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Opening up in the 21st century: A quantitative accounting of Chinese export growth[☆]

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ABSTRACT

China's rapid export growth has spurred extensive research investigating its effects on other economies. The exact causes of the boom as well as the slowdown in Chinese exporting after 2007 are less well-understood. We quantify the drivers of Chinese export growth using a general equilibrium model estimated with detailed trade and production data that capture rich heterogeneity across destinations, firm ownership types, production locations, and sectors. We find that the three key drivers of Chinese export growth overall are rising foreign demand, improvements in access to imported intermediates, and factor productivity growth within China. Weakening foreign demand and a lack of further improvements in imported inputs access largely explain the slowdown in exporting after 2007. Furthermore, important differences especially across sectors and firms of different ownership types caution against any single narrative.

1. Introduction

China's growing participation in the world market for goods and services has contributed to its economic success and been a defining feature of the global economy for nearly three decades. Between 1995 and 2019, exports from China grew at an annual rate of 15% compared with global export growth of 7% per year and export growth of OECD countries of 5% per year. As a result, China's share of world exports quadrupled from 3% to 12%. Unsurprisingly, these developments have been accompanied by a surge in research on Chinese trade. However, much of the more recent focus has been on the *consequences* of Chinese export growth for outcomes in other countries, while the *causes* of China's trade expansion remain less well understood.[1] Given the wide interest in the effects of Chinese exporting and the links between exporting success and economic growth, a deeper understanding of the sources of China's trade growth is equally important. In this paper, we provide this through a quantitative accounting of the drivers of Chinese exporting.

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[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, while Taniguchi et al. (2021) extend the analysis to examine effects on employment in Japan, South Korea, France, Germany, and the UK. 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.

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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, thus extending the empirical literature on Chinese trade patterns that has largely focused on the years just before and after China's accession to the WTO in 2001. We examine four key margins in particular: (i) the destination market for exports; (ii) the ownership of exporting firms; (iii) the sector of goods being exported; and (iv) the location of export production in China. 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; and a shift away from textiles and apparel towards machinery. At the same time, the geographic distribution of export production in China varies substantially by destination, firm ownership type, and sector.

To make sense of these patterns, we develop a structural model of Chinese trade and production. As summarized by Autor et al. (2018), the literature examining potential explanations for China's export surge has largely considered individual factors in isolation. Our approach contributes to the literature by building a framework that simultaneously captures multiple drivers of Chinese export growth in a general equilibrium setting, including 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, access to imported inputs, firm entry, investment efficiency, labor market factors, and consumer consumption and savings behavior. Motivated by the empirical patterns that we document, we allow these factors to vary across export markets, firm ownership types, sectors, and production locations within China. The structure of the model enables us to 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.

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 the three key drivers of Chinese export growth overall are rising foreign demand, improvements in access to imported intermediates, and factor productivity growth within China. However, weakening foreign demand and a lack of further improvements in imported input access largely explain the slowdown in exporting after 2007. Underlying these aggregate findings are also rich patterns of heterogeneity in export growth drivers across destinations, firm ownership types, sectors, and production locations, which cautions against any single narrative as an explanation for the observed dynamics in Chinese exporting.

Although 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

The goal of our analysis is to evaluate quantitatively alternative explanations for observed Chinese export dynamics in a coherent framework. Many of the drivers of export growth that we investigate have been viewed as salient for China's trade and production outcomes over the last two to three decades. To provide context for our findings, we briefly highlight here how our analysis connects with research on individual factors.

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 a decrease in innovation by 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.

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) also find that China's accession to the WTO raised both firm- and sector-level productivity through tariff reductions, an effect that Yu (2015) finds especially strong for non-processing

[2] For example, data from the UN Comtrade database show 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) indicate that the share of exports accounted for by foreign-owned firms increased from 27% to 47% over the same period.

exporters. In addition, Khandelwal et al. (2013) 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 also indicate a reversal in productivity growth trends in multiple sectors of the Chinese economy after 2007, with productivity growth contributing modestly 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 provided additional impetus for firm entry and export-related investment (Feng et al. (2017), Alessandria et al. (2022)). 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). This was complemented by a substantial increase in the number of companies authorized to conduct foreign trade in China between 1985 and 2001, which made the market for foreign trade services already reasonably competitive by the mid-1990s (Lardy, 2002). The granting of direct foreign trading rights to non-state domestic firms provided an additional impetus to Chinese export growth in the early 2000s (Bai et al., 2017). 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 contributed positively to 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.

Investment efficiencies and capital accumulation. Eaton et al. (2016) emphasize 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 the efficiencies of investment technologies for foreign-invested firms in China were particular low in sectors such as Machinery and Transportation from 2008 to 2010. We also estimate important differences in the efficiencies of investment technologies across firm ownership types, with state-owned firms having lower efficiencies than non-state firms. This is in line with findings by Chen et al. (2011), who argue that political connections of top executives at state-owned firms significantly lower investment efficiency at these firms. More broadly, we estimate that investment efficiencies for most firms in China were generally highest in the early 2000s but declined after. Despite this, we observe high rates of capital growth throughout our sample period, especially for non-state Chinese firms but also for foreign-invested firms, arising from high growth in the returns to investment as measured by the value of capital in a sector relative to the value of sector output. Hence, we find that capital accumulation in China was a positive albeit secondary source of export growth.

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 allow for aggregate employment growth and changes over time in location-specific amenities for workers. We find that changes in these labor market factors contribute positively to export growth throughout our sample period, although these contributions are secondary compared with other sources of export growth.

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 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 sector of exported goods, and the location within China where exports are produced.[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.

Fig. 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 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.

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 Fig. 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.

[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 5 m RMB (approximately 600,000 USD) in sales. For 2011 and after, the size threshold increases to 20 m RMB (approximately 2.4 m USD). To maintain consistency across years, we exclude firms with sales below 20 m 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.

[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, sectors, and production locations.

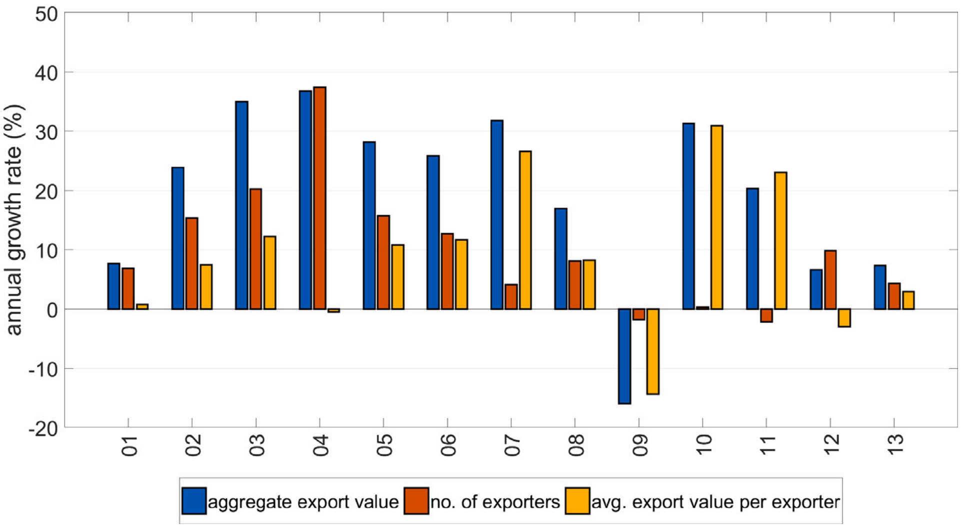

Fig. 1. Annual growth rates of exports, extensive margin, and intensive margin.

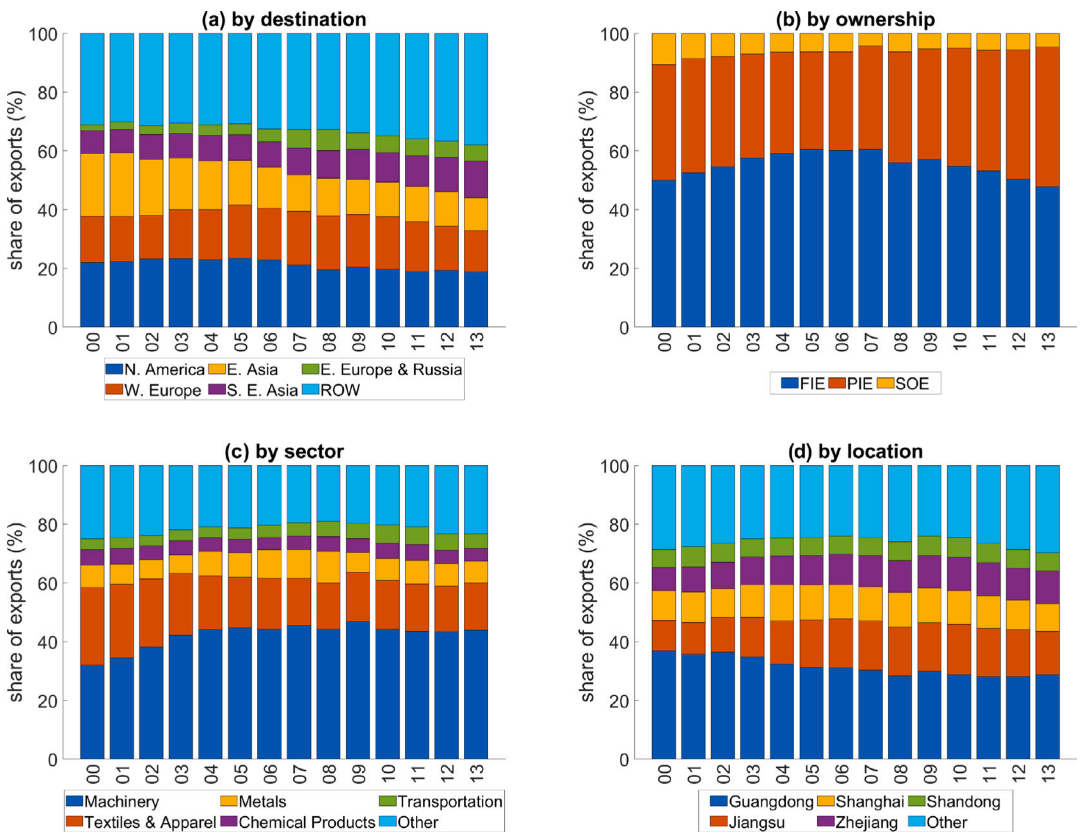

Fig. 2. Export shares by destination, ownership, sector, and production location.

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 Fig. 2 provides a breakdown of Chinese exports by ownership types: 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.

Fact 4 (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 (c) of Fig. 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 heterogeneity in the underlying drivers of export growth both across sectors as well as within sectors across firm ownership types.

Fact 5 (exports by production location). Production of Chinese exports is highly concentrated in coastal provinces, especially in Guangdong. However, there is substantial heterogeneity in the geographic distribution of export production for exports to different destinations, by firms of different ownership types, and in different sectors.

Panel (d) of Fig. 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, although these shares fall slightly after 2010 as a larger share of exports come from inland provinces.

In addition, the geographic distribution of export production varies substantially by destination, firm ownership type, and sector. This can be seen from Table 1, which shows the share of exports in the average year accounted for by the top two exporting regions (Guangdong, Jiangsu), the next three top exporting regions (Shanghai, Zhejiang, Shandong), and all other regions, for exports to different destinations, by firms of different ownership types, and in different sectors. Across destinations (rows 1 a.-f.), exports to North America and Western Europe tend to be more concentrated in the top two exporting regions, whereas the production of exports to other destinations is more geographically dispersed. Across firm ownership types (rows 2 a.-c.), more than half of FIE exports are produced in the top two exporting regions, whereas this share is only around 40% for PIEs, while regions outside of the top five exporting regions account for more than 40% of SOE exports. Across sectors (rows 3 a.-f.), the majority of Machinery exports are produced in the top two export regions, whereas exports in other sectors are more geographically dispersed. For example, around 40% of exports in the Chemicals sector is produced outside of the top five exporting regions. 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.

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.

[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.

[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.

Table 1
The geographic distribution of export production.

	Share of exports accounted for by:		
	Rank 1–2 regions	Rank 3–5 regions	All other regions
1. By destination			
a. North America	47.0	28.3	24.6
b. Western Europe	43.1	30.9	26.0
c. East Asia	36.3	33.8	29.9
d. South East Asia	41.8	27.4	30.8
e. Eastern Europe & Russia	33.8	29.3	36.9
f. ROW	38.9	31.8	29.3
2. By ownership			
a. FIEs	51.3	25.7	22.9
b. PIEs	42.3	30.2	27.5
c. SOEs	30.0	28.2	41.9
3. By sector			
a. Machinery	54.9	22.9	22.2
b. Textiles & Apparel	38.6	35.6	25.8
c. Metals	33.6	27.4	39.0
d. Chemical Products	29.6	29.9	40.6
e. Transportation	36.5	34.0	29.5
f. Others	47.3	27.6	25.2

Notes: This table shows the share of exports to different destinations, by firms of different ownership types, and in different sectors that are produced in the top two regions (Guangdong and Jiangsu), the next three top regions (Shanghai, Zhejiang, and Shandong), and all other regions, where regions are ranked according to total exports in the average year.

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, $d \in \{0, \ldots, D\}$, where market 0 is the domestic Chinese market and the remaining are export markets; (ii) firm ownership types, $n \in \{1, \ldots, N\}$; (iii) production locations in China, $h \in \{1, \ldots, H\}$; and (iv) sectors, $s \in \{1, \ldots, S\}$. We index time (years) by t. Within an nhs 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_{nhst}. In what follows, we will use terminology such as "$nhs\phi$-firms" to refer to firms of ownership type n producing in location h and sector s with idiosyncratic TFP ϕ.

The margins described above will matter as follows. First, firms operate production technologies that vary by sector, using labor, capital, domestic intermediates, and imported intermediates to produce. Second, factor augmenting productivities vary at the $nhst$ level. Third, workers sort to firms based on endogenous wages and exogenous amenities that vary at the $nhst$ level. Fourth, capital is accumulated via endogenous investment at the nst level. Fifth, the price of imported intermediates varies at the nst level. Sixth, the main determinants of Chinese export demand in foreign markets vary at the dst level. Finally, to access foreign markets, firms pay fixed exporting costs that vary at the $dnhst$ level. Note in particular that locations within China matter for four reasons: they have different numbers of producers, factor productivities, worker amenities, and fixed exporting costs.

When we take the model to the data, we will use the following definitions. 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)).[11]

3.2. Demand

3.2.1. Export demand

Foreign consumers in export market d spend nominal income E_{dst} on imports of sector s goods from all source countries. Within each sector s, these consumers have preferences over 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 $nhs\phi$-firms hence takes the following form:

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

[11] 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.

where $p_{dnhst}(\phi)$ is the price charged by a $\{n, h, s, \phi\}$-firm in market d and v_{dnhst} is a preference weight.[12] The term A_{dst} is a destination–sector specific demand shifter given by:

$$A_{dst} \equiv \frac{E_{dst}}{\left(P^*_{dst}\right)^{1-\sigma_s} + \left(\tau_{dst} P_{dst}\right)^{1-\sigma_s}} \tag{3.2}$$

This form follows from CES preferences, where P^*_{dst} is a price index for products supplied by firms outside of China and P_{dst} is a price index of products supplied by firms in China exclusive of iceberg trade costs $\tau_{dst} \geq 1$. Note that equilibrium outcomes will depend on P^*_{dst} and τ_{dst} only through the ratio $\bar{P}^*_{dst} \equiv P^*_{dst}/\tau_{dst}$, which we henceforth refer to as *foreign market access*. Variation in import expenditures and market access will be important for matching the distribution of Chinese exports across destinations (Fact 2).

Since we focus on the drivers of Chinese exporting rather than the global determinants of trade, we model China as a small open economy and treat $\left\{E_{dst}, P^*_{dst}\right\}$ as exogenous. As these are nominal variables, this assumption effectively imposes a choice of numeraire, so that all prices in the Chinese economy are uniquely determined in levels.[13] Note that in principle, both E_{dst} and P^*_{dst} could be partially dependent on outcomes in China. For example, declines in the cost of importing final goods from China might cause foreign consumers to reallocate expenditure from domestic to imported consumption, thereby increasing E_{dst}, while declines in the cost of imported intermediates from China may feed into reductions in P^*_{dst} via input–output linkages. For this to matter quantitatively, however, imports from China must make up a large share of total imports in a given foreign market. Throughout our sample period, this share remains low for most of China's major export destinations despite the fact that it tends to increase over time.[14]

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.[15] Across sectors, aggregate consumer utility takes the following Cobb–Douglas form:

$$U_t = \prod_{s=1}^{S} \left(X^F_{st}\right)^{\alpha^F_s} \tag{3.3}$$

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

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

$$X^F_{st} = \left[\left(\omega^F\right)^{\frac{1}{\epsilon^F_s}} \left(X^{FD}_{st}\right)^{\frac{\epsilon^F_s - 1}{\epsilon^F_s}} + \left(1 - \omega^F\right)^{\frac{1}{\epsilon^F_s}} \left(X^{FI}_{st}\right)^{\frac{\epsilon^F_s - 1}{\epsilon^F_s}}\right]^{\frac{\epsilon^F_s}{\epsilon^F_s - 1}} \tag{3.4}$$

where ω^F is a preference weight on domestic products.[16] Since we do not model production outside China, we assume that imported final goods in sector s are available at an exogenous price P^{FI}_{st}.[17] 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 output 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_{nhst} is produced by combining value-added V_{nhst} and materials M_{nhst}:

$$X_{nhst} = \phi \left[\left(\omega^X\right)^{\frac{1}{\epsilon^X_s}} V_{nhst}^{\frac{\epsilon^X_s - 1}{\epsilon^X_s}} + \left(1 - \omega^X\right)^{\frac{1}{\epsilon^X_s}} \left(T^M_{nhst} M_{nhst}\right)^{\frac{\epsilon^X_s - 1}{\epsilon^X_s}}\right]^{\frac{\epsilon^X_s}{\epsilon^X_s - 1}} \tag{3.5}$$

[12] 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.

[13] For example, see Demidova and Rodríguez-Clare (2009, 2013), and Caliendo and Feenstra (2022) for a discussion of the small open economy assumption and its implication for the determination of domestic prices.

[14] For example, the share of total US imports accounted for by China was only 10% on average between 2000–2007 and 17% on average between 2008–2013.

[15] Estimating internal barriers to trade requires data on internal trade flows, which are only available in China for select years and sectors in our sample. For example, Tombe and Zhu (2019) use data from regional input–output tables for 2002 and 2007, whereas our sample covers 2000–2013. Nonetheless, in Appendix A, we discuss a simple extension of our model in which factor productivities can be interpreted as partially capturing internal trade costs.

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

[17] Import prices P^{FI}_{st} 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.

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

$$V_{nhst} = \left[\left(\omega^V\right)^{\frac{1}{\epsilon_s^V}} \left(T_{nhst}^L L_{nhst}\right)^{\frac{\epsilon_s^V-1}{\epsilon_s^V}} + \left(1-\omega^V\right)^{\frac{1}{\epsilon_s^V}} \left(T_{nhst}^K K_{nhst}\right)^{\frac{\epsilon_s^V-1}{\epsilon_s^V}} \right]^{\frac{\epsilon_s^V}{\epsilon_s^V-1}} \tag{3.6}$$

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

$$M_{nhst} = \left[\left(\omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(M_{nhst}^I\right)^{\frac{\epsilon_s^M-1}{\epsilon_s^M}} + \left(1-\omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(M_{nhst}^D\right)^{\frac{\epsilon_s^M-1}{\epsilon_s^M}} \right]^{\frac{\epsilon_s^M}{\epsilon_s^M-1}} \tag{3.7}$$

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

$$M_{nhst}^D = \prod_{s'=1}^{S} \left(\frac{M_{nhss't}^D}{\alpha_{ss'}} \right)^{\alpha_{ss'}} \tag{3.8}$$

where $M_{nhss't}$ denotes usage of domestic intermediates from sector s'. We denote the marginal production cost implied by these technologies for $nhs\phi$-firms as η_{nhst}/ϕ, where η_{nhst} is the component of marginal cost common to all nhs-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_{nhst}^L, capital productivity T_{nhst}^K, and materials productivity T_{nhst}^M. We denote these jointly by $\bar{T}_{nhst}$. These productivity terms allow the model to better fit the factor shares of total production costs that we observe in the data. They are also a source of heterogeneity in export growth across firm ownership types, production locations, and sectors that we see in the data (Facts 3–5).

Second, production technologies are characterized by three substitution elasticities: between value-added and materials ϵ_s^X; between labor and capital ϵ_s^V, and between foreign and domestic intermediates ϵ_s^M. 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 Eq. (3.8), where $\left\{\alpha_{ss'}\right\}_{s,s'\in\Omega_S}$ 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_{nst}^I. Changes in these prices may reflect developments both outside China (e.g., more foreign sellers supplying better inputs to Chinese firms) and inside China (e.g., lowering of import tariffs). Variation in these import prices will allow the model to match imported shares of material expenditures observed in the data and are also a source of heterogeneity in export growth across firm ownership types and sectors (Facts 3 and 4). Since we abstract from internal trade costs, the price of imported intermediates is assumed to vary by ownership–sector–year but not across locations. Similarly, the price of the domestic intermediate input bundle (3.8) will be the same in all locations.[18]

Finally, since production uses four types of inputs (L_{nhst}, K_{nhst}, M_{nhst}^D, and M_{nhst}^I) with four terms that shift productivity-adjusted prices of these inputs (T_{nhst}^L, T_{nhst}^K, T_{nhst}^M, and P_{nst}^I), we normalize the mean of log idiosyncratic TFP to one in every nhs cell. We also assume without loss of generality that the production function weights ω^X, ω^V, and ω^M are constant over time.[19]

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 Eq. (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.

3.5. Factor stocks

3.5.1. Labor supply

There is an exogenous stock of workers in each year t denoted by $\bar{L}_t$. The measure of workers $\bar{L}_{nhst}$ that choose employment at nhs-firms depends on both the wages W_{nhst} and amenities g_{nhst} offered by these firms. We assume that labor supply is given by:

$$\frac{\bar{L}_{nhst}}{\bar{L}_t} = \frac{\left(W_{nhst}g_{nhst}\right)^{\gamma}}{\sum_{n'=1}^{N}\sum_{h'=1}^{H}\sum_{s'=1}^{S}\left(W_{n'h's't}g_{n'h's't}\right)^{\gamma}} \tag{3.9}$$

[18] See Appendix A for a discussion of how factor productivities may partially capture internal trade costs (as referenced in footnote 15).

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

where γ is the labor supply elasticity.[20] Intuitively, workers are more likely to be employed at firms that offer higher wages and amenities relative to the wages and amenities on offer by all firms in the labor market. While we treat amenities as exogenous, wages are endogenous and must be such that total labor demand by firms of each type is equal to the corresponding supply of labor as given by (3.9).[21] Furthermore, within an nhs cell, we assume that the labor market is perfectly competitive. Hence, all firms make production decisions taking wages as given.

3.5.2. Capital accumulation

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

$$\bar{K}_{nst} = \left(\frac{\bar{K}_{ns,t-1}}{\xi_s}\right)^{\xi_s} \left(\frac{T^I_{nst} I_{nst}}{1-\xi_s}\right)^{1-\xi_s} \tag{3.10}$$

where the parameter ξ_s controls the rate of capital depreciation conditional on a given level of investment I_{nst}. We assume that investment is paid in units of sector output (described below) at price P_{0st}, which allows the nominal cost of investment to respond directly to shocks at the sector level. The parameter T^I_{nst} 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 T^I_{nst}. 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 T^I_{nst}. We therefore refer to T^I_{nst} as *investment efficiency*.[22]

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.[23] Hence, we instead assume that households own all capital stocks in the economy and sell investment contracts for ns-capital at a nominal price P^I_{nst} that grant an investor control rights over the asset for one period. In equilibrium, free-entry of investors implies that the bid price P^I_{nst} exactly offsets any profits that are gained from investment. Investment decisions can then be characterized as a sequence of static 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:

$$\pi^I_{nst} = \max_{\bar{K}_{ns,t-1}, I_{nst}} \left\{ P^K_{nst} K_{nst} - P_{0st} I_{nst} - P^I_{nst} \bar{K}_{ns,t-1} \right\} \tag{3.11}$$

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

$$I_{nst} = \frac{1-\xi_s}{\xi_s} \left(T^I_{nst}\right)^{\frac{1-\xi_s}{\xi_s}} \left(\frac{P^K_{nst}}{P_{0st}}\right)^{\frac{1}{\xi_s}} \bar{K}_{ns,t-1} \tag{3.12}$$

which implies the following growth rate of the capital stock:

$$\frac{\bar{K}_{nst}}{\bar{K}_{ns,t-1}} = \frac{1}{\xi_s} \left(\frac{T^I_{nst} P^K_{nst}}{P_{0st}}\right)^{\frac{1-\xi_s}{\xi_s}} \tag{3.13}$$

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

$$P^I_{nst} = \left(P^K_{nst}\right)^{\frac{1}{\xi_s}} \left(\frac{P_{0st}}{T^I_{nst}}\right)^{-\frac{1-\xi_s}{\xi_s}} \tag{3.14}$$

Hence, investment, capital growth, and the investment bid price are all increasing in the capital price and investment efficiency but are decreasing in the cost of investment.[24]

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[20] As described in Appendix B, this functional form for the labor supply curve can be microfounded by a model of worker–firm sorting in which workers have idiosyncratic utility shocks from employment at firms of different types that follow a Gumbel (extreme value type I) distribution, where the labor supply elasticity γ is decreasing in the variance of the distribution and increasing in the correlation of utility shocks across firm types.

[21] Even though we refer to g_{nhst} as "amenities", this term has a more general interpretation: it is anything that systematically affects the utility of workers employed at nhs-firms except for wages. This may include literal workplace amenities or may reflect other things like differences in workplace culture and language.

[22] 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 fall in global trade during the Great Recession.

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

[24] Note from Eq. (3.13) that the capital growth rate depends on both an exogenous term T^I_{nst} and the contemporaneous price of capital relative to the cost of investment, P^K_{nst}/P_{0st}. One can think of this as an intermediate case between two extremes: with forward-looking investment behavior, the growth rate of capital would depend on both contemporaneous and future prices of capital and investment; with purely exogenous growth rates, neither contemporaneous nor future prices would matter.

3.6. Selection into exporting

To model the extensive margin of how many firms enter a given market, we assume that selling to market d requires an nhs-firm to pay a marketing cost f^M_{dnhst} 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_{0st}, which allows the nominal fixed cost of exporting to respond directly to shocks at the sector level.

If not all nhs-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_{dnhst} satisfying the following market entry condition:

$$\frac{1}{\sigma_s}\Phi_{dnhst}\left(\phi^M_{dnhst}\right)^{\sigma_s-1} = P_{0st} f^M_{dnhst} \tag{3.15}$$

where Φ_{dnhst} is an aggregate sales shifter:

$$\Phi_{dnhst} \equiv A_{dst}\nu_{dnhst}\left(\mu_s \tau_{dst}\eta_{nhst}\right)^{1-\sigma_s} \tag{3.16}$$

We assume that $f^M_{0nhst} = 0$, so that all firms sell to the domestic market with $\phi^M_{0nhst} = 0$.[25]

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[26]:

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

Note that this aggregator assumes costless trade of goods across locations within China. Domestic demand for output of a $nhs\phi$-firm is then given by:

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

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

where P_{0st} is the price index corresponding to the aggregator (3.17).

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

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

where ρ_{dnhst} is the fraction of nhs-firms that sell in market d:

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

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

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

As described above, sector-level output is used for four purposes: final consumption, domestic materials, investment, and marketing costs. The price of sector s output in destination d (including the domestic market, $d = 0$) can then be expressed as:

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

while the cost of domestic intermediates corresponding to the Cobb–Douglas aggregator (3.8) is given by:

$$P^D_{st} = \prod_{s'=1}^{S}\left(P_{0s't}\right)^{\alpha_{ss'}} \tag{3.24}$$

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_{nhst} as endogenously determined by forward-looking firm decisions about entry and exit becomes computationally

[25] Processing firms in China are largely 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.

[26] 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 Eq. (3.1).

Table 2
Summary of calibration and estimation strategy.

Parameter		Source/Targeted moments	Equation(s)
1. Directly measured or from literature			
a.	foreign import expenditures: E_{dst}	UN Comtrade	–
b.	firm counts: N_{nhst}	ASM (see online Appendix B)	–
c.	trade surplus-GDP ratios: Γ_t	ASM	–
d.	final consumption shares: α_s^F	WIOD tables	–
e.	input–output shares: $\alpha_{ss'}$	WIOD tables	–
f.	labor supply elasticity: γ	1.5 (Tombe and Zhu, 2019)	–
g.	sds of log idiosyncratic TFP: $\sigma_{\phi,nhs}$	Brandt et al. (2012)	–
h.	product eos: σ_s	sds of log sales	–
i.	dom.-imp. int. inputs eos: ϵ_s^M	set equal to 2b.	–
j.	dom.-imp. final goods eos: ϵ_s^F	set equal to 2b.	–
k.	utility/production function weights: $\bar{\omega}$	$\frac{1}{2}$ (normalization)	–
2. Calibrated to match empirical shares			
a.	foreign market access: $\bar{P}_{dst}^*$	Chinese export market shares	(D.1)
b.	imp. int. input prices: P_{nst}^I	imported shares of int. inputs	(D.2)
c.	imp. final goods prices: P_{st}^{FI}	imported shares of final consumption	(D.3)
d.	lagged capital investment shares: ξ_s	10% investment to capital value ratio	(D.4)
3. From export demand-supply decomposition			
a.	export marketing costs: f_{dnhst}^M	export propensities	(D.5)
b.	final consumption shocks: ν_{dnhst}	residual sales/export values	(4.2)
4. From production function estimation			
a.	factor productivities: $\bar{T}_{nhst}$	production costs and input shares	(4.4), (4.5)
b.	VA-materials eos: ϵ_s^X	VA-materials exp.-price relationship	(4.4), (4.5)
c.	labor-capital eos: ϵ_s^V	labor-capital exp.-price relationship	(4.4), (4.5)
5. Calibrated to match factor prices			
a.	labor stocks and amenities: $\bar{L}_t$, g_{nhst}	wages	(D.6)
b.	investment efficiencies: T_{nst}^I	capital prices	(D.7)

Notes: This table summarizes how values are assigned to model parameters. The table uses the following abbreviations for brevity – *sds*: standard deviations; *eos*: elasticities of substitution; *dom.*: domestic; *imp.*: imported; *int.*: intermediate; *exp.*: expenditure.

intractable.[27] Hence, in what follows, we treat N_{nhst} 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 the ratio of China's trade surplus to its GDP in each year, Γ_t. Appendix C provides a formal description of the market clearing and trade balance conditions, as well as a definition of an equilibrium of the model (see Definition 1).

4. Taking the model to data

The parameters of the model can be broadly divided into five groups based on our approaches for assigning values to them, as summarized in Table 2. We now describe these approaches in turn. We focus here on the economic intuition behind our approach and on a summary of our main findings, with technical details of the calibration and estimation approaches relegated to Appendix D and detailed reporting of our empirical estimates relegated to section H of the online data appendix for brevity.

4.1. Taking parameters directly from data or the literature

In the first step, we assign values for a set of parameters that can be measured directly from data or that have established estimates in the literature.

First, we calibrate foreign import demand E_{dst} using data on total imports from the UN Comtrade database. Second, we construct measures of firm counts N_{nhst} from the ASM data, using the 2004 Industrial Census to correct for censoring.[28] Third, we set the

[27] This would imply a dynamic state–space for firm entry of dimension $N \times H \times S = 363$.
[28] See section B of the online appendix for details.

trade surplus to GDP ratio Γ_t in each year equal to the corresponding sum of net exports in the customs data divided by total value-added in the ASM data. Fourth, the final consumption shares α_s^F and input–output coefficients $\alpha_{ss'}$ are calibrated using the WIOD input–output data for China.[29] Fifth, we set the labor supply elasticity γ equal to the value of 1.5 estimated by Tombe and Zhu (2019) for China (this value is also used by Liu and Ma (2018)). Sixth, we parameterize the distributions of idiosyncratic firm TFPs as mean-zero log-normal CDFs and set the standard deviation of each distribution $\sigma_{\phi,nhs}$ equal to the corresponding standard deviation of log TFP estimated by Brandt et al. (2012).[30] Seventh, we calibrate the product substitution elasticities σ_s to match the standard deviation of log firm sales within each sector.[31] Eighth, we assume that imported and domestic goods for both final consumption and intermediate use are as substitutable with each other as with different varieties of domestic goods within the sector, which implies $\epsilon_s^F = \sigma_s$ and $\epsilon_s^M = \sigma_s$.[32] 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 $\frac{1}{2}$.

4.2. Calibrating parameters to match empirical shares

A second set of parameters are calibrated to match empirical shares using the model's equilibrium conditions.

Foreign market access, $\bar{P}^*_{dst}$. These parameters are calibrated to match the share of total imports in each dsy cell accounted for by firms in China, conditional on Chinese export price indices P_{dst}. Intuitively, when $\bar{P}^*_{dst}$ is large, Chinese exporters are more likely to have a cost advantage over their competitors in export markets and hence tend to have larger market shares. Our estimates of market access are shown in Table OL-A.5 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. 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, suggesting 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.[33]

Imported intermediate and final goods prices, P^I_{nst} and P^{FI}_{st}. These prices are calibrated to match imported input shares of material costs and final consumption expenditures, conditional on the prices of domestic intermediates P^D_{st} and domestic final consumption P_{0st} respectively. Intuitively, import shares tend to be low when import prices are high. Our estimates of imported input prices are provided in Table OL-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.

Lagged capital investment shares, ξ_s. We set the share of lagged capital in capital formation at $\xi_s = 0.9$ in each sector. 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.

4.3. Decomposing exports and domestic sales

The calibration procedure described in Section 4.2 requires knowledge of two sets of prices: factor prices $\left\{W_{nhst}, P^K_{nst}\right\}$ and destination–sector price indices P_{dst}. We construct the former directly from the ASM data (see section G of the online data appendix for details). To construct the latter, we perform a decomposition of exports and domestic sales, as follows.

First, we decompose sales to any given market into an intensive and an extensive margin. From Eqs. (3.20)–(3.22), the aggregate sales shifter Φ_{dnhst} can be expressed as:

$$\Phi_{dnhst} = \frac{R_{dnhst}}{N_{nhst} \int_{F_{nhs}(\rho_{dnhst})}^{\infty} \phi^{\sigma_s - 1} dG_{nhs}(\phi)} \tag{4.1}$$

where $F_{nhs}\left(\rho_{dnhst}\right) \equiv G^{-1}_{nhs}\left(1 - \rho_{dnhst}\right)$ is the export market entry productivity cutoff ϕ^M_{dnhst}. Intuitively, Φ_{dnhst} is a measure 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. Eq. (4.1) makes it clear that Φ_{dnhst} is uniquely identified from data on sales R_{dnhst}, export propensities ρ_{dnhst}, and firm counts N_{nhst}, given knowledge of the productivity distribution G_{nhs}.[34] Hence, we construct Φ_{dnhst} using Eq. (4.1).

[29] 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.

[30] We 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.

[31] Since σ_s is equal in magnitude to the price elasticity of demand within sector s, this parameter determines how sensitive firm sales are to differences in idiosyncratic TFPs within the sector. Hence, conditional on knowing the dispersion of idiosyncratic TFPs, the dispersion of log firm sales within sector s uniquely determines σ_s. This approach yields estimates of σ_s between 5.2 and 6.4, which imply markups in the range of 18%–24%.

[32] We make this assumption as import prices are not directly observable and hence cannot be used to estimate ϵ_s^F and ϵ_s^M.

[33] For example, in machinery and textiles, market access tends to decline between 2000 and 2007 before trending upward from 2007 to 2013. In metals and chemicals, we observe similar reversals in market access trends around 2004.

[34] Section B of the online data appendix describes how we construct measures of export propensities using the customs, ASM, and 2004 Census data sets.

Since export propensities are also endogenous, we calibrate marketing costs f^M_{dnhst} to ensure that our model replicates these shares (see Appendix D for details).

Next, we decompose sales shifters Φ_{dnhst} into demand- and supply-side components. From Eq. (3.16), we can express the log sales shifter as:

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

In export markets, the term $A_{dst}\tau_{dst}^{1-\sigma_s}$ 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_{nhst} largely reflects supply-side factors that are internal to China: factor productivities and factor prices, for example. The factors on the right-hand side of Eq. (4.2) are then estimated via ordinary least squares (OLS) regression with fixed effects for the various demand- and supply-side terms.[35] Given estimates of market entry productivity cutoffs ϕ^M_{dnhst}, marginal costs η_{nhst}, and taste shifters ν_{dnhst} obtained above, we can also construct the destination–sector price indices P_{dst} following Eq. (3.23).

There are two main identifying assumptions for OLS estimation of Eq. (4.2) to deliver unbiased estimates. First, within each sector s, marginal costs η_{nhst} are uncorrelated with taste shifters ν_{dnhst}. 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 $A_{dst}\tau_{dst}^{1-\sigma_s}$ are uncorrelated with ν_{dnhst}. Since the cardinality of the set of ownership–locations $(N\times H)$ is large, we assume that variations in ν_{dnhst} for a given ownership–location nh have negligible effects on the price indices P_{dst} that enter into the demand shifters A_{dst}. 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_{dst} and market access $\bar{P}^*_{dst}$. Under these assumptions, we thus identify differences in demand shifters $A_{dst}\tau_{dst}^{1-\sigma_s}$ from differences in sales across destinations d for firms within an nhs cell. Similarly, we identify differences in marginal production costs from differences in sales across ownership–locations nh among all firms that sell to the same destination–sector ds.

Note that this approach identifies the fixed effects in Eq. (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^{NBS}_{0st}. 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:

$$P_{0st} = P^{NBS}_{0st} N_{st}^{\frac{1}{1-\sigma_s}} \tag{4.3}$$

where $N_{nst} \equiv \sum_{h=1}^{H} N_{nhst}$. 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 Eq. (4.2) not just relative to each other but in levels.

The procedure described in this section decomposes sales R_{dnhst} into six components: (i) demand shifters, $A_{dst}\tau_{dst}^{1-\sigma_s}$; (ii) production efficiency, $\left(\mu_s\eta_{nhst}\right)^{1-\sigma_s}$; (iii) firm selection, $\bar{\phi}^{\sigma_s-1}_{dnhst}$; (iv) sales propensities, ρ_{dnhst}; (v) firm entry, N_{nhst}; and (vi) residuals, ν_{dnhst}. We find that variation in demand shifters and firm entry explain the largest shares of total sales variance across $dnhsy$ 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%).[36] These estimates suggest that 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.

4.4. *Estimating production function parameters*

Next, we estimate factor-augmenting productivities $\left\{T^L_{nhst}, T^K_{nhst}, T^M_{nhst}\right\}$ and input substitution elasticities $\left\{\epsilon^X_s, \epsilon^V_s, \epsilon^M_s\right\}$ using a production function estimation approach. Cost-minimization under the nested CES technologies described in Section 3.3 implies that the ratio of labor expenditure E^L_{nhst} to capital expenditure E^K_{nhst} can be expressed as:

$$\log\left(\frac{E^L_{nhst}}{E^K_{nhst}}\right) = \log\frac{\omega^V}{1-\omega^V} + \left(\epsilon^V_s - 1\right)\log\left(\frac{P^K_{nst}}{P^L_{nhst}}\right) + \left(\epsilon^V_s - 1\right)\log T^{LK}_{nhst} \tag{4.4}$$

where $T^{LK}_{nhst} \equiv T^L_{nhst}/T^K_{nhst}$ denotes relative productivity of labor versus capital. Similarly, the ratio of value-added cost $E^V_{nhst} \equiv E^L_{nhst} + E^K_{nhst}$ to materials expenditure E^M_{nhst} can be expressed as:

$$\log\left(\frac{E^V_{nhst}}{E^M_{nhst}}\right) = \log\frac{\omega^X}{1-\omega^X} + \left(\epsilon^X_s - 1\right)\log\left(\frac{P^M_{nst}}{\tilde{P}^V_{nhst}}\right) + \left(\epsilon^X_s - 1\right)\log T^{LM}_{nhst} \tag{4.5}$$

[35] 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.

[36] Variance shares are computed by regressing the log of each component on log sales at the $dnhsy$ 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 $\bar{\phi}^{\sigma_s-1}_{dnhst}$ is negative (−19%), reflecting the fact that since only the best firms export, the average idiosyncratic productivity of exporters is higher whenever export propensity is lower.

where $\tilde{P}^V_{nhst} \equiv P^V_{nhst} T^L_{nhst}$ is the price of value-added in Eq. (3.6) adjusted by labor productivity, P^M_{nst} is the price of materials in Eq. (3.7), and $T^{LM}_{nhst} \equiv T^L_{nhst}/T^M_{nhst}$ denotes relative productivity of labor versus materials.[37]

Note that Eqs. (4.4) and (4.5) are standard specifications in the production function estimation literature that are used to estimate input substitution elasticities and factor-augmenting productivities under CES technologies 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. This uses a third-degree polynomial in one-year lags of the factor prices and expenditures in each equation (e.g. logs of $W_{nhs,t-1}$, $P^K_{ns,t-1}$, $E^L_{nhs,t-1}$, and $E^K_{nhs,t-1}$) to instrument for the relative factor price regressor (e.g. $\log \frac{P^K_{nst}}{W_{nhst}}$), as well as a third-degree polynomial control function in lagged relative factor expenditures and prices (e.g. logs of $\frac{P^K_{ns,t-1}}{W_{nhs,t-1}}$ and $\frac{E^M_{nhs,t-1}}{E^L_{nhs,t-1}}$) to control for the omitted productivity residual (e.g. $\log T^{LK}_{nhst}$). As discussed in Appendix E, this approach is valid under the assumption that all time-varying primitives determining factor costs and prices (including factor-augmenting productivities) follow first-order Markov processes.

To implement estimation of Eq. (4.4), we measure labor and capital expenditures and prices from the ASM data.[38] We then Eq. (4.4) separately for each sector, which gives estimates of the labor-capital substitution elasticities ϵ^V_s and relative productivities T^{LK}_{nhst}. Our estimates of ϵ^V_s are shown in the left panel of Figure OL-A.3 in the online appendix. We find that labor and capital are complements in all sectors.

Next, we use these estimates to construct adjusted value-added prices $\tilde{P}^V_{nhst}$ and material prices P^M_{nst} as implied by the model. Together with measures of material expenditures and value-added costs from the ASM data, we then estimate Eq. (4.5) using the same approach as for Eq. (4.4), which gives estimates of the value-added-materials substitution elasticities ϵ^X_s and relative productivities T^{LM}_{nhst}. Our estimates of ϵ^X_s are shown in the right panel of Figure OL-A.3 in the online appendix. We find value-added and materials to be complements in all sectors except for metals and chemical products.

Finally, we infer the *levels* of factor-augmenting productivities using our estimates of marginal costs η_{nhst} from the decomposition (4.2). We first recover labor-augmenting productivity by inverting the expression for marginal cost implied by the nested CES production technologies:

$$T^L_{nhst} = \frac{1}{\eta_{nhst}} \left[\omega^X \left(\tilde{P}^V_{nhst} \right)^{1-\epsilon^X_s} + \left(1 - \omega^X\right) \left(P^M_{nst} T^{LM}_{nhst} \right)^{1-\epsilon^X_s} \right]^{\frac{1}{1-\epsilon^X_s}} \tag{4.6}$$

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

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_{nhst}. Note that changes in efficiency stem from changes in both factor productivities and input costs (labor, capital, imported intermediates, and domestic intermediates). Hence, we define *productivity growth* as the change in efficiency that results only from productivity changes, holding input prices fixed.[39] These statistics are shown in Table 3 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 input prices. These statistics are presented in Table OL-A.8 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 (5.2% per year between 2000 and 2013), textiles and apparel (4.1%), and transportation (6.6%), compared with lower productivity growth in sectors such as metals (2.0%). Second, productivity growth rates in the two most important export sectors – machinery, and textiles and apparel – tend to be highest from 2004 to 2007 but decline after. For example, we observe average growth rates between 2004–2007 in these two sectors of 7.1% and 5.9% respectively, but see these rates fall to 1.9% and 4.3% respectively between 2010–2013. Third, in almost all sectors and years, nominal cost reductions induced by productivity growth are offset by growth in wages (which increase at 15.9% per year for the average firm) and growth in capital costs (10.5% per year), especially between 2004–2007 (see panels (a) and (b) of Table OL-A.8 in the online appendix). 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 (see panels (c) and (d) of Table OL-A.8 in the online appendix). 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

[37] Note that the price of materials P^M_{nst} does not vary by location h because neither imported intermediate prices P^I_{nst} nor domestic intermediate prices P^D_{st} vary by h.

[38] 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.

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

Table 3
Efficiency and productivity growth.

	(a) efficiency growth				(b) productivity growth			
	00–04	04–07	07–10	10–13	00–04	04–07	07–10	10–13
Machinery	3.5	0.5	2.3	2.0	6.4	7.1	5.0	1.9
Textiles & Apparel	0.7	−0.8	−0.6	1.2	2.6	5.9	4.4	4.3
Metals	−0.8	−3.9	−0.6	3.8	2.1	0.3	1.5	4.1
Chemical Products	0.3	−4.8	1.3	2.9	2.5	1.7	6.0	4.6
Transportation	4.5	1.9	1.9	2.0	7.5	8.7	6.9	2.8
Plastics & Rubber	2.1	−2.9	0.7	2.8	3.6	2.3	4.2	3.4
Stone & Glass	3.3	−5.3	−2.5	7.9	5.7	3.7	2.7	9.0
Leathers & Furs	1.1	−2.4	1.2	5.6	3.3	5.3	7.1	7.6
Wood Products	2.5	−2.5	−0.5	4.7	4.2	4.1	3.1	6.4
Foodstuffs	0.1	−0.6	−1.3	1.6	0.9	2.3	−0.3	0.9
Miscellaneous	1.6	−2.9	0.3	2.7	3.2	3.6	5.7	3.3

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.

Table 4
PIE and SOE productivity gaps relative to FIEs.

	(a) PIE-FIE productivity gap				(b) SOE-FIE productivity gap			
	00–03	04–07	08–10	11–13	00–03	04–07	08–10	11–13
Machinery	0.64	0.71	0.74	0.68	0.50	0.59	0.71	0.76
Textiles & Apparel	1.06	1.12	1.06	1.04	0.72	0.76	1.07	0.98
Metals	0.94	0.96	0.90	0.94	0.81	0.82	0.77	0.87
Chemical Products	0.97	0.93	0.81	0.87	0.71	0.74	0.67	0.80
Transportation	0.76	0.77	0.77	0.68	0.65	0.65	0.72	0.79
Plastics & Rubber	0.83	0.92	0.92	0.93	0.76	0.85	0.82	0.90
Stone & Glass	0.81	0.85	0.82	0.95	0.65	0.60	0.68	0.84
Leathers & Furs	1.07	1.23	1.17	1.19	0.64	0.70	0.65	0.71
Wood Products	0.87	0.91	0.79	0.84	0.48	0.51	0.47	0.53
Foodstuffs	0.83	0.76	0.71	0.72	0.69	0.70	0.63	0.78
Miscellaneous	0.81	1.04	1.10	1.07	0.52	0.67	0.83	0.93

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.

are attributable solely to differences in productivity.[40] 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 4 presents our estimates of these productivity gaps. We find that FIEs are more 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 between 2000 and 2007 of 32% and 45%, respectively. Catch-up by PIEs and SOEs narrows these productivity gaps slightly to averages of 29% and 27% respectively between 2008 and 2013, although the rate of catch-up for PIEs slows noticeably after 2007. In textiles and apparel, the productivity advantage that PIEs enjoy over FIEs diminishes from an average of 9% between 2000 and 2007 to 5% between 2007 and 2013, while SOEs exhibit rapid catch-up between 2007 and 2010.

4.5. Calibrating parameters to match factor prices

The decomposition of exports described above 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 is conditional on *measured* prices of labor and capital, $\{W_{nhst}, P^K_{nst}\}$, which are endogenous objects in the model. Hence, in the last step of our procedure, we use the market clearing and trade balance conditions of the model to calibrate labor stocks $\bar{L}_t$, amenities g_{nhst}, and investment efficiencies T^I_{nst} that are consistent with these observed factor prices.

First, since employment is endogenous due to worker sorting, we calibrate $\bar{L}_t$ and g_{nhst} to match employment by firms in each $nhsy$ cell, conditional on the wages W_{nhst} being offered by the respective firms. Our estimates of amenities by ownership-sector are

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

shown in Table OL-A.6 of the online appendix. Across firm ownership types, we find that PIEs tend to have the highest amenity values at the start of the sample followed by SOEs and then FIEs, perhaps reflecting more demanding work environments or easier worker dismissal at FIEs that initially makes employment at these firms less attractive. However, over time, we observe a sharp decline in amenities for SOEs relative to other firms, so that by the end of the sample, FIEs tend to offer better amenities than SOEs. Across sectors, amenities tend to be high in the two most important export sectors – Machinery and Textiles and Apparel – but are noticeably lower in other sectors such as Transportation. We also find that across locations, amenities are the lowest in Shanghai and Beijing/Tianjin, perhaps reflecting geographic frictions that make locating in these cities more difficult.

Second, since capital stocks are endogenous due to firm investment, we calibrate investment efficiencies T^I_{nst} to match capital stocks in each nsy cell, conditional on the value of capital P^K_{nst}, the cost of investment P_{0st}, and lagged capital $\bar{K}_{ns,t-1}$.[41] Our estimates of investment efficiencies are provided in Table OL-A.7 of the online appendix. We find comparable investment efficiencies for FIEs and PIEs before 2007, with FIEs dominating in some sectors and PIEs in others. After 2007, however, PIEs enjoy higher investment efficiencies than FIEs in virtually every sector, which is largely driven by a decline in investment efficiencies for FIEs. For example, we find that investment efficiencies are lower on average between 2007–2010 than between 2004–2007 for FIEs in almost every sector. On the other hand, investment efficiencies grow for PIEs after 2007 in sectors such as machinery, metals, chemical products, and plastics and rubber. We also find that SOEs typically have lower investment efficiencies than FIEs and PIEs, with SOE investment efficiency falling through the first half of the sample period but then rising between 2010 and 2013. These differences in investment efficiencies largely reflect differences in rates of capital accumulation. For instance, the aggregate capital stock for SOEs in all sectors declines at an average rate of −8.4% per year between 2000–2007, compared with positive growth rates of 11.1% and 14.1% for FIE and PIE capital stocks, respectively. After 2007, the growth rate of FIE capital declines to an average of 8.0% per year, whereas the growth rates of PIE and SOE capital increase to 20.9% and 5.2% per year, respectively.

5. Counterfactual simulations

5.1. Methodology

We now formally quantify the drivers of Chinese export growth by using the model to perform a series of counterfactual exercises. First, note that the estimated model exactly matches the value of exports R_{dnhst} in each $dnhsy$ cell by construction. We then group the time-varying primitives of the model into the following $K = 10$ sets: (i) foreign demand terms, $\left\{E_{dst}, \nu_{dnhst}\right\}$; (ii) market access, $\bar{P}^*_{dst}$; (iii) marketing costs, f^M_{dnhst}; (iv) firm entry, N_{nhst}; (v) factor productivities, $\bar{T}_{nhst}$; (vi) imported input prices, P^I_{nst}; (vii) capital growth terms, $\left\{T^I_{nst}, \bar{K}_{ns,t-1}\right\}$; (viii) labor supply terms, $\left\{\bar{L}_{ht}, g_{nhst}\right\}$; (ix) imported final goods prices, P^{FI}_{st}; and (x)trade surplus to GDP ratios, Γ_t. We refer to each set of primitives as a *growth factor* of the model and index these by $k \in \{1, \dots, K\}$. Note that changes over time in growth factors fully account for growth in exports in the model. To quantify the contribution of each growth factor to Chinese export growth, we then proceed as follows.

First, for each year t, let $\bar{R}_t$ denote the actual value of aggregate Chinese exports and let $\bar{\Delta}_t \equiv \frac{\bar{R}_t}{\bar{R}_{t-1}} - 1$ denote the corresponding annual growth rate. In addition, let Θ_{kt} denote the estimated value of growth factor k. Then, for some subset $\kappa \subseteq \{1, \dots, K\}$ of growth factors, let $\Theta_{\kappa t} \equiv \left\{\cup_{k\in\kappa}\theta_{k,t-1}\right\} \cup \left\{\cup_{k\notin\kappa}\theta_{kt}\right\}$ denote the set of growth factors with those in κ set to estimated values in year $t-1$ and all others set to estimated values in year t. Finally, define $\hat{R}\left(\Theta_{\kappa t}\right)$ as the aggregate value of Chinese exports with growth factors set to $\Theta_{\kappa t}$ and $\hat{\Delta}_t\left(\Theta_{\kappa t}\right) \equiv \frac{\hat{R}(\Theta_{\kappa t})}{\bar{R}_{t-1}} - 1$ as the corresponding annual growth rate. Note that with these definitions, $\hat{R}\left(\Theta_{\emptyset t}\right) \equiv \bar{R}_t$ and $\hat{\Delta}_t\left(\Theta_{\emptyset t}\right) \equiv \bar{\Delta}_t$ (where $\emptyset$ denotes the empty set).

We then measure the contribution of growth factor k to aggregate Chinese export growth between years t and $t-1$ in terms of the following Shapley value:

$$\delta_{kt} = \sum_{\kappa\subseteq\{1,\dots,K\}\setminus\{k\}} \frac{|\kappa|!\,(K! - |\kappa|! - 1)}{K!} \left[\hat{\Delta}_t\left(\Theta_{\kappa t}\right) - \hat{\Delta}_t\left(\Theta_{\kappa\cup\{k\},t}\right)\right] \tag{5.1}$$

Intuitively, the term $\hat{\Delta}_t\left(\hat{\Theta}_{\kappa t}\right)$ is the growth rate of exports shutting down changes in growth factors κ, while $\hat{\Delta}_t\left(\hat{\Theta}_{\kappa t} \cup \{k\}\right)$ is the growth rate of exports shutting down changes in growth factors κ and k. Hence, the difference between these two terms is a measure of the contribution of growth factor k to export growth. Summing over all possible sets of growth factors κ that exclude k and weighting by the appropriate Shapley weights then gives us δ_{kt} as a measure of the overall contribution of growth factor k to export growth.[42] We henceforth refer to δ_{kt} as the *export growth contribution* of growth factor k in year t.

Note that the Shapley approach has two advantages. First, it accounts for interdependencies between growth factors. In other words, the measure $\Delta_t\left(\hat{\Theta}_{\kappa t}\right) - \Delta_t\left(\hat{\Theta}_{\kappa t} \cup \{k\}\right)$ typically varies with κ and δ_{kt} is an average of this measure across all possible sets κ. Second, export growth contributions have the appealing property that $\sum_{k=1}^K \delta_{kt} = \bar{\Delta}_t$, so that the observed export growth rate is exactly decomposed into changes stemming from each of the K growth factors. However, the Shapley approach requires the simulation of a large number of counterfactuals ($2^K = 1,024$ for each of 13 years). Hence, while it is theoretically possible to compute export growth contributions at a more disaggregated level (e.g. the contribution of productivity growth among FIEs only),

[41] In the initial year of our sample, we set lagged capital by assuming that the annual growth rate of the capital stock in the first year is the same as the corresponding growth rate in the second year.

[42] Shorrocks (2013) provides a general discussion on the use of Shapley values for decomposing economic outcomes into contributions from various driving factors.

Table 5
Export growth contributions for aggregate exports.

	00–04	04–07	07–10	10–13	00–13
foreign demand	8.2	8.4	2.2	7.7	6.8
market access	−2.9	3.7	3.9	−1.3	0.5
marketing costs	−2.2	−5.2	−2.3	−3.1	−3.1
firm entry	2.2	0.5	−0.1	−0.3	0.7
productivities	2.4	6.2	5.6	2.4	4.0
imp. inputs	12.9	3.2	−0.1	1.4	5.0
capital growth	2.8	3.1	4.2	3.5	3.3
labor supply	1.6	1.0	0.4	0.9	1.1
imp. final goods	1.5	2.1	0.1	0.7	1.1
trade balance	−0.8	5.5	−3.2	−0.6	0.1
total	25.8	28.6	10.8	11.4	19.7

Notes: This table shows the export growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

in practice we compute δ_{kt} for growth factor k applied to all destinations, ownerships, locations, and sectors where applicable (e.g. the contribution of productivity growth among all firms).

Finally, note that our approach to quantifying the sources of Chinese export growth bears some similarities to the approach used by Eaton et al. (2016) to quantify the drivers of the decline in global trade during the Great Recession. In both cases, the model is saturated with enough shocks to be able to replicate the observed data exactly. Counterfactuals with different sets of shocks removed are then used to quantify how each shock contributes to changes over time in an outcome of interest. However, there are two important differences.

First, Eaton et al. (2016) back out shocks in their model only in changes, whereas we identify each growth factor in levels. The key steps in our procedure that allow us to do this are: (i) the decomposition of sales into demand-side and supply-side components (Section 4.3), which gives us estimates of variables such as marginal costs in levels; and (ii) our estimation of production functions (Section 4.4), which delivers estimates of factor productivities in levels. In contrast, Eaton et al. (2016) assume Cobb–Douglas technologies and hence do not estimate elasticities of substitution between different types of inputs. Our approach also has the added benefit of offering insights as to how growth factors compare across the various margins in our model in levels (for example, the comparison of factor productivity gaps across firm ownership types presented in Table 4). Second, the counterfactual simulations in Eaton et al. (2016) consider the removal of one set of shocks at a time, whereas we use the Shapley methodology described above to compute an exact decomposition of export growth.

5.2. Aggregate export growth

We begin by presenting results characterizing the drivers of aggregate Chinese export growth. Our findings are summarized in Table 5, which shows export growth contributions δ_{kt} in units of percentage points per annum (ppa), averaged across years in four windows (2000–2004, 2004–2007, 2007–2010, and 2010–2013) as well as over the entire sample period.[43] We highlight several important observations.

First, over the full sample period, the primary drivers of export growth overall are growth in foreign demand (6.8 ppa in the average year), better access to imported intermediates (5.0 ppa), and improvements in factor productivities (4.0 ppa), complemented by smaller contributions from capital growth (3.3 ppa).[44] Changes in labor supply factors (1.1 ppa), imported final goods prices (1.1 ppa), firm entry (0.7 ppa), export market access (0.5 ppa), and the trade balance (0.1 ppa) play relatively minor roles on average, while increases in export marketing costs contribute negatively to export growth (−3.1 ppa).[45]

Second, the growth rate of aggregate exports falls from almost 30 ppa before 2007 to just over 10 ppa after 2007. The main reasons for this sharp decline are a lack of further improvements in access to imported intermediates (with export growth contributions of 8.8 ppa on average before 2007 but only 0.7 ppa after 2007), weakening external market demand (8.3 ppa versus 5.0 ppa), and a deterioration of China's trade surplus to GDP ratio (1.9 ppa versus −1.9 ppa). The contributions from factor productivity growth also peak around 2007 and then decline after, while firm entry contributes negatively overall after 2007.

Third, examining each of the four periods in Table 5 in more detail, we observe important differences in the sources of export growth over time. Between 2000 and 2004, both external and internal factors are important in driving high rates of aggregate export growth of 25.8 ppa in the average year. Outside of China, growth in foreign demand contributes an average of 8.2 ppa –

43 For comparison, we provide similar results for growth in aggregate gross output in Appendix F.

44 We find positive contributions from capital growth despite the fact that investment efficiencies are generally lower after 2007 than before (see Table OL-A.7). This is because we observe high rates of capital growth throughout our sample period, especially for PIEs but also for FIEs. From Eq. (3.13), the growth rate of capital depends not only on investment efficiencies, but also on the value of capital relative to the cost of investment, P^K_{nst}/P_{0st}, which can be interpreted as a measure of the returns to investment. We find high growth in this relative price.

45 Note that we find secondary contributions from firm entry despite the fact that we abstract from entry costs that might be required to establish new firms. In this sense, our estimated contributions from firm entry are likely an upper bound since we allow the number of producers to increase over time without absorbing resources from the economy.

around a third of total export growth – although this is partially offset by stiffer competition in overseas markets, which lowers export growth by an average of 2.9 ppa. Greater access to imported inputs, which may reflect developments both outside and inside China, contributes 12.9 ppa – around half of the total export growth rate. Within China, capital growth (2.8 ppa), factor productivity growth (2.4 ppa), and firm entry (2.2 ppa) also exhibit positive albeit more modest contributions to export growth.

Between 2004 and 2007, external and internal factors are again important in sustaining high aggregate export growth rates of 28.6 ppa on average, with foreign demand remaining a particularly important source of export growth (8.4 ppa) and market access also beginning to contribute positively (3.7 ppa). However, the export growth contributions arising from improvements in imported input access fall dramatically (from 12.9 ppa to 3.2 ppa), suggesting that any gains from this export growth factor were quickly realized during the first few years of our sample. Within China, we see stronger contributions from factor productivity growth than in the earlier period (6.2 compared with 2.4 ppa), while capital growth also remains an important secondary source of export growth (3.1 ppa). Furthermore, the trade surplus to GDP ratio increases sharply from an average of around 1% in 2004 to more than 9% in 2007, which is reflected in high export growth contributions from this factor (5.5 ppa). However, the contributions from firm entry decline (from 2.2 to 0.5 ppa), indicating a slowdown in the rate of new firm growth within China.

Between 2007 and 2010, we observe a marked dissipation in the export growth contributions from foreign demand (2.2 ppa), likely reflecting the global decline in demand for tradeables during the Great Recession (Eaton et al., 2016). This is an important contributor to the decline in aggregate export growth overall, which falls to 10.8 ppa during this period. As in the preceding period, market access (3.9 ppa), factor productivity growth (5.6 ppa), and capital growth (4.2 ppa) are important sources of export growth. However, the export growth contributions arising from imported input access and firm entry are essentially zero during this period. Furthermore, the trade surplus to GDP ratio falls by more than half (from more than 9% in 2007 to around 4% in 2010), which is reflected in negative export growth contributions from this factor (−3.2 ppa).

Finally, between 2010 and 2013, aggregate export growth remains low (11.4 ppa) compared with pre-2007 growth rates, despite the recovery of export growth contributions from foreign demand (7.7 ppa). This is due in part to a worsening of export market access (−1.3 ppa), but stems mainly from a dissipation of the internal factors that were key drivers of export growth before 2007. The contributions of factor productivity growth fall by more than half relative to the preceding period (from 5.6 to 2.4 ppa), while the contribution of firm entry remains close to zero. Access to imported intermediates shows a slightly positive contribution to export growth (1.4 ppa), but this is nowhere near the large contributions observed from this factor in the early 2000s.

In sum, we observe four periods with fundamentally different sources of aggregate export growth: (i) high growth from 2000 to 2004, driven primarily by foreign demand and imported input access; (ii) sustained growth from 2004 to 2007, driven mainly by foreign demand and factor productivity growth in China; (iii) a marked slowdown in growth from 2007 to 2010, owing largely to a decline in foreign demand and a deteriorating trade balance; and (iv) stagnant growth from 2010 to 2013, due mainly to the dissipation of internal factors such as productivity growth that offset the recovery of foreign demand.

5.3. Disaggregated results

We next examine the drivers of export growth across different destinations, firm ownership types, production locations, and sectors. To do so, we again compute the export growth contributions δ_{kt} in Eq. (5.1), but replace aggregate exports with exports for each destination d, firm ownership type n, sector s, or production location h. For brevity, we report these results averaged over years in two windows only (2000–2007 and 2007–2013). Furthermore, to streamline the discussion of our findings, we focus on highlighting two sets of observations: (i) patterns that hold more or less symmetrically across all destinations, ownership types, sectors, or locations; and (ii) patterns that exhibit more noticeable heterogeneity across these margins.

5.3.1. Export growth by destination

Table 6 shows the export growth contributions for exports to different destinations, where all destinations outside of the top five in terms of total Chinese exports are aggregated into a single category (ROW) for brevity.

Symmetries. Before 2007, the three key drivers of aggregate export growth – greater foreign demand, improvements in imported input access, and factor productivity growth – are also central for the growth in exports to each destination individually, with the one exception being a negative contribution from foreign demand for exports to East Asia. After 2007, we also see symmetries in the dissipation of export growth contributions arising from imported input access, which fall to almost nothing for exports to all destinations, while productivity growth remains a positive contributor to export growth for all destinations.

Asymmetries. After 2007, we observe some heterogeneity across destinations in the export growth contributions arising from foreign demand. These contributions fall sharply for Western Europe (from 8.7 ppa before 2007 to −1.6 ppa after 2007) and Eastern Europe (from 33.4 to −11.1 ppa). In contrast, foreign demand begins to contribute positively for export growth to East Asia (5.6 ppa) and remains a robust source of growth for exports to South East Asia as well (9.1 ppa).

5.3.2. Export growth by firm ownership type

Table 7 shows the export growth contributions for exports by firms of different ownership types.

Symmetries. Before 2007, growth in foreign demand and improvements in imported input access are key drivers of export growth for all three firm ownership types, while after 2007, the export growth contributions arising from imported input access also largely disappear for all ownership types.

Table 6
Export growth contributions for exports by destination.

	N. America		W. Europe		E. Asia		S. E. Asia		E. Europe		ROW	
	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13
foreign demand	4.7	2.0	8.7	−1.6	−0.5	5.6	8.9	9.1	33.4	−11.1	10.4	3.9
market access	0.6	1.4	−4.4	−0.1	1.1	0.4	−1.0	4.8	3.8	6.9	6.5	5.7
marketing costs	−1.7	−1.4	−3.1	−0.1	−0.1	−1.1	−3.8	−5.4	−22.6	2.1	−10.7	−4.2
firm entry	2.0	0.0	2.1	−0.1	1.7	0.0	1.6	−0.1	0.7	−0.7	−0.5	−0.6
productivities	3.7	4.0	5.1	4.8	2.8	2.4	5.3	3.7	8.8	8.1	6.1	4.6
imp. inputs	9.2	0.6	11.5	0.7	6.6	0.5	10.1	0.8	12.2	0.8	12.1	0.7
capital growth	3.0	2.7	3.8	4.3	2.3	2.5	3.5	4.8	4.0	5.7	3.7	5.9
labor supply	1.6	0.5	1.9	0.6	0.8	0.1	1.3	1.0	2.9	0.5	1.8	0.8
imp. final goods	1.7	0.4	2.2	0.4	1.3	0.3	2.1	0.5	3.0	0.4	2.7	0.5
trade balance	1.6	−1.7	2.3	−2.3	1.4	−1.4	2.2	−2.2	3.1	−2.4	2.8	−2.6
total	26.3	8.5	30.2	6.7	17.4	9.3	30.0	16.9	49.4	10.3	34.9	14.6

Notes: This table shows the export growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row, but replacing total exports with exports to each destination. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

Table 7
Export growth contributions for exports by firm ownership type.

	FIE		PIE		SOE	
	00–07	07–13	00–07	07–13	00–07	07–13
foreign demand	9.8	0.6	6.8	11.3	6.1	6.1
market access	−1.6	0.2	2.0	3.0	2.9	4.0
marketing costs	−1.2	1.8	−7.2	−9.5	−4.1	0.7
firm entry	4.4	0.7	−2.7	−1.7	−0.2	2.5
productivities	2.6	5.0	4.6	2.0	11.9	7.2
imp. inputs	8.6	0.3	9.1	0.9	8.1	0.2
capital growth	3.3	−0.9	5.1	11.3	−11.6	−1.4
labor supply	2.1	−0.3	1.6	2.3	−4.6	−1.6
imp. final goods	1.3	0.3	2.6	0.5	1.8	0.6
trade balance	1.2	−1.1	3.2	−3.1	1.9	−1.6
total	30.5	6.6	25.1	17.0	12.2	16.8

Notes: This table shows the export growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row, but replacing total exports with exports by firms of each ownership type. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

Asymmetries. We observe substantial heterogeneity in the sources of export growth across firm ownership types. First, the decline in export growth contributions from foreign demand after 2007 primarily affects FIE exports (falling from 9.8 ppa to 0.6 ppa), whereas foreign demand remains important for PIE and SOE exports (11.3 ppa and 6.1 ppa, respectively). This partly reflects the fact that FIEs tend to export more to markets with declining demand during this period (particularly North America and Western Europe), whereas PIEs and SOEs export relatively more to markets where foreign demand remains strong (e.g., South East Asia).

Second, before 2007, factor productivity growth is more important for PIE and SOE exports (4.6 ppa and 11.9 ppa, respectively) compared with FIE exports (2.6 ppa), reflecting in part the catch-up of PIE and SOE productivities relative to FIE productivities in key export sectors such as Machinery (see Table 4). However, after 2007, productivity growth becomes more important for FIE exports (5.0 ppa), less important for PIE exports (2.0 ppa), and remains a key source of growth for SOE exports (7.2 ppa).

Third, capital growth factors contributed similarly to FIE and PIE export growth before 2007 (3.3 ppa and 5.1 ppa, respectively), but these contributions diverged sharply after 2007, with large positive contributions for PIE exports (11.3 ppa) and negative contributions for FIE exports (−0.9 ppa). This divergence may reflect in part government policies after 2007 that aimed to improve access to capital for PIEs. In addition, capital growth factors exhibited starkly negative contributions for SOE exports, especially before 2007 (−11.6 ppa), likely reflecting the downsizing of the state sector and the reallocation of productive assets from SOEs to PIEs through privatization of the former group of firms. Similarly, labor supply factors contributed negatively to SOE export growth, particularly from 2000 to 2007 (−4.6 ppa), reflecting the decline in amenities at SOEs relative to other firms associated with the massive layoffs in the SOE sector throughout this period.

Finally, firm entry exhibits positive contributions to export growth mainly for FIEs before 2007 (4.4 ppa), reflecting the high rates at which FIEs were entering China during this period. In contrast, firm entry contributes little toward PIE and SOE export growth, and also dissipates as a source of growth for FIE exports after 2007.

5.3.3. Export growth by sector

Table 8 shows the export growth contributions for exports in different sectors, where sectors outside of the top five in terms of total Chinese exports are aggregated into a single category (Other) for brevity.

Table 8
Export growth contributions for exports by sector.

	Machinery		Txtl. & Aprl.		Metals		Chem. Prod.		Transport.		Other	
	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13
foreign demand	10.0	4.4	5.0	4.6	16.6	−4.7	9.2	2.5	2.6	−0.4	6.7	13.1
market access	−3.8	−0.9	−0.6	2.9	25.8	7.7	−2.3	17.0	−5.6	1.7	1.3	0.8
marketing costs	−3.3	−1.2	−2.4	−2.4	−7.4	−2.8	−11.0	−4.6	−3.3	−0.8	−2.5	−6.8
firm entry	2.8	−0.1	0.5	−1.1	3.3	−0.4	−3.1	−0.1	3.7	0.3	0.4	0.2
productivities	9.1	2.3	6.4	9.7	−18.5	0.3	9.0	−8.0	17.0	8.0	−2.6	5.5
imp. inputs	9.7	0.8	4.1	−0.1	12.2	2.0	9.8	2.0	3.3	0.1	11.5	0.3
capital growth	4.1	4.5	0.3	−0.7	0.1	11.0	6.7	7.7	8.3	2.7	2.0	2.7
labor supply	1.8	1.6	2.3	−0.5	−4.1	−0.6	−1.7	−0.2	1.6	0.3	1.7	0.6
imp. final goods	1.7	0.3	1.3	0.0	1.9	0.6	2.7	0.9	3.2	2.2	1.8	0.2
trade balance	1.5	−1.6	1.4	−1.5	3.4	−2.9	5.4	−4.9	0.7	−0.6	2.0	−2.2
total	33.6	10.0	18.2	10.7	33.3	10.2	24.6	12.3	31.5	13.4	22.5	14.4

Notes: This table shows the export growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row, but replacing total exports with exports for each sector. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

Symmetries. We observe more symmetry in the sources of export growth across sectors before 2007. During this period, stronger foreign demand, improvements in imported input access, and growth in factor productivities are the main drivers of export growth in most sectors. The main exceptions to this are weaker contributions from foreign demand in Transportation, slightly less important roles for imported input access in Textiles and Apparel and Transportation, and negative contributions from factor productivity growth in Metals. After 2007, the positive contributions from imported input access also largely disappear in all sectors, which is an important explanation for the overall slowdown in export growth during this period.

Asymmetries. After 2007, export growth contributions arising from foreign demand fall in all five of the main export sectors, but these changes are noticeably heterogeneous across sectors, with much sharper declines in Metals, Chemical Products, and Machinery and a more modest decline in Textiles and Apparel. Outside of the top five sectors, the export growth contributions from foreign demand in fact increase after 2007. In addition, the contribution of improvements in factor productivities to export growth vary substantially across sectors after 2007, with large positive contributions in Textiles and Apparel and Transportation, smaller positive contributions in Machinery, Metals, and sectors outside of the top five, and negative contributions in Chemical Products.

5.3.4. *Export growth by production location*

Table 9 shows the export growth contributions for exports produced in different locations in China, where locations outside of the top five in terms of total Chinese exports are aggregated into a single category (Other) for brevity.

Symmetries. In all production locations, foreign demand is an important source of export growth throughout the entire sample period, but exhibits larger contributions before 2007 compared with after. In addition, improvements in imported input access are a key driver of export growth in all locations only before 2007.

Asymmetries. There is noticeable heterogeneity in the other drivers of export growth across production locations. First, before 2007, the export growth contributions from factor productivity growth are much larger in Jiangsu (13.7 ppa) and Shanghai (13.4 ppa) compared with other production locations, whereas after 2007, exports from Shandong (9.0 ppa) and locations outside of the top five (14.0 ppa) benefit more from productivity growth. Second, over the entire sample period, capital growth tends to matter more for export growth in Jiangsu and Zhejiang than in other locations. Finally, firm entry contributes positively to export growth mainly in Shandong (5.5 ppa), Jiangsu (4.4 ppa), and Guangdong (2.4 ppa) before 2007.

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 the three key drivers of Chinese export growth overall are rising foreign demand, improvements in access to imported intermediates, and factor productivity growth within China. However, weakening foreign demand and a tapering of improvements in imported input access largely explain the slowdown in export growth after 2007. At the same time, there is substantial heterogeneity in the drivers of export growth across export destinations, firm ownership types, sectors, and production locations.

There are indications that the downward trends we have identified in the drivers of Chinese export growth also persist through 2019 as export growth fell to only 2% per annum between 2013–2019. For instance, the role of manufacturing imported intermediates, measured here by the share of aggregate intermediate expenditures in manufacturing, remains largely unchanged between 2013 and 2017 at 11%. Data from China's Business Registry also 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. Furthermore, employment growth in manufacturing slows considerably as the number of migrants working in manufacturing in the major exporting provinces levels off.

Table 9
Export growth contributions for exports by production location.

	Guangdong		Jiangsu		Shanghai		Zhejiang		Shandong		Other	
	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13	00–07	07–13
foreign demand	6.6	4.5	13.7	4.5	7.8	3.9	13.6	8.0	7.5	5.1	5.9	5.1
market access	−1.6	0.1	−1.0	2.4	−0.8	1.7	1.2	1.7	1.6	2.4	1.8	1.5
marketing costs	1.0	4.1	−15.9	−1.9	−5.3	1.2	−6.4	−4.7	−6.1	−10.7	−0.3	−10.8
firm entry	2.4	−0.2	4.4	1.4	−0.6	−2.1	−1.6	−0.9	5.5	−1.5	0.0	0.3
productivities	1.7	−1.3	13.7	0.6	13.4	0.3	−4.4	3.4	5.1	9.0	1.9	14.0
imp. inputs	7.5	0.2	11.6	0.9	7.2	0.3	13.0	1.2	8.3	1.0	8.5	0.9
capital growth	1.6	−0.7	4.1	5.1	3.8	1.8	4.4	7.0	2.2	9.6	3.1	6.2
labor supply	1.5	4.1	1.4	−1.9	1.8	0.9	6.8	−1.1	−1.5	−2.4	−0.5	−0.3
imp. final goods	1.3	0.2	2.1	0.4	1.5	0.3	2.9	0.6	1.8	0.6	1.8	0.5
trade balance	1.4	−1.4	2.1	−2.3	1.4	−1.5	2.9	−2.7	2.3	−2.1	2.1	−2.1
total	23.4	9.7	36.2	9.1	30.3	6.8	32.4	12.4	26.6	11.0	24.3	15.4

Notes: This table shows the export growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row, but replacing total exports with exports from each production location. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

There are alternative explanations for these trends. One possibility is that the slowdown after 2007 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 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.[46]

We find however significant productivity gaps between FIEs and Chinese firms even at the end of our sample. This suggests 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 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 observe 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.[47] 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.

Finally, our analysis has potentially important implications for the welfare effects of the China shock in other countries. In the literature, China's rapid export growth between 1992–2007 is viewed largely as the product of productivity gains tied to the country's market opening (Autor et al., 2021). However, we find significant differences in the drivers of export growth across sectors, ownership types, and destinations, as well as over time. Furthermore, changes in welfare in other countries are likely to depend on exactly which growth factor explains observed levels of Chinese export growth. For example, a China shock driven by greater demand for Chinese products is likely to have very different welfare effects compared with a shock arising from Chinese factor productivity growth. Extending our analysis in this paper to consider these welfare implications is likely to yield important insights.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://data.mendeley.com/datasets/xx8d34s2vr/2.

Appendix A. Model extension with internal trade costs

We assume in our model that goods are freely tradable within China. Consider an alternative set of assumptions whereby sector s output M_{st} defined in Eq. (3.17) is assembled in a unique location $h^*(s)$ without being subject to internal trade costs, but that the

[46] 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.

[47] 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".

sourcing of this good for use in production by firms in any location h in year t incurs an iceberg trade cost $\tau_{h^*(s)ht} \geq 1$. In this case, the effective cost of sourcing intermediate inputs from sector s' for an nhs-firm is $\tau_{h^*(s')ht} P_{0st}$. One can then rewrite the production function for materials (3.7) as:

$$M_{nhst} = \left[\left(\omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(M_{nhst}^I\right)^{\frac{\epsilon_s^M - 1}{\epsilon_s^M}} + \left(1 - \omega^M\right)^{\frac{1}{\epsilon_s^M}} \left(T_{hst}^{MD} M_{nhst}^D\right)^{\frac{\epsilon_s^M - 1}{\epsilon_s^M}} \right]^{\frac{\epsilon_s^M}{\epsilon_s^M - 1}} \tag{A.1}$$

where $T_{hst}^{MD} \equiv \prod_{s'=1}^{S} \left(\tau_{h^*(s')ht}\right)^{\alpha_{ss'}}$ reflects internal trade costs associated with sourcing goods across all sectors with weights corresponding to the Cobb–Douglas production function for domestic materials (3.8). In this sense, one can interpret T_{hst}^{MD} as a "productivity" shifter that captures internal trade costs and their changes over time.

Appendix B. Microfoundation for labor supply curves

Suppose that the utility of a worker i from employment at a firm with ownership type n in location h and sector s in year t is given by:

$$V_{inhst} = \log \left[\frac{\left(1 + \tau_t\right) w_{nhst}}{P_t^F} \right] + \log g_{nhst} + \frac{1}{\beta} \varepsilon_{inhst} \tag{B.1}$$

where τ_t is a transfer that rebates profits to workers in proportion to their wages, P_t^F is the price index of final consumption corresponding to the preferences specified in Eq. (3.3), and ε_{inhst} is an idiosyncratic preference shock with β an inverse measure of the dispersion of these shocks. In other words, besides consumption utility $\frac{(1+\tau_t) w_{nhst}}{P_t^F}$, workers also care about amenities and idiosyncratic preference shocks.

Now suppose that the distribution of idiosyncratic preference shocks across workers, $\varepsilon_{it} \equiv \left\{\varepsilon_{inhst}\right\}$, is a multivariate Gumbel distribution with cumulative distribution function given by:

$$F_\varepsilon \left(\varepsilon_{it}\right) = exp \left[- \left(\sum_{n=1}^{N} \sum_{h=1}^{H} \sum_{s=1}^{S} e^{-\frac{\varepsilon_{inhst}}{\rho}} \right)^{\rho} \right] \tag{B.2}$$

where $\rho \in (0, 1]$ controls the correlation of idiosyncratic preferences across firms. As ρ approaches zero, workers view all firms as perfect substitutes, whereas as ρ approaches one, idiosyncratic preferences across firms become independent random variables.

Workers observe wages w_{nhst} and amenities g_{nhst} and choose the $\{n, h, s\}$-tuple of their employment to maximize utility. Under the Gumbel distribution for the preference shocks, the quantity of workers that choose employment at $\{n, h, s\}$-firms is then given by Eq. (3.9), where the labor supply elasticity is given by $\gamma = \beta / \rho$.

Appendix C. Equilibrium definition

To formally define an equilibrium of the model, we require a few additional equations. First, the marginal cost η_{nhst}, value-added price index P_{nhst}^V, and material price index P_{nst}^M for an nhs-firm corresponding to the CES production technologies specified in Eqs. (3.5)–(3.7) are given respectively by:

$$\eta_{nhst} = \left[\omega^X \left(P_{nhst}^V\right)^{1-\epsilon_s^X} + \left(1 - \omega^X\right) \left(P_{nst}^M / T_{nhst}^M\right)^{1-\epsilon_s^X} \right]^{\frac{1}{1-\epsilon_s^X}} \tag{C.1}$$

$$P_{nhst}^V = \left[\omega^V \left(W_{nhst} / T_{nhst}^L\right)^{1-\epsilon_s^V} + \left(1 - \omega^V\right) \left(P_{nst}^K / T_{nhst}^K\right)^{1-\epsilon_s^V} \right]^{\frac{1}{1-\epsilon_s^V}} \tag{C.2}$$

$$P_{nst}^M = \left[\omega^M \left(P_{nst}^I\right)^{1-\epsilon_s^M} + \left(1 - \omega^M\right) \left(P_{st}^D\right)^{1-\epsilon_s^M} \right]^{\frac{1}{1-\epsilon_s^M}} \tag{C.3}$$

Second, the share of value-added in production cost s_{nhst}^V, the share of labor in value-added cost s_{nhst}^L, and the share of imported intermediates in material cost s_{nst}^I for an nhs-firm are given respectively by:

$$s_{nhst}^V = \omega^X \left(\frac{P_{nhst}^V}{\eta_{nhst}} \right)^{1-\epsilon_s^X} \tag{C.4}$$

$$s_{nhst}^L = \omega^V \left(\frac{W_{nhst} / T_{nhst}^L}{P_{nhst}^V} \right)^{1-\epsilon_s^V} \tag{C.5}$$

$$s_{nst}^I = \omega^M \left(\frac{P_{nst}^I}{P_{nst}^M} \right)^{1-\epsilon_s^M} \tag{C.6}$$

Similarly, the share of imported final goods in final consumption expenditure on sector s goods is:

$$s_{st}^{FI} = \frac{\left(1-\omega^{F}\right)\left(P_{st}^{FI}\right)^{1-\epsilon_{s}^{F}}}{\omega^{F}\left(P_{0st}\right)^{1-\epsilon_{s}^{F}} + \left(1-\omega^{F}\right)\left(P_{st}^{FI}\right)^{1-\epsilon_{s}^{F}}} \tag{C.7}$$

Third, the total value of sales by nhs-firms is:

$$\bar{R}_{nhst} = \left[v_{onhst} N_{nhst} \left(\frac{\mu_s \eta_{nhst} / \bar{\phi}_{0dnhs}}{P_{0st}} \right)^{1-\sigma_s} \right] R_{0st} + \sum_{d=1}^{D} R_{dnhst} \tag{C.8}$$

where $R_{0st} \equiv P_{0st} M_{st}$ is the total value of sector s output. Fourth, the trade deficit is:

$$\Gamma_t E_t = \sum_{d=1}^{D}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{s=1}^{S} R_{dnhst} - \sum_{s} \gamma_s s_{st}^{FI} E_t - \sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{s=1}^{S} \frac{1}{\mu_s}\left(1 - s_{nhst}^{V}\right) s_{nst}^{I} \bar{R}_{nhst} \tag{C.9}$$

where E_t is aggregate value-added in China. The first term on the right-hand side of (C.9) is aggregate exports, the second term is the value of imported final goods, and the third term is the value of imported intermediate goods. Fifth, sector s market clearing requires:

$$\begin{aligned} R_{0st} = {} & \gamma_s \left(1 - s_{st}^{FI}\right) E_t \\ & + \sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{s'=1}^{S} \frac{1}{\mu_{s'}}\left(1 - s_{nhs't}^{V}\right)\left(1 - s_{ns't}^{I}\right) \alpha_{s's} \bar{R}_{nhst} \\ & + \sum_{d=1}^{D}\sum_{n=1}^{N}\sum_{h=1}^{H}\sum_{s=1}^{S} \rho_{dnhst} N_{nhst} P_{0st} f_{dnhst}^{M} \\ & + \sum_{n=1}^{N} \left(1 - \xi_s\right) P_{nst}^{K} K_{nst} \end{aligned} \tag{C.10}$$

where the first term on the right-hand side is the value of domestic final consumption, the second term is the value of domestic intermediate purchases, the third term is the value of export marketing costs, and the fourth term is the value of capital investment. Sixth, labor market clearing requires:

$$W_{nhst} \bar{L}_{nhst} = \frac{1}{\mu_s} s_{nhst}^{V} s_{nhst}^{L} \bar{R}_{nhst} \tag{C.11}$$

Finally, capital market clearing requires:

$$P_{nst}^{K} \bar{K}_{nst} = \sum_{h=1}^{H} \frac{1}{\mu_s} s_{nhst}^{V}\left(1 - s_{nhst}^{L}\right) \bar{R}_{nhst} \tag{C.12}$$

We can now define an equilibrium of the model as follows.

Definition 1. An equilibrium of the model at time t is a set of values for export demand shifters A_{dst} (3.2), employment $\bar{L}_{nhst}$ (3.9), capital stocks $\bar{K}_{Nst}$ (3.13), export market entry margins ϕ_{dnhst}^{M} (3.15), sales shifters Φ_{dnhst} (3.16), exports R_{dnhst} (3.20), export propensities ρ_{dnhst} (3.21), average productivities $\bar{\phi}_{dnhst}$ (3.22), price indices P_{dst} (3.23), domestic intermediate prices P_{st}^{D} (3.24), marginal costs η_{nhst} (C.1), value-added price indices P_{nhst}^{V} (C.2), materials price indices P_{nst}^{M} (C.3), value-added shares s_{nhst}^{V} (C.4), labor shares s_{nhst}^{L} (C.5), imported intermediate shares s_{nst}^{I} (C.6), imported final goods shares s_{st}^{FI} (C.7), total sales $\bar{R}_{nhst}$ (C.8), aggregate value-added E_t (C.9), sector sales R_{0st} (C.10), wages W_{nhst} (C.11), and capital prices P_{nst}^{K} (C.12), all satisfying the set of equations listed in parentheses.

Appendix D. Details on calibration of model parameters

Product substitution elasticities, σ_s. Under the CES demand described in Section 3.2.1, firms within a sector s differ in sales only in relation to $\phi^{\sigma_s - 1}$. Hence, the standard deviation of log sales across firms within sector s is equal to $\left(\sigma_s - 1\right)\sigma_{\phi,s}$, where $\sigma_{\phi,s}$ is the standard deviation of log TFP across all firms in sector s. We construct the latter as a weighted average of $\sigma_{\phi,nhs}$ across nh within each sector s, where the weights are the share of nh firms in the sector in the average year of our sample. Given $\sigma_{\phi,s}$, σ_s is then easily recovered.

Foreign market access, $\bar{P}_{dst}^{*}$. We first construct Chinese export price indices P_{dst} from Eq. (3.23) given our estimates of export productivity cutoffs ϕ_{dnhst}^{M} and marginal costs η_{nhst} described in Section 4.3. We then measure market shares for firms in China in each destination–sector–year, s_{dst}^{X}, using UN Comtrade data. Finally, we recover the market access terms from the relationship between market shares and import prices implied by consumer utility maximization under the CES preferences described in Section 3.2.1:

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

Imported intermediate and final good prices, P^I_{nst} and P^{FI}_{st}. We first measure imported shares of material expenditures, s^I_{nst}, as the ratio of total imports of raw materials, capital goods, and intermediates (as defined by the BEC classification) in the customs data relative to total material costs constructed from the ASM data (see section F of the online data appendix for a more detailed discussion of the data). We then recover imported intermediate input prices from the relationship between import shares and prices implied by firm cost minimization under the materials technology in Eq. (3.7):

$$P^I_{nst} = \left[\left(\frac{1-\omega^M}{\omega^M} \right) \left(\frac{s^I_{nst}}{1-s^I_{nst}} \right) \right]^{\frac{1}{1-\epsilon^M_s}} P^D_{st} \tag{D.2}$$

Domestic input prices P^D_{st} are constructed as the price indices corresponding to the Cobb–Douglas technology in Eq. (3.8), given the input–output shares $\{\alpha_{ss'}\}$ and estimates of sector prices P_{0st} described in Section 4.3. Similarly, final consumption import shares, s^{FI}_{st} are computed as the ratio of total consumer goods imports (based on the BEC classification) in the customs data relative to domestic final consumption expenditures from the WIOD. We then recover imported final goods prices from the relationship between import shares and prices implied by consumer utility maximization under Eq. (3.4):

$$P^{FI}_{st} = \left[\left(\frac{1-\omega^F}{\omega^F} \right) \left(\frac{s^{FI}_{st}}{1-s^{FI}_{st}} \right) \right]^{\frac{1}{1-\epsilon^F_s}} P_{0st} \tag{D.3}$$

Lagged capital investment shares, ξ_s. Combining Eqs. (3.12) and (3.13), we obtain:

$$1 - \xi_s = \frac{P_{0st} I_{nst}}{P^K_{nst} K_{nst}} \tag{D.4}$$

Hence, the share of lagged capital in investment is equal to one minus the ratio of investment expenditure to the value of the contemporaneous capital stock.

Export marketing costs, f^M_{dnhst}. From Eqs. (3.15) and (3.21), nominal marketing costs can be calibrated according to:

$$P_{0st} f^M_{dnhst} = \frac{1}{\sigma_s} \Phi_{dnhst} \left[F_{nhs} \left(\rho_{dnhst} \right) \right]^{\sigma_s - 1} \tag{D.5}$$

where $F_{nhs}(\rho) \equiv G^{-1}_{nhs}(1-\rho)$. This ensures that the model replicates observed export propensities conditional on replicating the value of Φ_{dnhst} constructed from Eq. (4.1). Nominal marketing costs are easily converted into real costs given the values of P_{0st} that we construct following estimation of Eq. (4.2).

Amenities, g_{nhst}. First, note from Eq. (3.9) that all equilibrium outcomes are invariant to scaling amenities by a constant in each period. Hence, we can normalize amenities within each period without loss of generality. We choose a normalization such that the denominator on the right-hand side of Eq. (3.9) is equal to one in every period. This allows us to solve for amenities as:

$$g_{nhst} = \frac{\left(\bar{L}_{nhst} / \bar{L}_t \right)^{\frac{1}{\gamma}}}{W_{nhst}} \tag{D.6}$$

Investment efficiencies, T^I_{nst}. From Eq. (3.13), we recover the investment efficiencies as:

$$T^I_{nst} = \left(\frac{\xi_s K_{nst}}{K_{ns,t-1}} \right)^{\frac{\xi_s}{1-\xi_s}} \left(\frac{P^K_{nst}}{P_{0st}} \right)^{-1} \tag{D.7}$$

Appendix E. Production function estimation details

This section provides details on the production function estimation procedure following Doraszelski and Jaumandreu (2018) as outlined in Section 4.4. We describe this for a generic CES production function that produces some output X_t by combining two inputs, A_t and B_t, as follows:

$$X_t = \left[\omega^{\frac{1}{\epsilon}} \left(T^A_t A_t \right)^{\frac{\epsilon-1}{\epsilon}} + (1-\omega)^{\frac{1}{\epsilon}} \left(T^B_t B_t \right)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \tag{E.1}$$

where $\{T^A_t, T^B_t\}$ are factor-augmenting productivities, ϵ is the elasticity of substitution between the two inputs, and ω is a production function weight. Suppose that firms operating this production technology face prices P^A_t and P^B_t for the two inputs and choose input quantities to minimize production costs. Then, the ratio of expenditure on input A, E^A_t, to expenditure on input B, E^B_t, satisfies:

$$\log \left(\frac{E^A_t}{E^B_t} \right) = c + (\epsilon - 1) \log \left(\frac{P^B_t}{P^A_t} \right) + (\epsilon - 1) \log T^{AB}_t \tag{E.2}$$

where $T^{AB}_t \equiv T^A_t / T^B_t$ and $c \equiv \log \frac{\omega}{1-\omega}$ is a constant.

Now suppose that T^{AB}_t follows a first-order Markov process:

$$\log T^{AB}_t = F\left(\log T^{AB}_{t-1} \right) + \xi_t \tag{E.3}$$

Table A.1
Growth contributions for aggregate gross output.

	00–04	04–07	07–10	10–13	00–13
foreign demand	1.1	4.2	0.2	−1.2	1.1
market access	−0.7	1.3	1.0	−0.2	0.2
marketing costs	−0.6	−1.8	−0.7	−0.9	−1.0
firm entry	7.0	6.6	2.5	2.5	4.8
productivities	7.1	8.4	8.5	7.4	7.8
imp. inputs	−0.3	0.0	−0.4	−0.3	−0.3
capital growth	2.4	3.5	9.7	8.0	5.6
labor supply	0.1	1.0	0.0	1.4	0.6
imp. final goods	−0.3	−0.4	−0.2	−0.2	−0.3
trade balance	0.2	−1.5	1.2	0.2	0.0
total	16.0	21.3	21.7	16.7	18.7

Notes: This table shows the growth contributions δ_{kt} defined in Eq. (5.1) for the growth factor k listed in each row, except that we replace aggregate exports with aggregate gross output. Statistics are shown in units of percentage points per annum and averaged over the years indicated in the column headers.

where F is a Markov transition function and ξ_t is an innovation. Using this to substitute for T_t^{AB} in Eq. (E.2), we obtain:

$$\log\left(\frac{E_t^A}{E_t^B}\right) = c + (\epsilon - 1)\log\left(\frac{P_t^B}{P_t^A}\right) + (\epsilon - 1)\,F\left(\log T_{t-1}^{AB}\right) + (\epsilon - 1)\,\xi_t \tag{E.4}$$

Furthermore, the $t-1$ version of Eq. (E.2) allows us to write:

$$\log T_{t-1}^{AB} = \frac{c}{1-\epsilon} + \frac{1}{\epsilon - 1}\log\left(\frac{E_{t-1}^A}{E_{t-1}^B}\right) - \log\left(\frac{P_{t-1}^B}{P_{t-1}^A}\right) \tag{E.5}$$

$$\equiv G\left[\log\left(\frac{E_{t-1}^A}{E_{t-1}^B}\right), \log\left(\frac{P_{t-1}^B}{P_{t-1}^A}\right)\right] \tag{E.6}$$

Using this to substitute for T_{t-1}^{AB} in Eq. (E.4), we obtain:

$$\log\left(\frac{E_t^A}{E_t^B}\right) = c + (\epsilon - 1)\log\left(\frac{P_t^B}{P_t^A}\right) + H\left[\log\left(\frac{E_{t-1}^A}{E_{t-1}^B}\right), \log\left(\frac{P_{t-1}^B}{P_{t-1}^A}\right)\right] + (\epsilon - 1)\,\xi_t \tag{E.7}$$

where $H(\cdot,\cdot) \equiv (\epsilon - 1)\,F\,[G(\cdot,\cdot)]$.

Now, suppose that the underlying primitives determining factor prices, stocks, and expenditures follow first-order Markov processes with innovations that are orthogonal to ξ_t. Then, the term H in Eq. (E.7) is uncorrelated with the residual ξ_t and one-year lags of factor prices and factor stocks are valid instruments for $\log\left(\frac{P_t^B}{P_t^A}\right)$. In practice, we treat H as a third-degree polynomial in its arguments and also use a third-degree polynomial in the instruments for the first stage.

Appendix F. Decomposition of growth in gross output

Table A.1 shows the contributions to growth in aggregate gross output arising from each of the growth factors in our model. This table is analogous to Table 5 in the main text, except that the outcome variable is growth in aggregate gross output instead of growth in aggregate exports. In contrast with export growth, we find that internal factors such as firm entry, factor productivity growth, and capital growth are much more important for growth in gross output. On the other hand, external factors such as foreign demand that are key for export growth matter much less for growth in gross output.

Appendix G. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jinteco.2024.103895.

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