(8.900)
z_t	-0.009^{*}		0.004^{**}	0.002	0.009^{**}	-0.005
	(-2.093)		(2.161)	(1.301)	(2.803)	(-1.288)
w_t	0.181^{***}			-0.151^{***}	-0.139^{**}	-0.120
	(4.070)			(-4.961)	(-2.664)	(-1.289)
Constant	0.017^{**}		0.003		-0.009	0.028^{***}
	(2.808)		(1.228)		(-1.473)	(4.444)
N	19	20	19	20	20	20

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.8: Eurasia

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{25,t-1}$						
$\Delta m_{25,t}$	1.064^{***}					
	(16.872)					
$\Delta y_{26,t-1}$						
$\Delta m_{26,t}$		0.986^{***}				
		(20.691)				
$\Delta y_{27,t-1}$						
$\Delta m_{27,t}$			0.919^{***}			
			(42.238)			
$\Delta y_{28,t-1}$						
$\Delta m_{28,t}$				0.966^{***}		
				(17.920)		
$\Delta y_{29,t-1}$					-0.082	
					(-1.137)	
$\Delta y_{29,t}$					0.971^{***}	
					(12.966)	
$\Delta y_{30,t-1}$						
$\Delta y_{30,t}$						0.647^{***}
						(3.846)
z_t			-0.035^{***}	-0.031	-0.027	-0.047
			(-3.245)	(-1.299)	(-1.471)	(-1.332)
w_t	0.224^{*}				-0.267^{**}	-0.778^{***}
	(2.014)				(-2.192)	(-2.958)
Constant			0.018^{**}			0.046
			(2.763)			(1.598)
N	20	20	20	20	19	20

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.9: Middle East & Africa

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{31,t-1}$	0.133					
	(1.459)					
$\Delta m_{31,t}$	0.781***					
	(5.602)					
$\Delta y_{32,t-1}$						
$\Delta m_{32,t}$		1.014***				
		(43.380)				
$\Delta y_{33,t-1}$			0.152***			
			(4.869)			
$\Delta m_{33,t}$			0.847***			
			(10.661)			
$\Delta y_{34,t-1}$						
$\Delta m_{34,t}$				0.864***		
				(14.214)		
$\Delta y_{35,t-1}$					0.128	
					(1.271)	
$\Delta m_{35,t}$					0.889***	
					(8.010)	
$\Delta y_{36,t-1}$						
$\Delta m_{36,t}$						0.909***
						(11.281)
z_t			−0.010			
			(−1.294)			
w_t	1.009***	−0.099***	−0.092**	−0.168**	−0.158*	−0.121
	(11.609)	(−3.476)	(−2.545)	(−2.660)	(−1.823)	(−1.176)
Constant		0.006**	0.014**	0.008		
		(2.547)	(2.425)	(1.350)		
N	19	20	19	20	19	20

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.10: Latin America

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
$\Delta y_{37,t-1}$						
$\Delta m_{37,t}$	1.078^{***}					
	(17.165)					
$\Delta y_{38,t-1}$						
$\Delta m_{38,t}$		0.903^{***}				
		(24.088)				
$\Delta y_{39,t-1}$			0.015			
			(1.053)			
$\Delta m_{39,t}$			0.960^{***}			
			(66.148)			
$\Delta y_{40,t-1}$				0.085^{**}		
				(2.203)		
$\Delta m_{40,t}$				0.942^{***}		
				(20.903)		
$\Delta y_{41,t-1}$					0.056	
					(1.217)	
$\Delta m_{41,t}$					0.822^{***}	
					(12.060)	
$\Delta y_{42,t-1}$						
$\Delta m_{42,t}$						0.695^{***}
						(8.021)
z_t	-0.027	0.012	-0.009	0.008	-0.022	-0.033
	(-1.520)	(1.645)	(-1.079)	(1.032)	(-1.305)	(-1.051)
w_t	0.117^{**}	-0.111^{***}	-0.045^{**}	-0.139^{**}	-0.345^{***}	-0.289^{**}
	(2.131)	(-3.192)	(-2.290)	(-2.692)	(-4.092)	(-2.304)
Constant	0.009		0.004		0.024^{*}	0.023^{*}
	(1.442)		(1.490)		(2.085)	(1.954)
N	20	20	19	19	19	20

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.5 Input Intervention Effect by Region and by Sector

Table D.11: OECD

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	-0.001^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	$(9.17e^{-5})$	$(7.43e^{-5})$	$(7.68e^{-5})$	$(9.65e^{-5})$	(0.000)	(0.000)
w_t	0.926^{***}	1.033^{***}	0.901^{***}	1.073^{***}	1.156^{***}	1.318^{***}
	(-0.217)	(-0.176)	(-0.182)	(-0.229)	(-0.281)	(-0.269)
Constant	0.0186^{***}	0.0339^{***}	0.0315^{***}	0.0276^{***}	0.0229^{***}	0.0348^{***}
	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.006)
N	800	760	736	780	800	800

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.12: China

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	-0.016	-0.030^{***}	0.037	-0.064^{***}	0.068^{*}	0.066^{*}
	(0.028)	$(1.81e^{-10})$	(0.031)	$(2.36e^{-10})$	(0.045)	(0.035)
w_t	0.504^{***}		0.529^{***}		0.842^{***}	0.215
	(-0.170)		(-0.187)		(-0.275)	(-0.209)
Constant	0.010	0.008^{***}	-0.042^{***}	0.026^{***}	-0.001	-0.007
	(0.008)	$(7.68e^{-11})$	(0.009)	$(9.96e^{-}11)$	(0.013)	(0.010)
N	749	804	640	780	670	667

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.13: India

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	0.193^{**}	0.285^{**}	-0.057^{*}	0.046	-0.292^{***}	0.003
	(0.097)	(0.098)	(0.049)	(0.059)	(0.0734)	(0.174)
w_t	0.744^{**}	0.731^{*}	0.365^{**}	0.174	0.283	0.694
	(-0.345)	(-0.364)	(-0.176)	(-0.212)	(-0.264)	(-0.666)
Constant	-0.057^{*}	-0.078^{**}	0.007	-0.008	0.043^{*}	-0.006
	(0.028)	(0.030)	(0.014)	(0.017)	(0.021)	(0.054)
N	608	628	708	624	723	444

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.14: Asia

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	0.021^{***}	0.001	0.002	0.002	-0.019^{***}	-0.021^{***}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)
w_t	0.658^{***}	0.732^{***}	0.785^{***}	0.604^{***}	1.003^{**}	0.160
	(-0.227)	(-0.224)	(-0.273)	(-0.199)	(-0.399)	(-0.427)
Constant	-0.0365^{***}	0.010^{**}	-0.014^{**}	0.004	0.057^{***}	0.063^{***}
	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)	(0.008)
N	800	689	713	689	630	603

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.15: Eurasia

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	0.040^{***}	0.046^{***}	0.048^{***}	0.106^{***}	0.0429^{***}	0.0642^{***}
	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.005)
w_t	0.304	0.316^{**}	0.554^{***}	0.661^{***}	0.665^{**}	0.475^{*}
	(-0.233)	(-0.132)	(-0.174)	(-0.190)	(-0.309)	(-0.258)
Constant	-0.021^{***}	-0.028^{***}	-0.059^{***}	-0.072^{***}	-0.031^{***}	-0.035^{***}
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
N	738	746	753	749	702	761

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.16: Middle East & Africa

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	-0.031^{***}	0.005	0.045^{***}	0.0006	0.028^{***}	-0.077^{***}
	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.014)
w_t	-0.361^{**}	0.567^{***}	0.750^{**}	0.869^{***}	0.483^{***}	0.637^{*}
	(−0.139)	(−0.145)	(−0.126)	(−0.137)	(−0.16)	(−0.339)
Constant	0.032^{***}	−0.007	-0.009^{**}	0.008^{**}	-0.015^{***}	0.097^{***}
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)
N	740	720	751	713	713	665

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.17: Latin America

	Nonmanufacturing	Energy-intensive manufacturing	Non energy-intensive manufacturing	Services	Transport	Utilities
z_t	0.042^{**}	-0.053^{***}	−0.024	-0.027^{**}	-0.066^{***}	−0.016
	(0.018)	(0.018)	(0.019)	(0.011)	(0.015)	(0.038)
w_t	0.502^{***}	0.664^{***}	0.540^{***}	0.682^{***}	0.655^{***}	1.099^{***}
	(−0.166)	(−0.168)	(−0.177)	(−0.109)	(−0.144)	(−0.365)
Constant	-0.010^{***}	0.018^{***}	0.015^{***}	0.025^{***}	0.016^{***}	0.028^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)
N	700	740	600	676	745	603

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$