University of Toronto
Department of Economics

Working Paper 680

Accounting for Chinese Exports

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November 28, 2020

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Abstract

Rapid growth in Chinese exporting has spurred extensive research across multiple fields of economics investigating its effects. Yet, the causes of this growth remain less well-understood. We quantify the drivers of Chinese exporting using a general equilibrium model, estimated with detailed trade and production data that capture rich heterogeneity across destinations, firm ownerships, production locations, and sectors. Both external (foreign demand) and internal factors (productivity, firm entry, imported input access) were important drivers of high export growth from 2000-2007. A slowdown in export growth post-2007 is largely attributable to the disappearance of internal drivers, reinforced by weakening external factors.

JEL Codes: F14, F47, O47, O53

*We are grateful to participants at the following workshops, seminars, and conferences for invaluable feedback: CCER International Trade seminar (Peking University), Firms in Emerging Economies Workshop (Jinan University), Danish International Economics Workshop (Aarhus University), SAET Annual Conference, China Economics Summer Institute (Guanghua School of Management), and the Stanford International Trade workshop. Brandt acknowledges support from Canada's SSHRC. We also thank Torsten Jaccard for excellent research assistance.

1 Introduction

China's growing participation in the world market for goods and services has been a defining feature of the global economy for more than two decades. Between 1995 and 2019, China's exports grew at an annual rate of 15% compared with world export growth of 7% per year and export growth of OECD countries of 5% per year. In the process, China's share of world exports rose substantially from 3% to 12%. Unsurprisingly, this rapid growth in Chinese exporting has been accompanied by an explosion of research, not only in international trade, but spanning other fields of economics. However, much of this work has focused on the *consequences* of China's growth in world markets for outcomes in other countries, while the *causes* of China's trade expansion remain less well understood.[1] Given the extensive interest among both researchers and policymakers in the effects of Chinese export growth, a deeper understanding of the sources of this growth is equally important. In this paper, we focus on quantifying the drivers of Chinese export growth.

To do so, we study detailed trade and production data for firms in China from 2000 to 2013. We first document how patterns of Chinese exporting have changed over this period, focusing on four key margins: (i) the destination market for exports; (ii) the ownership of exporting firms; (iii) the location of export production in China; and (iv) the sector of goods being exported. We show that there have been important changes in the dynamics and composition of Chinese exports along these dimensions: a marked slowdown in aggregate export growth after the mid-2000s; a shift away from markets in advanced countries to those of emerging economies; a rise and then fall in the share of exports produced by foreign-owned firms, as exports of privately-owned Chinese firms come to rival those of foreign firms; a slight decline in the concentration of export production in coastal provinces; and a shift away from textiles and apparel towards machinery.

To make sense of these patterns, we construct a model of Chinese trade that captures multiple drivers of Chinese export growth in a general equilibrium setting. We examine both external and internal sources of growth. The former comprise changes in foreign demand, competition from the rest of the world, and costs of accessing foreign markets, while the latter consist of changes in factor-augmenting productivities, firm entry, access to imported inputs, investment efficiency, and employment. Motivated by the empirical patterns that we document, we allow these factors to vary across export markets, firm ownership types, production locations within China, and sectors. The structure of the model enables us to

[1] On the consequences, Autor et al. (2013, 2016), Pierce and Schott (2016), Feenstra and Sasahara (2018), and Bloom et al. (2019) consider the effects of Chinese import competition on labor markets in the US. di Giovanni et al. (2014) and Hsieh and Ossa (2016) estimate the effects of Chinese productivity growth on real incomes in the rest of the world through trade, while Autor et al. (2017), Bloom et al. (2016), and Hombert and Matray (2018) consider the impact of Chinese exporting on innovation by firms outside of China.

map each of these potential drivers of export growth to a corresponding set of structural parameters that we then estimate using the Chinese trade and production data. Finally, to quantify the contributions of each factor to aggregate export growth, we simulate model-based counterfactuals that predict the patterns of Chinese exporting in the absence of changes in each factor.

Our findings indicate that both external factors (growth in foreign demand) and internal factors (productivity growth, firm entry, and improved access to imported inputs) were primary drivers of high export growth rates between 2000 and 2007. By contrast, the slowdown in aggregate export growth after 2007 is largely explained by a weakening of internal sources of growth, reinforced by diminishing external factors. Underlying these aggregate findings are rich patterns of heterogeneity in export growth drivers across destinations, firm ownership types, production locations, and sectors, which cautions against a reading of aggregate Chinese export dynamics that ignores these differences.

We focus our analysis on the years from 2000 to 2013 due to data availability. A case can be made that our study is broadly reflective of Chinese export dynamics over a much longer period. The rapid growth in aggregate Chinese exports that we document predates 2000, with exports growing at an average annual rate of 19.5% between 1993 and 2000. Similarly, the decline in the role of textiles and the shift in export composition towards machinery between 2000 and 2007 begins in the early 1990s, as does the growing role of foreign- and privately-owned Chinese firms in exporting.[2] Conversely, aggregate data suggest that critical shifts in the drivers of Chinese export growth that emerge after 2007 persist until more recently, and may be responsible for the sharp fall in annual export growth to only 2% between 2013-2019. Included here, for example, is a further decline in the share of foreign firms in China's total exports to 39% in 2019. In the conclusion, we consider a number of alternative interpretations for these changes and their implications.

1.1 Related literature

Many of the drivers of export growth that we investigate are viewed as central to China's trade and production outcomes over the last two to three decades. One of our main contributions to this literature is to account for the alternative explanations for the observed dynamics in Chinese export patterns in a coherent general equilibrium framework and evaluate them quantitatively. To provide context, we briefly highlight here how our analysis connects with various strands of research.

[2]For example, data from the UN Comtrade database shows that the share of textiles in total export value fell from 42% in 1993 to 27% in 2000, while the share of machinery increased from 18% to 32%. Data from the Chinese Customs reported in Feenstra and Wei (2010) indicates that the share of exports accounted for by foreign-owned firms increased from 27% to 47% over the same period.

Productivity growth. Brandt et al. (2012) estimate firm-level productivity for China's manufacturing sector from 1998 to 2007, finding high rates of productivity growth on average. Brandt et al. (2017) find positive contributions of China's accession to the WTO through tariff reductions that raised both firm- and sector-level productivity, an effect that Yu (2015) finds especially strong for non-processing exporters. Khandelwal et al. (2013) also find productivity-enhancing effects from the removal of externally-imposed quotas for Chinese textile and apparel exports after 2004 with the end of the Multi-Fibre Agreement (MFA). Our productivity estimates are broadly consistent with these findings: we estimate positive productivity growth between 2000 and 2007 in sectors such as machinery, textiles, and transportation, at average rates of around 5% per year. We find this productivity growth to be a key internal source of export growth during this period. However, our estimates indicate a sharp reversal in productivity growth trends in multiple sectors of the Chinese economy after 2007, with productivity growth contributing little to export growth in later years.

Firm entry. Branstetter and Lardy (2008) argue that China benefited from an increasingly liberalized domestic environment for foreign direct investment, especially for firms involved in exporting, leading up to and running through China's accession to the WTO. A reduction in trade policy uncertainty following China's WTO accession provided additional impetus for firm entry into exporting (Feng et al. (2017)). At the same time, barriers to entry for non-state domestic firms fell, especially in the mid-to-late 1990s with the downsizing of the state sector (Brandt et al. (2020)). It was not until the early 2000s that non-state firms had direct export rights, but with a substantial increase in the number of companies authorized to conduct foreign trade in China between 1985 and 2001, Lardy (2002) argues that the market for foreign trade services was already reasonably competitive by the mid-1990s. Nonetheless, important differences in export participation persisted across firms of different ownership types (Feenstra (1998) and Blonigen and Ma (2010)). In line with this research, we find that firm entry was a key driver of high export growth from 2000 to 2007, especially for foreign-owned firms in machinery but also for privately-owned Chinese firms. However, firm entry declines noticeably after 2007 and along with it entry's contributions to export growth.

Imported intermediates. Ma et al. (2015) document substantial variation in the use of imported intermediates across different firm ownership types in China. Based on reduced-form estimates, Feng et al. (2016) find evidence that improved import access between 2002 and 2006 had positive effects on Chinese exporting, especially for privately-owned firms. Fan et al. (2015) similarly argue that import tariff reductions between 2001 and 2006 contributed to export quality upgrading by Chinese firms, which they link indirectly to better access to imports. Liu and Qiu (2016) also provide evidence that tariff reductions lead to greater usage of imported intermediates, but argue this was offset by lower innovation rates for Chinese firms as reflected in patenting activity. Consistent with these findings, our quantitative simulations indicate that improvements in imported input access were extremely important for export growth in the initial years after China's accession to the WTO, especially between 2000 and 2004. However, we also find that these effects dissipate quickly, with much smaller contributions to export growth after 2007. In addition, we find substantial heterogeneity in these effects across firm ownership types and sectors.

Investment efficiency. Eaton et al. (2016) find that declines in the efficiency of durable goods investment largely account for the slowdown in global trade during and after the Great Recession of 2008-2009. In a separate but closely related context, we find that investment efficiencies were generally declining in China, which contributed to the slowdown in aggregate export growth. We also estimate important differences across firm ownership types, with state-owned firms having lower investment efficiencies than non-state firms. This is in line with findings by Chen et al. (2011), who find that political connections of top executives at state-owned firms significantly lowers investment efficiency at these firms.

Employment growth. There is a substantial literature documenting the decline in labor mobility barriers in China, especially out of the countryside (Chan (2012)). Recent work by Liu and Ma (2018) investigates how falling barriers to internal migration within China shaped long differences in exporting between 1990 and 2005. Fan (2019) also considers how the effects of international trade within China depend on internal migration. Although we do not model migration within China, we find employment growth to be an important secondary source of export growth. Furthermore, we find that after 2007, employment growth becomes more important in the interior provinces of China relative to coastal provinces where export production is concentrated, highlighting the importance of the reallocation of labor across space, whether through migration or other channels.

1.2 Outline

Section 2 describes the main data sources that we use to study the patterns of Chinese trade and documents a set of stylized facts that motivate our analysis. Section 3 then develops a structural model of Chinese trade that we use to study the drivers of Chinese exporting, while section 4 describes the estimation procedure that we use to connect the model with data. Section 5 presents the counterfactual exercises that we employ to quantify the drivers of Chinese export growth and discusses our main findings. Finally, section 6 concludes.

2 Data and Empirical Patterns

2.1 Data sources

We first summarize the main features of the datasets that we utilize in this paper. A detailed description of the more technical data processing procedures required for our quantitative analysis is relegated to the online appendix.

Customs data. The main source of trade data that we study is a transactions-level dataset of Chinese exports and imports collected by the Customs Administration of China. These data provide measures of exporting and importing by destination and source country respectively, firm ownership type, sector (at the HS-8 classification), and location of production of the exported goods. We use data for 2000-2013 and focus on trade in manufacturing (HS-2 codes 15-23 and 28-96), which accounts for more than 90% of the value of Chinese exports in each year of the sample.

Production data. We utilize information from the Chinese Annual Survey of Manufacturing (ASM) for 2000-2013.[3] This provides firm-level production data for all manufacturing sectors (CIC-2 codes 13-42), covering all state-owned enterprises and all non-state firms with sales above a threshold.[4] We employ information from the ASM primarily for two purposes. First, we use data on factor inputs (labor, capital, and materials) from the ASM to measure factor expenditures and prices. This is important for the estimation of production functions in the model that we develop below and allows us to decompose production costs into factor prices and factor-augmenting productivities. Second, we use the ASM data to estimate counts of both exporters and non-exporters.

Industrial Census data. To address concerns that the ASM data only include non-state firms that are above-scale, we use information from the 2004 Chinese industrial census. These data provide information for all industrial firms in China irrespective of size and hence allow us to assess and partially correct for size censoring in the ASM.[5]

Input-output data. In studying the drivers of Chinese exports, we take sector-level input-output linkages into account. To do so, we use data on inter-sectoral sales and

[3]For all years in the sample except 2009 and 2010, the ASM variables that we utilize are available by firm ownership type, province, and main industry (at the CIC-4 classification). For 2009 and 2010, these variables are reported by the Chinese National Bureau of Statistics (NBS) only at the ownership-location and ownership-sector levels. Hence, we impute variables at the ownership-location-sector level for 2009 and 2010 using the NBS data for these years and data from the ASM for 2008 and 2011. This imputation procedure is described in section A of the online data appendix.

[4]For years before and including 2008, the size threshold is 5m RMB (approximately 600,000 USD) in sales. For 2011 and after, the size threshold increases to 20m RMB (approximately 2.4m USD). To maintain consistency across years, we exclude firms with sales below 20m RMB from the datasets for years before and including 2008.

[5]This correction procedure is applied to measures of firm and exporter counts in the ASM data. The details of this procedure are described in section B of the online data appendix.

expenditures for the Chinese economy from the World Input-Output Database (WIOD), which provides input-output data by industry (at the ISIC-2 classification) for multiple countries (including China), for the years 2000-2014. We also obtain estimates of domestic final consumption by sector in China from the WIOD. The WIOD data are constructed directly from make-use tables provided by the Chinese NBS.

Aggregate trade data. To measure world demand for goods from each sector, we use data on aggregate imports by HS-2 sector from each country in the world, obtained from the UN Comtrade database.

Concordances. As the datasets that we draw upon categorize goods using different sector classifications, we develop concordances between these classifications. First, to match the customs data with the ASM data, we construct a concordance between the CIC-2 and HS-2 classifications. Second, to match the customs data with the input-output data from WIOD, we construct a concordance between the ISIC-2 (Rev. 4) and HS-2 classifications.[6]

2.2 Patterns of Chinese exports

We now present five stylized facts about Chinese exporting. These facts motivate the structural framework that we develop in section 3 and set the context for the counterfactual results that we present in section 5. We focus on the aggregate behavior of Chinese exports and four key margins of heterogeneity: the destination market for exports, the ownership of exporting firms, the location within China where exports are produced, and the sector of exported goods.[7]

Fact 1 (aggregate dynamics): The aggregate value of Chinese exports grows quickly from 2000 to 2007, a product of high growth in both the number of exporting firms and the average value of exports per exporter. Export growth declines after 2007, accompanied by a sharp fall in growth of the number of exporters.

Figure 1 shows the annual growth rates of three exporting measures: the aggregate value of Chinese exports, the number of exporting firms (the extensive margin), and the average value of exports per exporting firm (the intensive margin). Aggregate exports grow rapidly between 2000 and 2007 at an average annual rate of 27.0%, with growth on both the extensive margin (averaging 16.1% per year) and the intensive margin (averaging 9.8% per year) high. Following the Great Recession, aggregate export growth declines by more than half to an average of 11.1% per year between 2007 and 2013, with the decline on the

[6]Details for the procedure that we use to construct these concordances are provided in section C of the online data appendix.

[7]Section D of the online data appendix provides detailed definitions of the categories that we use throughout the paper for destination markets, firm ownership types, production locations, and sectors.

extensive margin of growth to only 3.1% per annum especially pronounced. Explaining the rapid growth in exports before 2007 and the subsequent slowdown is a key focus of our quantitative analysis.

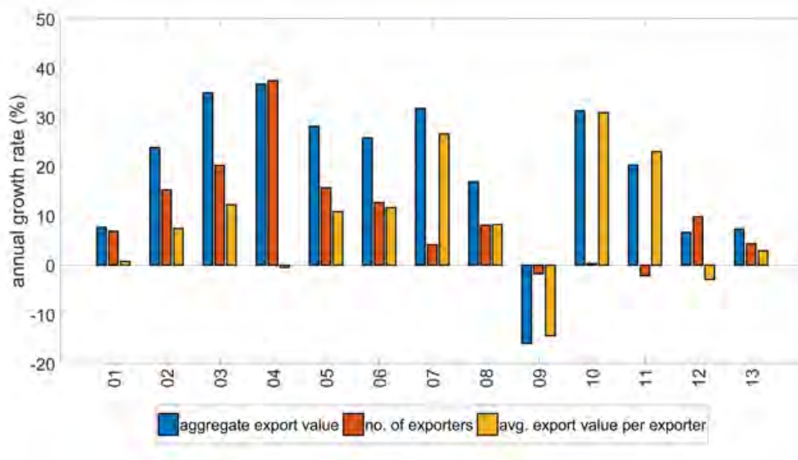

Figure 1: Annual growth rates of exports, extensive margin, and intensive margin

Fact 2 (exports by destination): A majority of China's exports are destined for markets in developed countries in North America, Western Europe, and East Asia. However, there is a marked shift to markets in lower and middle-income countries over time.

Panel (a) of Figure 2 shows the shares of Chinese exports by geographic regions. In 2000, 58.6% of Chinese exports are sold in North America, Western Europe, and East Asia. This share falls throughout the sample period, with the decline accelerating from 2006 onward, and by 2013 is 43.9%. This decline reflects the more rapid growth in China's exports to markets in lower and middle-income countries in South East Asia, Eastern Europe and Russia, and Africa between 2000 to 2013. These patterns hint at changes in the relative demand for Chinese exports across geographic locations and motivates the modeling of heterogeneous export markets in the framework that we develop below.

Fact 3 (exports by firm ownership): Foreign-invested enterprises (FIEs) are the source of a majority of Chinese exports followed by private-invested enterprises (PIEs) and then state-owned enterprises (SOEs). The share of PIEs increases over time, initially at the expense of SOEs, and subsequently and more importantly, the FIEs. The share of exports of SOEs falls throughout most of the period. Export propensities decline for FIEs and PIEs but remain constant for SOEs.

Panel (b) of Figure 2 provides a breakdown of Chinese exports by ownership types:

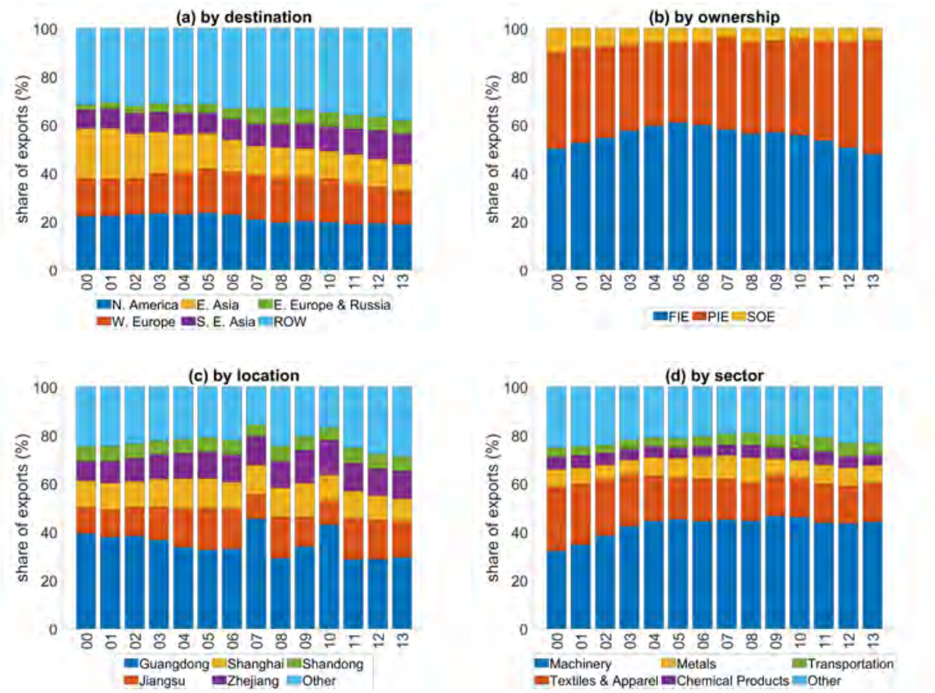

Figure 2: Export shares by destination, ownership, production location, and sector

FIEs, PIEs, and SOEs.[8] FIEs capture a rising share of exports through the mid-2000s before falling to slightly less than half in 2013. Over the same period, the share of exports of PIEs rises from less than 40% to 47.8% in 2013, with most of this occurring later in the period, and at the expense of the FIEs. The share for SOEs, on the other hand, declines continuously from 10.0% in 2000 to 4.7% in 2013. These shifts in the ownership composition of exports occur in parallel with changes in export propensities. FIEs tend to exhibit substantially higher export propensities than either PIEs or SOEs, but their overall export propensity declines from 53.0% in 2000 to 45.6% in 2013. Similarly, PIE export propensity falls from 6.6% in 2000 to 3.4% in 2013. SOE export propensity, on the other hand, remains relatively constant at approximately 13% throughout the sample period.

These empirical patterns motivate our modeling of distinct firm ownership types in the framework that we develop in section 3. Quantitative findings that we present in section 5 also indicate significantly different dynamics for the underlying drivers of exports by ownership types.

[8]Throughout the paper, we allocate exports by ownership type following a procedure that captures potential indirect exporting by PIEs through state-owned trading companies. This procedure is described in section E of the online data appendix. The findings that we present in section 5 are qualitatively similar with or without the adjustment for indirect exporting.

Fact 4 (exports by production location): Production of Chinese exports is highly concentrated in coastal provinces, and especially in Guangdong. Over time, we observe a slight shift from Guangdong to other coastal provinces, and after 2010 towards interior provinces.

Panel (c) of Figure 2 shows the share of Chinese exports produced in different locations within China. Exporting is dominated by Guangdong followed by Jiangsu, Shanghai, Zhejiang, and Shandong, with the identity of the top five exporting provinces remaining the same over the period. Between 2000 and 2010, the top three and top five provinces are the source of 61.7% and 78.5% respectively of annual total exports. These shares fall slightly between 2010 and 2013 as a larger share of exports come from firms producing in inland provinces. This observed heterogeneity in export production across provinces within China motivates the modeling of heterogeneous production locations that have access to different factor stocks and production technologies.

Fact 5 (exports by sector): The majority of exports from China are comprised of machinery (HS-2 codes 84-85) and textiles and apparel (HS-2 codes 50-67). FIEs are dominant in machinery, while Chinese firms are dominant in textiles and apparel. Over time, there is a shift away from textiles and apparel toward machinery.

Panel (d) of Figure 2 shows the composition of Chinese exports by sector. On average, machinery and textiles and apparel make up 61.3% of China's exports.[9] This share remains fairly constant throughout the sample period, but this conceals a noticeable shift between the two. The share of machinery rises from 32.2% in 2000 to 44.1% in 2013, accompanied by a fall in textiles from 26.5% to 16.1% over the same period.

There are also important differences in export shares across firm ownership types within each sector. FIEs are particularly dominant in machinery, consistently the source of around 75% of total exports within the sector throughout the sample period.[10] FIEs are also important for export production in transportation (an average of 47.4% of sector exports), plastics and rubber (51.7%), and foodstuffs (50.9%), although the FIE share in all of these sectors declines over time, especially from 2006 and onward. Chinese firms, on the other hand, are most dominant in textiles and apparel (66.6%), metals (69.1%), and chemical products (69.3%). The total share of PIEs and SOEs in textile and apparel exports also rises steadily over time, increasing from 63.9% in 2000 to 75.6% by 2013.

The quantitative findings that we present in section 5 are indicative of substantial het-

[9] For brevity, we often refer to textiles and apparel as "textiles", although this also includes apparel sectors (HS-2 codes 64-67).

[10] The FIE share of machinery exports falls in the last few years of the sample, from 73.5% in 2011 to 66.6% in 2013.

erogeneity in the underlying drivers of export growth both across sectors as well as within sectors across firm ownership types.

3 Model

We now develop a structural model of Chinese trade to investigate the underlying drivers of the export patterns documented above. This model will serve two purposes. First, it provides a framework that allows us to account for multiple drivers of Chinese exports in a general equilibrium setting. Each driver will map to a set of structural parameters in the model, which we will then estimate using the data described above. Second, we use the model to quantify the contribution of each driver to changes in Chinese exports through counterfactual simulations.

3.1 General environment

In parallel with the empirical patterns described in section 2.2, we first define the margins of Chinese exports as follows: (i) destination markets, $d \in \{0, \cdots, D\}$, where market 0 is the domestic Chinese market and the remaining are export markets; (ii) firm ownership types, $n \in \{1, \cdots, N\}$; (iii) production locations in China, $h \in \{1, \cdots, H\}$; and (iv) sectors, $s \in \{1, \cdots, S\}$. We index time (years) by y. Within an $\{n, h, s\}$-cell, firms are also heterogeneous in idiosyncratic TFP ϕ, with distribution (CDF) denoted by G_{nhs} and the total measure of active firms (including non-exporters) denoted by N_{nhsy}.[11]

When we take the model to the data, we will use the following definitions of destinations, ownership types, locations, and sectors. Destination markets d are 11 geographic regions (for example, North America and Western Europe). Firm ownership types n are FIEs, PIEs, and SOEs. Production locations h are 11 groupings of Chinese provinces and municipalities (for example, Guangdong and Northwest China). Sectors s are 11 groupings of HS-2 manufacturing categories (for example, machinery (HS-2 codes 84-85) and chemicals (HS2-codes 28-38)).[12]

3.2 Demand

3.2.1 Export demand

Foreign consumers in export market d spend nominal income E_{dsy} on imports of sector s goods from all source countries. Within each sector s, these consumers have preferences over

[11] Firm heterogeneity within an $\{n, h, s\}$-cell will be important for modeling firm selection into exporting.

[12] The exact list of countries, firm ownership definitions, provinces, and sectors belonging to each region d, ownership type n, production location h, and sector group respectively are reported in section D of the online data appendix.

a continuum of differentiated products from all source countries with a constant elasticity of substitution (CES) across products denoted by σ_s. Demand in market d for Chinese exports by $\{n, h, s, \phi\}$-firms hence takes the following form:

$$X_{dnhsy}(\phi) = A_{dnhsy} \left[p_{dnhsy}(\phi) \right]^{-\sigma_s} \tag{3.1}$$

where $p_{dnhsy}(\phi)$ is the price charged by a $\{n, h, s, \phi\}$-firm in market d.[13] The term A_{dnhsy} is a demand shifter given by:

$$A_{dnhsy} \equiv A_{dsy} \nu_{dnhsy} \tag{3.2}$$

$$A_{dsy} \equiv \frac{E_{dsy}}{\left(P^*_{dsy}\right)^{1-\sigma_s} + \left(\tau_{dsy} P_{dsy}\right)^{1-\sigma_s}} \tag{3.3}$$

where ν_{dnhsy} is a preference weight and A_{dsy} is a destination-sector specific component of the demand shifter. The form of the latter follows from CES preferences, where P^*_{dsy} is a measure of competition from firms outside of China and P_{dsy} is a price index of sector s products exported to market d by firms in China exclusive of iceberg trade costs $\tau_{dsy} \geq 1$. Since we focus on the drivers of Chinese exporting rather than the global determinants of trade, we treat E_{dsy} and P^*_{dsy} as exogenous variables, while the Chinese export price indices P_{dsy} and domestic demand shifters A_{0sy} are endogenously determined.

3.2.2 Domestic demand

Domestic households in all locations h have identical preferences. We assume that all goods are freely tradable within China so that consumers in each location also face identical prices for final goods.[14] Across sectors, aggregate consumer utility takes the following Cobb-Douglas form:

$$U_y = \prod_{s=1}^{S} \left(X^F_{sy} \right)^{\gamma_s} \tag{3.4}$$

where X^F_{sy} is final consumption of sector s products and $\sum_{s=1}^{S} \gamma_s = 1$.

Within each sector s, consumers have CES preferences over consumption of domestically-produced final goods X^{FD}_{sy} and imported final goods X^{FI}_{sy} with sector-specific elasticity of

[13] Differences in product quality across firm types are isomorphic to differences in total factor productivities. Hence, we do not include quality as a separate structural parameter.

[14] Estimating internal barriers to trade requires data on internal trade flows. These data are only available in China for select years and sectors in our sample. See Tombe and Zhu (2019) for a discussion.

substitution ϵ_s^F:

$$X_{sy}^F = \left[\left(\omega^F\right)^{\frac{1}{\epsilon_s^F}} \left(X_{sy}^{FD}\right)^{\frac{\epsilon_s^F - 1}{\epsilon_s^F}} + \left(1 - \omega^F\right)^{\frac{1}{\epsilon_s^F}} \left(X_{sy}^{FI}\right)^{\frac{\epsilon_s^F - 1}{\epsilon_s^F}} \right]^{\frac{\epsilon_s^F}{\epsilon_s^F - 1}} \tag{3.5}$$

where ω^F is a preference weight on domestic products.[15] Since we do not model production outside China, we assume that imported final goods in sector s are available at an exogenous price P_{sy}^{FI}.[16] Variation in these import prices will allow the model to match imported shares of final consumption observed in the data.

3.3 Production

Firms in China produce using four types of inputs: labor, capital, domestic materials, and imported materials. These inputs are aggregated via nested CES production technologies as follows. Output X_{nhsy} is produced by combining value-added V_{nhsy} and materials M_{nhsy}:

$$X_{nhsy} = \phi \left[\left(\omega^X\right)^{\frac{1}{\epsilon_s^X}} V_{nhsy}^{\frac{\epsilon_s^X - 1}{\epsilon_s^X}} + \left(1 - \omega^X\right)^{\frac{1}{\epsilon_s^X}} \left(T_{nhsy}^M M_{nhsy}\right)^{\frac{\epsilon_s^X - 1}{\epsilon_s^X}} \right]^{\frac{\epsilon_s^X}{\epsilon_s^X - 1}} \tag{3.6}$$

while value-added is produced by combining labor L_{nhsy} and capital K_{nhsy}:

$$V_{nhsy} = \left[\left(\omega^V\right)^{\frac{1}{\epsilon_s^V}} \left(T_{nhsy}^L L_{nhsy}\right)^{\frac{\epsilon_s^V - 1}{\epsilon_s^V}} + \left(1 - \omega^V\right)^{\frac{1}{\epsilon_s^V}} \left(T_{nhsy}^K K_{nhsy}\right)^{\frac{\epsilon_s^V - 1}{\epsilon_s^V}} \right]^{\frac{\epsilon_s^V}{\epsilon_s^V - 1}} \tag{3.7}$$

Materials are produced by combining imported inputs M_{nhsy}^I with domestic inputs M_{nhsy}^D:

$$M_{nhsy} = \left[\left(\omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(M_{nhsy}^I\right)^{\frac{\epsilon_s^M - 1}{\epsilon_s^M}} + \left(1 - \omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(M_{nhsy}^D\right)^{\frac{\epsilon_s^M - 1}{\epsilon_s^M}} \right]^{\frac{\epsilon_s^M}{\epsilon_s^M - 1}} \tag{3.8}$$

Finally, domestic inputs are produced by combining inputs from all sectors:

$$M_{nhsy}^D = \prod_{s'=1}^{S} \left[\frac{M_{nhss'y}^D}{\alpha_{ss'}} \right]^{\alpha_{ss'}} \tag{3.9}$$

[15] This weight will play no role in the analysis or quantitative results.

[16] Import prices P_{nsy}^{FI} capture not only the cost of imported goods but also differences in the quality of imported versus domestic final goods. In addition, changes in import prices capture changes in import tariffs and in the value of the RMB throughout the sample period. In particular, appreciation of the RMB from 2005 onward maps to a fall in import prices.

where $M_{nhss'y}$ denotes usage of domestic intermediates from sector s'. We denote the marginal production cost implied by these technologies for a $\{n, h, s, \phi\}$-firm as η_{nhsy}/ϕ, where η_{nhsy} is the component of marginal cost common to all $\{n, h, s\}$-firms.

There are several features of these production technologies that are worth noting. First, in addition to firm-level TFP ϕ, we allow for three types of factor-augmenting productivities that vary at the ownership-location-sector-year level: labor productivity T^L_{nhsy}, capital productivity T^K_{nhsy}, and materials productivity T^M_{nhsy}. We denote these jointly by $\bar{T}_{nhsy}$. These productivity terms allow the model to better fit the factor shares of total production costs that we observe in the data.

Second, production technologies are characterized by three substitution elasticities: between value-added and materials ϵ^X_s; between labor and capital ϵ^V_s, and between foreign and domestic intermediates ϵ^M_s. We allow each of these to vary by sector to account for potential differences in substitution possibilities. However, to simplify the calibration of input-output shares, we assume a Cobb-Douglas technology in equation (3.9), where $\{\alpha_{ss'}\}_{s,s'\in\Omega_S}$ is the sector-level input-output matrix with $\sum_{s'=1}^{S}\alpha_{ss'} = 1$ for all $s \in \Omega_S$.

Third, as with imported final goods, we assume that the imported input bundle is available at an exogenous price P^I_{nsy}. Since we abstract from internal trade costs, this price is assumed to vary by ownership-sector-year but not across locations.[17] Variation in these import prices will allow the model to match imported shares of material expenditures observed in the data.

Finally, since production uses four types of inputs (L_{nhsy}, K_{nhsy}, M^D_{nhsy}, and M^I_{nhsy}) with four terms that shift productivity-adjusted prices of these inputs (T^L_{nhsy}, T^K_{nhsy}, T^M_{nhsy}, and P^I_{nsy}), we normalize the mean of log idiosyncratic firm TFP, $\log\phi$, to one in every $\{n, h, s\}$-cell. We also assume without loss of generality that the production function weights ω^X, ω^V, and ω^M are constant over time.[18]

3.4 Market structure and markups

We assume a market structure of monopolistic competition in output markets: each firm produces a unique product and chooses its output price to maximize profits, taking as given the prices charged by all other firms. Recall from equation (3.1) that all firms exporting in sector s face a demand price elasticity of $-\sigma_s$. As discussed in section 3.7 below, domestic demand is characterized by the same price elasticity. Hence, all firms within a sector s charge a common and constant markup $\mu_s = \frac{\sigma_s}{\sigma_s - 1}$ over their respective marginal costs.

[17] As with prices of imported final goods, prices of imported inputs P^I_{nsy} capture both differences in quality and changes in the value of the RMB. See footnote 16.

[18] These weights will play no role in the analysis or quantitative results.

3.5 Factor stocks

3.5.1 Labor supply

Each location h is endowed with an exogenous and time-varying quantity of inelastically supplied labor, L_{hy}, that is immobile across locations. We denote the prices of labor by P^L_{hy}. Changes in labor stocks over time account for population growth, migration within China, and labor supply decisions. Since we treat labor supply as exogenous, however, we abstract from the responses of these margins to other changes in economic fundamentals.

3.5.2 Capital accumulation

Capital stocks are ownership-sector specific and are denoted by K_{nsy} with prices P^K_{nsy}. These capital stocks are accumulated endogenously via the following investment technology:

$$K_{nsy} = \left(\frac{K_{ns,y-1}}{\xi_s}\right)^{\xi_s} \left(\frac{\theta_{nsy} I_{nsy}}{1-\xi_s}\right)^{1-\xi_s} \tag{3.10}$$

where the parameter ξ_s controls the rate of capital depreciation conditional on a given level of investment I_{nsy}. We assume that investment is paid in units of sector output (described below) at price P_{0sy}, which allows the nominal cost of investment to respond directly to shocks at the sector level. The parameter θ_{nsy} then determines the rate at which sector output can be transformed into new units of capital. In practice, this rate may vary for several reasons. For example, technological improvements that enable the completion of investment projects using fewer resources map to higher values of θ_{nsy}. On the other hand, mismanagement of investment projects (due to corruption of state-run construction programs, for instance) or policy barriers that limit firm choice (such as local sourcing or technology transfer requirements for FIEs) map into lower values of θ_{nsy}. We therefore refer to θ_{nsy} as *investment efficiency*.[19]

Since we assume that capital stocks are ownership-sector specific, the number of distinct types of capital is large. As a result, solving for optimal investment paths within each ownership-sector under standard assumptions about the capital accumulation process is computationally infeasible.[20] Hence, we instead assume that households own all capital stocks in the economy and sell investment contracts for $\{n, s\}$-capital at a nominal price P^θ_{nsy} that grant an investor control rights over the asset for one period. In equilibrium, free-entry of investors implies that the bid price P^θ_{nsy} exactly offsets any profits that are gained from investment. Investment decisions can then be characterized as a sequence of static

[19]Our notion of investment efficiency is the same as in Eaton et al. (2016), who find that declining investment efficiency in consumer durables largely explains the decline in global trade during the Great Recession.

[20]This would imply a dynamic state-space for capital of dimension $N \times S = 33$.

problems. Although this abstracts from the savings incentive for capital accumulation, it allows the model to capture endogenous changes in year-to-year capital growth rates that are heterogeneous across a finely disaggregated set of firms. We view this as a tradeoff worth making given the goal of the export accounting exercise.

Under these assumptions, the profit-maximization problem for a representative $\{n, s\}$-investor can be expressed as:

$$\pi^{\theta}_{nsy} = \max_{K_{ns,y-1}, I_{nsy}} \left\{ P^{K}_{nsy} K_{nsy} - P_{0sy} I_{nsy} - P^{\theta}_{nsy} K_{ns,y-1} \right\} \tag{3.11}$$

subject to the investment technology (3.10) and the existing capital stock $K_{ns,y-1}$. Optimal investment is:

$$I_{nsy} = \frac{1-\xi_s}{\xi_s} \left(\theta_{nsy}\right)^{\frac{1-\xi_s}{\xi_s}} \left(\frac{P^{K}_{nsy}}{P_{0sy}} \right)^{\frac{1}{\xi_s}} K_{ns,y-1} \tag{3.12}$$

which implies the following growth rate of the capital stock:

$$\frac{K_{nsy}}{K_{ns,y-1}} = \frac{1}{\xi_s} \left(\frac{\theta_{nsy} P^{K}_{nsy}}{P_{0sy}} \right)^{\frac{1-\xi_s}{\xi_s}} \tag{3.13}$$

Furthermore, the free-entry condition for investors requires $\pi^{\theta}_{nsy} = 0$, which implies the following investment bid price:

$$P^{\theta}_{nsy} = \left(P^{K}_{nsy}\right)^{\frac{1}{\xi_s}} \left(\frac{P_{0sy}}{\theta_{nsy}} \right)^{-\frac{1-\xi_s}{\xi_s}} \tag{3.14}$$

Hence, investment, capital growth, and the investment bid price are all increasing in the capital price and investment shock but are decreasing in the cost of investment.

3.6 Market entry costs

To model the extensive margin of how many firms enter a given market, we assume that selling to market d requires a $\{n, h, s\}$-firm to pay a marketing cost f^{M}_{dnhsy} in every period that the firm actively sells in the market. As with investment costs, marketing costs are paid in units of sector output at price P_{0sy}, which allows the nominal fixed cost of exporting to respond directly to shocks at the sector level.

If not all $\{n, h, s\}$-firms sell to market d, the fact that firm sales are increasing in idiosyncratic TFP ϕ implies that the marginal firm entering the market must have idiosyncratic TFP ϕ^{M}_{dnhsy} satisfying the following market entry condition:

$$\frac{1}{\sigma_s} \Phi_{dnhsy} \left(\phi^{M}_{dnhsy}\right)^{\sigma_s - 1} = P_{0sy} f^{M}_{dnhsy} \tag{3.15}$$

where Φ_{dnhsy} is an aggregate sales shifter:

$$\Phi_{dnhsy} \equiv A_{dnhsy} \left(\mu_s \tau_{dsy} \eta_{nhsy}\right)^{1-\sigma_s} \tag{3.16}$$

We assume that $f^M_{0nhsy} = 0$, so that all firms sell to the domestic market with $\phi^M_{0nhsy} = 0$.[21]

3.7 Aggregation

Output produced at the firm-level for the domestic market is aggregated to the sector-level under perfect competition using a CES technology combining output from firms across all ownership-locations within the sector:

$$M_{sy} = \left[\sum_{n=1}^{N} \sum_{h=1}^{H} \int_{\phi^M_{0nhsy}}^{\infty} N_{nhsy} \nu_{0nhsy}^{\frac{1}{\sigma_s}} \left[X_{0nhsy}(\phi)\right]^{\frac{\sigma_s - 1}{\sigma_s}} dG_{nhs}(\phi)\right]^{\frac{\sigma_s}{\sigma_s - 1}} \tag{3.17}$$

As described above, sector-level output is used for four purposes: final consumption, domestic materials, investment, and marketing costs. As is standard in the literature, the elasticity of substitution in the sector production function σ_s is assumed to be the same as the price elasticity in export demand in equation (3.1). Domestic demand for output of a $\{n, h, s, \phi\}$-firm is then given by:

$$X_{0nhsy}(\phi) = A_{0sy} \nu_{0nhsy} p_{0nhsy}(\phi)^{-\sigma_s} \tag{3.18}$$

where the domestic demand shifter is:

$$A_{0sy} \equiv M_{sy} \left(P_{0sy}\right)^{\sigma_s} \tag{3.19}$$

and P_{0sy} is equal to the ideal price index corresponding to the aggregator (3.17).

Under CES markups μ_s, sales generated in market d for $\{n, h, s\}$-firms are then given by $R_{dnhsy}(\phi) = \Phi_{dnhsy} \phi^{\sigma_s - 1}$. Aggregating this across all $\{n, h, s\}$-firms, we can express total sales to market d as:

$$R_{dnhsy} = \Phi_{dnhsy} N_{nhsy} \rho_{dnhsy} \bar{\phi}_{dnhsy}^{\sigma_s - 1} \tag{3.20}$$

where ρ_{dnhsy} is the fraction of $\{n, h, s\}$-firms that sell in market d:

$$\rho_{dnhsy} = \int_{\phi^M_{dnhsy}}^{\infty} dG_{nhs}(\phi) \tag{3.21}$$

[21] An important empirical violation of this assumption is that processing firms in China are restricted from selling to the domestic market. Although we are able to identify processing firms in the customs data, we cannot identify such firms in the ASM data. Hence, we abstract from processing in the model.

and $\bar{\phi}_{dnhsy}$ is a measure of average idiosyncratic productivity among these firms:

$$\bar{\phi}_{dnhsy} \equiv \left[\frac{1}{\rho_{dnhsy}} \int_{\phi_{dnhsy}^{M}}^{\infty} \phi^{\sigma_s - 1} dG_{nhs}(\phi) \right]^{\frac{1}{\sigma_s - 1}} \tag{3.22}$$

The destination-sector price indices can also be expressed as:

$$P_{dsy} = \mu_s \left[\sum_{n=1}^{N} \sum_{h=1}^{H} N_{nhsy} \rho_{dnhsy} \nu_{dnhsy} \left(\eta_{nhsy} / \bar{\phi}_{dnhsy} \right)^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}} \tag{3.23}$$

Note that since the number of ownership-location-sectors that we allow for in the model is very large, characterizing the measure of active firms N_{nhsy} as endogenously determined by forward-looking firm decisions about entry and exit becomes computationally intractable.[22] Hence, in what follows, we treat N_{nhsy} as exogenous. This allows us to examine how heterogeneous changes in entry across a finely disaggregated set of firms matters for aggregate export growth, but precludes us from accounting for endogenous responses of entry to changes in other economic fundamentals. As with our assumptions about the dynamics of capital accumulation described above, we view this tradeoff as worth making given the goal of the accounting exercise.

3.8 Market clearing and trade balance

To close the model, we impose market clearing and a trade balance condition. Market clearing requires the equality of supply and demand for labor markets in each location, capital markets in each ownership-sector, and output markets for each sector. Since we do not model general equilibrium in the rest of the world, we assume exogenous values for China's trade surplus in each year, S_y.[23] In equilibrium, S_y is equal to the difference between total exports and the sum of final and intermediate imports.[24]

4 Estimation Procedure

The model developed in section 3 offers a framework for studying the drivers of Chinese exporting. These drivers map to the following structural parameters of the model: (i) foreign import expenditures, E_{dsy}; (ii) foreign competition, P^{*}_{dsy} (iii) trade costs, τ_{dsy}; (iv) factor productivities, $\left\{T^{L}_{nhsy}, T^{K}_{nhsy}, T^{M}_{nhsy}\right\}$; (v) imported input prices, P^{I}_{nsy}; (vi) investment effi-

[22]This would imply a dynamic state-space for firm entry of dimension $N \times H \times S = 363$.

[23]Alternatively, one could assume that the trade surplus is an exogenous fraction of aggregate consumer expenditure. Our quantitative findings are insensitive to adopting this alternative assumption.

[24]Since the market clearing and trade balance conditions are standard, we omit their formal description.

ciencies, θ_{nsy}; and (vii) employment, L_{hy}. The counterfactual simulations that we use to quantify the contributions of these factors to Chinese export growth also require estimation of the following model parameters: (viii) idiosyncratic TFP distributions, G_{nhs}; (ix) final consumption shares, γ_s; (x) input-output shares, $\alpha_{ss'}$; (xi) investment shares in capital formation, ξ_s; (xii) imported final goods prices, P_{sy}^{FI}; (xiii) export marketing costs, f_{dnhsy}^{M}; and (xiv) substitution elasticities $\left\{\sigma_s, \epsilon_s^F, \epsilon_s^X, \epsilon_s^V, \epsilon_s^M\right\}$.

We now describe in detail how we assign values to these parameters through a series of estimation steps.[25] For brevity, we highlight the key findings from our estimation results in the main text and relegate detailed reporting of the estimates themselves to section H of the online appendix.

Step 1: Direct calibration of parameters

In the first step, we calibrate a set of parameters directly from data or by borrowing from estimates in the literature. First, we parameterize the distributions of idiosyncratic firm-level TFPs, G_{nhs}, as mean-zero log-normal CDFs. We then calibrate the standard deviation of each distribution $\sigma_{\phi,nhs}$ and the elasticity of substitution for each sector σ_s using measures of sales and TFP dispersions.[26] The former are obtained from the ASM data while the latter are obtained from Brandt et al. (2012).[27] Second, the final consumption shares γ_s and input-output coefficients $\alpha_{ss'}$ are calibrated using the WIOD input-output data for China.[28] Third, we calibrate foreign import demand E_{dsy} using data on total imports from the UN Comtrade database. Fourth, we set the share of lagged capital in capital formation at $\xi_s = 0.9$. This implies that investment expenditure is equal to 10% of the value of the contemporaneous capital stock, which is approximately equal to the ratio of aggregate investment in capital construction to total capital costs reported in the ASM data. Finally, utility and production function weights $\left\{\omega^F, \omega^X, \omega^V, \omega^M\right\}$ are normalized without loss of generality to a value of $\frac{1}{2}$.

[25] For brevity, we refer to the approach as "estimation" although it also involves calibration of some model parameters.

[26] Log sales for $\{n, h, s, \phi\}$-firms are equal to an nhs-specific constant plus $(\sigma_s - 1)\log\phi$. Hence, the standard deviation of log sales is equal to $(\sigma_s - 1)\,\sigma_{\phi,nhs}$. Our estimates of the substitution elasticities σ_s range from 5.2 to 6.4, which imply markups in the range of 18-24%.

[27] We then concord these measures from CIC-2 to HS-2 and take averages across years, weighting by the number of firms in each cell at each step.

[28] Since the WIOD data are provided at the ISIC-2 classification, we first concord this to HS-2 and then take averages of input-output shares across years. We use this time-averaged input-output matrix for the calibration.

Step 2: Decomposing the intensive and extensive margins of firm sales

In the second step of the estimation, we decompose firm sales into an intensive and an extensive margin. From equations (3.20)-(3.22), the aggregate sales shifter Φ_{dnhsy} can be expressed as:

$$\Phi_{dnhsy} = \frac{R_{dnhsy}}{N_{nhsy} \int_{\phi^M_{dnhsy}}^{\infty} \phi^{\sigma_s - 1} dG_{nhs}(\phi)} \tag{4.1}$$

Intuitively, Φ_{dnhsy} is an estimate of the intensive margin of sales after controlling for differences in both the number of firms that sell in the market and the average productivity of these firms.

Together with the market entry and sales propensity equations (3.15) and (3.21), equation (4.1) defines a system in three variables: market entry productivity cutoffs ϕ^M_{dnhsy}, nominal marketing costs $P_{0sy} f^M_{dnhsy}$, and sales shifters Φ_{dnhsy}. Given observed values for sales, firm counts, and export propensities, we solve this system numerically for each $\{d, n, h, s, y\}$-cell.[29] In addition to providing us with estimates of the intensive margin of sales Φ_{dnhsy}, this step of the procedure also calibrates export marketing costs to match observed export propensities.[30]

Step 3: Separating demand from marginal production costs

In the third step, we decompose the sales shifters Φ_{dnhsy} obtained from step 2 into demand- and supply-side components. Using equations (3.2) and (3.16), we can express the log sales shifter as:

$$\log \Phi_{dnhsy} = \log\left(\mu_s^{1-\sigma_s}\right) + \underbrace{\log\left(A_{dsy} \tau_{dsy}^{1-\sigma_s}\right)}_{\text{demand-side}} + \underbrace{\log\left(\eta_{nhsy}^{1-\sigma_s}\right)}_{\text{supply-side}} + \underbrace{\log\left(\nu_{dnhsy}\right)}_{\text{residual}} \tag{4.2}$$

In export markets, the term $A_{dsy} \tau_{dsy}^{1-\sigma_s}$ is a demand shifter that largely reflects factors external to China: foreign demand for imports and competition in Chinese exports markets from the rest of the world. On the other hand, the marginal cost term η_{nhsy} largely reflects supply-side factors that are internal to China: factor productivities and factor stocks changes, for example. The factors on the right-hand side of equation (4.2) are then estimated via ordinary least squares (OLS) regression with fixed effects for the various demand- and supply-side terms.[31]

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[29] Section B of the online data appendix describes how we construct measures of firm and exporter counts from the customs and ASM datasets.

[30] We compute real marketing costs from nominal costs after estimating domestic sector prices P_{0sy} below.

[31] This estimation procedure can only be implemented for $\{n, h, s, y\}$-cells that have strictly positive exports. Hence, we drop from our sample all firms in cells that have no exports. This accounts for a very small share of total gross output (around 0.05%) in the ASM data.

There are two main identifying assumptions for OLS to deliver unbiased estimates. First, within each sector s, marginal costs η_{nhsy} are uncorrelated with ν_{dnhsy}. This is innocuous under constant returns production technologies, since the marginal cost of production is independent of differences in scale arising from differences in demand. Second, the demand shifters $A_{dsy}\tau_{dsy}^{1-\sigma_s}$ are uncorrelated with ν_{dnhsy}. Since the cardinality of the set of ownership-locations $(N \times H)$ is large, we assume that variations in ν_{dnhsy} for a given ownership-location $\{n, h\}$ have negligible effects on the price indices P_{dsy} that enter into the demand shifters A_{dsy}. Furthermore, in export markets, this assumption allows foreign consumers to discriminate Chinese imports by firm ownership type and production location but implies that these preference biases are not systematically correlated with total import expenditures E_{dsy}, trade barriers τ_{dsy}, and foreign competition P^*_{dsy}.

Under these assumptions, we thus identify differences in demand shifters $A_{dsy}\tau_{dsy}^{1-\sigma_s}$ from differences in sales across destinations d for firms within an $\{n, h, s\}$-cell. Similarly, we identify differences in marginal production costs from differences in sales across ownership-locations $\{n, h\}$ among all firms that sell to the same destination-sector $\{d, s\}$.

Note that this approach identifies the fixed effects in equation (4.2) within each sector-year up to a constant. Hence, for comparisons across years to be meaningful, we require additional empirical moments to determine the appropriate normalization. To deal with this, we utilize data on output price deflators by CIC-2 sector from the Chinese NBS, denoted by P_{0sy}^{NBS}. These price deflators provide measures of average producer prices for all firms in a sector without correcting for variety. Hence, we assume that the NBS prices are related to our model-based domestic sector price indices as follows:

$$P_{0sy}^{NBS} = P_{0sy} N_{nhsy}^{\frac{1}{1-\sigma_s}} \tag{4.3}$$

This allows us to pin down the *level* of prices and hence marginal production costs within a sector-year, thereby enabling estimation of the fixed effects in equation (4.2) not just relative to each other but in levels.

Steps 2 and 3 of the estimation procedure effectively decompose sales R_{dnhsy} into six components: (i) demand shifters, $A_{dsy}\tau_{dsy}^{1-\sigma_s}$; (ii) production efficiency, $(\mu_s \eta_{nhsy})^{1-\sigma_s}$; (iii) firm selection, $\bar{\phi}_{dnhsy}^{\sigma_s-1}$; (iv) sales propensities, ρ_{dnhsy}; (v) firm entry, N_{nhsy}; and (vi) residuals, ν_{dnhsy}. We find that variation in demand shifters and firm entry explain the largest shares of total sales variance across $\{d, n, h, s, y\}$-cells (32% and 34% respectively), followed by slightly smaller roles for production efficiency (22%) and sales propensities (23%). Reassuringly, variation in residuals plays a smaller role (8%).[32] These estimates suggest that

[32] Variance shares are computed by regressing the log of each component on log sales at the $\{d, n, h, s, y\}$-level. The coefficient on log sales is equal to the share of log sales variance explained by variation in the component in question. The share of variance explained by the firm selection term $\bar{\phi}_{dnhsy}^{\sigma_s-1}$ is negative (-19%),

both external and internal factors are important in explaining the variation in exporting observed in the data. However, note that this decomposition captures variation in both the cross-section and over time, while the counterfactual simulations that we study in section 5 isolate the contributions of various factors to growth in exports over time.

Step 4: Decomposing export demand

Given estimates of the demand shifters $A_{dsy}\tau_{dsy}^{1-\sigma_s}$ for each export market from step 3, we further decompose these into foreign import expenditures and access to these markets for firms in China. Note that since we treat foreign prices P_{dsy}^{*} as exogenous, only the ratios of these prices to the corresponding iceberg trade costs τ_{dsy} are relevant for determining equilibrium outcomes. Hence, we refer to the ratio $\bar{P}_{dsy}^{*} \equiv P_{dsy}^{*}/\tau_{dsy}$ as *market access* for firms exporting from China, which is high if either foreign prices are high or trade costs are low.

The market access terms are then identified from variation in observed market shares for firms in China across destination-sector-years, denoted by s_{dsy}^{X}. We first construct export price indices P_{dsy} from equation (3.23) given the estimates of export productivity cutoffs ϕ_{dnhsy}^{M} and marginal costs η_{nhsy} from steps 2 and 3 respectively. We then measure market shares using UN Comtrade data and recover the market access terms as:

$$\bar{P}_{dsy}^{*} = \left(\frac{s_{dsy}^{X}}{1 - s_{dsy}^{X}} \right)^{\frac{1}{\sigma_s - 1}} P_{dsy} \tag{4.4}$$

Intuitively, market access is estimated to be high if firms operating in China have a large share of an export market after controlling for estimated Chinese export prices.

Our estimates of market access are shown in Table A.4 in the online appendix. Across destinations, we find that market access in most sectors tends to be highest in Asia and lowest in Western Europe. We also estimate better market access in North America than in Western Europe in all sectors. Across sectors, we find better market access in metals, textiles, and leathers and furs. Market access in chemical products, on the other hand, is particular low, while access in machinery is moderate despite the dominance of this sector in Chinese exports.

Furthermore, although China's share in most destination-sector export markets increases over time, we estimate that market access typically *declines* in the first few years of the sample before increasing in subsequent years. For example, in machinery and textiles, market access tends to decline between 2000 and 2007 before trending upward from 2007

reflecting the fact that since only the best firms export, the average idiosyncratic productivity of exporters is higher whenever export propensity is lower.

to 2013. In metals and chemicals, we observe similar reversals in market access trends around 2004. These estimates suggest that during the high-growth period for Chinese exports, competition faced by firms in China from producers in the rest of the world initially intensified but weakened significantly in later years.

Step 5: Decomposing production costs

Given estimates of marginal costs η_{nhsy} from step 3, we further decompose these into factor-augmenting productivities and input prices. Imported input prices P^I_{nsy} are first calibrated to match imported shares of material expenditures s^I_{nsy}:

$$P^I_{nsy} = \left[\left(\frac{1-\omega^M}{\omega^M}\right)\left(\frac{s^I_{nsy}}{1-s^I_{nsy}}\right)\right]^{\frac{1}{1-\epsilon^M_s}} P^D_{sy} \tag{4.5}$$

Import shares are measured as the ratio of total imports of raw materials, capital goods, and intermediates (as defined by the BEC classification) relative to total material costs, while domestic input prices P^D_{sy} are constructed using estimates of sector prices P_{0sy} and the input-output matrix $\{\alpha_{ss'}\}$.[33] Intuitively, import prices are estimated to be high if imported shares of materials are low after controlling for domestic input prices. Note that the estimated import prices rationalize observed import shares exactly. Since we do not have additional variation to estimate the elasticity of substitution ϵ^M_s, we assume that $\epsilon^M_s = \sigma_s$, which implies that imported and domestic materials are as substitutable with each other as with different varieties of domestic materials within the sector.[34]

Our estimates of imported input prices are shown in Table A.5 in the online appendix. We find that FIEs face lower import prices than Chinese firms, which is indicative of the higher imported input shares that we observe for these firms in the data. For example, we estimate that FIEs in machinery and textiles enjoy imported input prices that are 23% and 20% lower respectively than those faced by PIEs in the average year of the sample. We also estimate more rapid declines in import prices before 2004 than afterwards. This reflects the observation that growth in import shares for FIEs and SOEs occurs primarily between 2000 and 2004, with shares leveling off or declining after 2004, while PIE import shares remain low throughout the sample period and even decline in some sectors.

Next, we estimate factor-augmenting productivities $\left\{T^L_{nhsy}, T^K_{nhsy}, T^M_{nhsy}\right\}$ and input sub-

[33] Imports are measured from the customs data while material costs are constructed from the ASM data. The exact procedure that we use to construct measures of imported input shares is described in section F of the online data appendix.

[34] We calibrate prices for imported final goods P^{FI}_{sy} using the same approach as for intermediate input prices. Final consumption import shares are computed using measures of imported consumer goods from the customs data (based on the BEC classification) and measures of domestic final consumption from the WIOD.

stitution elasticities $\left\{\epsilon_s^X, \epsilon_s^V, \epsilon_s^M\right\}$ using observed data on input expenditures and input prices. Cost-minimization under the nested CES technologies described in section 3.3 implies that the ratio of labor expenditure E_{nhsy}^L to capital expenditure E_{nhsy}^K can be expressed as:

$$\log\left(\frac{E_{nhsy}^L}{E_{nhsy}^K}\right) = \log\frac{\omega^V}{1-\omega^V} + \left(\epsilon_s^V - 1\right)\log\left(\frac{P_{nsy}^K}{P_{hy}^L}\right) + \left(\epsilon_s^V - 1\right)\log T_{nhsy}^{LK} \tag{4.6}$$

where $T_{nhsy}^{LK} \equiv T_{nhsy}^L / T_{nhsy}^K$ denotes relative productivity of labor versus capital. Similarly, the ratio of value-added cost $E_{nhsy}^V \equiv E_{nhsy}^L + E_{nhsy}^K$ to materials expenditure E_{nhsy}^M can be expressed as:

$$\log\left(\frac{E_{nhsy}^V}{E_{nhsy}^M}\right) = \log\frac{\omega^X}{1-\omega^X} + \left(\epsilon_s^X - 1\right)\log\left(\frac{P_{nsy}^M}{\tilde{P}_{nhsy}^V}\right) + \left(\epsilon_s^X - 1\right)\log T_{nhsy}^{LM} \tag{4.7}$$

where $\tilde{P}_{nhsy}^V \equiv P_{nhsy}^V T_{nhsy}^L$ denotes the price of value-added in equation (3.7) adjusted by labor productivity and $T_{nhsy}^{LM} \equiv T_{nhsy}^L / T_{nhsy}^M$ denotes relative productivity of labor versus materials.

Equations (4.6) and (4.7) resemble specifications in the production function estimation literature that are commonly used to estimate input substitution elasticities and factor-augmenting productivities by regressing relative factor expenditures on relative factor prices. The standard omitted variable bias problem is that factor productivities are unobserved and are likely to be correlated with the factor price regressors. Hence, we follow the approach in Doraszelski and Jaumandreu (2018) and estimate these equations using an instrumental variables method, as follows.

First, to estimate equation (4.6), we measure labor and capital expenditures and prices from the ASM data.[35] We then instrument for relative factor prices using a third-degree polynomial in one-year lags of the same factor prices and factor stocks. To control for potential serial correlation in factor productivities, we also include as a regressor in equation (4.6) a third-degree polynomial control function in lagged relative factor expenditures and prices. The instruments and control function are valid under the assumption that factor-augmenting productivities follow first-order Markov processes.[36] Using this approach, we estimate equation (4.6) separately for each sector, which gives estimates of the labor-capital substitution elasticities ϵ_s^V and relative productivities T_{nhsy}^{LK}. Our estimates of ϵ_s^V are shown in the left panel of Figure A.5 in the online appendix. We find that labor and capital are complements in all but one sector (plastics and rubber) and estimate lower substitution elasticities in sectors such as machinery and transportation.

[35] Details of the procedure that we use to construct measures of factor costs and prices from the ASM data are described in section G of the online data appendix.

[36] See Doraszelski and Jaumandreu (2018) for details.

Next, we use these estimates to construct adjusted value-added prices $\tilde{P}^V_{nhsy}$ and material prices P^M_{nsy} as implied by the model. Together with measures of material expenditures and value-added costs from the ASM data, we then estimate equation (4.7) using the same approach as for equation (4.6), which gives estimates of the value-added-materials substitution elasticities ϵ^X_s and relative productivities T^{LM}_{nhsy}. Our estimates of ϵ^X_s are shown in the right panel of Figure A.5 in the online appendix. We find value-added and materials to be complements in some sectors (e.g. machinery and transportation) and substitutes in others (e.g. textiles and metals).

Finally, we infer the *levels* of factor-augmenting productivities using our estimates of marginal costs from step 3 of the estimation procedure. We first recover labor-augmenting productivity by inverting the expression for marginal cost implied by the nested CES production technologies:

$$T^L_{nhsy} = \frac{1}{\eta_{nhsy}} \left[\omega^X \left(\tilde{P}^V_{nhsy} \right)^{1-\epsilon^X_s} + \left(1 - \omega^X \right) \left(P^M_{nsy} T^{LM}_{nhsy} \right)^{1-\epsilon^X_s} \right]^{\frac{1}{1-\epsilon^X_s}} \tag{4.8}$$

where all variables and parameters on the right-hand side are known. We then recover capital productivity as $T^K_{nhsy} = T^L_{nhsy}/T^{LK}_{nsy}$ and material productivity as $T^M_{nhsy} = T^L_{nhsy}/T^{LM}_{nsy}$. This approach ensures that the marginal costs of production implied by the model match exactly with the marginal cost estimates that we obtain from the fixed-effects regressions in step 3.

To summarize how our estimates of factor-specific productivities and costs evolve over time, we first define *efficiency growth* as the growth in inverse marginal cost, η_{nhsy}. Note that changes in efficiency stem from changes in both factor productivities and factor costs. Hence, we define *productivity growth* as the change in efficiency that results only from productivity changes, holding factor prices fixed.[37] These statistics are shown in Table 1 for the average firm within each sector, averaged across four year windows for brevity. We also define growth in wage, capital cost, imported input cost, and domestic input cost efficiency as the changes in efficiency that result only from changes in the respective factor prices. These statistics are presented in Table A.6 of the online appendix. We highlight four main observations.

First, there is noticeable heterogeneity in productivity growth across sectors, with more positive growth in sectors such as machinery (2.2% per year between 2000 and 2013), textiles (3.5%), and transportation (2.8%), compared with lower productivity growth in sectors such as metals (-0.3%) and chemical products (0.8%). Second, productivity growth rates tend to be higher before 2007 than after. For example, we observe average growth rates in machinery and textiles of 3.5% and 5.7% respectively between 2000 and 2007, but see these rates fall to

[37] This is equivalent to TFP growth in a model with only factor-neutral productivity.

	(a) efficiency growth				(b) productivity growth			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	1.4	1.5	-1.7	-3.2	1.8	5.8	2.2	-0.9
Textiles & Apparel	0.5	1.5	-4.4	-3.0	2.9	9.5	1.5	0.5
Metals	-2.5	-4.0	-4.9	-1.0	0.5	0.6	-2.4	-0.3
Chemical Products	0.4	-1.0	-5.8	-5.5	2.5	4.3	-0.6	-3.4
Transportation	-0.4	3.0	-4.1	-4.2	2.8	8.6	1.3	-1.4
Plastics & Rubber	-1.0	-2.0	-3.6	-4.0	-0.2	3.0	1.6	-1.9
Stone & Glass	0.2	-2.4	-4.4	-4.1	2.4	6.0	0.9	-2.5
Leathers & Furs	-0.2	-1.1	-2.5	-1.0	1.7	6.9	5.1	1.8
Wood Products	-0.7	1.6	-3.9	-2.9	0.7	8.2	0.9	0.0
Foodstuffs	-1.8	-0.9	-10.9	-7.5	-0.5	2.2	-8.3	-7.1
Miscellaneous	-0.4	-0.6	-2.6	-3.2	-0.2	6.7	3.9	-1.6

Table 1: Efficiency and productivity growth

Notes: Panel (a) shows annual efficiency growth rates, while panel (b) shows the contributions to efficiency growth arising from changes in factor productivities. All values are computed for the average firm in each sector-year and then averaged across years in each window. All values are in units of percentage points.

0.7% and 1.0% respectively between 2007 and 2013. Third, nominal cost reductions induced by productivity growth are largely offset by growth in wages (which increase at 14.9% per year for the average firm) and growth in capital costs (10.1% per year).[38] Wage growth tends to be more important in labor-intensive sectors such as textiles, whereas capital cost growth dominates in capital-intensive sectors such as transportation. Fourth, reductions in both imported and domestic input prices tend to contribute positively to efficiency growth, although the decline in import prices occurs primarily before 2004 with much larger effects in machinery than in other sectors. Efficiency improvements from falling domestic input costs reflect not only productivity growth but also firm entry in upstream sectors.

There are also stark differences in estimated productivity levels across firm ownership types. To summarize these patterns, we first compute efficiency for a PIE in a given location-sector-year if the firm faced estimated PIE factor productivities but FIE factor prices. The difference between this measure and FIE efficiency in the same location-sector-year reflects differences in efficiency that are attributable solely to differences in productivity.[39] We then compute the average of the counterfactual efficiency measure for all PIEs within a sector and compare this to the average efficiency for FIEs. This gives us a sector-level measure of the productivity gap between PIEs and FIEs. We construct similar measures for SOEs using FIEs as the baseline.

Table 2 presents our estimates of these productivity gaps. We find that FIEs are more

[38]The negative efficiency growth that we observe in most sector-years largely reflects inflation in the NBS producer price indices that we use to pin down levels of marginal costs in equation (4.2).

[39]This is equivalent to differences in TFP in a model with only factor-neutral productivities.

	(a) PIE-FIE productivity gap				(b) SOE-FIE productivity gap			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	0.68	0.73	0.74	0.73	0.53	0.56	0.65	0.69
Textiles & Apparel	1.10	1.12	1.04	1.08	0.70	0.69	0.96	0.89
Metals	0.97	0.97	0.89	0.98	0.76	0.75	0.72	0.81
Chemical Products	1.05	0.97	0.82	0.93	0.73	0.73	0.67	0.77
Transportation	0.84	0.83	0.82	0.77	0.68	0.63	0.71	0.75
Plastics & Rubber	0.86	0.93	0.90	0.99	0.75	0.78	0.77	0.84
Stone & Glass	0.84	0.85	0.80	1.01	0.65	0.57	0.66	0.79
Leathers & Furs	1.09	1.20	1.13	1.23	0.53	0.54	0.56	0.56
Wood Products	0.92	0.93	0.78	0.90	0.46	0.47	0.45	0.49
Foodstuffs	0.87	0.79	0.70	0.77	0.72	0.71	0.62	0.77
Miscellaneous	0.87	0.95	0.89	1.05	0.60	0.57	0.60	0.74

Table 2: PIE and SOE productivity gaps relative to FIEs

Notes: Productivity gaps are computed as the ratio of counterfactual PIE/SOE efficiency under FIE factor prices for the average PIE/SOE in each sector-year relative to average FIE efficiency in the same sector-year. Productivity gaps are averaged across years in each window.

productive than PIEs and SOEs in all sectors except two − textiles, and leathers and furs − where PIEs tend to dominate. Furthermore, PIEs are estimated to be more productive than SOEs in all sectors. We estimate the average productivity gap for PIEs and SOEs relative to FIEs across all sectors and years to be 11% and 31% respectively. Underlying these aggregate statistics, however, are important differences across both sectors and time. In machinery, for example, we estimate large average productivity gaps for PIEs and SOEs relative to FIEs of 29.4% and 46.0%, respectively between 2000 and 2007. Catch-up by PIEs and SOEs reduces these productivity gaps to averages of 26.9% and 32.9% respectively between 2007 and 2013, although the rate of catch-up for PIEs slows noticeably after 2007. In textiles, the productivity advantage that PIEs enjoy over FIEs diminishes from an average of 11.2% between 2000 and 2007 to 6.2% between 2007 and 2013, while SOEs exhibit rapid catch-up between 2007 and 2010.

Step 6: Calibrating factor stocks and investment efficiencies

The decomposition of exports described in steps 2-5 generates estimates of model parameters that allow the model to match observed exports exactly by construction. However, note that the decomposition of marginal costs into factor-augmenting productivities in step 5 is conditional on *measured* prices of labor and capital, $\left\{P^L_{hy}, P^K_{nsy}\right\}$, which are endogenous objects in the model. Hence, in the last step of the estimation procedure, we use the market clearing and trade balance conditions of the model to calibrate labor and capital stocks $\{L_{hy}, K_{nsy}\}$ that are consistent with these observed factor prices.[40] We find strong correlation between measured factor stocks and the calibrated factor stocks obtained using this procedure.[41]

Note that since capital is endogenous, this procedure also requires calibrating the investment efficiencies θ_{nsy} to ensure that the calibrated capital stocks are consistent with the investment technology. From equation (3.13), we recover the investment efficiencies as:

$$\theta_{nsy} = \left(\frac{\xi_s K_{nsy}}{K_{ns,y-1}}\right)^{\frac{\xi_s}{1-\xi_s}} \left(\frac{P^K_{nsy}}{P_{0sy}}\right)^{-1} \tag{4.9}$$

We therefore infer investment efficiencies to be high if capital growth rates are high or if the relative cost of capital to investment P^K_{nsy}/P_{0sy} is low. Note that the latter is equivalent to the rate of return on a nominal unit of investment when investment efficiency is equal to one. Hence, we refer to this as the *unadjusted* return on investment. When this return is low, investment efficiencies must be high so that returns adjusted by θ_{nsy} are commensurate with the observed rate of capital growth.

Our estimates of investment efficiencies are shown in Table A.7 of the online appendix. To help interpret these findings, we also provide detailed estimates of capital growth rates and the unadjusted returns to investment in Figures A.6 and A.7 respectively. Several observations are noteworthy.

First, we find that SOEs typically have lower investment efficiencies than FIEs and PIEs. This largely reflects lower rates of capital accumulation for SOEs.[42] Second, we find comparable investment efficiencies for FIEs and PIEs before 2007, with FIEs dominating in some sectors and PIEs in others. After 2007, however, we find that PIEs enjoy higher investment efficiencies than FIEs in virtually every sector. Third, investment efficiency tends to decline over time. For example, we find that investment efficiencies are lower on average between 2010-2013 than between 2000-2004 for both FIEs and PIEs in almost every sector.[43] While the unadjusted returns to investment for FIEs and PIEs rise steadily throughout the sample, implying strong incentives for capital accumulation, capital growth rates remain either relatively constant (PIEs) or, after initially rising, drift downwards (FIEs). This behavior is

[40] The market clearing and trade balance conditions constitute a linear system in $\{L_{hy}, K_{nsy}\}$. Hence, this step of the estimation procedure is computationally straightforward.

[41] We find correlation coefficients of 0.95 between estimated and measured labor stocks at the province-year and 0.83 between estimated and measured capital stocks at the ownership-sector-year level.

[42] For instance, the aggregate capital stock for SOEs in all sectors declines at an average rate of -1.6% per year, compared with positive growth rates of 9.8% and 17.4% for FIE and PIE capital stocks respectively. We also estimate that SOEs have lower unadjusted rates of return on investment. This would imply higher investment efficiencies for SOEs, but this is more than offset by differences in capital growth rates.

[43] SOE investment efficiency also falls through the first half of the sample period but then begins to rise, especially between 2010 and 2013.

indicative of growing obstacles for firms in taking advantage of profitable investment opportunities. Finally, within each ownership type, investment efficiency is consistently higher in more labor-intensive sectors such as textiles, leathers and furs, and wood products, than in more capital intensive such as machinery and transportation. This relationship is also robust over time.

5 Counterfactual Simulations

5.1 Methodology

Having estimated the structural parameters of the model, we now formally quantify how changes in these factors have shaped the dynamics of Chinese exporting. To do so, we use the model to perform a series of counterfactual exercises.

Under the estimation procedure described in section 4, the export values R_{dnhsy} implied by the model match the corresponding export values in the data exactly by construction for every $\{d, n, h, s, y\}$-cell. Hence, to quantify the contribution of each structural factor to Chinese export growth, we adopt the following approach. First, for each year y, let R_y^X denote the aggregate value of Chinese exports observed in the data. Then, for a given set of structural parameters Θ, let $\hat{R}_y^X(\Theta)$ denote the equilibrium value of exports in the model when all structural parameters are set at their estimated values in year y except for Θ, which is set at its estimated value in year $y-1$. We then measure the contribution of changes in Θ to changes in aggregate Chinese exports in each year using the following statistic:

$$\delta_y(\Theta) \equiv R_y^X / R_{y-1}^X - \hat{R}_y^X(\Theta) / R_{y-1}^X \tag{5.1}$$

Intuitively, this measures the decline in percentage growth of aggregate exports between years $y-1$ and y that would result from eliminating changes in Θ between years $y-1$ and y.[44] We hence refer to $\delta_y(\Theta)$ as the *export growth contribution* of factor Θ.

We then compute export growth contributions for seven sets of factors: (i) foreign demand for exports, E_{dsy}; (ii) foreign market access, $\bar{P}^*_{dsy}$; (iii) factor productivities, $\bar{T}_{nhsy}$; (iv) firm entry, N_{nhsy}; (v) imported input access, P^I_{nsy}; (vi) investment efficiencies, θ_{nsy}; and (vii) employment, L_{hy}. In each case, we simulate counterfactuals holding parameter values fixed along all the relevant margins simultaneously to examine aggregate effects, as

[44] Alternatively, one could measure the contribution of Θ to aggregate export growth using the statistic $\delta_y^+(\Theta) \equiv \hat{R}_{y-1}^{X+}(\Theta) / R_{y-1}^X - 1$, where $\hat{R}_{y-1}^{X+}(\Theta)$ denotes the equilibrium value of exports when all structural parameters are set at their estimated values in year $y-1$ except for Θ, which is set at its estimated value in year y. This measures how many percentage points of aggregate export growth between years $y-1$ and y are accounted for solely by changes in Θ between $y-1$ and y. The main findings that we highlight below are qualitatively similar when using either δ_y or δ_y^+ as the relevant metric.

		2000-2004	2004-2007	2007-2010	2010-2013
foreign demand	E_{dsy}	8.4	10.9	3.2	5.5
market access	$\bar{P}^*_{dsy}$	-4.6	-1.7	2.5	1.9
factor productivities	$\bar{T}_{nhsy}$	1.4	5.4	0.7	-2.3
firm entry	N_{nhsy}	3.0	1.3	0.0	0.0
imported input access	P^I_{nsy}	13.0	3.4	-0.1	1.5
investment efficiencies	θ_{nsy}	-0.1	-2.4	0.9	-0.8
employment	L_{hy}	1.5	1.7	1.3	0.5
aggregate export growth		25.8	28.6	10.8	11.4

Table 3: Aggregate export growth contributions

Notes: Each cell of the table shows the export growth contributions $\delta_y(\Theta)$ defined in equation (5.1) for the parameters Θ indicated in the respective row, applied along all the relevant margins simultaneously. The statistics are averaged over the years y indicated in the columns of the table and shown in units of percentage points.

well as along each margin separately to examine the heterogeneity of these effects across different destinations, firm ownership types, production locations, and sectors.[45]

5.2 Results

5.2.1 Aggregate results

We begin by presenting aggregate results, where export growth contributions $\delta_y(\Theta)$ are computed by holding each set of parameters Θ constant for all relevant destinations, firm ownership types, production locations, and sectors. These simulations highlight the primary drivers of growth in aggregate Chinese exports. Our findings are summarized in Table 3, where we present export growth contributions in units of percentage points per annum (ppa), averaged across years in four windows (2000-2004, 2004-2007, 2007-2010, and 2010-2013).[46] We highlight two sets of insights from these aggregate results.

First, from 2000 to 2007, both external and internal factors were important in driving high rates of export growth. Growth in foreign demand contributed an average of 9.5 ppa during this period, although this was partially offset by stiffer foreign competition in Chinese export markets, which lowered growth by an average of 3.4 ppa. Within China, growth in factor productivities, improvements in access to imported inputs, and firm entry

[45]We find that changes in factor-augmenting productivities are strongly correlated, with positive correlation between changes in labor and capital productivities and negative correlation between changes in value-added productivities and material productivities. Hence, we perform counterfactual simulations on all three types of factor productivities jointly instead of individually.

[46]Note that the export growth contributions are not additive due to interactions between the factors and do not necessarily sum up to aggregate export growth in each year.

were primary drivers of export growth. We find that productivity growth played a larger role between 2004 and 2007, contributing an average of 5.4 ppa, while improved import access and firm entry contributed more positively before 2004. Improvements in imported input access were particularly important during this period, contributing 13.0 ppa on average, while high rates of firm entry contributed an average of 3.0 ppa. Employment growth was a positive secondary driver of aggregate export growth with an average contribution of 1.6 ppa between 2000 and 2007. On the other hand, we find that declining investment efficiencies contributed negatively to export growth during this period.

Second, we observe important structural changes in the underlying drivers of export growth after 2007. Most notably, we find that the slowdown in aggregate export growth during this period arises from a weakening in both external and internal factors, with the contribution of internal factors declining the most. As a result, external factors become relatively more important. For instance, the contribution of foreign demand growth falls by more than half to an average of 4.4 ppa between 2007 and 2013, but this is partially offset by changes in market access, which begin to contribute positively to export growth rather than negatively. Recall that changes in market access reflect changes in either the prices of foreign competitors in these markets or iceberg trade costs. Within China, on the other hand, the positive drivers of export growth largely disappear. The contributions arising from factor productivity growth fall to 0.7 ppa between 2007 and 2010 and turn negative between 2010 and 2013, while firm entry contributes virtually nothing on net between 2007 and 2013. Contributions from improvements in imported input access are also marginal compared to pre-2007 levels, averaging only 0.7 ppa between 2007 and 2013. Even though employment growth continues to contribute positively, its effects weaken over time, while improvements in investment efficiency exhibit positive contributions only between 2007 and 2010.

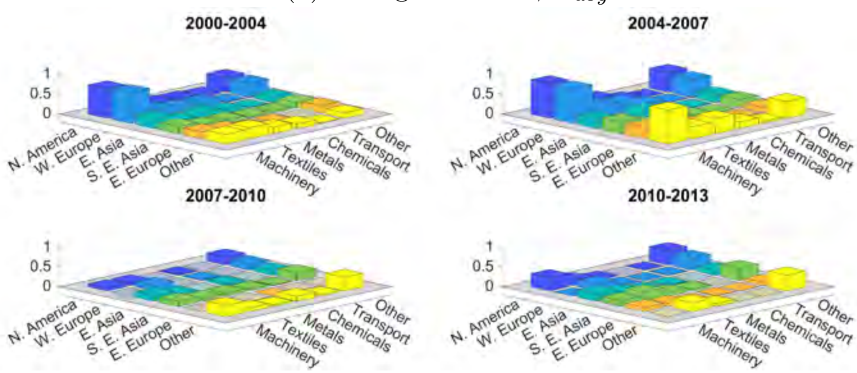
To further investigate these aggregate results, we now examine the heterogeneity of each of these factors in their contributions to export growth, paying particular attention to differences across destinations, firm ownership types, production locations, and sectors.

5.2.2 Foreign demand

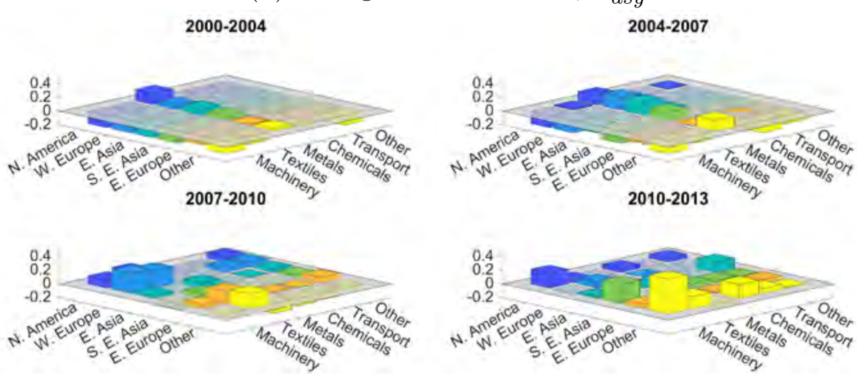
Panel (a) of Figure 3 shows the breakdown of export growth contributions arising from changes in foreign demand E_{dsy} by destination-sectors. Export growth contributions between 2000 and 2007 are typically highest in each sector for the North American market, with growth in demand from Western Europe and East Asia also contributing positively. Across sectors, growth in demand for products in the machinery and textiles sectors are especially important.

Between 2007 and 2013, however, the overall decline in export growth contributions is

(a) Foreign demand, E_{dsy}



(b) Foreign market access, $\bar{P}^{*}_{dsy}$



(c) Factor productivities, $\bar{T}_{nhsy}$

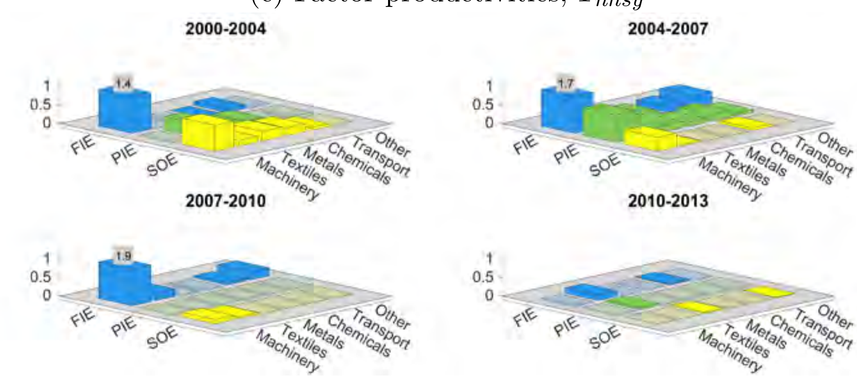
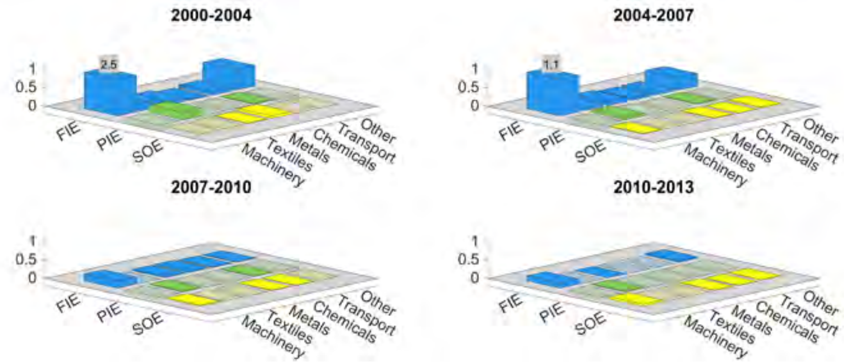


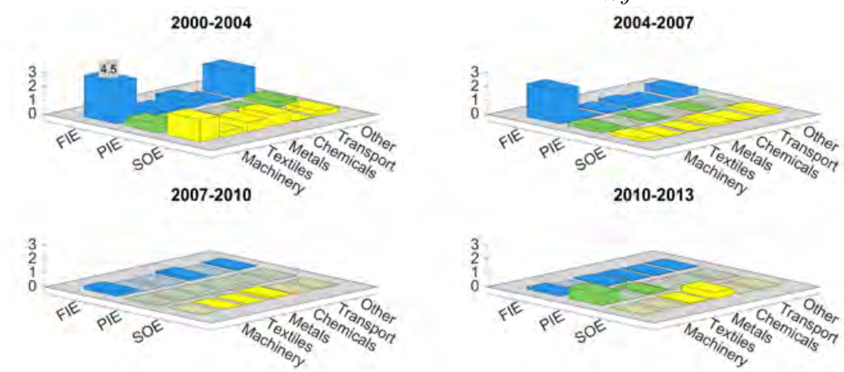
Figure 3: Detailed counterfactual results

Notes: Vertical axes show averages of the export growth contribution $\delta_y(\Theta)$ defined in equation (5.1), applied along the indicated margins and averaged across years in each window. For presentation clarity, negative values are truncated and positive outliers are indicated with values at the top of the relevant bars.

(d) Firm entry, N_{nhsy}



(e) Imported input access, P^I_{nsy}



(f) Investment efficiencies, θ_{nsy}

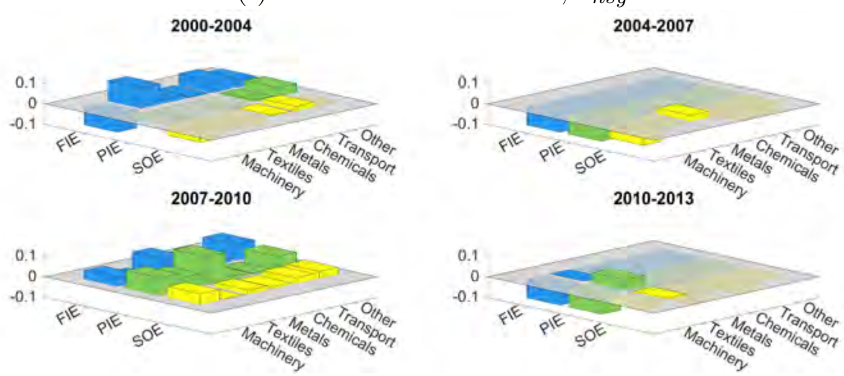


Figure 3: Detailed counterfactual results (continued)

Notes: Vertical axes show averages of the export growth contribution $\delta_y(\Theta)$ defined in equation (5.1), applied along the indicated margins and averaged across years in each window. For presentation clarity, negative values are truncated and positive outliers are indicated with values at the top of the relevant bars.

also largely explained by lower contributions from high-income markets in North America, Western Europe, and East Asia. The decline in contributions from North American demand for machinery and textiles is especially pronounced. Contributions from regions in the periphery, on the other hand, remain at levels that are similar to pre-2007 values. These patterns reflect systematic changes in the geographic distribution of Chinese exports, as the share of exports accounted for by developed country markets in North America, Western Europe, and East Asia declines from 2007 onward (Fact 2).

5.2.3 Foreign market access

Panel (b) of Figure 3 shows the breakdown of export growth contributions arising from changes in foreign market access $\bar{P}^*_{dsy}$ by destination-sectors. Before 2007, we observe positive contributions from improvements in market access only in metals, indicating that firms in China faced stiffening competition in all other export markets despite enjoying rapid export growth to these markets. One potential explanation for this is that productivity growth within and outside China is positively correlated, which would imply that the positive productivity growth that we observe within China during this period (as documented in panel (b) of Table 1) occurred in parallel with productivity improvements in other countries that also made exporters from these locations more competitive. In the later years of the sample, however, we observe substantial changes, with positive contributions from improved market access materializing in North America and Western Europe in the markets for machinery and textiles, and in Eastern Europe across almost all sectors.

5.2.4 Factor productivities

Panel (c) of Figure 3 shows the breakdown of export growth contributions from changes in factor-augmenting productivities by ownership-sectors. Here, we observe substantial heterogeneity across both firm ownership types and sectors.

For FIEs, we find that productivity improvements contribute positively to export growth mainly in machinery and transportation. These effects are particularly strong in machinery, contributing an average of 1.5 ppa between 2000 and 2007, and persist through the Great Recession, with contributions of 1.9 ppa between 2007 and 2010. By the end of the sample period, however, the positive effects of FIE productivity growth in both machinery and transportation largely disappear, although we begin to see positive contributions in textiles.

For PIEs, export growth contributions from productivity improvements are largest in textiles between 2000 and 2007, indicative of the huge gains tied to the end of MFA. During this period, PIE productivity improvements in the sector contribute an average of 0.5 ppa to export growth. This is nearly five times larger than the combined contributions from FIE and SOE, despite the fact that the export market shares of PIEs and non-PIEs (FIE plus SOE) were roughly the same. We also observe positive contributions from PIE productivity growth in machinery and transportation between 2004 and 2007, averaging 0.7 ppa and 0.2 ppa, respectively. Export growth contributions from PIE productivity improvements in other sectors, however, are more muted and even negative in some years. Furthermore, PIE productivity growth across all sectors contributes little after 2007, with the exception of growth in textiles and apparel between 2010 and 2013.

Finally, we find that productivity improvements for SOEs contribute strongly to export growth in machinery before 2007, at rates that are initially on par with contributions from FIE productivity growth in the sector. However, while FIE gains persist until 2010, the contributions from SOE productivity growth diminish much earlier and are near zero by 2007. We also observe positive contributions from SOE productivity growth in metals and chemicals before 2004, but find that these two sectors otherwise exhibit substantially lower export growth contributions from productivity improvements, consistent with the lower productivity growth rates for these sectors shown in panel (b) of Table 1.

5.2.5 Firm entry

Panel (d) of Figure 3 shows the breakdown of export growth contributions from firm entry by ownership-sector. We find that entry by FIEs in machinery is particularly important during the high export growth period, with average contributions of 1.9 ppa between 2000 and 2007. This is more than eighty percent of the total contribution of 2.3 ppa from net entry by all firms during this period. The overall decline in contributions from firm entry after 2007, however, is also largely explained by a sharp drop in contributions from FIE entry in machinery to an average of only 0.2 ppa between 2007 and 2013. This reflects the fact that FIE entry in machinery falls from an average of 21.2% per year between 2000 and 2007 to an average of just 2.9% per year between 2007 and 2013. We also see positive but smaller contributions from FIE entry in all other sectors before 2007, but these effects largely disappear by the end of the sample period.

Entry by PIEs, on the other hand, exhibits positive contributions primarily in textiles, dominating the contributions of FIE entry in this sector before 2007. We also find PIE entry in transportation to be important, with export growth contributions on par with those tied to FIE entry in the sector between 2004 and 2007. The export growth contributions from PIE entry in textiles and transportation are also noticeably smaller after 2007, as reflected by the fall in PIE firm entry rates in these two sectors from 23.3% between 2000 and 2007 to 8.7% between 2007 and 2013. For SOEs, entry remains at similar levels or declines throughout the sample period in most sectors, with an average annual growth rate between 2000 to 2013 of less than 0.1%, and sector-level average growth rates between -3.1% and

3.3%. As a result, SOE entry contributes little to export growth.

These patterns in entry contributions help to explain the observed changes in export shares by firm ownership type (Fact 3). Between 2000 and 2007, FIE and PIE entry rates are high while SOE entry rates are low, which contributes to an increase in FIE and PIE export shares during this period and a decline in SOE shares. After 2007, entry rates for FIEs and PIEs both decline, but the slowdown in entry is more pronounced for FIEs. At the same time, SOE entry remains neglible. This contributes to an increase in PIE shares after 2007 and declines in shares for FIEs and SOEs.

5.2.6 Imported input access

Panel (e) of Figure 3 shows the breakdown of export growth contributions arising from changes in imported input access P^I_{nsy} by ownership-sector. The positive aggregate contributions that we observe between 2000 and 2004 are comprised of positive contributions in almost all ownership-sectors, with the most important effects stemming from improvements in imported input access for firms in machinery, textiles, and chemicals, and especially for FIEs in machinery. These effects dissipate quickly between 2004 and 2007, with improvements in imported input access making significant positive export contributions only for FIEs in machinery. After 2007, import access contributes little if at all to export growth, with the exception of PIEs in machinery and SOEs in metals between 2010 and 2013.

5.2.7 Investment efficiencies

Panel (f) of Figure 3 shows the breakdown of export growth contributions arising from changes in investment efficiencies θ_{nsy} by ownership-sector. We observe positive contributions mainly in two instances: (i) for FIEs in most sectors from 2000 to 2004, and (ii) between 2007 and 2010 for almost all ownership-sectors. The first likely reflects an abundance of new investment opportunities for foreign firms entering China associated with WTO accession, while the second stems mainly from atypically high capital growth rates between 2007 and 2008, followed by high growth in both 2009 and 2010 tied to the RMB 4 trillion ($US 586 billion) economic stimulus program in the wake of the Great Recession. In most other instances, however, we find typically negative export growth contributions, which is consistent with the lack of overall improvement in investment efficiencies documented in Table A.7.

5.2.8 Employment

Table 4 shows the breakdown of export growth contributions arising from changes in employment across production locations. Prior to 2007, we find positive contributions from

	2000-2004	2004-2007	2007-2010	2010-2013
Guangdong	2.4	4.2	1.4	-0.2
Jiangsu	0.8	0.8	3.6	2.0
Shanghai	0.5	0.5	-0.2	-0.4
Zhejiang	5.2	1.5	2.2	-1.7
Shandong	1.2	0.4	-0.4	0.3
Other	-0.6	-0.2	1.5	2.6

Table 4: Export growth contributions of employment L_{hy}

Notes: Each cell of the table shows the export growth contributions $\delta_y(\Theta)$ defined in equation (5.1) from changes in employment L_{hy} for the production location(s) indicated in the respective row. The statistics are averaged over the years y indicated in the columns of the table and shown in units of percentage points.

employment growth in all of the top five export provinces. Note that this occurs in parallel with positive wage growth in all provinces during this period (as reflected in panel (c) of Table 1), indicating a strengthening of labor demand in these provinces. On the other hand, we see negative contributions from production locations outside of the top five export provinces on net before 2007.

After 2007, however, there is a noticeable geographic shift in these patterns. Among the top five export provinces, only Jiangsu exhibits higher contributions from employment growth between 2007 and 2013 as compared with earlier years. Production locations outside the top five export provinces, on the other hand, begin to show large and positive contributions from employment growth. These findings reflect the shift in export production away from coastal provinces toward interior locations (Fact 4).

Although we do not model internal migration in China, these findings are consistent with patterns in migration flows between provinces calculated using Chinese population census data. Between 2000 and 2010, the share of total manufacturing employment in the top five export provinces comprised of inter-province migrants increased substantially from 29.7% to 38.5%. Between 2010 and 2015, however, migration to coastal provinces slowed, with the share of inter-province migrants in total manufacturing employment remaining at 38.5% in 2015. These observations are in line with our finding that export growth contributions from employment growth along the coast were more important in the earlier years of the sample than in later years.

6 Conclusion

We document substantial changes in the dynamics of Chinese exports and their composition between 2000 and 2013. To make sense of these complex empirical patterns, we develop a structural model of Chinese exporting that can account for the role of multiple drivers of export growth in a general equilibrium framework. Our counterfactual simulations indicate that both external and internal factors were key drivers of the high rates of aggregate export growth between 2000 and 2007. However, marked diminution in many of these sources of growth after 2007, especially internal factors, are responsible for the slowdown in China's export growth. Contributions from improvements in imported input access, productivity growth and firm entry largely disappear.

There are clear indications that these downward trends persist through 2019 as export growth falls to only 2% per annum between 2013-2019. Aggregate data from China's Business Registry reveal both a decline in new FIE entry and fewer FIEs operating in China's manufacturing sector in 2019 than there were in either 2013 or even 2008. Employment growth in manufacturing also slows considerably in tandem with a leveling off in the absolute number of migrants working in manufacturing in the major exporting provinces. Finally, the value of total manufacturing imports as a share of aggregate intermediate expenditures in manufacturing (gross output less value-added) remains largely unchanged between 2013 and 2017 at around 11%, suggesting little growth in the importance of imported intermediate inputs.

There are alternative explanations for these trends. One possibility is that the slowdown reflects the exhaustion of one-time gains garnered from a series of internal and external reforms to the Chinese economy. This perspective suggests that the Chinese economy converged to a new steady-state growth path by the mid-to-late 2000s, with lower rates of firm entry and productivity growth simply reflecting fewer opportunities for rapid growth moving forward. Smaller trade and investment flows in the years following the Global Financial Crisis, and lower productivity growth in manufacturing in advanced countries would have only reinforced such trends.[47]

We find however significant productivity gaps between FIEs and Chinese firms even at the end of our sample. This suggests more broadly the persistence of productivity gaps between China and advanced countries and thus room for continued productivity growth for Chinese firms. Moreover, even with the sharp decline in export growth, China continues to enjoy growth rates of GDP that are substantially higher than those observed in both advanced economies and many other developing countries. These observations hint that

[47]For example, Eaton et al. (2016) document a decline in consumer spending on tradable goods during the Great Recession and in the years following. Syverson (2017) and Decker et al. (2017) discuss competing explanations for low rates of productivity growth in the US from the early 2000s onward.

opportunities for future growth − for Chinese as well as foreign firms − in fact exist, but are not being realized.

Chinese economic policy may be salient here. Beginning in the mid-2000s, we see a marked shift in Chinese development strategy as policy has become more centralized and top-down, with a renewed focus on import substitution, indigenous innovation, and the building of national champions, often SOEs, in strategic and emerging industries.[48] This shift was reinforced by policy during the Global Financial Crises and strengthened under the leadership of Xi Jinping (Lardy (2019); Economy (2018)). Sorting out these alternative explanations seems essential to explaining China's current macroeconomic trajectory, as well as its influences on the rest of the world. Data availability for later years will help make such analysis possible.

[48]These policy changes are reflected, for example, in the 2006 "National Medium- and Long-term Plan for the Development of Science and Technology" and the 2010 "Decision of the State Council on Accelerating the Fostering and Development Strategic Emerging Industry", both of which are precursors to "Made in China 2025".

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Appendix for "Accounting for Chinese Exports"

For Online Publication

A Imputing ASM production data for 2009 and 2010

Firm-level data for 2009 and 2010 from the ASM are not publicly available. For each of these years, the Chinese National Bureau of Statistics (NBS) reports information in the *Statistical Yearbook of China* at the owner-location and owner-sector level for a subset of variables that we require. Hence, an imputation procedure is required in order to facilitate the inclusion of 2009 and 2010 in our analysis. We implement this as follows.

First, let X^{nbs}_{nsy} denote any variable that we observe at the ownership-sector level in the NBS data for 2008-2010. The first step in our imputation procedure is to impute these variables at the ownership-sector-location level for 2009 and 2010. To do so, we first compute the shares of variable X accounted for by each location within an ownership-sector cell in 2008 and 2011 from the main ASM data:

$$s^X_{h|nsy} \equiv \frac{X^{asm}_{nhsy}}{\sum_{h'=1}^{H} X^{asm}_{nh'sy}} \tag{A.1}$$

for $y \in \{2008, 2011\}$. We then linearly interpolate these shares to generate estimated shares in 2009 and 2010. We then compute *growth rates* of variable X in the NBS data at the ownership-sector level for 2009 and 2010 relative to 2008:

$$g^X_{nsy} \equiv \frac{X^{nbs}_{nsy}}{X^{nbs}_{ns,2008}} \tag{A.2}$$

for $y \in \{2009, 2010\}$. We then apply the imputed location shares and growth rates to impute values at the ownership-location-sector level as follows:

$$\hat{X}_{nhsy} = X^{asm}_{ns,2008} \times g^X_{nsy} \times s^X_{h|nsy} \tag{A.3}$$

for $y \in \{2009, 2010\}$, where $\hat{X}$ denotes the imputed value of X and $X^{asm}_{ns,2008}$ denotes the value of X in the 2008 ASM data at the ownership-sector level. The implicit assumption here is that time trends in shares across locations within an ownership-sector are well-approximated by linear trends and were not significantly affected by events during 2009 and 2010, in particular the Great Recession.

We follow the above procedure to impute the three variables that we are able to observe directly in the NBS data: gross output, firm counts, and employment. We then impute all remaining variables in the ASM data as follows. Let Z denote the variable being imputed. We first compute the ratio of Z to gross output in 2008 and 2011 from the main ASM data:

$$r^{Z}_{nhsy} \equiv \frac{Z^{asm}_{nhsy}}{GO^{asm}_{nhsy}} \tag{A.4}$$

for $y \in \{2008, 2011\}$. We then linearly interpolate these ratios to generate estimated ratios in 2009 and 2010. We then impute variable Z in 2009 and 2010 using the corresponding imputed values of gross output:

$$\hat{Z}_{nhsy} = r^{Z}_{nhsy} \times \hat{GO}_{nhsy} \tag{A.5}$$

for $y \in \{2009, 2010\}$. The implicit assumption here is that time trends in the ratio of each variable Z to gross output within each ownership-location-sector cell are well-approximated by linear trends and were not significantly affected by events during 2009 and 2010, in particular the Great Recession. We adopt the above procedure to impute the following variables at the ownership-location-sector level in 2009 and 2010: labor costs, value-added, profits, exports, capital stocks, and exporter counts.[49]

Figure A.1 shows the time series of the variables that we impute for 2009 and 2010 in the ASM data. For brevity, we show this only by ownership, although plots by location and sector look similar. In general, the imputed values for 2009 and 2010 connect smoothly with values in the surrounding years, with a dip in most variables in 2009 followed by recovery.

B Measuring exporter and firm counts

We require measures of exporter counts by destination-ownership-location-sector-year and of firm counts by ownership-location-sector-year. Let the true values of these measures be denoted by N^{X}_{dnhsy} and N_{nhsy} respectively. In the customs data, we observe exporter counts by destination-ownership-location-sector-year, $N^{X,cus}_{dnhsy}$, and by ownership-location-sector-year, $N^{X,cus}_{nhsy}$. Furthermore, in the ASM data, we observe exporter counts by ownership-location-sector-year, $N^{X,asm}_{nhsy}$, and firm counts by ownership-location-sector-year, N^{asm}_{nhsy}.

If both the customs and ASM data were accurate representations of the universe of firms, the following would hold:

$$N^{X}_{dnhsy} = N^{X,cus}_{dnhsy} \tag{B.1}$$

$$N_{nhsy} = N^{asm}_{nhsy} \tag{B.2}$$

[49]For exporter counts, we use ratios relative to firm counts instead of gross output.

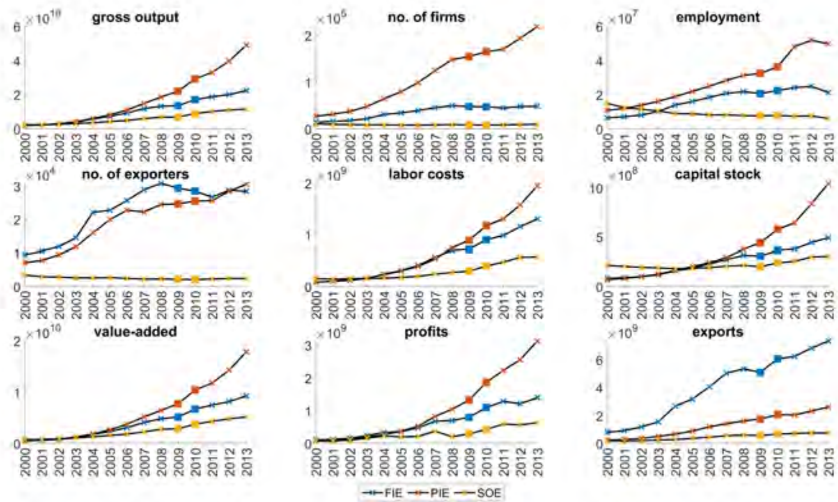

Figure A.1: Time series of variables imputed in ASM data for 2009 and 2010

Notes: All nominal variables in the above figure are in 1000 RMB.

We would then measure exporter counts from the customs data and firm counts from the ASM data. However, there are two reasons why we do not think that these equations are likely to be satisfied. First, equation (B.1) is likely to be violated due to the issue of indirect exporting by PIEs, as discussed in section E. Second, equation (B.2) is likely to be violated since the ASM data do not include below-scale non-state firms.

To deal with these issues, we first make the following assumptions:

1. The extent to which exporter and firm counts are censored in the ASM data does not vary over time:

$$N_{nhsy}^{X,asm} = \rho_{nhs}^{X} N_{nhsy}^{X} \tag{B.3}$$

$$N_{nhsy}^{asm} = \rho_{nhs} N_{nhsy} \tag{B.4}$$

where $\rho_{nhs}^{X}, \rho_{nhs} \in (0, 1)$ are constants of proportionality that capture the extent of censoring in the ASM data.

2. The customs data accurately reflect the share of exporters within each $\{n, h, s, y\}$-cell that export to each destination d:

$$\frac{N_{dnhsy}^{X}}{N_{nhsy}^{X}} = \frac{N_{dnhsy}^{X,cus}}{N_{nhsy}^{X,cus}} \tag{B.5}$$

where N_{nhsy}^{X} denotes the true number of $\{n, h, s\}$-firms that export to any destination in year y. Implicit in this assumption is that conditional on exporting, the likelihood of exporting to each destination d is the same for firms that export either directly or indirectly through trading companies.

Assumption 1 implies that we can measure exporter and firm counts at the ownership-location-sector-year level from the ASM data if we know the extent of censoring, ρ^X_{nhs} and ρ_{nhs}. To measure these censoring ratios, we use the 2004 census data, where we observe information for the universe of manufacturing firms in China and hence can directly measure the fraction of exporters and firms that are below the size threshold for inclusion in the ASM. We use these measures to determine ρ^X_{nhs} and ρ_{nhs}, which then allows us to compute measures of exporter and firm counts at the ownership-location-sector-year level from equations (B.3) and (B.4). Having constructed measures of exporter and firm counts at the ownership-location-sector-year level, we then construct measures of exporter counts at the destination-ownership-location-sector-year level. Assumption 2 implies that we can simply measure these as:

$$N^X_{dnhsy} = N^X_{nhsy}\left(\frac{N^{X,cus}_{dnhsy}}{N^{X,cus}_{nhsy}}\right) \tag{B.6}$$

C Concordances

The various datasets that we utilize report information using three different goods classifications: HS-2 (the customs data), CIC-2 (the ASM data), and ISIC-2 Rev. 4 (the WIOD data). Hence, we develop concordances between these three classifications as follows.

First, to construct the concordance between HS-2 and CIC-2, we proceed as follows. Let c_2 and c_4 index CIC 2-digit and 4-digit codes respectively, and let h_2 and h_4 index HS 2-digit and 4-digit codes respectively. Then, for each CIC 2-digit code c_2, we identify the set of CIC 4-digit codes that belong to the 2-digit sector, $C_4(c_2)$. For each $c_4 \in C_4(c_2)$, we measure the share of gross output accounted for by the 4-digit sector within the 2-digit group in a given year y:

$$s^{c_2}_{c_4,y} = \frac{R_{c_4,y}}{\sum_{c\in C_4(c_2)} R_{c,y}} \tag{C.1}$$

We then use a manually-constructed correspondence to identify the set of HS 4-digit codes to which each CIC 4-digit code maps, denoted by $H_4(c_4)$. Note that this set may contain multiple HS 4-digit codes. If so, we compute the share of *Chinese exports* accounted for by each $h_4 \in H_4(c_4)$ in a given year y within the corresponding set:

$$r^{c_4}_{h_4,y} = \frac{R^X_{h_4,y}}{\sum_{h\in H_4(c_4)} R^X_{h,y}} \tag{C.2}$$

Finally, for each variable $X_{c_2,y}$ that we observe by CIC 2-digit and year in the ASM data, we construct the corresponding measure $X_{h_2,y}$ at the HS 2-digit classification as follows:

$$X_{h_2,y} = \sum_{c_2 \in C_2} \sum_{c_4 \in C_4(c_2)} \sum_{h_4 \in H_4(c_4) \cup H_4(h_2)} \left(X_{c_2,y} \times s_{c_4,y}^{c_2} \times r_{h_4,y}^{c_4} \right) \tag{C.3}$$

where C_2 denotes the set of all CIC 2-digit codes and $H_6\,(h_2)$ denotes the set of HS 4-digit codes that belong to the HS 2-digit code h_2.

Next, to construct the concordance between HS-2 and ISIC-2 Rev. 4, we first map the ISIC-2 Rev. 4 sectors to ISIC-2 Rev. 3 sectors using a concordance provided by Eurostat. We then map the ISIC-2 Rev. 3 sectors to HS-2 sectors using a concordance provided by the World Integrated Trade Solution (WITS) platform.

D Dimensions and groupings

We group destinations for Chinese exports into the eleven regions shown in Table A.1 on the basis of geography and total imports from China from 2000 to 2013. Note that we do not observe whether exports from mainland China to Hong Kong and Macau are re-exported to other destinations. Hence, we treat Hong Kong and Macau as a separate market.

We group firms by ownership type into three categories: foreign-invested enterprises (FIEs), private-invested enterprises (PIEs), and state-owned enterprises (SOEs). In the customs data, there are seven different firm ownership types: (i) Sino-foreign contractual joint venture; (ii) Sino-foreign equity joint venture; (iii) foreign-owned enterprises; (iv) state-owned enterprises; (v) private enterprises; (vi) collective enterprises; and (vii) other enterprises. We treat categories (i)-(iii) as FIEs, categories (v)-(vii) as PIEs, and category (iv) as SOEs. We note that many collective enterprises (category (vi)) were only titularly collective. Furthermore, by the late 1990s, most of these firms had already been privatized. Hence, we include these as PIEs. Regardless, categories 6-7 account for a very small fraction of total exports. Hence, our results are insensitive to whether or not we treat these firms as PIEs or simply drop them from the sample.

We group Chinese provinces and municipalities into the eleven regions shown in Table A.2 on the basis of geography and export production.

We group exports by sector into 69 HS2 manufacturing categories (HS2 codes 28-76 and 78-97). We treat each of these as separate sectors, although we sometimes present results averaging estimates across sector groups. These groups are defined in Table A.3.

No.	Group	Destinations	Export share (%)
1.	North America	USA; Canada	20.1
2.	Western Europe	Germany; Netherlands; United Kingdom; Italy; France; Spain; Belgium; Finland; Sweden; Denmark; Switzerland; Norway; Ireland	17.0
3.	East Asia	Japan; Republic of Korea	12.6
4.	South East Asia	Singapore; Malaysia; Indonesia; Vietnam; Thailand; Philippines; Myanmar; Cambodia; Australia; New Zealand	10.1
5.	Eastern Europe & Russia	Russian Federation; Poland; Hungary; Kazakhstan; Ukraine; Czechia; Kyrgyzstan; Greece; Romania; Slovakia; Mongolia; Malta; Croatia	5.0
6.	Middle East	United Arab Emirates; Turkey; Saudi Arabia; Egypt; Israel; Iran; Jordan; Syria; Kuwait; Iraq	4.7
7.	Central & South America	Brazil; Chile; Argentina; Venezuela; Colombia; Peru; Ecuador; Mexico; Panama; Uruguay	4.6
8.	South Asia	India; Bangladesh; Pakistan; Sri Lanka	3.0
9.	Africa	South Africa; Nigeria; Algeria; Morocco; Benin; Angola; Ghana; Liberia; Kenya; Togo; Libya	2.3
10.	Rest of World	all other countries	4.0
11.	Special Administrative Regions (SARs)	Hong Kong; Macao	16.2

Table A.1: Export destination groupings

Notes: Export shares are of total Chinese manufacturing exports from 2000 to 2013.

No.	Group	Provinces/Municipalities	Export share (%)
1.	Guangdong	Guandong	33.7
2.	Jiangsu	Jiangsu	14.7
3.	Shanghai	Shanghai	11.5
4.	Zhejiang	Zhejiang	11.4
5.	Shandong	Shandong	5.4
6.	Beijing & Tianjin	Beijing; Tianjin	5.4
7.	Fujian	Fujian	4.6
8.	Central	Anhui; Henan; Jiangxi; Hubei	3.5
9.	Northeast	Liaoning; Heilongjiang; Jilin	3.4
10.	Southwest	Sichuan; Chongqing; Guangxi; Yunnan; Guizhou; Hainan; Xizang	3.3
11.	Northwest	Shaanxi; Shanxi; Inner Mongolia; Xinjiang; Gansu; Ningxia; Qinghai	2.3

Table A.2: Production location groupings

Notes: Export shares are of total Chinese manufacturing exports from 2000 to 2013.

No.	Group	HS2 Codes
1.	Foodstuffs	15-23
2.	Chemical Products	28-38
3.	Plastics and Rubber	39-40
4.	Leathers and Furs	41-43
5.	Wood Products	44-49
6.	Textiles and Apparel	50-67
7.	Stone and Glass	68-71
8.	Metals	72-76; 78-83
9.	Machinery	84-85
10.	Transportation	86-89
11.	Miscellaneous	90-96

Table A.3: Sector groupings

E Measuring export values

We require measures of the value of exports from China by destination-ownership-location-sector-year. Let the true values of this export measure be denoted by R^{X}_{dnhsy}. The data that we use offer two measures of exports: one from the customs data, $R^{X,cus}_{dnhsy}$, and one from the ASM data, $R^{X,asm}_{nhsy}$. If the customs data were an accurate representation of the universe of firms, the following would hold:

$$R^{X}_{dnhsy} = R^{X,cus}_{dnhsy} \tag{E.1}$$

We would then measure export values using the customs data and would not need to rely on the ASM data for this. However, equation (E.1) does not likely hold in earlier years of the sample because PIEs did not have direct export rights and were likely exporting indirectly through state-owned trading firms.[50] This implies that the allocation of exports within a $\{d, h, s, y\}$-cell between PIEs and SOEs is likely to be inaccurate.

This conjecture is supported by panels (a) and (b) of Figures A.2 and 2, which plot export levels and shares by firm ownership type. While the total value of exports reported for FIEs in the customs and ASM data are very similar, the values reported for PIEs and SOEs differ substantially in the earlier years of the sample. In the customs data, PIEs account for only 5.2% of total exports in 2000 with an aggregate export value of around 11.5bn USD. In contrast, PIEs account for 18.3% of exports in the ASM data in 2000 and report a substantially larger total export value of 26.4bn USD. SOEs, on the other hand, report much larger export values and shares in the customs data relative to the ASM data. We interpret these stark differences between exports in the customs and ASM data for PIEs and SOEs as evidence that many PIEs were exporting indirectly through SOE trading companies in the earlier years of the sample, and that the customs data reflect only direct exports while the ASM data reflect both direct and indirect exports.

We deal with this issue as follows. First, we make the following assumptions:

1. The customs data accurately reflect exports by the universe of FIEs:

$$R^{X}_{d,FIE,hsy} = R^{X,cus}_{d,FIE,hsy} \tag{E.2}$$

   Implicit in this assumption is that FIEs do not export indirectly through non-FIEs.

2. The customs data accurately reflect the shares of exports within an $\{n, h, s, y\}$-cell

[50] In January of 1999, China's central government announced that private firms would be given direct trading rights. Through the first half of the year, 142 licenses had been issued.

that are exported to each destination d:

$$s^X_{d|nhsy} \equiv \frac{R^X_{dnhsy}}{\sum_{d'=1}^D R^X_{d'nhsy}} = \frac{R^{X,cus}_{dnhsy}}{\sum_{d'=1}^D R^{X,cus}_{d'nhsy}} \equiv s^{X,cus}_{d|nhsy} \tag{E.3}$$

Implicit in this assumption is that the propensity for indirect exporting by PIEs through SOEs does not vary by the destination of exports but potentially varies by production location, sector, and year.

3. The ASM export data for SOEs accurately reflect exports by the universe of SOEs and excludes indirect exports for PIEs.

$$R^X_{SOE,hsy} = R^{X,asm}_{SOE,hsy} \tag{E.4}$$

4. The customs data accurately reflect exports by the universe of PIEs and SOEs jointly within each $\{h, s, y\}$-cell:

$$R^X_{PIE,hsy} + R^X_{SOE,hsy} = R^{X,cus}_{PIE,hsy} + R^{X,cus}_{SOE,hsy} \tag{E.5}$$

Assumption 1 implies that we can measure FIE exports from the customs data directly using equation (E.2). Hence, it only remains to measure R^X_{dnhsy} for $n \in \{PIE, SOE\}$. Assumption 2 implies that we only need to measure this aggregated across destinations, i.e. $R^X_{nhsy} \equiv \sum_{d=1}^D R_{dnhsy}$, since we can then recover:

$$R^X_{dnhsy} = s^{X,cus}_{d|nhsy} R^X_{nhsy} \tag{E.6}$$

Now assumption 3 allows us to use equation (E.4) as our measure of exports for SOEs, while assumption 4 allows us to combine this with equation (E.5) to measure PIE exports as:

$$R^X_{PIE,hsy} = R^{X,cus}_{PIE,hsy} + R^{X,cus}_{SOE,hsy} - R^{X,asm}_{SOE,hsy} \tag{E.7}$$

The export values that we obtain from this adjustment procedure are shown in panel (c) of Figure A.2. Note that the adjustment increases the share of exports accounted for by PIEs relative to the raw customs data and reduces the share accounted for by SOEs, while leaving the share accounted for by FIEs unchanged. Furthermore, the effects of these adjustments are more noticeable in the earlier years of the sample period, which is consistent with the extension of direct trading rights to PIEs over time. Note also that even though the adjustment alters the export shares by ownership significantly, the changes in levels are less stark, since they occur primarily at the start of the sample when PIEs and SOEs had

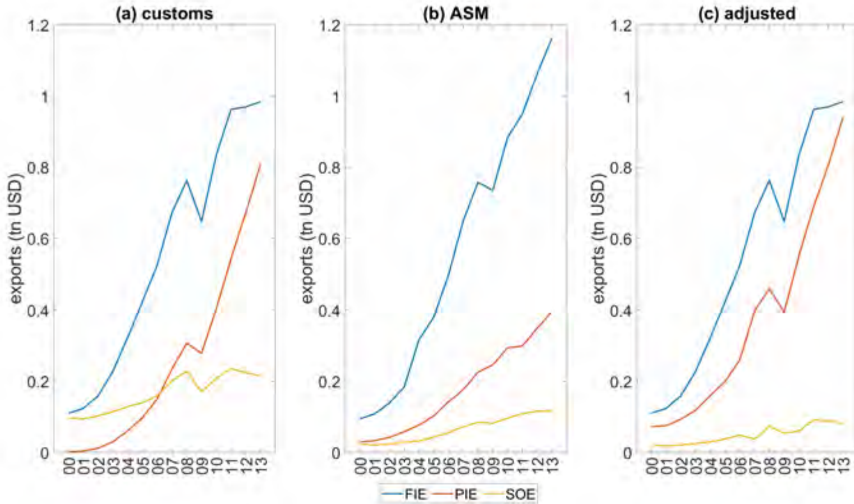

Figure A.2: Exports by firm ownership type: customs, ASM, and adjusted data

lower levels of exports than in later years. Furthermore, the export shares that we obtain following this adjustment procedure are comparable to other estimates of export shares by firm ownership type in the literature. For example, Perotti et al. (1999) report that township and village enterprises (TVEs) accounted for 46.3% of all exports in 1997, which is close to our adjusted measure of around 40% in 2000.

F Measuring imported input shares

To calibrate prices of imported inputs, we require measurement of the shares of materials expenditures that are spent on imported inputs at the ownership-sector-year level. To measure the value of imported inputs, we first utilize information on firm-level imports of raw materials, capital goods, and intermediates (as defined by the BEC classification) in the customs data. We treat the sum of these three types of imports as imports of intermediate inputs in the model.

Since we are concerned with imports of inputs that are used for production by firms in different $\{n, s, y\}$-cells, however, we also need to identify both the ownership type of the importing firm as well as the HS-2 sector(s) in which the importing firm produces. Given that the customs and ASM data are not matched at the firm-level, this is feasible using the customs data only when an importing firm simultaneously exports. Hence, in measuring import shares, we use only the import transactions by exporting firms, allocating import values to the corresponding $\{n, s, y\}$-cell of the importing firm's exports. For cases in which a firm exports in multiple HS2 sectors, we allocate the firm's imports to these sectors in proportion to the shares of the firm's exports accounted for by each sector. We also scale imports in each year so that the total value of imported intermediates is consistent with the total in the customs data. We note that in the average year in our sample, exporting firms account for 83% of total imports.

The above procedure gives us measures of imports by firms within each $\{n, s, y\}$-cell. To compute imported shares of materials expenditures, we would like to compare these to our estimates of material costs E^M_{nhsy} as constructed in section G. However, these two measures are not directly comparable, for two reasons. First, just as PIEs were likely restricted to exporting indirectly through state-owned trading companies in the earlier years of the sample (see the discussion in section E), similar restrictions likely applied to imports as well. Second, since the ASM data do not include below-scale non-state firms, the comparison between imports in the customs data and materials expenditure in the ASM data likely overstates the role of imported inputs. Hence, we account for the former issue by scaling PIE and SOE imports by the same proportion in which exports are adjusted to account for indirect trade by PIEs (see section E), and we account for the latter issue by scaling imports in each year so that the aggregate import share of material cost matches the corresponding share reported in the WIOT data (which are constructed directly from make-use data provided by the Chinese NBS).

G Measuring factor costs and prices

Estimation of the model's production technology parameters requires measurement of factor expenditures and prices. The ASM data provide direct measurements of gross output GO_{nhsy}, profits π_{nhsy}, labor costs E^L_{nhsy}, and employment L_{nhsy}, all at the ownership-location-sector-year level (where values for 2009 and 2010 have been imputed as described in section A). Our measures of labor costs are adjusted following the procedure in Brandt et al. (2018), which accounts for the fact that not all components of labor costs (e.g. housing and pension benefits) are reported in every year of the ASM dataset. We also use measures of capital stocks constructed by Brandt et al. (2012) and value-added VA_{nhsy} constructed by Brandt et al. (2018). The value-added measures are reported directly at the firm-level in the ASM before and including 2008 and are imputed after 2008 using estimates of production costs, labor costs, and capital costs.

We then use the ASM data to construct measures of materials expenditures E^M_{nhsy}, wages P^L_{hy}, and capital prices P^K_{nsy} as follows. First, we measure materials expenditures as the difference between gross output and value-added:

$$E^M_{nhsy} = GO_{nhsy} - VA_{nhsy} \tag{G.1}$$

Next, we measure wages as the ratio of total labor costs to total employment within a

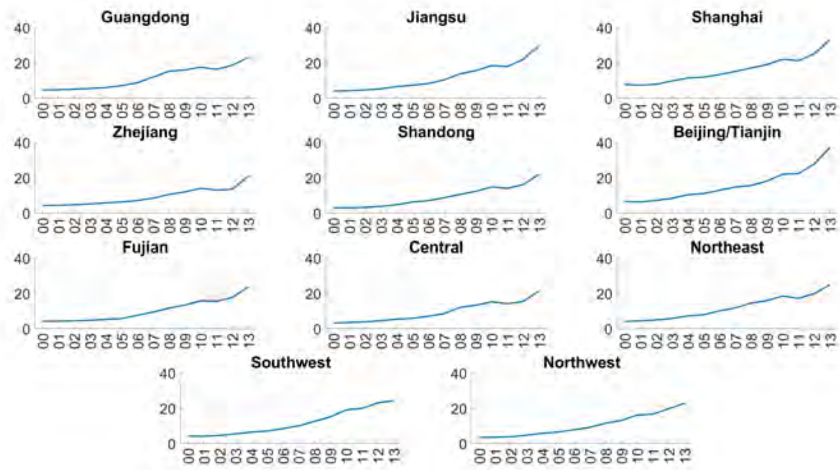

Figure A.3: Wage estimates

Notes: The plots above show estimated wages P^L_{hy} in each production location. Values are shown in levels and in units of thousands of USD.

location:

$$P^L_{hy} = \frac{\sum_{n=1}^{N} \sum_{s=1}^{S} E^L_{nhsy}}{\sum_{n=1}^{N} \sum_{s=1}^{S} L_{nhsy}} \tag{G.2}$$

Finally, to construct measures of capital prices, we estimate capital costs as value-added less profits and labor costs:

$$E^K_{nsy} = \sum_{h=1}^{H} \left(VA_{nhsy} - \pi_{nhsy} - E^L_{nhsy} \right) \tag{G.3}$$

Note that there are a small number of cells in which reported profits are negative. We treat these as zero profits instead. We then measure capital prices as:

$$P^K_{nsy} = \frac{E^K_{nsy}}{\sum_{h=1}^{H} K_{nhsy}} \tag{G.4}$$

Figure A.3 shows our estimates of wages by production location while Figure A.4 shows our estimates of capital prices by ownership-sector. Wages are generally rising over time in all provinces, with a noticeable slowdown following the Great Recession. Wages are also noticeably higher in locations such as Shanghai, Beijing, and Tianjin than elsewhere. Similarly, capital prices are generally rising throughout the sample period, although the slowdown in growth begins earlier (around 2007) and is more persistent than for wages.

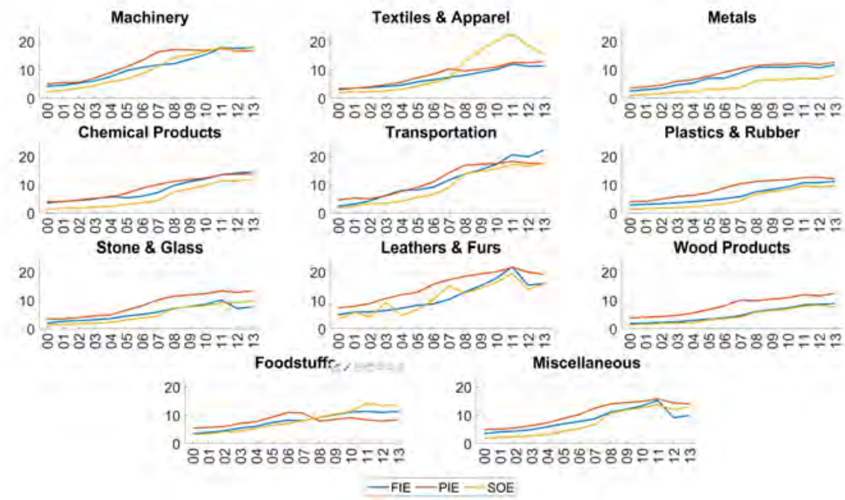

Figure A.4: Capital cost estimates

Notes: The plots above show estimated capital costs P^K_{nsy} for firms in each ownership-sector. Values are shown in levels and in units of thousands of USD. Capital costs are normalized so that the relative cost of labor versus capital for the median firm in 2000 is equal to one.

H Detailed estimation results

This section provides detailed estimation results for the following: market access $\bar{P}^*_{dsy}$ (Table A.4), imported input prices P^I_{nsy} (Table A.5), production function substitution elasticities $\left\{\epsilon^V_s, \epsilon^X_s\right\}$ (Figure A.5), factor cost efficiency growth rates (Table A.6), investment efficiencies θ_{nsy} (Table A.7), capital growth rates $K_{ns,y+1}/K_{nsy}$ (Figure A.6), and unadjusted returns to investment P^K_{nsy}/P_{0sy} (Figure A.7).

	(a) North America				(b) Western Europe			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	0.63	0.55	0.56	0.59	0.45	0.36	0.36	0.39
Textiles & Apparel	1.52	1.51	1.57	1.65	1.37	1.33	1.38	1.46
Metals	1.94	2.10	2.17	2.22	1.70	1.84	1.92	1.99
Chemical Products	0.29	0.30	0.34	0.47	0.09	0.06	0.10	0.22
Transportation	1.08	1.00	0.99	0.98	0.88	0.80	0.89	0.85
Plastics & Rubber	1.51	1.58	1.64	1.74	1.25	1.23	1.29	1.38
Stone & Glass	1.08	1.01	1.04	1.10	0.81	0.84	0.86	0.82
Leathers & Furs	2.39	2.42	2.47	2.39	2.19	2.14	2.17	2.11
Wood Products	1.07	1.12	1.15	1.19	0.83	0.81	0.82	0.89
Foodstuffs	0.84	0.98	1.11	1.23	0.70	0.70	0.78	0.90
Miscellaneous	1.36	1.30	1.35	1.37	1.15	1.06	1.11	1.13

	(c) East Asia				(d) South East Asia			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	0.66	0.60	0.60	0.61	0.55	0.49	0.50	0.56
Textiles & Apparel	1.86	1.82	1.83	1.85	1.55	1.50	1.50	1.57
Metals	2.06	2.24	2.31	2.38	1.92	2.13	2.17	2.27
Chemical Products	0.54	0.59	0.60	0.72	0.45	0.45	0.49	0.61
Transportation	1.34	1.22	1.28	1.21	1.28	1.14	1.15	1.21
Plastics & Rubber	1.51	1.58	1.65	1.75	1.37	1.43	1.50	1.61
Stone & Glass	1.16	1.13	1.21	1.35	1.02	0.96	0.97	1.00
Leathers & Furs	2.28	2.27	2.34	2.32	2.10	2.11	2.12	2.15
Wood Products	1.24	1.21	1.19	1.29	1.02	1.04	1.07	1.15
Foodstuffs	1.37	1.36	1.40	1.53	1.10	1.03	1.10	1.25
Miscellaneous	1.32	1.28	1.31	1.38	1.16	1.11	1.18	1.23

	(e) Eastern Europe & Russia				(f) Other			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	0.58	0.51	0.54	0.58	0.65	0.57	0.57	0.62
Textiles & Apparel	1.29	1.28	1.32	1.47	1.45	1.42	1.45	1.53
Metals	1.75	1.90	2.03	2.09	1.85	1.97	2.08	2.15
Chemical Products	0.28	0.16	0.19	0.33	0.35	0.35	0.37	0.48
Transportation	1.07	0.99	1.01	1.04	1.16	1.15	1.03	1.07
Plastics & Rubber	1.26	1.30	1.41	1.51	1.43	1.45	1.49	1.60
Stone & Glass	1.03	1.10	1.15	1.26	0.78	0.79	0.85	0.82
Leathers & Furs	1.95	1.92	2.04	2.02	2.10	2.21	2.25	2.22
Wood Products	0.92	0.89	0.89	0.99	0.96	1.07	1.05	1.15
Foodstuffs	0.74	0.85	0.93	1.03	0.87	0.85	0.95	1.05
Miscellaneous	1.22	1.11	1.12	1.22	1.23	1.23	1.26	1.30

Table A.4: Estimates of market access

Notes: Each cell shows the log value of estimated market access $\bar{P}^*_{dsy}$ for the indicated destination-sector, averaged across years in each window. All values are normalized by a constant such that the smallest log value across destination-sector-years is equal to zero.

	(a) FIEs				(b) PIEs				(c) SOEs			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	0.73	0.50	0.47	0.42	1.04	0.92	0.93	0.86	0.94	0.65	0.65	0.70
Textiles & Apparel	0.94	0.85	0.87	0.92	1.08	1.06	1.17	1.21	1.05	0.80	0.77	0.79
Metals	1.08	1.00	1.03	0.99	1.43	1.35	1.36	1.33	1.18	0.98	0.97	0.95
Chemical Products	0.95	0.76	0.69	0.69	0.97	1.01	1.10	1.10	1.14	0.87	0.77	0.61
Transportation	1.01	0.88	0.87	0.83	1.34	1.16	1.12	1.22	1.09	0.83	0.77	0.87
Plastics & Rubber	0.76	0.57	0.56	0.53	1.00	0.90	0.95	0.96	1.17	0.90	0.79	0.79
Stone & Glass	0.82	0.51	0.41	0.49	1.17	1.06	1.16	1.11	0.84	0.58	0.41	0.65
Leathers & Furs	0.78	0.66	0.69	0.66	0.90	0.82	0.92	0.99	0.09	0.11	0.20	0.14
Wood Products	0.86	0.67	0.63	0.61	1.05	0.99	1.14	1.18	1.37	0.81	0.71	0.70
Foodstuffs	1.05	0.82	0.67	0.79	1.29	1.37	1.28	1.31	1.17	0.94	0.91	0.94
Miscellaneous	0.52	0.15	0.08	0.08	0.77	0.79	0.84	0.86	0.67	0.18	0.08	0.39

Table A.5: Estimates of imported input prices

Notes: Each cell shows the log value of the estimated import price P^I_{nsy} for the indicated ownership-sector, averaged across years in each window. All values are normalized by a constant such that the smallest log value across ownership-sector-years is equal to zero.

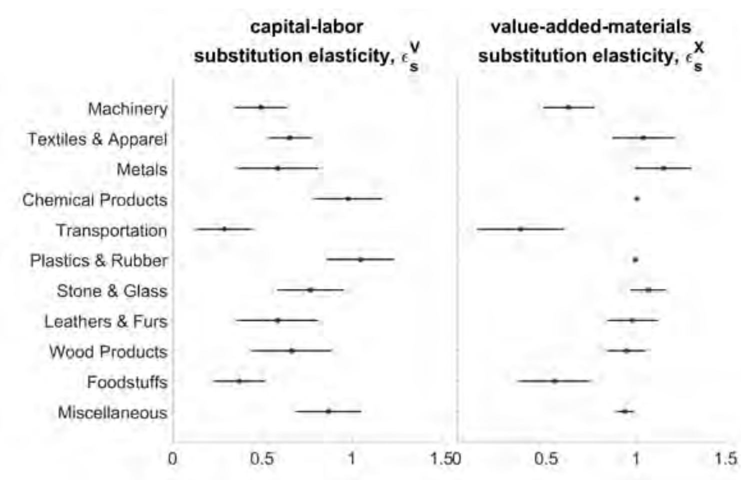

Figure A.5: Estimates of substitution elasticities by sector

Notes: The blue and red circles indicate our point estimates of ϵ_s^V and ϵ_s^X respectively. The black lines indicate the 95% confidence intervals from the corresponding instrumental variables regression used for the estimation.

	(a) efficiency growth				(b) productivity growth			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	1.4	1.5	-1.7	-3.2	1.8	5.8	2.2	-0.9
Textiles & Apparel	0.5	1.5	-4.4	-3.0	2.9	9.5	1.5	0.5
Metals	-2.5	-4.0	-4.9	-1.0	0.5	0.6	-2.4	-0.3
Chemical Products	0.4	-1.0	-5.8	-5.5	2.5	4.3	-0.6	-3.4
Transportation	-0.4	3.0	-4.1	-4.2	2.8	8.6	1.3	-1.4
Plastics & Rubber	-1.0	-2.0	-3.6	-4.0	-0.2	3.0	1.6	-1.9
Stone & Glass	0.2	-2.4	-4.4	-4.1	2.4	6.0	0.9	-2.5
Leathers & Furs	-0.2	-1.1	-2.5	-1.0	1.7	6.9	5.1	1.8
Wood Products	-0.7	1.6	-3.9	-2.9	0.7	8.2	0.9	0.0
Foodstuffs	-1.8	-0.9	-10.9	-7.5	-0.5	2.2	-8.3	-7.1
Miscellaneous	-0.4	-0.6	-2.6	-3.2	-0.2	6.7	3.9	-1.6

Table A.6: Factor cost efficiency growth

Notes: This table shows the contributions to efficiency growth arising from changes in factor input prices. All values are computed for the average firm in each sector-year and then averaged across years in each window. All values are in units of percentage points.

	(a) FIEs				(b) PIEs				(c) SOEs			
	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13	00-04	04-07	07-10	10-13
Machinery	5.13	4.33	3.38	3.13	4.99	4.34	4.90	4.09	3.68	2.67	3.72	3.68
Textiles & Apparel	4.91	5.34	4.40	4.58	5.99	4.98	4.89	5.05	4.31	3.80	3.82	3.90
Metals	6.07	6.30	5.53	5.64	7.10	6.10	6.22	6.20	5.42	5.10	5.28	5.30
Chemical Products	4.85	5.08	3.89	3.44	5.79	4.62	4.75	4.31	4.73	3.40	2.80	4.17
Transportation	4.92	6.27	4.01	3.14	6.30	6.34	4.68	4.00	3.59	4.94	4.15	3.49
Plastics & Rubber	6.25	5.84	4.78	4.57	5.83	5.60	5.72	5.57	5.82	4.29	3.85	5.50
Stone & Glass	5.10	5.45	3.97	4.80	5.75	4.98	4.83	4.87	4.89	3.63	3.81	4.89
Leathers & Furs	6.14	5.54	4.89	5.19	5.04	5.09	5.66	5.69	4.78	3.33	3.63	7.84
Wood Products	6.31	5.47	4.55	4.20	6.07	5.28	5.39	4.81	5.21	4.13	4.11	4.86
Foodstuffs	5.03	4.75	4.41	4.38	5.70	4.91	5.98	5.51	3.84	3.16	4.37	4.40
Miscellaneous	5.31	5.25	3.85	5.09	5.47	4.94	4.90	5.03	4.68	3.60	3.77	4.82

Table A.7: Estimates of investment efficiencies

Notes: Each cell shows the log value of estimated investment efficiency θ_{nsy} for the indicated ownership-sector, averaged across years in each window. All values are normalized by a constant such that the smallest log value across ownership-sector-years is equal to zero.

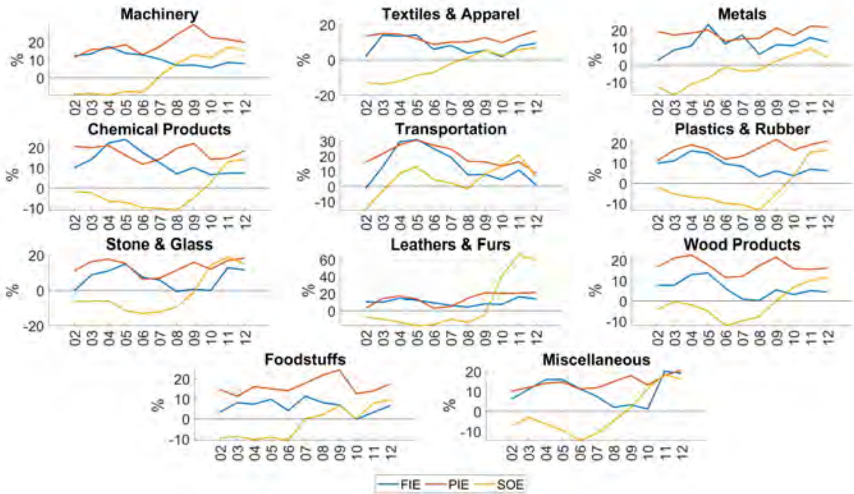

Figure A.6: Estimates of capital growth rates

Notes: The plots above show growth rates of the total capital stock for firms in each ownership-sector. To smooth out yearly fluctuations, growth rates are shown as rolling three-year averages.

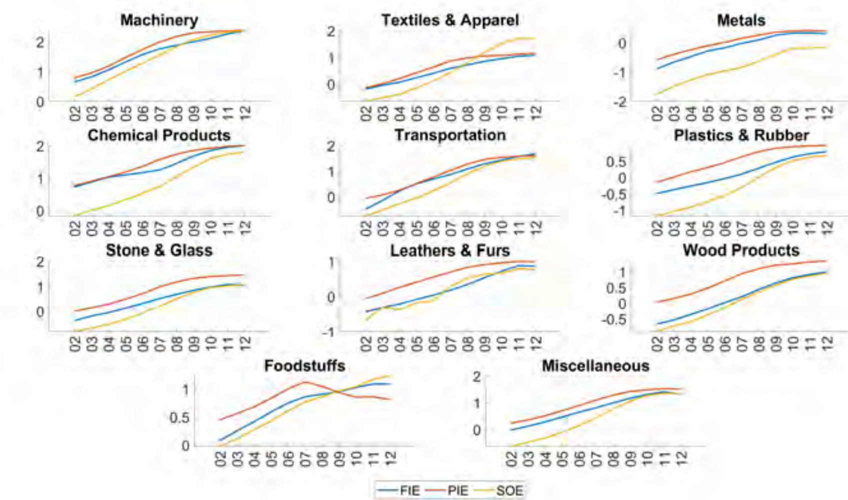

Figure A.7: Estimates of unadjusted returns to investment

Notes: The plots above show estimated unadjusted returns to investment, P^K_{nsy}/P_{0sy}, for firms in each ownership-sector. Values are shown in logs and normalized so that the average firm in 2000 has log returns equal to zero. To smooth out yearly fluctuations, values are shown as rolling three-year averages.