Global Supply Chain and the Comparative Advantage of Firms

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Abstract

In the context of global production, this paper examines the effect of input-based comparative advantages on export industry decisions of multi-product firms, as well as the role of trade policy shocks in shaping the patterns of exports within firms. Using firm-level data of Chinese processing trade over the period 2000-2006, this paper constructs the key measure of input similarity according to the imported inputs and exports of processing firms along the global supply chain. Our results indicate that processing exporters tend to diversify into industries and are less likely to drop industries sharing similar imported inputs. In response to a positive trade policy shock, this cross-industry spillover through imported inputs exists in industries with the reduction in trade policy uncertainty. These results are robust for cross-sectional data, the alternative measure of industry adoption, and the possible effect of economic changes.

Keywords: multi-product firms, processing trade, input capability, comparative advantage, trade policy uncertainty, global supply chain

JEL Codes: L2; F1; O1

Contents

1 Introduction

Involved in international markets, firms face both opportunities and uncertainties along the global value chain. On one hand, because of the specific know-how needed in production, the input capability is one of the most important factors in the comparative advantage of firms (Boehm, Dhingra, & Morrow, 2019). On the other hand, from the perspective of export markets, uncertainty in the trade environment is found to be systematically related to changes in activities at the firm level (Bernard, Jensen, & Schott, 2006; Nocke & Yeaple, 2006; Eckel & Neary, 2010; Iacovone & Javorcik, 2010), particularly for multi-product firms.

Recent studies suggest the crucial role of multi-product firms in production and export activities. For example, Bernard, Jensen, Redding, and Schott (2010) demonstrate that activities within multi-product firms are influential on both firm and aggregate outputs. Compared to single-product firms, multi-product firms exert a considerable influence on trade flows of the world (Mayer, Melitz, & Ottaviano, 2014). Processing trade firms are no exception. Taking China as an example, multi-industry processing exporters account for more than 50% of all processing firms, and their processing exports makes up nearly 90%. Different from the ordinary trade, firms engaged in processing trade are involved in global supply chain by processing imported intermediate inputs and re-exporting to final producers and retailers in foreign countries.

Taking advantage of Chinese processing firms' import and export activities, this paper attempts to study how trade shocks interact with firms' global import capabilities affect the diversification of firm exports in China. Specifically, this paper explores whether firm comparative advantages in imported inputs affect export industry decisions within firms, and how these changes respond to trade shocks.

It is well established that firms engaged in export activities need to pay large fixed costs and sunk costs. Actually, not only the exports, firm import activities also incur numerous costs. To start importing, firms have to search for overseas suppliers, check the integration of imported inputs into the existing production process, study customs procedures, acquire import licenses and so on (Imbruno, 2019). For processing firms, this cost could be higher than ordinary trade because of the extra customs procedures needed.

Except for the large costs of imports, the ability to engage imports in a particular product or industry depends on attributes of both the firm and industry, which are similar to the production of firms. Boehm et al. (2019) find that the input capability is one of the determinants of production patterns within firms. Bernard et al. (2010) document a sizable amount of co-production between industries having similar input needs, like textiles and apparel industry. That is, the knowhow or input capability required for different products and industries is crutial to the production. Considering this pattern of production in the context of the global supply chain, this paper attempts to explore the existence of within-firm allocations of import-related resources across products or industries.

To inflect the correlation in imports needed between processing firms and industries, this paper measures the similarity of imported inputs as the inner product of a firm's import shares and an industry's import shares (Boehm et al., 2019) using the micro transaction-level data of Chinese processing firms. Our empirical results show that this import linkage between firms and industries does predict the diversification of firm exports. This indicates the role of imported inputs related comparative advantage on the patterns of exports in the global value chain.

Connecting this input similarity with the policy changes in export markets, this paper further explores how multi-product firms react to trade shocks and shape their input-based comparative advantages. Studies demonstrate that trade participation or trade policy affects the product mix of multi-product firms (Nocke & Yeaple, 2006; Bernard, Redding, & Schott, 2011). After China's WTO accession in 2001, tariff bindings promoted the trade flows of China, including processing exports. As is shown in sections 3 and 4, there is a remarkable growth in processing exports after China's 2001 WTO entry, and industry-level export activities are also frequent for processing exporters. Hence, it is worthy of investigation what exactly changes the trade policy uncertainty causes in export industry mix within processing exporters. Are these changes within firms related to the input capability of firms?

The questions this paper discusses incorporate foreign intermediate inputs with trade shocks and firm export decisions. Taking an example, the problem this paper aims to study is: for firms engage in global production and trade in textiles, does a positive trade shock in the apparel industry make these textile exporters more likely to start exporting in apparel industry in the future? We know that experienced producers in textiles can better access inputs required, and the production of textiles and apparel industries share similar inputs, like cotton, yarn, etc.

The empirical results emphasize the role of imported inputs in the churning of export industries for processing firms in China. We find that industry adding is positively correlated with the input-based comparative advantage of firm, which makes it more likely to add an export industry to their industry portfolios and increase exports in this industry. However, this relationship between industry dropping and input similarity is the converse. The more similar the imports between the firm and the industry, the less likely that the processing exporter drops this industry. These result show that the input capability is one of the driving forces behind the co-production patterns across industries. Connecting this pattern of co-production within firms with the trade shock, the positive variation in trade policy is found to drive firms to add industries and increase exports towards those with intensive imported inputs in common. These results imply the important role of both the input capability and trade policy uncertainty in shaping the decisions of exporters and determining patterns of export.

Main contributions of this paper are threefold. First, by demonstrating a connection between input similarity, the reduction in trade policy uncertainty, and export activities of processing firms, this paper thus contributes to the intersection of three literatures: firm comparative advantages, trade shocks and the global supply chain. Based on imports and exports of Chinese processing firms, this paper finds the input-based export spillover in the context of the global supply chain. Second, referring to the most recent literature on firm comparative advantage, this paper constructs the firm-level measure of imported input comparative advantage using Chinese processing trade data and helps to understand the export patterns of China. Third, our results confirm that firm-industry import relatedness plays a role in the export activity of Chinese processing firms.

The remainder of the paper is organized as follows. Section 2 is the literature review. Section 3 describes the data and stylized facts. Section 3 documents the measure of input similarity, industry churning and trade policy uncertainty. Section 4 examines the impacts of input comparative advantages and trade policy shocks on the industry churning within firms, and also explores the robustness of our results. Section 4 concludes.

2 Literature Review

2.1 Firm Comparative Advantage

This paper is most related to the topic about *firm comparative advantage*. Many studies on firm-level comparative advantage point out that firm performance is affected by their core competencies which can be measured according to the efficiency of producing a particular variety, product sales, productivity and so on (Arkolakis, Ganapati, & Muendler, 2010; Eckel & Neary, 2010; Mayer et al., 2014). Based on these firm and firm-product characteristics, firms rationalize their product scope and contribute to the reallocation of resources within firms toward their core competences (Bernard et al., 2010; Mayer et al., 2014).

Not only the firm and firm-product specific drivers, firm comparative advantages and production patterns are also affected by other factors like firm-industry attributes, geography, etc. For example, Breschi, Lissoni, and Malerba (2003) find firms diversify their innovative activities across fields by sharing a common knowledge base. According to the human capital similarity and skill requirement among industries, Neffke and Henning (2013) conclude that firms tend to to diversify into industries having ties to their core activities in terms of skill-relatedness. Poncet and Starosta de Waldemar (2015) concentrate on the relationship of a product with the local pattern of specialization, and show export-enhancing spillovers that exports grow faster for products having denser links with those currently produced in the firm's locality. Lo Turco and Maggioni (2016) suggest that firm and local product-specific capabilities have a role in promoting the introduction of new products within firms. Rachapalli (2021) points out that international knowledge diffusion between buyers and sellers impacts the introduction of products across different production stages within firms and the expansion of the firm value chain.

The production of products or industries differs in competence or capability required, and firms differ in the capabilities they have. Existing resources of production within firms are able to provide a number of production advantages. Hidalgo, Klinger, Barabsi, and

Hausmann (2007) point out products are skewed to those that firms are currently specialized in, which supports the fact of cross-industry spillovers through inputs within firms. This input-based comparative advantage is also confirmed by Boehm et al. (2019), which is mostly related to this paper. They find that complementarity driven by the input capability increases the likelihood of firms diversifying into the industry. Referring to the method in Boehm et al. (2019), this paper adds to this literature by constructing a firm-level index of input similarity using Chinese data.

Building on these studies, this paper attempts to find the driver of exporting industry diversification from the perspective of input capabilities using Chinese processing trade data. How does the tendency for processing firms to export to multiple industries driven by firms' input capabilities? Whether trade policy shocks affect this direction of input-based comparative advantage on firm's export diversification? While asking a different question, our findings for within firm export decisions show the existence of input-based cross-industry spillovers.

2.2 Trade Shock

The second set of literature this paper related to is the *trade shock*. One important topic is the trade policy uncertainty. In this paper, we focus on the trade policy uncertainty associated with China's WTO accession. Some studies seek to understand how do changes in this trade policy influence US economic outcomes. For example, Pierce and Schott (2016) link the decline in US manufacturing employment to the elimination of possible tariff increases in the future after China's WTO accession. Handley and Limao (2017) prove that the reduction in policy uncertainty following China's accession to WTO lowers US product prices and increases the real income of consumers.

A large literature highlights the impact of this substantial decline in trade policy uncertainty on Chinese firms' export behaviors. Feng, Li, and Swenson (2017) provide evidence that the reduction in trade policy uncertainty induces both the entry and exit of firms from export activities within product-level markets. Liu, Pei, Wu, and Zhang (2020) study the reduction of trade policy uncertainty on the export mode of firms, and suggest that firms are more likely to conduct ordinary exports than processing exports. Crowley, Meng, and Song

(2018) imply that the decline in trade policy uncertainty plays a key role in the dramatic rise of Chinese exports over the last twenty years.

Besides the heterogeneous impacts of trade policy uncertainty, there are also many studies in this field focusing on different measures of trade policy uncertainty. A widely used measure is according to the gap between tariffs. Handley (2014) quantifies the policy uncertainty through gaps between applied and binding tariffs. Because the tariff applied can be higher than the binding rate. This method is also applied in a number of studies (Handley & Limao, 2015; Pierce & Schott, 2016; Liu et al., 2020). Another method uses the newspaper coverage frequency to measure the uncertainty of economic policy. For example, Baker (2016) uses the newspaper coverage frequency to index movements in policy-related economic uncertainty depending on articles in newspapers. However, this measure of policy uncertainty are strong subjective. In this paper, we measure the trade policy uncertainty after China's WTO accession according to the first method, and use the gap between MFN tariffs and "Smoot-Hawley" tariffs.

Apart from trade policy uncertainty, topics on trade shocks also include the impacts of demand shocks, exchange rate fluctuation, trade liberalization and so on (Berman, Berthou, & Hricourt, 2015; Mayer, Melitz, & Ottaviano, 2020; Chatterjee, Dix-Carneiro, & Vichyanond, 2013; Bernard et al., 2006). For instance, Berman et al. (2015) find that demand conditions in destination markets affect domestic sales through changes in exports. Mayer et al. (2020) study the influence of demand shocks in export markets on the product mix of multi-product exporters, and find that firms skew their exports towards their best performing products.

The existing literature on trade shocks mainly considers the impact of trade variations on firm behaviors, but neglects the potential impact from the input side as an important factor, and the impact of trade shocks on processing exports which are different in terms of production from ordinary exports. From a new channel, input capabilities, this paper contributes to the literature by identifying the role of trade shock on revealed comparative advantages of multi-industry processing firms, and its impact on export decisions of processing exporters after China's WTO accession.

2.3 Global Supply Chain

Finally, this paper also extends the growing literature on the global supply chain. In this increasingly globalized economy, the production process which consists of numerous sequential stages involves the participation of multiple countries. A number of studies analyze the determinants of this fragmentation of production in global value chains across firms and countries. Yi (2003) theoretically analyses the vertical specialization and finds that it is related to the reductions in transportation costs, tariffs, and trade barrier. From the perspective of financial frictions, Manova and Yu (2012) suggest that because of the working capital required to conduct more steps of the global supply chain, credit constraints restrict firms from stages to production with low value-added.

The fragmentation of production process across countries is of great importance to the world economy. For example, using country-level data, Hummels, Ishii, and Yi (2001) find that the growth in vertical specialization contributes to the growth of exports. Broda and Weinstein (2006) find that the potential for accessing a greater range of imported inputs enables the increase in productivity of firms. Goldberg, Khandelwal, Pavcnik, and Topalova (2010) show that firms gain from the availability to cheaper inputs and the wider scope of imported intermediate products. Grossman and Rossi-Hansberg (2008) study the effect of the decline in offshoring costs on factor prices and suggest that it benefits the factor whose tasks are more easily moved offshore.

As the world's largest exporter, processing trade which is involved in the global production plays an important role in China's trade activities (Yu, 2015). This is mainly because of the stimulation of trade policy in China, especially the exemption for import duties which reduces the cost of imported inputs and encourages firms to engage in processing trade. In addition, evidence finds that increased access to imported intermediate inputs benefits firms through higher-quality inputs and products, the introduction of new products, and greater revenues in the developing economy (Goldberg et al., 2010; Kugler & Verhoogen, 2009; Manova & Yu, 2012).

Thus, it makes sense to explore the impact of policy changes in export markets and the characteristics of imported intermediate inputs on exporting behaviors of processing firms.

Incorporating both international imports and export activities, this research contributes to the intersection of all three literatures: firm comparative advantages, trade shocks and global supply chain. Our findings extend this stream of work by analyzing how do export shocks and input-based comparative advantages influence processing firms' export patterns in the context of the global supply chain.

3 Data

To investigate firm-level industry decisions, this paper exploits datasets for Chinese processing firms over the period 2000-2006. In this section, this paper also presents the stylized facts about the export of Chinese processing firms.

3.1 Processing Trade

The transaction-level data of firms is provided by Chinese Customs Trade Statistics (CCTS). This Customs dataset reports the value of firm-level imports and exports by HS 8-digit product, and distinguishes between trade flows performed under the processing and ordinary trade regimes. Processing trade is a type of trade mode in which firms import raw materials, materials or parts from other countries as intermediate inputs, then export the final products to worldwide markets after processing. This feature of processing trade makes it ideal for this study since it allows us to regard imports and exports of processing exporters as inputs and outputs approximately.

To explore the question of export decisions among industries, we aggregate the imports and exports at the HS 8-digit product level to HS 4-digit industry level which corresponds to 1,317 industries. For a deeper understanding of this industry-level dataset, this paper describes the industry mix of processing exporters, which also motivates our empirical analysis.

Table 1 presents the summary statistics for multi-industry processing exporters. This paper categorizes processing exporters according to the number of industries they export from 2000 to 2006, and reports the number of firms, the shares of firms and value of processing

Table 1: Multi-Industry Exporters

# Industries	# Firms	% Firms	% Processing Exports
1	34,935	43.6	10.8
2	14,908	18.6	10.9
3	8,498	10.6	8.0
4	5,433	6.8	6.7
5	3,585	4.5	5.7
6	2,642	3.3	4.4
7	1,949	2.4	3.2
8	1,473	1.8	2.6
9	1,116	1.4	2.2
10	962	1.2	3.3
11-20	3,515	4.4	14.9
21-30	638	0.8	5.1
31-40	207	0.3	4.3
41-50	103	0.1	3.6
> 50	212	0.3	14.2

exports for each category of the export industry number[1]. Single-industry firms make up for more than 40% of firm observations, but they are only responsible for about 11% of the total processing exports. While processing firms that export to multiple industries account for a considerable portion of processing exports. Multi-industry processing exporters make up 57% of all firms, but they account for 89% of all processing exports in the economy. This fact indicates that multi-industry processing exporters dominate processing exports in China, and also motivates our study what plays a role in the industry mix of processing exporters.

[1]This paper also reports the summary statistics when the number of industries is defined at the firm-year level in appendix.

3.2 Trade Shocks

The import tariff data are from the United States Import Tariff Database. This dataset covers various tariff rates imposed by the US on each HS 8-digit product against normal and irregular trading partners from 1989 to 2001, which is always used to measure the trade policy uncertainty.

After the accession to WTO, China's exports to the United States can permanently enjoy Most Favored Nation (MFN) treatment, which is far lower than the general "Smoot-Hawley" tariff. As one of the most important export markets for Chinese exporters, this US bound tariff rate has a substantial influence on export activities of Chinese firms, including processing trade.

Figure 1 shows the total value of Chinese processing exports from 2000 to 2006. We can see a considerable increase in processing exports after China joined the WTO. This feature of processing exports raises a question of what exactly changes do processing exporters make after 2001? Does China's WTO entry affect export activities within firms?

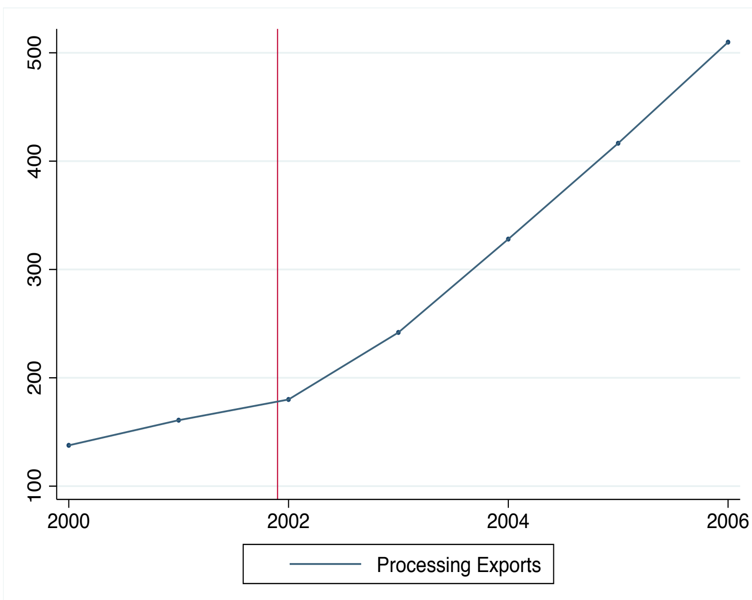

Figure 1: China's Processing Exports from 2000 to 2006

Notes: The red line represents the time of China's WTO accession (November 2001). Source: 2000-2006 processing export data from Chinese Customs.

We have shown that there was a significant growth in Chinese processing exports, where multi-industry firms played a key role, after 2001. Treating China's WTO entry as a trade shock, this paper attempts to understand what changes has China's WTO accession made in processing exports for multi-industry firms. In addition, from the perspective of production, this paper interacts the input capability of firms with this lower tariff uncertainty, and explores their impacts on multi-industry processing exporters.

4 Methodology

A key element of this paper is to construct the similarity of inputs between firms and industries. In this section, this paper presents the measures of input similarity, industry churning, and trade policy uncertainty, which are required to analyze the role of input relatedness in firm export decisions under trade shocks.

4.1 Input Similarity

This paper aims to tease out the effect of input relatedness between firms and industries on Chinese processing exporters' industry decisions. Different from ordinary trade, processing trade firms can only use imported inputs to produce exporting products rather than domestic production. In addition, processing exports rely heavily on imported inputs. This implies that, if a firm engage in processing trade, its imported input – export relationships can be considered similarly to the firm's input – output relationships. Thus, the input relatedness can be treated as the linkage of processing imports for processing firms. This is one of the reasons why the focus of this paper will be on Chinese firms that engage in processing trade activities, and their processing imports and exports.

To capture the extent of similarity between a processing trade firm's and an industry's import mixes, this paper refers to Boehm et al. (2019) and constructs the firm-level measure of input similarity using the inner product of the vector of processing import expenditure shares of a firm, with the industry's vector of processing import expenditure shares. Specifically, we calculate this input similarity index as:

$$\text{Input Similarity}_{jk}^{t} = \sum_{i=1}^{N} \theta_{ij}^{t} \overline{\theta}_{ki} \tag{1}$$

where θ_{ij}^{t} is processing trade firm j's expenditure share, which is defined as firm j's expenditure on processing imports in HS 4-digit industry i at time t, divided by firm j's total expenditure on processing imports at time t; $\overline{\theta}_{ki}$ is the aggregate expenditure share, which is defined as the sum of expenditures of single industry exporters that export only processing products in industry k on processing imports from industry i, divided by total expenditure of these exporters on processing imports. This firm-level input similarity captures the proximity between in firm j and industry k in the mix of processing imports. According to the definition, this measure of input similarity ranges from zero to one. The more similar the imported intermediate inputs of firm j and industry k, the greater the value of Input Similarity$_{jk}^{t}$. When this input similarity measure equals one, it signifies that firm j and industry k have the identical processing import shares.

Using Chinese processing trade data from 2000 to 2006, we first construct the aggregate import share according to the information on imports for all 933 single-exporting industries[2]. Then, for all the firms having processing imports, we can compute their import shares in each HS 4-digit industry. Given these two information sets, this paper thus constructs the measure of input similarity between each processing firm and the 933 single-exporting industries. According to the summary statistics, the mean of this input similarity is 0.0005. Considering the import patterns of Chinese firms, as well as the characteristics of the processing industry, this value is close to the feature shown in Boehm et al. (2019) using India data, which is 0.0007.

Let us take an example to better grasp this measure of input similarity. For a firm with processing imports from textile, plastics and machinery industries, this input similarity measure is higher in industries such as footwear, headgear, textile, machinery and mechanical appliances. Because the inputs required in these industries are more similar to this firm's processing import mix. However, for mineral or chemical industries, this input similarity measure is close to zero, because this firm and these industries have essentially no inputs in

[2] Here single industry exporters is defined according to the total number of processing export industries from 2000 to 2006.

common.

4.2 Industry Churning

To explore how does input based comparative advantage affect firm-level dynamics in exporting industries, this paper constructs two industry churning measures: industry add and drop. Specifically,

$$\text{Add}_{jk}^{t} = \begin{cases} 1, & \text{if exports}_{jk}^{t} = 0 \text{ and exports}_{jk}^{t+1} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

and

$$\text{Drop}_{jk}^{t} = \begin{cases} 1, & \text{if exports}_{jk}^{t} > 0 \text{ and exports}_{jk}^{t+1} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The industry addition dummy Add_{jk}^{t} is one if and only if firm j does not have processing exports in HS 4-digit industry k at time t, but has processing exports in k at time $t+1$; industry drop dummy Drop_{jk}^{t} is one if and only if firm j does have processing exports in HS 4-digit industry k at time t, but does not have processing exports in k at time $t+1$. These two measures of industry churning capture whether a firm will add or drop industries in the future.

Table 2 shows the number of firms and firm-industry pairs that add or drop industries from 2000 to 2005. On average, there are more than 24% of processing exporters adding industries every year, and the number of industries added each firm is about 2. The pattern of industry drop is similar to industry adoption. From 2000 to 2005, nearly 25% of processing exporters dropped industries, and the average number of industries dropped was likewise roughly 2. These figures indicate that industry switching is common among processing exporters. This pattern of industry add and drop is also reflected in the 6-year time window of the cross-sectional summary. Studies point out that the churning of industries can have significant effects on firm activities. Hence, it is critical to understand what factors underlying behind this diversification of exporting industries within firms.

Table 2: Industry Churning

	# Firm		# Firm-Industry	
	Total	Add	Total	Add
A. Panel				
2000	31,478	9,670	29,368,974	19,880
2001	38,206	10,775	35,646,198	21,891
2002	45,379	11,499	42,338,607	23,103
2003	53,202	12,985	49,637,466	25,445
2004	61,790	14,100	57,650,070	27,851
2005	70,024	14,174	65,332,392	26,756
B. Cross-Section				
	31,478	17,889	29,368,974	73,826
	Total	Drop	Total	Drop
C. Panel				
2000	30,227	12,712	90,609	26,346
2001	32,759	14,087	93,205	27,310
2002	34,826	14,364	98,086	27,416
2003	37,602	15,201	106,659	29,509
2004	41,383	16,745	115,496	30,962
2005	44,749	18,502	124,684	33,840
D. Cross-Section				
	29,475	24,107	89,596	67,839

Besides the above two measures of industry churning changing over time, this paper also constructs the alternative measure of industry adoption and drop, which are defined as

$$\text{Add}_{jk} = \begin{cases} 1, & \text{if exports}_{jk}^{2000} = 0 \text{ and exports}_{jk}^{t} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

and

$$\text{Drop}_{jk} = \begin{cases} 1, & \text{if exports}_{jk}^{2000} > 0 \text{ and exports}_{jk}^{t} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where t can be any point from 2001 to 2006. That is, Add_{jk} is one if and only if firm j does not have processing exports in HS 4-digit industry k in 2000, and has processing exports in k at any point between 2001 and 2006, and Drop_{jk} is one if and only if firm j does have processing exports in HS 4-digit industry k in 2000, but does not have processing exports in k at any point between 2001 and 2006.

Using these two time invariant measures of industry churning, this paper explores the long-term effect of input-based comparative advantages. The advantage of these two cross-sectional measures of industry churning is that they make industry churning more likely to happen within firms and make computation more feasible, particularly for the industry adoption index. Because for the time variant measure of industry adoption, the potential that firms want to have processing exports in all industries should be taken into consideration.

4.3 Trade Policy Uncertainty

The empirical strategy in this paper is also based on an exogeneous shock to Chinese exporters. Although China was granted temporary normal trade relations (NTR) and enjoyed MFN tariff treatment for exports to the United States before 2001, it was subject to yearly renewal which created great uncertainty for Chinese exporters. Because if the resolution is not passed, Chinese exporters have to face exorbitant "Smoot-Hawley" tariffs. However, after joining the WTO, China's exports to the United States are eligible for the permanent MFN tariffs which removes the threat associated with possible increase in tariffs in the future. That is, there are large reductions in the trade policy uncertainty to Chinese exporters and exports can undoubtedly gain from China's WTO entry.

According to Pierce and Schott (2016), based on the 1999 US tariff data collected by Romalis, we compute the tariff gap between punitive column 2 tariffs and the MFN tariffs as the measure of trade policy uncertainty faced by HS 8-digit products before 2001. To obtain the industry-level measure of trade policy uncertainty, this paper employs the arithmetic average method (Liu et al., 2020) and aggregates the product-level tariffs to HS 4-digit industry levels. Specifically,

$$\mathrm{TPU}_k = \mathrm{non\_NTR}_k - \mathrm{NTR}_k \tag{6}$$

where $\mathrm{non\_NTR}_k$ is industry k's "Smoot-Hawley" tariff in 1999, and NTR_k is industry k's MFN tariff in 1999. The larger the value is, the greater the trade policy uncertainty faced by the industry. This also indicates that there is a greater reduction in trade policy uncertainty in this industry after China's WTO entry. According to the definition, it is obvious that this index of trade policy uncertainty is exogenous to China's exports because this measure is determined by the "Smoot-Hawley" tariff which was established in 1930.

Appendix Table 3 shows the summary statistics for all the variables mentioned in our empirical analysis.

5 Empirical Specifications and Results

We now turn to examine the determinants of processing exporters' extensive and intensive margins of the industry mix, which interacts with trade policy shocks to shape the comparative advantage of firms.

5.1 Input Similarity and Industry Decisions within Firms

One aim of this paper is to investigate whether input proximity between the firm and industry is an important driver of firm's choices in export industries. Using the linear probability model, this paper first examines how the similarity of imported inputs predicts changes in industry mix within firms. Because of the possibility that firms have new processing imports before they actually report new processing exports, this paper uses the measure of input similarity at the first year of processing imports, which is denoted by a '0' superscript. The baseline specification is:

$$\text{Industry Churning}_{jk}^{t} = \beta \cdot \text{Input Similarity}_{jk}^{0} + \alpha_j^t + \alpha_k^t + \varepsilon_{jk}^t \tag{7}$$

where the dependent variable industry churning includes three measures: the industry adoption Add_{jk}^t, industry drop Drop_{jk}^t, and the intensive margin of industry mix $\log(\text{exports})_{jk}^t$ (exports_{jk}^t is firm j' total value of processing exports in industry k at time t); α_j^t is the firm-year fixed effect which captures the industry churning for firm-year pair; α_k^t is the industry-year fixed effect which captures changes that impact the activities in a specific industry at a particular point of time; ε_{jk}^t is the firm-industry-year level idiosyncratic error term. This regression is also clustered at the firm-industry level. The coefficient of interest β reflects the correlation between processing exporter's industry choices in the future and the input similarity between the firm and industries.

Table 3 shows the results of equation (7). The first panel is results for industry adoption, the second panel for industry drop, and the intensive margin in the last panel. Column (1), (3) and (5) include only firm-year fixed effects, thereby estimating movements in the industry. Column (2), (4) and (6) additionally include industry-year fixed effects to control for any systematic demand or supply shocks that can affect the likelihood of firms commencing or halting production in a particular industry.

Table 3: Industry Churning and Input Similarity

	Add_{jk}^t		Drop_{jk}^t		$\log(\text{exports})_{jk}^t$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}_{jk}^0$	0.0244***	0.0227***	-0.4317***	-0.4577***	5.1461***	5.0929***
	(0.0002)	(0.0002)	(0.0063)	(0.0070)	(0.0574)	(0.0588)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE		Yes		Yes		Yes
N	279973707	279973707	519144	518697	519144	518697
R^2	0.005	0.009	0.403	0.435	0.382	0.47

Notes: Standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors clustered at the firm-industry level.

In the first panel, the coefficient of input similarity in column (1) is positive and statistically significant. This indicates that firms are more likely to start exporting in industries that sharing the similar processing import mix to the firm's initial import mix in the next year. The inclusion of industry-year fixed effects in column (2) does not influence the magnitude and significance of the coefficient on input similarity. According to the results in this specification, we learn that firms are 2.3% more likely to add an export industry when there is a denser relatedness of imported inputs between firms and industries. Similarly to our results, the estimated obtained using Indian data is 2.2% (see Boehm et al. (2019)).

Looking for the results of industry drop in the second panel, as expected, coefficients of input similarity are both significantly negative with and without the industry-year fixed effects: firms with an initial processing import mix that is relatively intensive in imports that an industry relies on are less likely to drop exporting in this industry. The coefficient for the specification of industry add is about -0.44, which implies that the processing exporter's industry drop probability decreases by 44 percent. This result of industry drop is consistent with that for industry adoption. This estimated coefficient of industry drop in Boehm et al. (2019) is -0.112, which is significant smaller than our results using Chinese processing trade data.

Finally, from the results in the last panel, there also exists a positive and significant correlation between input similarity and the value of firm processing exports. This further confirms that firm's input similarity does predict the movements in the industry mix.

Studies show that there exists large sunk cost in import activities (Kasahara & Rodrigue, 2008; Kasahara & Lapham, 2013; Imbruno, 2019), let alone the processing imports. Firms conducting processing trade also have to be familiar with relevant customs procedures, like the declaration of tariff relief, etc. As a result, greater expertise and knowledge in processing trade and the network of suppliers make it easier for processing firms to access similar imports (Zhang, 2017). For example, processing exporters in textiles can easily access imported inputs required in apparel industries and start production in these industries based on their existing knowledge, expertise, and technology. That is to say, processing exporters are more likely to expand into industries that rely on similar processing imports. This creates the pattern of input-based co-production within firms.

Except the results of the panel model, this paper also investigates the long-term effect of the input-based comparative advantage according to the following cross-sectional specification:

$$\text{Industry Churning}_{jk} = \beta \cdot \text{Input Similarity}^0_{jk} + \alpha_j + \alpha_k + \varepsilon_{jk} \tag{8}$$

where cross-sectional industry churning index includes the industry adoption Add_{jk}, industry drop Drop_{jk}, and the intensive margin of industry mix $\log(\text{exports})_{jk}$ (exports_{jk} is firm j' processing export in industry k in 2000); α_j is the firm fixed effect which captures the industry churning for each firm; α_k is the industry fixed effect which captures changes that could impact the activities in a particular industry; ε_{jk} is the firm-industry level idiosyncratic error term. In addition, the regression is clustered at the firm level.

As Table 4 shows, the results of the long-term effect using the cross-sectional data are consistent with the results in Table 3. The coefficients of the input similarity remain positive and statistically significant in the industry adoption and intensive margin specifications, and significantly negative in the specification of industry drop. These results provide support to the previous argument that processing exporters add industries and increasing exports in industries with similar imported inputs, and drop industries with less processing imports in common. These activities within firms shape the input-based co-production.

Table 4: Industry Churning and Input Similarity: Long-Term Effect

	Add_{jk}		Drop_{jk}		$\log(\text{exports})_{jk}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}^0_{jk}$	0.1031***	0.0943***	-0.4610***	-0.5186***	5.7858***	5.8634***
	(0.0003)	(0.0003)	(0.0156)	(0.0169)	(0.1077)	(0.1072)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes		Yes		Yes
N	29368974	29368974	75555	75476	75555	75476
R^2	0.017	0.03	0.485	0.521	0.373	0.466

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm level.

In addition to the above relationships between firm input-based attributes and industry churning, this paper also examines how the interaction of input similarity and trade policy changes impacts the changes in industry mix of firms.

5.2 The Impact of China's WTO Accession

Using China's accession to WTO in 2001 as a trade policy shock that exporters face in international markets, we now study how the reduction in trade policy uncertainty interacts with input similarity affects firm industry mix decisions. The specification is as follow:

$$\text{Industry Churning}_{jk}^{t} = \beta_1 \cdot \text{IS}_{jk}^{0} \cdot \text{TPU}_k + \beta_2 \text{IS}_{jk}^{0} + \alpha_j^t + \alpha_k^t + \varepsilon_{jk}^t \tag{9}$$

where TPU_k is the trade policy uncertainty in industry k, and definitions of other variables are the same as in equation (7). The coefficient of the interaction term in this equation predicts the activities of firms when they are exposed to the trade shock in industries with different levels of input similarity.

Table 5: Industry Churning and Input Similarity: Trade Policy Uncertainty

	Add_{jk}^{t}		Drop_{jk}^{t}		$\log(\text{exports})_{jk}^{t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}_{jk}^{0}$ # TPU_k	0.0202***	0.0119***	-0.5132***	-0.4328***	3.0155***	3.9562***
	(0.0008)	(0.0008)	(0.0272)	(0.0324)	(0.2383)	(0.2617)
$\text{InputSimilarity}_{jk}^{0}$	0.0168***	0.0182***	-0.2428***	-0.2935***	4.0340***	3.5882***
	(0.0003)	(0.0003)	(0.0114)	(0.0137)	(0.1021)	(0.1114)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE		Yes		Yes		Yes
N	277573075	277573075	517220	516775	517220	516775
R^2	0.005	0.009	0.404	0.435	0.383	0.471

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm-industry level.

From the results shown in Table 5, the coefficients of input similarity in columns (1) and (2) are significantly positive. That is, the reduction in trade policy uncertainty makes processing exporters more likely to enter into the industry with similar imports to the firms' initial import mix. The explained variable in columns (3) and (4) is industry drop, and the results in these two columns indicate that processing exporters tend to drop industries that are dissimilar to their initial import mix even when the trade policy uncertainty in these industries decreases. Looking at the results for the intensive margin of exports in the last two columns, the estimated coefficients of the interaction term are significantly positive with and without the industry-year fixed effect. This suggests that the reduction of trade policy uncertainty encourages processing exporters to increase their exports in industries with similar inputs.

When faced with a positive export shock, such as a reduction in trade policy uncertainty, processing exporters are more inclined to adjust their production and enter into industries that use similar processing imports. This is due to the fact that, aside from the decrease of trade policy uncertainty, the production in these industries requires similar technology and input capabilities. Depending on the existing input-based comparative advantages, processing exporters are encouraged to expand their exports into these industries and benefit from economies of scope.

For example, when there is a positive trade shock in apparel industry, firms who are now undertaking processing exports in textiles are more willing to expand their production and export in apparel industry in the future. Because many of the imported inputs required in the apparel and textile industries are similar. This also suggests an increase in the processing exports of apparel industry. However, for those industries that do not share similar processing imports as the firm in textiles, the reduction of trade policy uncertainty in these industries are unlikely to induce this firm to engage in processing exports in these industries. Because this would incur a large sunk cost.

Similar to the baseline specification, this paper also examine the impact of trade policy uncertainty using the cross-sectional specification as follows:

$$\text{Industry Churning}_{jk} = \beta_1 \cdot \text{IS}^0_{jk} \cdot \text{TPU}_k + \beta_2 \text{IS}^0_{jk} + \alpha_j + \alpha_k + \varepsilon_{jk} \tag{10}$$

The cross-sectional industry churning index includes the industry adoption Add_{jk}, industry drop Drop_{jk}, and the intensive margin of industry mix $\log(\text{exports})_{jk}$, fixed effects in this equation are the same as equation (8).

Generally speaking, the cross-sectional results in Table 6 are consistent with Table 5. The estimated coefficients of the interaction term that we are interested in are significantly

Table 6: Industry Churning and Input Similarity: Trade Policy Uncertainty

	Add_{jk}		Drop_{jk}		$\log(\text{exports})_{jk}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}^0_{jk}$ # TPU_k	0.094***	0.054***	-0.628***	-0.534***	3.671***	4.484***
	(0.006)	(0.005)	(0.065)	(0.073)	(0.419)	(0.464)
$\text{InputSimilarity}^0_{jk}$	0.067***	0.073***	-0.225***	-0.315***	4.403***	4.146***
	(0.003)	(0.002)	(0.028)	(0.032)	(0.185)	(0.199)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes		Yes		Yes
N	29117150	29117150	75510	75431	75510	75431
R^2	0.017	0.03	0.486	0.521	0.374	0.467

Notes: Standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors clustered at the firm level.

positive in the industry addition and intensive margin panels, while it is significantly negative in the specification of industry drop. That is, when there is a positive trade policy shock in an industry, the input-based comparative advantage will encourage exporters to entry into and increase processing exports in this industry in the long run. This is not true, however, for industries that do not have processing import mix in common.

5.3 Robustness Checks

In this section, this paper checks the robustness of the baseline results and the impact of trade shocks with respect to the alternative measure of industry adoption, other possible determinants of co-production, and the impact of demand shocks.

Alternative Measure of Industry Adoption

Firstly, this paper considers an alternative way of measuring industry adoption and checks the sensitivity of the results with respect to the input similarity and industry adoption. Specifically, we define industry add as newly entry into processing industries. That is, the difference between this measure of industry add and the definition in equation (2) is that Add^t_{jk} is missing for those with positive processing exports at time t.

Table 7 shows the results of this alternative measure of industry adoption. Columns

(1) and (2) of Table 7 confirm that the baseline findings hold. Processing exporters are more likely to start export in industries relying relatively on processing imports as the firm's imports mix. In addition, results for the trade policy shock in columns (3) and (4) remain robust. With a positive trade policy shock, exporters who share similar processing imports are more willing to expand their export industries into these industries. Overall, both panels of the empirical results in Table 7 further support the fact that input capabilities induce processing exporters to start export in their comparative advantage industries.

Table 7: Industry Adoption and Input Similarity: Alternative Measure

	Add^t_{jk}			
	(1)	(2)	(3)	(4)
$\text{InputSimilarity}^0_{jk}$	0.0264***	0.0249***	0.0184***	0.0197***
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
$\text{InputSimilarity}^0_{jk}$ $\#\text{TPU}_k$			0.0214***	0.0139***
			(0.0009)	(0.0008)
Firm-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE		Yes		Yes
N	279347781	279347781	276949263	276949263
R^2	0.006	0.009	0.006	0.009

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm-industry level.

Other Factors of Industry Co-production

Secondly, one potential threat to the baseline identification is that firms tend to co-product in industries with the core competence. In addition, studies point out that economic shocks, such as changes in supply, demand and technology, might affect the co-production across industries. In this case, the possible effect of the core competence on firm activities cannot be ignored. To make sure that our findings of industry co-production are driven by input-output linkages, this paper takes into account the possible effect of the main industry of firm and includes the industry pair fixed effect based on the baseline specification. The regression is as follows:

$$\text{Industry Churning}_{jk}^{t} = \beta \cdot \text{Input Similarity}_{jk}^{0} + \alpha_j^t + \alpha_k^t + \alpha_{kk'}^t + \varepsilon_{jk}^t \tag{11}$$

where $\alpha_{kk'}^t$ is the industry-pair-year fixed effect which captures changes that might affect firms in industry k' to start export in industry k, here k' is the industry from which firm derives the highest fraction of processing exports each period. The introduction of this fixed effect leaves our estimates only intra-industry changes which is driven by the firm's input-output linkages within its main industry.

Similarly, the cross-sectional specification with the inclusion of industry-pair fixed effect is:

$$\text{Industry Churning}_{jk} = \beta \cdot \text{Input Similarity}_{jk}^{0} + \alpha_j + \alpha_k + \alpha_{kk'} + \varepsilon_{jk} \tag{12}$$

where $\alpha_{kk'}$ is the industry-pair fixed effect, here k' is the industry from which firm derives the highest fraction of processing exports in 2000.

Table 8: Robustness Checks: Possible Impacts of Economic Shocks

	Add_{jk}^t	Drop_{jk}^t	$\log(\text{exports})_{jk}^t$	Add_{jk}	Drop_{jk}	$\log(\text{exports})_{jk}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}_{jk}^0$	0.0090***	-0.2367***	2.3622***	0.0322***	-0.3331***	2.8788***
	(0.0002)	(0.0089)	(0.0539)	(0.0012)	(0.0237)	(0.1202)
Firm-Year FE	Yes	Yes	Yes			
$k \times k' \times t$ FE	Yes	Yes	Yes			
Firm FE				Yes	Yes	Yes
$k \times k'$ FE				Yes	Yes	Yes
N	204276618	431745	431745	27414339	61525	61525
R^2	0.046	0.573	0.719	0.105	0.649	0.717

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm-industry level in column (1) - (3), and at the firm level in column (4) - (5).

These two specifications are stringent, which control for the industry adoption for each industry and the core industry of each firm for each period. From the results in Table 8, the positive correlation between industry addition and input similarity remains when controlling for the industry-pair-year fixed effect in column (1) and industry-pair fixed effect in column (4). As in our baseline, the results for industry dropping also remain negatively significant in columns (2) and (5). Finally, the sign and significance patterns for the intensive margin of industry mix in columns (3) and (6) are robust as well. The only difference between this specification and the baseline specifications in Table 3 and Table 4 is that the magnitudes of the coefficients are relatively smaller in this table but these are not large enough to generate quantitatively different conclusions. This difference in coefficient magnitudes reflects that the economic shocks do have an impact on co-production.

Table 9: Robustness Checks: Possible Impacts of Economic Shocks

	Add^t_{jk}	Drop^t_{jk}	$\log(\text{exports})^t_{jk}$	Add_{jk}	Drop_{jk}	$\log(\text{exports})_{jk}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}^0_{jk}$	0.0016**	-0.1723***	0.9895***	-0.0040	-0.3360***	1.6380***
	(0.0008)	(0.0412)	(0.2316)	(0.0050)	(0.1070)	(0.5280)
$\text{InputSimilarity}^0_{jk}\#\text{TPU}_k$	0.0083***	-0.1668***	1.9644***	0.034***	-0.192***	2.189***
	(0.0004)	(0.0183)	(0.1033)	(0.0020)	(0.0500)	(0.2460)
Firm-Year FE	Yes	Yes	Yes			
$k \times k' \times t$ FE	Yes	Yes	Yes			
Firm FE				Yes	Yes	Yes
$k \times k'$ FE				Yes	Yes	Yes
N	202525050	430348	430348	27179275	61501	61501
R^2	0.045	0.573	0.719	0.104	0.649	0.717

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm-industry level.

Table 9 presents the results for the impact of trade policy uncertainty when the industry-pair fixed effect is included. These results confirm the findings in Table 5 and Table 6 that the trade shock is influential in determining industry switching within firms. Processing exporters tend to enter into and increase exports in industries with similar imports to the firms' initial import mix when facing the reduction in trade policy uncertainty. Although this result is not robust in column (4) when using the cross-sectional data, the positive relationship between industry adoption and firm-industry input similarity still exists.

Anyway, results in Table 8 and Table 9 confirm that the co-production across industries are robust to possible changes in economic shocks.

Impact of Demand Shock

Thirdly, except the trade policy uncertainty, the positive world demand shock is also one of the important factors that makes firms more likely to add industries and increase exports. Referring to Mayer et al. (2020), this paper constructs an industry-year specific indicator of demand shock which measures the world demand the following year. The specific definition is as follows:

$$\text{Demand Shock}_k^{t+1} = \log(\text{M})_k^{t+1} \tag{13}$$

where M_k^{t+1} is the world's total trade flows in industry k at time $t+1$ excluding China.

Table 10: Robustness Checks: Possible Impacts of Demand Shock

	Add_{jk}^t		Drop_{jk}^t		$\log(\text{exports})_{jk}^t$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{InputSimilarity}_{jk}^0$ # TPU_k	0.0295***	0.0202***	-0.5518***	-0.4330***	3.6824***	4.2063***
	(0.0008)	(0.0008)	(0.0283)	(0.0327)	(0.2455)	(0.2665)
$\text{InputSimilarity}_{jk}^0$ # DS_k^{t+1}	0.0118***	0.0103***	-0.0874***	-0.0054	1.2729***	0.5135***
	(0.0001)	(0.0001)	(0.0036)	(0.0042)	(0.0355)	(0.0361)
$\text{InputSimilarity}_{jk}^0$	-0.1535***	-0.1308***	1.1143***	-0.2098***	-15.7823***	-4.4260***
	(0.0016)	(0.0016)	(0.057)	(0.0665)	(0.5516)	(0.5682)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE		Yes		Yes		Yes
N	277272996	277272996	517081	516634	517081	516634
R^2	0.006	0.009	0.405	0.435	0.39	0.471

Notes: Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the firm-industry level.

Table 10 reports the results when the interaction of input similarity and trade policy uncertainty, and the interaction of input similarity and demand shock are included simultaneously. As the results shown in Table 10, the interaction terms of input similarity and trade policy uncertainty in three panels (industry add, drop, and intensive margin) are consistent with the results in Table 5. Based on the results of the interaction terms of input similarity and demand shock, exporters are more likely to add industries and increase exports in industries with a positive demand shock in the future. However, the estimated coefficients of input similarity in Table 10 are not as expected. Linking the summary statistics of this demand shock variable, there might exists a critical point when the possible effect of demand shock is taken into consideration. In a word, results in Table 10 can still indicate that the impact of trade policy uncertainty on industry decisions of processing exporters is robust.

All of the robustness checks confirm the relationship between the similarity of firm and industry import mix and industry activities within processing exporters, as well as the impact of trade shocks in this process.

6 Conclusions

Depending on the existing literature, this paper provides evidence that input capability plays a role in exporting patterns within Chinese firms. Using detailed transaction-level data on imports and exports of Chinese processing firms over the period 2000 to 2006, this paper constructs the measure of firm-industry imported input similarity and investigates the co-production across exporting industries within firms. The baseline result shows that processing exporters tend to add industries with similar import mix, drop industries with less imports in common, and increase processing exports in industries sharing similar imported inputs. Using China's WTO accession in 2001 as a positive trade shock in the export market, this paper finds that the reduction in trade policy uncertainty makes processing exporters more likely to entry into and increase exports in industries sharing input capabilities, and this result for industry drop is the converse. These findings are robust for the cross-sectional processing trade date, the alternative measure of industry churning, possible determinants of industry co-production, and the possible effect of demand shocks.

Considering the future work, there are two further empirical extensions to the current work. First, the impact of ordinary trade has not been taken into consideration in this paper. A possible concern is that because firms can engage in both processing and ordinary trade, it is plausible that firms share capabilities between these two modes of trade. From this perspective, changes in processing export activities within firms may be partly due to the ordinary trade. In addition, studies point out that some firms that previously participate only in processing exports begin to engage in ordinary exports with the reduction of trade policy uncertainty. Hence, to exclude these concerns, the empirical analysis can be extended by merging the current Customs data with firm-level production data from China Industrial Enterprise Database and making corresponding analysis. Another advantage is that we can also consider the effect of firm productivity and size with the firm-level production data.

Second, to establish a causal channel, another empirical extension is to construct the instrumental variables for the input similarity index. As in Boehm et al. (2019), they exploit the exogeneous de-reservation policy change and construct the corresponding instrumental variables.

Finally, one theoretical extension is to build a structural model and quantify the role of input-based comparative advantage to better understand the empirical results.

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Appendix

Appendix Table 1: Multi-Industry Exporters

# Industries	# Firms	% Firms	% Processing Exports
1	57,200	40.8	19.3
2	28,771	20.5	14.7
3	17,116	12.2	9.3
4	11,065	7.9	7.4
5	7,453	5.3	5.8
6	5,229	3.7	4.3
7	3,787	2.7	3.2
8	2,740	2	2.6
9	1,955	1.4	1.7
10	1,495	1.1	1.6
11-20	2,438	1.7	9.5
21-30	458	0.3	3.7
31-40	173	0.1	2.7
41-50	100	0.1	3.0
> 50	118	0.1	11.2

Notes: The number of industries is calculated at the firm-year level, which is defined as the number of processing exporting industries for each firm in each period from 2000 to 2006.

Appendix Table 2 presents the characteristics of the four datasets used in the empirical analysis, including the panel data of industry add and drop, and the cross-section data of industry add and drop. For example, the panel data of industry add consists of 279,973,707 firm-year-industry observations, 70,024 processing firms, and 933 HS 4-digit industries. The average value of processing exports at the firm-year level is 2,399,501, and at the firm-industry level is 1,415,589. We also report the characteristics for two sub-samples: single-industry and multi-industry processing exporters. Specifically, roughly 40% of all firms in this dataset are classified as single-industry exporters, and multi-industry processing exporters account for more than 60%.

Appendix Table 2: Sample Characteristics

	Processing Exporters		
	All	Single-Industry	Multi-Industry
A. Add Dataset (Panel)			
# Observations	279,973,707	101,483,343	178,490,364
Firm-Year	300,079	108,771	191,308
Firm-Industry	65,332,392	25,786,254	39,546,138
# Firms	70,024	27,638	42,386
# Industries (HS4)	933	933	933
Average Value of Processing Exports (Firm-Year)	2,399,501	2,242,475	2,466,716
Average Value of Processing Exports (Firm-Industry)	1,415,589	1,591,344	1,394,790
B. Add Dataset (Cross-Section)			
# Observations	29,368,974	9,509,136	19,859,838
# Firms	31,478	10,192	21,286
# Industries (HS4)	933	933	933
Average Value of Processing Exports (Firm-Industry)	1,511,705	1,701,349	1,490,140
C. Drop Dataset (Panel)			
# Observations	628,739	66,618	562,121
Firm-Year	221,546	66,618	154,928
Firm-Industry	250,042	26,576	223,466
# Firms	68,566	26,576	41,990
# Industries (HS4)	933	917	925
Average Value of Processing Exports (Firm-Year)	2,382,392	2,219,733	2,452,334
Average Value of Processing Exports (Firm-Industry)	1,409,077	1,572,776	1,389,609
D. Drop Dataset (Cross-Section)			
# Observations	89,596	9,148	80,448
# Firms	29,475	9,148	20,327
# Industries (HS4)	889	699	878
Average Value of Processing Exports (Firm-Industry)	1,511,705	1,701,349	1,490,140

Appendix Table 3: Summary Statistics

	Obs	Mean	StdDev	Min	Max
A. Add Dataset (Panel)					
Industry Add Dummy (Add_{jk}^{t})	279,973,707	0.0005	0.02	0	1
Input Similarity (IS_{jk}^{0})	279,973,707	0.004	0.03	0	1
Trade Policy Uncertainty (TPU_{k})	277,573,075	0.3168	0.19	0	1.45
Demand Shock (DS_{k}^{t+1})	277,873,154	14.471	1.62	8.78	20.09
B. Add Dataset (Cross-Section)					
Industry Add Dummy (Add_{jk})	29,368,974	0.0025	0.05	0	1
Input Similarity (IS_{jk}^{0})	29,368,974	0.0041	0.03	0	1
Trade Policy Uncertainty (TPU_{k})	29,117,150	0.3168	0.19	0	1.45
C. Drop Dataset (Panel)					
Industry Drop Dummy (Drop_{jk}^{t})	628,739	0.2789	0.45	0	1
Exports ($\log(\text{exports})_{jk}^{t}$)	628,739	11.465	2.61	0	22.44
Input Similarity (IS_{jk}^{0})	628,739	0.0978	0.17	0	1
Trade Policy Uncertainty (TPU_{k})	626,620	0.437	0.17	0	1.45
Demand Shock (DS_{k}^{t+1})	626,873	15.58	1.43	8.78	20.09
D. Drop Dataset (Cross-Section)					
Industry Drop Dummy (Drop_{jk})	89,596	0.7572	0.43	0	1
Exports ($\log(\text{exports})_{jk}$)	89,596	11.389	2.55	0	20.27
Input Similarity (IS_{jk}^{0})	89,596	0.0935	0.16	0	1
Trade Policy Uncertainty (TPU_{k})	89,551	0.4413	0.17	0	1.45