Capital Accumulation, Trade, and China's Economic Rise

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Abstract

This paper examines the effect of China's economic rise on the global trade of high-tech manufacturing goods and the capital accumulation dynamics around the world. We study these effects for resource-rich (RREs) and high-tech-intensive economies (HTEs), which exhibit distinct comparative-advantage patterns. We use a dynamic Eaton-Kortum model of trade with capital accumulation to conduct our analysis. We find a positive effect of China's rise on the imports of high-tech manufacturing goods, investment, and capital in HTEs, and an even larger positive effect in RREs. Although export diversification decreases in RREs, accelerating deindustrialization, the increased capital accumulation enhances welfare. The welfare gains from China's impact on RREs are smaller than the effects from local improvements in investment efficiency and productivity. Finally, we find negative effects for HTEs from the increasing trade costs of importing high-tech manufacturing goods in China during 2006-2014, which diminished capital accumulation and gains from trade.

Keywords: Primary Goods, High-Tech Manufacturing Goods, Intermediate Inputs, Deindustrialization, Resource-Rich Countries, Welfare.
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1 Introduction

High-tech manufactured goods are highly tradable, comprising nearly half of global merchandise exports and imports. In 2000, they accounted for 53% of global goods exports and 52% of imports.

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By 2020, these figures remained substantial, at 49% and 50%, respectively.[1] While the share of high-tech goods in global trade has remained relatively stable, the ranking of leading exporter and importer countries has shifted significantly. The United States saw its share of global high-tech exports decline from 16% in 2000 to 8% in 2020, while its share of imports fell from 20% to 14% over the same period. In contrast, China experienced substantial growth, increasing its share of global high-tech exports from 6% in 2000 to 23% in 2020, and its share of imports from 7% to 18%.

This paper explores the impact of China's economic rise on global high-tech manufacturing trade and capital accumulation dynamics in both developing and advanced economies. While extensive research has examined China's influence during the 1990s and early 2000s, less attention has been given to its more recent emergence as a dominant player in high-tech trade. A variety of factors are behind China's gradual shift from producing and exporting labor-intensive goods to capital-intensive products. China's economic reforms and its eventual accession to WTO in 2001, resulted in the removal of barriers on foreign investment, exports, and imports, as well as China's insertion into global value chains (Hanson (2020)). By the late 1990s, foreign direct investment increasingly targeted capital-intensive sectors (Chen and Zha (2024)). As a result, foreign-invested firms and multinationals account for a non-trivial fraction of high-tech production and exports in China (Xing (2012)). In addition, in 1998 there was a shift in China's economic policy, where preferential credit instruments were introduced to support entry in capital-intensive sectors (Chen and Zha (2024)). This policy shift was reinforced by the launching of modern industrial policies, notably the National Medium- and Long-Term Program of Science and Technology in 2006, whose implementation was stepped up during the global financial crisis of 2008, and culminated with the rolling out of the Strategic Emerging Industry program in 2010 (Naughton (2021)).

Our focus on the impact of China on the global trade of high-tech manufacturing goods and on capital accumulation can be motivated in at least three ways. First, high-tech goods, which include machinery, electrical equipment, computer and electronic products, and transport equipment, are primarily used as intermediate and capital goods. High-tech goods also account for almost 90% of capital goods categories under the 6-digit HS classification.[2] Therefore, importing high-trade goods

[1] High-tech manufacturing goods include machinery, electrical equipment, computer and electronic products, transport equipment, and chemicals. These correspond to industries C20, C21, and C26 to C30 under the International Standard Industrial Classification (ISIC) Rev.4. We use the United Nations Commodity Trade Statistics Database (COMTRADE) to obtain these global trade shares. For this purpose, we start with Harmonized System (HS) 6-digit goods and map them into the relevant ISIC Rev.4 industries using the conversion key from the Organization for Economic Cooperation and Development (OECD).

[2] We obtain information on the uses of high-tech goods from COMTRADE. HS 6-digit goods can be classified as capital, intermediate or consumption goods using the United Nations Broad Economic Categories (BEC), with the conversion key provided by the OECD. For year 2014, among the 2,088 high-tech manufacturing goods in COMTRADE, 1,243 (60%) are classified as intermediate goods, 627 (30%) as capital goods, and 184 (9%) as consumption goods, with the remaining unclassified. In addition, among the 708 goods classified as capital goods in COMTRADE, 627 (89%) are high-tech manufacturing goods.

has a direct effect on local capital accumulation, as well as an indirect effect on the overall productive capacity through intermediate input use. Second, for many countries, particularly resource-rich economies (RREs), high-tech goods represent the largest share of imports. If China's economic rise resulted in lower investment good prices (relative to consumption prices), this could have fostered capital accumulation and transitional growth in RREs. But there is also a flip side to this story: in addition to China's increasing share in the global trade of high-tech goods, China has become a major destination of primary goods exports (agriculture, animal production, and mining) since 2000. Driven in part by China's rapid growth and sheer size, a significant commodity boom occurred between 2000 and 2014. This may have contributed to the intensification of comparative advantage of RREs, discouraging export diversification and possibly reinforcing deindustrialization. Third, more advanced and high-tech-intensive economies (HTEs) are known to engage in intra-industry trade of high-tech manufacturing goods. China's insertion into the global production chain of high-tech goods altered this market, creating shifts in trading partners among HTEs. It is in principle unclear how the relative productivity growth among HTEs and China interacts with evolving trade costs to affect capital accumulation, an analysis that requires developing a quantitative model.

We use a dynamic Eaton-Kortum model of trade with capital accumulation to conduct our analysis. The model features the following essential ingredients. First, we include four distinct sectors: primary (commodities), low-tech manufacturing (including construction), high-tech manufacturing and services. These four sectors capture in a stark manner the evolution of comparative advantage among RREs and HTEs. Specifically, RREs exported more primary goods and imported more high-tech goods from China since 2000, while there were shifts in intra-industry trade of high-tech manufacturing goods among HTEs and China. Second, we introduce separate consumption and investment good aggregators to capture differences in the sectoral composition of consumption and investment expenditures. Notably, high-tech and low-tech manufacturing goods account for the largest share of the investment good aggregator. As high-tech manufacturing goods are highly tradable, investment in high-tech goods becomes a channel by which China's rise may affect capital accumulation.

Third, capital accumulation in our model features adjustment costs and an investment efficiency term as in as Eaton et al. (2016), which results in two properties: capital adjustment costs contribute to differences between short and long-run (steady state) macroeconomic effects, underscoring the importance of transitional dynamics in the model. In addition, the presence of an investment efficiency term captures country-specific local factors affecting the price of new capital in the model. These local factors interact with the global environment, for instance lower investment prices from China's economic rise, to affect the dynamics of capital accumulation. In this respect, our model allows us evaluate the relative importance of external versus local factors on macroeconomic outcomes. Last, we depart from a common assumption in the Eaton-Kortum class of models by allowing for differences in the intensity of factor use in production across countries and sectors. In fact, data from the World Input-Output Database (WIOD) reveals variation in capital, labor, and value added shares across sectors and countries. In this respect, our model incorporates elements of the Heckscher-Ohlin framework, with differences in factor intensities playing role in determining trade patterns.

We calibrate the model using a similar approach to Eaton et al. (2016) and Caliendo, Dvorkin and Parro (2019), where given some exogenous parameters and data moments, time-varying fundamentals are backed out to exactly fit the data moments during 2000-2014. The sample period corresponds to the latest available from WIOD (2016 release). This time period covers China's accession to the WTO in 2001, the implementation of China's industrial policy program in 2006, and it coincides with the commodity boom. We use WIOD data because different from other international input-output sources, it provides gross output prices at the sectoral level. We include all economies available in WIOD, grouping those in Western Europe and Eastern Europe as two blocks, which results in a total of 16 economies and groups. This grouping is enough for our purpose, and it facilitates the computation of multiple time-varying fundamentals over time to exactly fit thousands of data moments, including gross sectoral output, bilateral trade by sector, net exports and investment spending. The main time-varying fundamentals we obtain in our quantitative analysis are bilateral trade costs (exports and imports), sectoral productivities, and investment efficiency.

We use the calibrated model to perform counterfactual analysis. The main purpose is to evaluate the relative importance of time-varying fundamentals on the global trade of high-tech goods and capital accumulation, by setting fundamentals back to their 2000 values, one at a time. We focus attention on China's fundamentals, separately evaluating the role of export costs, import costs, sectoral productivity growth, and investment efficiency. We also evaluate the full "China shock" by simultaneously setting all these fundamentals back to their 2000 values.[3] In addition, we use the model to understand the drivers of China's rise in the global trade of high-tech goods, in a spirit similar to Brandt and Lim (2024). For this purpose we evaluate the role of global trade costs and global productivity growth, comparing it with the role of China's local fundamentals. Finally, we quantify the role of local (sectoral productivities and investment efficiency) and trade-related fundamentals (trade costs) in RREs. We illustrate the case of Brazil, a RRE developing country that mostly exports primary products, but it has also developed a high-tech manufacturing base. The comparison between the effects of local, trade-related, and external (China) fundamentals is useful to understand which factors matter the most for the macroeconomic outcomes of RREs since

[3] Earlier work by Autor, Dorn and Hanson (2013) empirically evaluated the effects of the China shock in US manufacturing for an earlier period, from 1990 to 2007, when labor-intensive products were still predominant among China's exports. Caliendo, Dvorkin and Parro (2019) examined the China shock using a multi-country trade model for the period 2000-2007. As we consider the period 2000-2014, our evaluation of "China shock" captures some of the transition of China's exports from low-tech manufacturing to high-tech goods.

2000. Similar to development accounting exercises, these findings inform policy makers as well as future research.

Our analysis yields several main insights. The first main insight is that the China shock had asymmetric effects on the exports of HTEs, with bilateral trade costs with China playing a major role on this asymmetry. The impact on the exports of RREs was more symmetric. The bulk of bilateral trade between HTEs and China is accounted for by intra-industry trade in high-tech manufacturing goods. Under a counterfactual where the China shock does not occur, we find some HTEs would have exported even more to China in 2014 than it was observed in the data. For example, Taiwan would have exported 51% of its total exports to China in 2014, instead of the 32% in the data, and Japan would have exported 19% instead of 16%. But the opposite would have occurred in other HTEs —South Korea would have exported 9% of all their total exports to China in 2014 instead of 24% observed in the data; the US 2% instead of 6%, and Western Europe 2% instead of 8%. The most important force behind these asymmetric results are Chinese importing costs. Our calibration reveals that China's costs of importing high-tech goods from HTEs decreased between 2000 and 2006-2008, but this trend was subsequently reversed, resulting in higher importing costs in China in 2014 relative to 2000. These higher trading costs varied in magnitude, being larger for Japan and Taiwan, and smaller for the US and South Korea. Although the higher import costs may reflect a variety of factors, the timing coincides with the implementation of industrial policies in China that emphasized domestic production, the rising trends of non-tariff barrier measures, and the trade collapse during the 2007-2009 Great Recession. Finally, regarding exports of RREs, we find that in the absence of the China shock, the share of primary goods in their total exports would have still been large —51% in Australia and 32% in Brazil in 2014, instead of the corresponding 57% and 39% in the data. Without the China shock countries like Brazil would have achieved some export diversification, increasing the share of overall high-tech exports from 16 to 20%.

The second insight of our analysis is that the China shock had relatively homogeneous effects on the imports of high-tech manufacturing goods by RREs and HTEs, a channel to potentially foster capital accumulation. High-tech manufacturing goods are not only highly tradable, but they represent about a third of total investment spending. In 2014, high-tech manufacturing imports accounted for at least 30% of total imports in HTEs, and at least 40% among RREs. In addition, high-tech imports from China accounted for between 22 and 38% of all high-tech imports in HTEs, and about 20% in RREs. We find that in a counterfactual where the China shock does not occur, all of these economies would have not only imported a very small share of high-tech good from China, but would have imported an overall smaller share of high-tech goods. This fall in the overall share of high-tech imports occurs because countries reallocate resources towards home production of high-tech goods, and they also shift to importing from other less productive HTEs. These effects ultimately translate into lower investment and capital accumulation, our third main finding.

The third main insight of our analysis is that in the absence of the China shock, investment in high-tech goods, total investment, and capital would have been lower in all countries both in the short and long run. The advantage of our dynamic model is that it allows us to evaluate these short-term and long-term macroeconomic effects. We measure short-term effects by comparing outcomes in year 2014 under the counterfactual and the benchmark (data), where 2014 is the last year we observe in our calibration period. Long-run effects refer to a steady-state comparison of the counterfactual and benchmark. We find that short-term effects are overall smaller than long-term effects. For example, in the absence of the China shock, investment in high-tech goods (quantities) would have been between 1% and 13% lower in the short run, and 11% and 31% smaller in the long run across economies other than China. Long-run falls in total investment and capital (quantities) would have been between 5% and 16%. These effects are overall larger among RREs than HTEs, highlighting a positive effect of China's rise on investment and capital accumulation in RREs.

We use our calibrated model to compute welfare changes. Our fourth main insight is that in the absence of the China shock welfare losses in other countries would have been between -0.25% and -1.44% in the short run, and between -4.27% and -11.93% in the long run. The smaller welfare losses in the short run relative to the long run suggest the importance of including the dynamics of capital accumulation in welfare evaluations, a point also raised in Ravikumar, Santacreu and Sposi (2019). We also find that welfare losses would have been relatively larger for RREs than for HTEs. For example, long-run welfare changes are about -12% in Australia, -10% in Brazil, and about -6% in Japan and the US. Last, under the counterfactual where only the import costs in China are set to 2000 levels, we find that there would have been welfare gains for all HTEs, and losses for all RREs, a finding consistent with other results described above. Including the full transition, the welfare gains of setting import costs in China back to 2000 levels would have been 13% in Taiwan and 2% in Japan, while welfare losses would have been -0.3% in Brazil and -0.1% in Australia.

Regarding the the driver's of China's economic rise, we find that global fundamentals matter relatively more for China's high-tech trade than for investment and capital accumulation in China. In contrast, local China fundamentals matter for both trade and capital accumulation. For example, if productivity in all countries other than China had remained at the level of 2000, the share of high-tech goods in China's exports in 2014 would have increased from the observed 50% to 60%. Local factors in China matter as well –if sectoral productivities would have remained at the 2000 level in China, the share of high-tech good exports in 2014 would have been 31% instead of the observed 50%. These findings parallel those of Brandt and Lim (2024) who also find foreign demand and factor productivity growth in China to be the main drivers of Chinese exports during 2000-2013. When it comes to macroeconomic outcomes, local China fundamentals are quantitatively more important than global fundamentals. For example, in the absence of the China shock, i.e., if trade costs, sectoral productivities, and investment efficiency in China had remained at the levels of 2000, the change in investment between 2014 and 2000 would only have been 17% of the change observed in the data. The long-term effects for capital are even higher – in the absence of the China shock, the change in capital between the steady state and 2000 would have been 11% of the change in the benchmark, suggesting a strong effect of local fundamentals on local macroeconomic outcomes.

Our last main finding provides insights into the relative importance of local fundamentals and the China shock in developing countries, where we focus in the case of Brazil, a RRE that had also developed a high-tech manufacturing base by 2000. We find that although Brazil's long-run capital would have been lower without the China shock, the quantitatively strongest factor in increasing capital in Brazil is investment efficiency –had Brazil kept the higher investment efficiency levels of 2000, long-run capital would have multiplied by a factor of 2.58. Brazilian import trade costs also play role in long-term capital accumulation –had Brazil kept the lower import costs of 2000, particularly for high-tech goods, capital in the steady state would have been 9% higher. These results hint at the importance of understanding the decrease in investment efficiency in Brazil, as well as the detrimental effects of high import costs for high-tech goods. We also find that even though the China shock adversely affects export diversification in Brazil in the long run, local high-tech productivity growth in Brazil also plays a major role –without the China shock, the share of high-tech exports in Brazil would have been 67% higher, but it would have been 42% lower had Brazil's high-tech productivity remained at the level of 2000.

Our paper relates to several literatures. First, our paper relates to others focusing on trade in capital goods and capital accumulation dynamics. Eaton and Kortum (2001) is an early paper on trade in capital goods, although it does not model capital accumulation. Similar to our paper, Mutreja, Ravikumar and Sposi (2018) consider trade in capital goods, motivated by the fact that developing countries heavily import these goods. Different from our paper, they focus on steady states, assume trade is frictionless, and do not focus on the effects from the China shock. Our paper is closer to Ravikumar, Santacreu and Sposi (2019), who analyze capital accumulation and dynamic gains from trade. They use an Eaton-Kortum model with capital accumulation and endogenous trade imbalances to simulate the welfare effects of a world-wide trade liberalization that decreases trade costs uniformly starting at a 2014 steady state. Similar to our results, they also find that capital accumulation accounts for substantial welfare gains, and that welfare measures including the transition are lower than the steady-state measures. Our work differs from theirs in multiple dimensions –we have a richer modeling of production sectors (primary, low-tech, high-tech and services), since we examine comparative advantage. Modeling these sectors also allows us to differentiate consumption and investment goods according to the share of sectors in these expenditures. We use data for the 2000-2014 period together with the model equilibrium conditions to extract multiple time-varying fundamentals. Since our main focus is on the China shock in capital goods, our model allows us to evaluate the separate role of fundamentals (productivity growth and trade costs), providing a more nuanced view of China's rise in this global market.

Second, among the extensive literature analyzing the global impact of China, we relate more closely to papers analyzing the macroeconomic and general equilibrium impacts, notably di Giovanni, Levchenko and Zhang (2014).[4] They find that welfare gains for all countries would be much larger if starting in 2007 China's comparative disadvantaged sectors (office, accounting, computing and other machinery, medical and optical instruments) grew disproportionately faster. One of our motivating facts is precisely that between 2000 and 2014, China's revealed comparative advantage in low-tech manufacturing goods (e.g., coke and refined petroleum, wearing apparel) has declined, while it has increased in high-tech manufacturing goods (e.g., machinery, electrical equipment, computers). Our paper is distinct because we model capital accumulation, solving for the transitional dynamics, and focusing on the short and long-run effects of the China shock on macroeconomic outcomes, trade and welfare. Our paper is also different in that we follow the calibration strategy of Eaton et al. (2016) and Caliendo, Dvorkin and Parro (2019), where we obtain time-varying fundamentals by exactly fitting bilateral trade, sectoral output, investment, and net exports data for the period 2000-2014. Taking this period as part of a transition to a future steady state, we compute the full transitional dynamics, which allows us to determine the short and long-term effects of a variety of counterfactuals, providing a nuanced understanding of the China shock.

Our analysis also relates to Brandt and Lim (2024), who rather than analyzing the global impact of China, explore the drivers of Chinese export growth in the 21st century. Using customs and firm-level data for China they find that the main drivers of China's exports are rising foreign demand, improvements in access to intermediates, and factor productivity growth within China. While our paper uses more aggregated sectoral data, we conduct our analysis using a dynamic general equilibrium multi-country model, while Brandt and Lim (2024) model China as a small open economy, treating export demand as exogenous. Our model allows us to identify the time-varying fundamentals underlying the evolution of trade and macroeconomic outcomes both in China and in all other countries.

Third, our paper shares some common themes with the literatures on the effects of trade liberalization in developing countries and deindustrialization. The papers on the effects of trade liberalization tend to focus on labor markets and inequality (see Dix-Carneiro and Kovak (2023) for a review of this literature), while our focus is on capital accumulation, comparative advantage and macroeconomic outcomes. Although our focus is not restricted to developing countries, some of our results echo those from the deindustrialization literature (Rodrik (2015), Sposi (2019), and Michael Sposi and Zhang (2024)). Relative to these papers, our model and calibration strategy

[4]Other papers such as Caliendo, Dvorkin and Parro (2019) and Dix-Carneiro and Traiberman (2023) also formulate general equilibrium models but focus more on labor markets.

allow us to compare the relative importance of local fundamentals (sectoral productivity and investment efficiency) versus external factors such as the China shock on deindustrialization trends. As mentioned, we report on this for the case of Brazil for illustration purposes.

In terms of calibration strategy, our paper is most similar to Eaton et al. (2016) and Caliendo, Dvorkin and Parro (2019). More specifically, Eaton et al. (2016) use an Eaton-Kortum model with capital accumulation to quantify the relative importance of fundamentals on the global decline of manufacturing trade during the 2007-2009 recession. Their calibration strategy uses model inversion to identify time-varying fundamentals, i.e., time-varying fundamentals are computed from the model equations as residuals that allow the model to exactly fit relevant sectoral-level data moments over time and across the countries in the sample. Other than the calibration strategy, we differ from Eaton et al. (2016) our question, our focus, model structure, and the implementation of counterfactuals.

The remainder of the paper is organized as follows. Section 2 presents some motivating facts. The model is presented in Section 3. Section 4 discusses the calibration, which includes the computation of time-varying fundamentals. Counterfactuals are presented in Section 5. Section 6 presents the robustness analysis and Section 7 concludes.

2 Motivating Facts

We start our analysis by providing some motivating facts on the transformation of bilateral trade with China between 2000 and 2014, the composition of these trade flows by sector, and revealed comparative advantage. Our sample includes 16 countries and regions representing all countries in the WIOD.[5] As mentioned, we collapse all sectors to four: primary, low-tech manufacturing, high-tech manufacturing, and services.[6] For the reminder of the paper, rather than reporting statistics for all countries in the sample, and to highlight the differences between RREs and HTEs, we include in our tables a sub-sample of these countries to capture our main message.

[5]The 16 countries and regions included are: Australia, Brazil, Canada, China, Indonesia, India, Japan, South Korea, Mexico, Russia, Turkey, Taiwan, United States, Western Europe (Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, and Sweden), Eastern Europe (Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Lithuania, Latvia, Poland, Romania, Slovakia and Slovenia), and Rest of the World.

[6]Since our main data source for the quantitative analysis is the World Input-Output Database (WIOD), our model sector classification is based on ISIC Rev. 4. The primary sector (agriculture, animal production, and mining) includes WIOD sectors 1 to 4 (A01-A03, B in ISIC Rev. 4) and sector 15 (C24). Low-tech manufacturing (basic manufacturing, utilities and construction) includes WIOD sectors 5 to 10 (C10 to C19), 13 (C22), 14 (C23), 16 (C25), 22 to 27 (C31 to 33, D 35, E36 to 39 and F). High-tech manufacturing (chemicals, computers, equipment, machinery) includes WIOD sectors 11 (C20), 12 (C21), 17 to 21 (C26 to C30). Last, services includes WIOD sectors 28 to 56 (G45 to G47, H50 to H53, I, J58 to J63, K64 to K66, L68, M69 to M75, N, O84, P85, Q, R, S, T and U).

Table 1: Export Shares to Destination Country or Region - 2000 and 2014
(% of total exports)

	To United States		To Western Europe		To China	
	2000	2014	2000	2014	2000	2014
Resource-rich economies						
Australia	8	4	12	4	5	27
Brazil	22	11	27	16	3	15
High-tech intensive economies						
Japan	25	15	14	8	6	16
South Korea	22	11	13	7	10	24
Taiwan	22	9	15	7	13	32
United States	-	-	24	24	1	6
Western Europe	23	14	-	-	2	8
China	20	14	16	14	-	-

Notes: Data is from the World Input-Output Database. The full sample includes 16 countries and regions, representing all the countries in the WIOD. Western Europe includes Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, and Sweden.

2.1 Trade Facts

Table 1 reports the share of total exports from a sub-sample of RREs and HTEs that are shipped to the US, Western Europe and China, both in 2000 and 2014. The table illustrates important shifts during this period, with a lower share of exports having the US and Western Europe as destination, and a higher share of exports going to China for all origins. As seen on the table, this shift has been remarkable, with RREs multiplying the share of exports to China by a factor of about five –Australia's exports to China went from 5% of total exports in 2000 to 27% in 2014, and from 3% to 15% in Brazil. In the case of HTEs, increases are also large, more than doubling in South Korea from 10% to 24% and in Taiwan from 13% to 32%, and increasing by a factor of six in the US, going from 1% to 6%. Although the US and Western Europe have sustained their trade links, the rising importance of China is clear. This is particularly true for Australia, Japan, Taiwan and South Korea, where geographic proximity clearly plays a role. In the case of Japan, Taiwan and South Korea, higher exports to China are also associated the establishment of production chains through multinational enterprises (Xing (2012), Hanson (2020)).

China's rise as a key destination partner is mirrored by its rise as source country, as we document in Table 2. By 2014, Japan, South Korea, and Taiwan were importing a larger share from China than from the US and Western Europe. For RREs like Australia and Brazil, there was a substantial increase in imports from China, and a decrease in the share of imports from Western Europe,

Table 2: Import Shares from Origin Country or Region - 2000 and 2014
(% of total imports)

	From United States		From Western Europe		From China	
	2000	2014	2000	2014	2000	2014
Resource-rich economies						
Australia	16	9	21	18	5	16
Brazil	18	13	25	21	1	12
High-tech intensive economies						
Japan	16	7	14	10	9	19
South Korea	18	8	12	14	6	18
Taiwan	12	6	11	10	3	15
United States	-	-	21	21	4	14
Western Europe	24	17	-	-	4	13
China	6	6	13	15	-	-

Notes: Same as Table 1.

although the latter continues to account for a larger share. For example, China's share in Australia's total imports went from 5% in 2000 to 16% in 2014, with Western Europe accounting for 18% in 2014. In Brazil the increase was even larger, going from 1% to 12%, although again here Western Europe accounted for 21% in 2014.

Turning now to the sectoral composition of bilateral trade, clear inter-industry and intra-industry patterns emerge, very much along the lines Hanson (2012) characterizes world trade since the integration of middle-income in the global economy. RREs export mostly primary goods to China and import high-tech goods. The share of both primary exports and high-tech imports increased between 2000 and 2014. For example, Table 3 shows that 76% of exports from Australia to China were primary products in 2014, and 51% of imports were high-tech goods. The corresponding shares for Brazil were 72% and 64%. In contrast with the inter-industry trade between RREs and China, trade in both primary products and high-tech goods between HTEs and China is intra-industry, although the bulk of trade is on high-tech goods. Between 2000 and 2014, the share of high-tech exports to China went up in Japan, South Korea and Taiwan, while it decreased in the US and Western Europe. For example, the share of high-tech exports from Japan to China was 73% in 2014, while it was 76% in Korea and 83% in Taiwan. In contrast with the share of exports, the share of high-tech imports from China went up in all HTEs reported on the table. By 2014, the share of high-tech imports from China to HTEs ranged between 52 and 71%, up from a range between 29 and 49% in 2000. As mentioned, foreign-invested firms and multinationals account for some of

Table 3: Composition of Bilateral Trade with China: 2000 and 2014
(% of total bilateral flow with China)

	Exports to China				Imports from China			
	Primary		High-tech		Primary		High-tech	
	2000	2014	2000	2014	2000	2014	2000	2014
Resource-rich economies								
Australia	49	76	6	1	4	4	28	51
Brazil	29	72	8	3	4	5	64	64
High-tech intensive economies								
Japan	11	9	65	73	11	5	29	56
South Korea	8	3	54	76	28	12	32	54
Taiwan	11	4	63	83	26	10	49	71
United States	6	13	67	46	3	3	43	59
Western Europe	5	6	60	56	4	3	41	52

Notes: Data is from the World Input-Output Database. The primary sector (agriculture, animal production, and mining) includes WIOD sectors 1 to 4 (A01-A03, B in ISIC Rev. 4) and sector 15 (C24). Low-tech manufacturing (basic manufacturing, utilities and construction) includes WIOD sectors 5 to 10 (C10 to C19), 13 (C22), 14 (C23), 16 (C25), 22 to 27 (C31 to 33, D 35, E36 to 39 and F). High-tech manufacturing (chemicals, computers, equipment, machinery) includes WIOD sectors 11 (C20), 12 (C21), 17 to 21 (C26 to C30). Last, services includes WIOD sectors 28 to 56 (G45 to G47, H50 to H53, I, J58 to J63, K64 to K66, L68, M69 to M75, N, O84, P85, Q, R, S, T and U).

the increase in exports and imports of high-tech goods, particularly for China's bilateral trade with Japan, South Korea and Taiwan.

Although Table 3 suggests certain patterns of comparative advantage, in Table 4 we compute revealed comparative advantage following Hanson (2020), which better controls for changes in good prices over time. Revealed comparative advantage corresponds to the country's share of world exports in a sector, relative to the country's share of world exports in all sectors. The most salient fact from this table is while between 2000 and 2014 China lost comparative advantage in low-tech manufacturing, it increased it in high-tech goods. Notice that this measure of revealed comparative advantage does not reflect the value-added of trade, a distinction that becomes important when global value chains are present (Koopman, Wang and Wei (2014)). However, in the case of the pattern we document in Table 4, this concern is ameliorated by the facts that multi-stage production in China occurs both in low and high-tech manufacturing; that export processing went from 55% of manufacturing exports in 2005 to 35% in 2015; and that there has been an increase in the domestic content of China's exports since the early 2000s (Hanson (2020)).

Another notable pattern in Table 4 is that HTEs also increased their revealed comparative advantage in high-tech manufacturing goods between 2000 and 2014. These include Japan, South Korea, Taiwan and Western Europe. The US is the only among the reported HTEs for which comparative advantage in high-tech goods decreased between 2000 and 2014. Notice that China

Table 4: Revealed Comparative Advantage - 2000 and 2014

	Primary		Low-tech		High-tech		Services	
	2000	2014	2000	2014	2000	2014	2000	2014
Resource-rich economies								
Australia	3.43	3.43	0.85	0.53	0.24	0.13	1.07	1.04
Brazil	1.73	2.33	1.62	1.39	0.68	0.47	0.59	0.53
High-tech intensive economies								
Japan	0.36	0.51	0.48	0.63	1.66	1.69	0.77	0.70
South Korea	0.35	0.31	1.17	0.80	1.47	1.80	0.46	0.53
Taiwan	0.33	0.29	0.91	0.73	1.53	1.69	0.61	0.75
United States	0.33	0.41	0.73	0.91	1.17	0.95	1.30	1.53
Western Europe	0.51	0.38	0.91	0.86	1.04	1.05	1.26	1.46
China	0.56	0.28	1.75	1.32	0.87	1.41	0.76	0.62

Notes: Same as Table 3. Revealed comparative advantage corresponds to the country's share of world exports in a sector, relative to the country's share of world exports in all sectors as in Hanson (2020).

does not have the highest revealed comparative advantage in high-tech goods in 2014 –South Korea is first, with Japan and Taiwan tied second, and China ranking fourth. This paper examines the role sectoral productivity growth played on these outcomes, as well as the potential role of trade policies as reflected in trade costs.

To provide a more concrete picture of China's high-tech exports in 2014, we use HS 6-digit COMTRADE data to identify examples of high-tech goods for which China represented a large share of global exports. For example, focusing attention on high-tech goods classified as capital goods under the United Nations BEC, China accounted for at least 25% of global exports in goods such as passenger boarding bridges (41% of global exports), instant print cameras (41%), combining machines for preparing or weaving textile fibers (40%), railway or tramway coaches (34%), escalators and moving walkways (34%), metallurgy ladles (33%), tractors (32%), cranes (31%), and air pumps (31%). Interestingly, most of the producers of these goods are Chinese-owned companies, some of them state-owned.[7] Regarding China's high-tech imports in 2014, the following are examples of high-tech manufacturing goods classified as capital goods and representing at least 25% of global

[7] Passenger boarding bridges are produced by CIMC-Tianda and Shandong Lingong Machinery Co.; combining machines for preparing or weaving textile fibers are produced by Jingwei Textile Machinery Co. and Qingdao Textile Machinery Co.; railway or tramway coaches are produced by CRRC Corporation Limited; escalators and moving walkways are produced by Guangri Elevator Industry Co. and Ife Elevators Co.; tractors are produced by YTO Group Corporation and Foton Lovol International Heavy Industry Co.; cranes are produced by Xuzhou Construction Machinery Group Co. and Sany Heavy Industry Co.; and air pumps are produced by Shanghai Pacific Pump Manufacture Co. and Zhejiang Taiko Air Compressor Manufacturing Co. Among these companies, some are state-owned including CIMC-Tianda, CRRC Corporation, YTO Group, and Xuzhou Construction.

Table 5: Sectoral Composition of Investment Spending

	Investment % GDP (2014)	Average share of investment spending (2000-2014)			
		Primary	Low-tech	High-tech	Services
Resource-rich economies					
Australia	26.9	3.5	59.0	17.4	20.1
Brazil	21.1	4.1	52.2	27.1	16.5
High-tech intensive economies					
Japan	21.6	0.5	57.3	23.5	18.6
South Korea	25.0	0.8	52.0	30.5	16.7
Taiwan	19.3	0.1	39.3	38.8	21.8
United States	19.3	3.2	34.9	24.3	37.6
Western Europe	18.9	1.5	51.2	20.8	26.5
China	40.0	3.4	58.4	30.0	8.2

Notes: Data is from the World Input-Output Database. Shares are computed using final investment demand, aggregating sectors into primary, low-tech manufacturing, high-tech manufacturing and services. Low-tech manufacturing includes construction.

imports: machines to manufacture flat panel displays, optical devices, broaching machines, machines to texture and cut textile materials, electrical capacitors, and machines for working glass.

2.2 Investment Facts

The purpose of this paper is to study the effect of China's economic rise on the global trade of high-tech goods and the capital accumulation dynamics in developing and advanced economies. To understand the channel by which capital accumulation might be affected, Table 5 displays the average sectoral composition of investment spending during 2000-2014 for our sub-sample of RREs and HTEs. As seen in the table, primary goods represent a very small fraction of the investment. Services play different roles across countries, with a relatively large share in the US, around 38%, and a small share in China, around 8%. The largest shares are in low-tech manufacturing, due mostly to construction sector, where these are in the order of 58% in China, and 52% in Brazil, and much lower in the US, at 34%. The share high-tech manufacturing goods in investment is the largest in Taiwan at 39%, followed by South Korea and China, around 30%. Since high-tech goods are highly tradable, and China's revealed comparative advantage in these goods increased between 2000 and 2014, this represents a direct channel by which China's rise may affect capital accumulation. Finally, Table 5 also reports investment as a share of GDP in 2014, which is relatively large in China, Australia, Korea, Japan and Brazil. Differences in this share will drive the impact of China on capital accumulation in these countries.

3 Model

The theoretical framework of this paper corresponds to an Eaton-Kortum model with capital accumulation. The model features four distinct sectors: primary (commodities), low-tech manufacturing, high-tech manufacturing and services. This allows us to capture a pattern of comparative advantage where RREs export primary goods and import high-tech manufacturing goods. In contrast, HTEs import primary goods and engage in intra-industry trade in low and high-tech manufacturing goods. We introduce Heckscher-Ohlin elements in the model by allowing differences in the intensity of factor use in production across countries and sectors. Our model also features different consumption and investment good aggregators, properly capturing the shares of each of the four sectors in consumption and investment expenditures. Finally, there are adjustment costs of capital accumulation, as well as an investment efficiency component, which affect the rate at which investment can be transformed into new capital.

3.1 Production

Let subscript i denote the country, k the sector, and t the time period. We model four sectors: primary, low-tech manufacturing, high-tech manufacturing and services. A continuum of varieties within each of the four sectors is combined into a composite good of the form

$$Q_{it}^k = \left[\int q_{it}^k(x)^{\frac{\eta}{\eta-1}} dx\right]^{\frac{\eta}{\eta-1}},$$

where $x \in [0,1]$ indexes varieties, Q_{it}^k the composite good in sector k, $q_{it}^k(x)$ is the quantity of variety x used (which imported or produced domestically), and η is the elasticity of substitution between varieties. The composite good for each sector is used for intermediate demand, and final consumption or investment demand.

Each variety x within sector k is produced using the following technology

$$Y_{it}^k(x) = z_{it}^k(x)\left[K_{it}^k(x)^{\alpha_i^k} L_{it}^k(x)^{1-\alpha_i^k}\right]^{\varphi_i^k}\left[\prod_j M_{it}^{kj}(x)^{\mu_i^{kj}}\right]^{1-\varphi_i^k},$$

where $z_{it}^k(x)$ is country i's idiosyncratic productivity, $K_{it}^k(x)$ is the capital used, $L_{it}^k(x)$ is labor input used, $M_{it}^{kj}(x)$ is the quantity of composite good j used as intermediate good, α_i^k is the share of capital in sector k, φ_i^k is the value-added share in sector k, and μ_i^{kj} is the share of good j in total intermediates spending in sector k.

As it is standard in the literature, $z_{it}^k(x)$ is drawn from independent Frechet distributions across countries and sectors with distribution $F_{it}^k(z) = Pr[z_{it}^k \leq z] = exp(-T_{it}^k z^{-\theta})$, where θ is the inverse of productivity dispersion, and T_{it}^k measures the overall productivity. To reflect well the data, we let factor shares α_i^k, value-added shares φ_i^k and intermediate spending shares μ_i^{kj} vary across countries and sectors, assuming them to be constant over the period we study.[8] Overall productivity T_{it}^k varies by sector, country and time.

3.2 Investment

The investment composite good is given by

$$X_{it} = \prod_k (X_{it}^k)^{\omega_{it}^k}, \tag{1}$$

where X_{it}^k is the quantity of composite good k used in investment, and ω_{it}^k is the share of investment spending in good k in aggregate investment. A time-varying ω_{it}^k guarantees that in the calibration we can exactly match sector-specific investment demand in data.

The law of motion of capital K_{it} is given by

$$K_{i,t+1} = (1-\delta)K_{it} + A_{it}X_{it}^{\lambda}K_{it}^{1-\lambda}, \tag{2}$$

where δ is depreciation. As in Eaton et al. (2016), $0 < \lambda \leq 1$ is a capital adjustment cost, with $\lambda = 1$ representing no adjustment costs, and A_{it} is investment efficiency. Capital adjustment costs have been commonly used in the macro literature to capture disruptions during the installation of new capital, any costs of learning incurred with changes in the production process as a result of the new capital, and overall time-to-install or time-to-build costs. As these convex adjustment costs are not sufficient to capture the bursts of investment and periods of inaction observed in the data, the investment efficiency term A_{it} can be introduced to better track investment turning points over time, simulating the non-convexities found in plant-level data (Cooper and Haltiwanger (2006)). In fact, in the calibration A_{it} is computed to exactly match aggregate investment spending in the data over the 2000-2014 period.

3.3 Preferences

The representative household in country i maximizes

$$U_i = \sum_{t=0}^{\infty} \beta^t lnC_{it}, \tag{3}$$

[8] We do not let factor shares α_i^k, value-added shares φ_i^k and intermediate spending shares μ_i^{kj} vary over time, as otherwise productivity growth rates would not be comparable across sectors and countries. Productivity levels T_{it}^k in our model are not comparable across sectors and countries given the sector and country-specific α_i^k, φ_i^k and μ_i^{kj}, but having comparable growth rates is useful for the counterfactual analysis.

where β is the discount factor and aggregate consumption C_{it} is given by

$$C_{it} = \prod_k (C_{it}^k)^{\psi_{it}^k}, \tag{4}$$

where C_{it}^k is the quantity of composite good k used in consumption, and ψ_{it}^k is the share of consumption spending in good k in aggregate consumption. As we explain below, a time-varying ψ_{it}^k is necessary for the model to simultaneously match sectoral gross output, sectoral bilateral trade shares, aggregate investment and net exports.

The aggregate budget constraint for the representative household is

$$\sum_k P_{it}^k C_{it}^k + \sum_k P_{it}^k X_{it}^k + NX_{it} = P_{it}^c C_{it} + P_{it}^x X_{it} + NX_{it} = w_{it} L_{it} + r_{it} K_{it}, \tag{5}$$

where P_{it}^k is the price of composite good k, P_{it}^c is the price of the composite consumption good in (4), P_{it}^x is the price of the composite investment good in (1), w_{it} is the wage, r_{it} the return to capital, and NX_{it} aggregate net exports. The model's numeraire each period is world GDP, which we denote $WGDP_t = 1$. Capital and labor are perfectly mobile across sectors.

In order to allow for trade imbalances, we take an approach similar to Caliendo, Dvorkin and Parro (2019), but adjust it to our context. As in Caliendo, Dvorkin and Parro (2019) trade imbalances are static, but we tie payments to GDP rather than population.[9] Specifically, NX_{it} is given by

$$NX_{it} = (\rho_{it} - B_t) GDP_{it}, \tag{6}$$

where $\rho_{it} GDP_{it}$ is country i's remittance to a global portfolio and B_t is an static portfolio return computed as

$$B_t = \frac{\sum_m \rho_{mt} GDP_{mt}}{\sum_m GDP_{mt}}. \tag{7}$$

We calibrate the global portfolio share ρ_{it} to match net exports as a fraction of GDP in the data for each country. As in Caliendo, Dvorkin and Parro (2019), we do not model the dynamic aspects of international debt, but the static trade imbalances allows net exports to change under the counterfactuals.

[9] Caliendo, Dvorkin and Parro (2019) apply this static trade imbalance approach among US states. In our context, where we apply it to countries, we find that distributing the portfolio return according to population does not allow us to exactly fit the data on net exports as a fraction of GDP because of the presence of very large countries in population such as China and India. By distributing the portfolio according the GDP, we avoid corner solutions for the portfolio shares ρ_{it}, which allow us to fit the data best. In addition, welfare computations under the counterfactual are robust under our approach.

3.4 Market Clearing

The factor markets clearing conditions are given by

$$K_{it} = \sum_k K_{it}^k = \sum_k \int K_{it}^k(x)dx,$$

$$L_{it} = \sum_k L_{it}^k = \sum_k \int L_{it}^k(x)dx.$$

All goods are potentially traded. As it is standard, trade is subject to iceberg costs. Country i must purchase $\tau_{imt}^k \geq 1$ units of goods from country m to get one unit of the good delivered. As we show below, by definition $\tau_{iit}^k = 1$.

The goods market clearing condition is

$$P_{it}^k Y_{it}^k = \sum_m \pi_{mit}^k P_{mt}^k Q_{mt}^k,$$

where π_{mit}^k is the bilateral trade share, which captures the share of expenditure on sector k goods in country m produced in country i, and the demand for sector composite goods Q_{it}^k is given by

$$Q_{it}^k = C_{it}^k + X_{it}^k + \sum_j M_{it}^{jk} = C_{it}^k + X_{it}^k + \sum_j \int M_{it}^{jk}(x)dx.$$

The associated GDP accounting is given by

$$GDP_{it} = \sum_k (P_{it}^k Y_{it}^k - \sum_j P_{it}^j M_{it}^{kj}) = \sum_k (w_{it} L_{it}^k + r_{it} K_{it}^k) = \sum_k P_{it}^k C_{it}^k + \sum_k P_{it}^k X_{it}^k + NX_{it},$$

so that total value added equals total factor payments and total final expenditures.

3.5 Equilibrium Conditions

In this section we summarize the optimality conditions of the model.

3.5.1 Static Conditions

Cost minimization by firms producing varieties within sector k yields the following unit cost

$$u_{it}^k = \left(\frac{r_{it}}{\alpha_i^k \varphi_i^k}\right)^{\alpha_i^k \phi_i^k} \left(\frac{w_{it}}{(1-\alpha_i^k)\varphi_i^k}\right)^{(1-\alpha_i^k)\phi_i^k} \left[\prod_j \left(\frac{P_{it}^j}{\mu_i^{kj}(1-\varphi_i^k)}\right)^{\mu_i^{kj}}\right]^{1-\phi_i^k}, \tag{8}$$

where this unit cost is common to all producers in sector k. Intuitively, unit costs depend on the rental rate of capital, wages, and the prices of intermediates. The marginal cost is variety specific and given by $MC_{it}^k(x) = u_{it}^k / z_{it}^k(x)$. Delivering any variety from sector k produced in country i to country m costs $MC_{it}^k(x)\tau_{mit}^k$.

As it is standard in this class of models, Frechet distribution properties imply that the price of sector-k composite good is given by

$$P_{it}^k = \gamma(\Phi_{it}^k)^{-\frac{1}{\theta}},$$

with

$$\gamma = [\Gamma((\theta + 1 - \eta)/\theta)]^{\frac{1}{1-\eta}},$$

where Γ is the Gamma distribution, and

$$\Phi_{it}^k = \sum_{m=1}^{I} T_{mt}^k (u_{mt}^k \tau_{imt}^k)^{-\theta}.$$

Therefore, we can write

$$P_{it}^k = \gamma \left[\sum_{m=1}^{I} T_{mt}^k (u_{mt}^k \tau_{imt}^k)^{-\theta} \right]^{-\frac{1}{\theta}} \tag{9}$$

so that prices are inversely related to the productivities of sector k in all countries, and positively related to the unit costs and trade costs. The properties of the Frechet distribution also imply that bilateral trade shares are given by

$$\pi_{imt}^k = \frac{T_{mt}^k (u_{mt}^k \tau_{imt}^k)^{-\theta}}{\Phi_{it}^k} = \frac{T_{mt}^k (u_{mt}^k \tau_{imt}^k)^{-\theta}}{\sum_{m=1}^{I} T_{mt}^k (u_{mt}^k \tau_{imt}^k)^{-\theta}} \tag{10}$$

so that the share of sector-k goods country i buys from country m is proportional to the productivity of sector k in country m, and inversely related to the unit costs in country m and the cost of shipping from m to i.

Given sector-k prices, we can also obtained the prices of composite consumption and investment goods from sectoral final demands. Specifically,

$$P_{it}^k X_{it}^k = \omega_{it}^k P_{it}^x X_{it},$$

$$P_{it}^k C_{it}^k = \psi_{it}^k P_{it}^c C_{it},$$

with

$$P_{it}^{x} = \prod_{k} \left(\frac{P_{it}^{k}}{\omega_{it}^{k}} \right)^{\omega_{it}^{k}}, \tag{11}$$

and

$$P_{it}^{c} = \prod_{k} \left(\frac{P_{it}^{k}}{\psi_{it}^{k}} \right)^{\psi_{it}^{k}}.$$

3.5.2 Dynamic Conditions

The main dynamic optimality condition is the Euler equation. Following Eaton et al. (2016), we assume perfect foresight. The Euler equation is given by

$$\frac{C_{i,t+1}}{C_{it}} = \frac{\beta}{P_{it}^{K}/P_{it}^{c}} \left[\frac{r_{i,t+1}}{P_{i,t+1}^{c}} + \frac{1-\lambda}{\lambda} \frac{P_{i,t+1}^{x} X_{i,t+1}/P_{i,t+1}^{c}}{K_{i,t+1}} + \frac{1-\delta}{\lambda} \frac{P_{i,t+1}^{x} X_{i,t+1}/P_{i,t+1}^{c}}{K_{i,t+2} - (1-\delta) K_{i,t+1}} \right] \tag{12}$$

where the price of new capital is given by

$$\frac{P_{it}^{K}}{P_{it}^{c}} = \frac{1}{\lambda A_{it}} \left(\frac{X_{it}}{K_{it}} \right)^{1-\lambda} \frac{P_{it}^{x}}{P_{it}^{c}}.$$

In our model, the price of new capital is not the same as the price of investment due to the presence of adjustment costs and the investment efficiency term A_{it}. Notice that if there were no adjustment costs or $\lambda = 1$, the price of new capital would reduce to $P_{it}^{K} = P_{it}^{x}/A_{it}$, which indicates that the price of new capital is proportional to the price of investment goods, and that higher investment efficiency reduces the price of new capital. Euler equation (12) suggests that the growth rate of consumption is inversely proportional to the price of new capital relative to the price of consumption, and proportional to the future return of new capital, which is the term in brackets. Therefore, a higher investment efficiency lowers the price of new capital relative to the price of consumption, encouraging investment and higher consumption growth.

Notice that if there were no adjustment costs $\lambda = 1$ and full depreciation $\delta = 1$, the Euler equation would reduce to

$$\frac{C_{i,t+1}}{C_{it}} = \frac{\beta A_{it}}{P_{it}^{x}/P_{it}^{c}} \frac{r_{i,t+1}}{P_{i,t+1}^{c}},$$

which given the log utility it predicts the growth rate of consumption as proportional to the return to capital properly adjusted with the price of investment relative to consumption.

3.5.3 Steady State

We define a steady state in which the fundamentals for all sectors k and countries i, m are constant are given by T_{i}^{k}, τ_{im}^{k}, ω_{i}^{k}, ψ_{i}^{k}, A_{i}, L_{i}, and ρ_{i}. Since the steady state is trivial for the static optimality conditions, we focus here on the dynamic ones. The law of motion of capital in (2) implies that in the steady state

$$\frac{A_{it}^{1/\lambda} X_{it}}{K_{it}} = \delta^{1/\lambda},$$

so that when $\lambda = 1$ and there are no adjustment costs, the ratio of effective investment $A_{it}X_{it}$ to capital is given by δ, as it is standard. The Euler equation (12) together with the equation above imply

$$\frac{r_i K_{it}}{P_i^x X_{it}} = \frac{1-\beta+\lambda\delta\beta}{\lambda\delta\beta},$$

so that the ratio of rental income to investment spending is constant.

4 Calibration

The calibration of this model follows a similar approach to Eaton et al. (2016) and Caliendo, Dvorkin and Parro (2019), where given some exogenous parameters and data moments, the time-varying fundamentals are backed out to exactly fit the data moments during 2000-2014.[10] Recall that the 2000-2014 period coincides with the commodity boom in RREs, China's entry into the WTO, and China's transformation into a high-tech intensive economy. The dynamic nature of this paper requires that we compute the whole transition to the steady state in order to back out some of the fundamentals, particularly investment efficiency A_{it} and sectoral productivities T_{it}^k.

The overall calibration strategy proceeds as follows. First, we set some parameters exogenously from other papers in the literature. Second, we use 2000-2014 labor, input-output, and sector price data to compute the following constant production parameters: α_i^k, φ_i^k, and μ_i^k, as well as the following time-varying production, demand and trade parameters: L_{it}, ψ_{it}^k, ω_{it}^k, τ_{imt}^k, and ρ_{it}. Last, we use data on investment and compute the model's full transitional path to the steady state, which allow us to back out the following time-varying fundamentals: A_{it} and T_{it}^k.

4.1 Exogenous Parameters

We draw some exogenous parameters from the literature. In particular, we set the following parameters as in Eaton et al. (2016): the dispersion of productivity for the Frechet distributions is set to $\theta = 2$; the elasticity of substitution between varieties within sector is set to $\eta = 2$; the adjustment cost $\lambda = 0.55$; the depreciation $\delta = 0.06$; and the annual discount factor is set to $\beta = 0.96$. As

[10] Different from these papers, here we cannot use the hat algebra approach. In our calibration the shares of goods in investment and consumption expenditures (ω_{it}^k and ψ_{it}^k) are time-varying, in part to capture some structural change trends in the data. In this case, we cannot express all model equations in changes, but require the computation of some levels.

Eaton et al. (2016) discuss, trade elasticity parameter $\theta = 2$ is smaller relative to the values used in the trade literature, but more consistent with that of the open-economy macro literature. In Section 6 we provide a robustness analysis for θ.

4.2 Data Moments

4.2.1 Data Sources

Our main data source is the 2016 release of World Input-Output Database (WIOD) from 2000-2014, which is the latest year available. We also use the 2005 benchmark price data from the Groningen Growth and Development Center (GGDC) Productivity Level Database to inform relative price levels. As mentioned, our sample includes 16 countries and regions representing all countries in the WIOD, and four sectors: primary, low-tech manufacturing, high-tech manufacturing, and services.

4.2.2 Sectoral Price Data Moments

Sectoral prices P_{it}^k are used as data moments to back-out time-varying fundamentals. We construct internationally comparable sectoral price levels from the GGDC Productivity Level Database 2005 benchmark data. We first aggregate the 35 industry gross output prices to the four sectors in our model by using the corresponding gross output shares from the 2005 WIOD IO table. The four sectors in our model are primary, low-tech manufacturing, high-tech manufacturing, and services.

Next, to construct the changes in these prices over time, we use the sectoral measures of nominal and real gross output from the Socio Economic Account (SEA) module of the WIOD from 2000 to 2014. Since these measures in SEA are in local currencies, we adjust them to also reflect nominal exchange variations over time, as all other moments from WIOD are in US dollars.

Last, we need to deal with the fact that in the Groningen data benchmark prices are expressed relative to the 2005 GDP price in the US, while in the model prices are in terms of world GDP each year. Our calibration preserves these relative prices in 2005, and we pin down the price level in the model by imposing the additional condition that the 2005 price of consumption in the US is one --or that real GDP in the model equals nominal GDP in the data for the US in 2005.

4.2.3 Data Moments from Input-Output Tables

We use the WIOD 2002 input-output tables for each country to compute the following exogenous parameters, which we assume to be constant over time: sector value added shares φ_i^k, the capital shares α_i^k, and intermediate shares μ_i^{kj}.[11] Table 6 displays capital shares and value added shares by

[11] We use 2002 IO tables to guarantee non-negative final demand for all sectors and countries during 2000-2014. In a few instances we made adjustments to output in the primary sector for a few countries and years to satisfy this condition.

Table 6: Capital and Value-Added Share Parameters by Sector - 2002

	Brazil	China	United States
Capital share of value added			
Primary	0.62	0.34	0.52
Low-tech manufacturing	0.63	0.59	0.38
High-tech manufacturing	0.60	0.62	0.43
Services	0.51	0.54	0.41
Value added share of gross output			
Primary	0.54	0.49	0.44
Low-tech manufacturing	0.37	0.27	0.43
High-tech manufacturing	0.33	0.26	0.40
Services	0.67	0.53	0.64

Notes: Data is from the World Input Output Database.

sector for Brazil, China and the US. Many papers in the literature assume that capital shares are the same across countries and sectors. But as seen in the top panel of Table 6, capital shares in value added vary substantially across countries reflecting differences in both the structure of production and the level of development.[12] For example, Brazil's primary sector is more capital intensive than China's due to the high importance of mining in Brazil and of agriculture in China. The share of capital in China is much higher in manufacturing (particularly high-tech) and services than in the primary sector. The capital share in the US tends to be the lowest among all countries, reflecting perhaps workers high human capital. The bottom panel of Table 6 suggests large differences in value added shares of gross output across sectors. For example, value added shares are particularly high in the service sector, which tends to buy less intermediate inputs.

Table 7 reports the intermediate input shares μ_i^{kj} in gross output for Brazil, China and the US, where each column on the table represents sector k, and each row sector j, so that the shares on each column for each country add up to one. Notice that these shares include imported intermediates. As it is standard at this level of aggregation, the diagonal in each input-output table tends to represent the largest shares. Interestingly, the intermediate input structure is overall similar across countries and sectors. Some exceptions include the service sector in China, which buys a larger share of intermediates from high-tech manufacturing relative to all other countries. The service sector in China buys a smaller share of intermediates from itself relative to other countries. Finally, the primary sector in China buys a larger share from itself compared to the rest of the countries.

[12] Notice that the WIOD properly measures the labor share by correcting for self-employment and family-owned businesses using detailed national account data for each country. The capital share is computed as the difference between value added and the labor share, so that it includes profits and value added tax payments. Value added shares are computed from the ratio between value added and nominal gross output.

Table 7: Intermediate Shares by Sector - 2002

	Primary	Low-tech	High-tech	Services
BRAZIL				
Primary	0.28	0.26	0.11	0.01
Low-tech manufacturing	0.26	0.40	0.19	0.22
High-tech manufacturing	0.17	0.09	0.37	0.06
Services	0.29	0.25	0.34	0.71
CHINA				
Primary	0.41	0.28	0.15	0.05
Low-tech manufacturing	0.27	0.39	0.22	0.33
High-tech manufacturing	0.13	0.14	0.47	0.20
Services	0.19	0.20	0.17	0.43
UNITED STATES				
Primary	0.33	0.19	0.07	0.01
Low-tech manufacturing	0.20	0.34	0.19	0.16
High-tech manufacturing	0.09	0.10	0.43	0.06
Services	0.37	0.36	0.31	0.78

Notes: Data is from the World Input Output Database.Each column reports the share of intermediates used in production and purchased from each of the other sectors (rows).

These differences likely reflect diverse development stages among these countries.

In addition, we use the 4×4 input-output tables for all countries and regions in 2000-2014 to extract information on the following data moments: sectoral gross output $P^k_{it}Y^k_{it}$, bilateral trade shares π^k_{imt}, and aggregate investment spending $P^x_{it}X_{it}$. To be consistent with the model's numeraire, we normalize $P^k_{it}Y^k_{it}$ and $P^x_{it}X_{it}$ by world's GDP on each year when we input these data moments into the model. Finally, we also extract two time-varying fundamentals from WIOD input-output tables: the sectoral shares of investment spending ω^k_{it}, and aggregate employment L_{it}.

4.3 Time-Varying Fundamentals from Static Equations

As mentioned, we compute the following time-varying fundamentals either directly from the data or using the model's equations and the data: L_{it}, ψ^k_{it}, ω^k_{it}, τ^k_{imt}, and ρ_{it}. First, L_{it} and ω^k_{it} are directly taken from the input-output data. Next, ψ^k_{it}, τ^k_{imt}, and ρ_{it} are constructed using data moments together with the model's static equations.

4.3.1 Sectoral Investment Expenditure Shares

The investment expenditure shares for each sector ω_{it}^k are taking directly from the data as they satisfy

$$P_{it}^k X_{it}^k = \omega_{it}^k P_{it}^x X_{it},$$

where Table 5 in Section 2 displays the average ω_{it}^k over time from WIOD for our sub-sample of RREs and HTEs. Recall from this table that high-tech and low-tech manufacturing (construction) account for the bulk of investment spending.

4.3.2 Sectoral Consumption Expenditure Shares

We now show how the data moments we target together with some of the model's static equations automatically imply values for sectoral consumption expenditure shares ψ_{it}^k. As mentioned, our calibration strategy exactly matches the following data moments during 2000-2014: P_{it}^k, $P_{it}^k Y_{it}^k$, π_{imt}^k and $P_{it}^x X_{it}$. To start, notice that if the calibrated model can match $P_{it}^k Y_{it}^k$, π_{mit}^k, and $P_{it}^x X_{it}$, then it will also automatically match $P_{it}^k Q_{it}^k$, NX_{it}^k, and NX_{it}. First, with $P_{it}^k Y_{it}^k$ and π_{mit}^k matched, then $P_{it}^k Q_{it}^k$ is also matched since

$$P_{it}^k Y_{it}^k = \sum_m \pi_{mit}^k P_{mt}^k Q_{mt}^k.$$

Then, with $P_{it}^k Y_{it}^k$ and $P_{it}^k Q_{it}^k$ matched, NX_{it}^k is also matched since

$$NX_{it}^k = P_{it}^k Y_{it}^k - P_{it}^k Q_{it}^k.$$

Last, by definition

$$NX_{it} = \sum_k NX_{it}^k, \tag{13}$$

so NX_{it} is also matched.

Next, once the calibrated model matches $P_{it}^k Y_{it}^k$ we can construct a model-based measure of GDP from

$$GDP_{it} = \sum_k \varphi_i^k P_{it}^k Y_{it}^k, \tag{14}$$

where recall that value added shares φ_i^k are assumed constant over time (Table 6). With this model-based measure of GDP and matching both $P_{it}^x X_{it}$ and NX_{it} we can construct a model-based measure of aggregate consumption from

$$P_{it}^c C_{it} = GDP_{it} - P_{it}^x X_{it} - NX_{it}. \tag{15}$$

Table 8: Average Shares of Goods in Consumption - 2000-2014

	Primary	Low-tech	High-tech	Services
Resource-rich economies				
Australia	0.9	10.8	4.3	83.9
Brazil	2.8	17.6	9.1	70.5
High-tech intensive economies				
Japan	4.6	12.2	4.9	78.3
South Korea	7.0	18.2	5.6	69.2
Taiwan	10.0	12.5	6.5	71.1
United States	2.6	10.8	4.6	82.0
Western Europe	2.6	15.4	5.6	76.4
China	17.4	22.5	10.2	50.0

Notes: Time-varying shares of goods in consumption are computed as part of the calibration process. Given that the calibration strategy exactly matches sectoral gross output, aggregate investment spending, and bilateral trade shares, the model's equations automatically imply sectoral consumption for each country and year.

Given that the calibrated model matches $P^k_{it}Y^k_{it}$ and π^k_{mit}, we can use the value added shares φ^k_i and intermediate shares μ^{kj}_i in the following model equation to construct final sector demand F^k_{it}

$$\begin{aligned}P^k_{it}Y^k_{it} &= \sum_m \pi^k_{mit}P^k_{mt}Q^k_{mt} = \sum_m \pi^k_{mit}(P^k_{mt}C^k_{mt} + P^k_{mt}X^k_{mt} + \sum_j P^k_{mt}M^{jk}_{mt}) \\ &= \sum_m \pi^k_{mit}F^k_{mt} + \sum_m \pi^k_{mit}(\sum_{j\neq k} \mu^{jk}_m(1-\varphi^j_m)P^j_{mt}Y^j_{mt}) + \sum_m \pi^k_{mit}(\mu^{kk}_m(1-\varphi^k_m)P^k_{mt}Y^k_{mt}),\end{aligned}$$

where $F^k_{it} = P^k_{it}C^k_{it} + P^k_{it}X^k_{it}$. Since we calibrate the model to exactly match $P^x_{it}X_{it}$ and we choose ω^k_{it} from the data, then we automatically have $P^k_{it}X^k_{it}$. Therefore, with sectoral final demand constructed from the equation above, we have that sectoral consumption $P^k_{it}C^k_{it}$ will be implied from the calibration. Since aggregate consumption will be constructed from (15), then the calibration strategy will automatically imply the time-varying shares of consumption ψ^k_{it} from

$$\psi^k_{it} = \frac{P^k_{it}C^k_{it}}{P^c_{it}C_{it}} = \frac{P^k_{it}C^k_{it}}{\sum_k P^k_{it}C^k_{it}} = \frac{F^k_{it} - P^k_{it}X^k_{it}}{\sum_j(F^j_{it} - P^j_{it}X^j_{it})}. \tag{16}$$

Table 8 displays the average shares of goods in consumption ψ^k_{it} over 2000-2014. The table reflects the patterns of structural transformation, with services being the largest share in consumption in the US, around 82%, and the lowest in China, about 50%. Despite its level of development, the share of services in Brazil is also large, around 71%. Also consistent with structural transformation, the share of primary goods in consumption is large in China and lower in the US.

4.3.3 Bilateral Trade Costs

Bilateral trade costs τ^k_{imt} can be obtained directly from data moments π^k_{imt} and P^k_{it} from

$$\tau^k_{imt} = \left(\frac{\pi^k_{imt}}{\pi^k_{mmt}}\right)^{-\frac{1}{\theta}} \frac{P^k_{it}}{P^k_{mt}},$$

which follows from equations (9) and (10). In this respect τ^k_{imt} is computed to rationalize any movements in the ratio π^k_{imt}/π^k_{mmt} that are not captured by changes in the price ratio P^k_{it}/P^k_{mt}. To better understand what τ^k_{imt} captures, we can rewrite the equation above as

$$\frac{\pi^k_{imt}}{\pi^k_{mmt}} = \left(\frac{P^k_{it}}{P^k_{mt}}\right)^{\theta} \frac{1}{(\tau^k_{imt})^{\theta}},$$

so that in the model, when country m produces good k, it will sell some to country i and some locally at home. The share that goes to country i (π^k_{imt}) relative to the share that stays home (π^k_{mmt}) will be higher if the relative price of good k in country i is higher, and the costs of shipping good k to country i (τ^k_{imt}) is lower. In other words, once we measure π^k_{imt}/π^k_{mmt} and P^k_{it}/P^k_{mt} in the data, whatever is a residual will be measured as τ^k_{imt}. In this sense, τ^k_{imt} may capture changes in shipping costs or in trade policies, namely tariffs in country i or export subsidies in country m. In addition, since there are nominal exchange rate variations in the data not captured in the model, these would also be reflected in the measured τ^k_{imt}.

Given the large number of bilateral trade costs we calibrate, we only highlight some interesting patterns here, focusing on the trade of primary and high-tech manufacturing goods. Table 9 displays the bilateral trade costs resource-rich Brazil and Australia face when exporting primary goods (2014 cost relative to 2000). Exporting costs from RREs all reported destinations in the table fell between 2014 and 2000, with the exceptions of Australia exporting to South Korea, the US and Western Europe.

Table 10 focuses on bilateral trade costs for high-tech manufacturing goods (2014 relative to 2000). For this case we separately report exports and import costs, since high-tech goods are both exported and imported by HTEs. Several interesting patterns emerge. First, resource-rich Australia and Brazil faced differential import costs across source-countries. While between 2000 and 2014 importing high-tech goods from the US and Western Europe became more costly, the importing costs from China went down substantially. Since transportation costs have generally declined over time, the increasing import costs from the US and Western Europe may reflect a mix of exchange rate variations and bilateral trade policies.

To explore the case of RREs in more detail, Figure 1 displays the full evolution of high-tech bilateral export and imports costs for Brazil and Australia during 2000-2014. The figure confirms

Table 9: Primary Export Trade Costs for Resource-Rich Economies
(2014 relative to 2000 levels)

	Australia	Brazil
Exports to		
Japan	0.49	0.35
South Korea	1.20	0.51
Taiwan	0.38	0.20
United States	1.83	0.55
Western Europe	1.38	0.55
China	0.82	0.39

*Notes:*Bilateral trade costs are computed from the model equations using bilateral trade share data from the World Input-Output Database (WIOD) as well as price data from the Socio-Economic Accounts of the WIOD.

Table 10: High-Tech Manufacturing Trade Costs
(2014 relative to 2000 levels)

	Imports from			Exports to		
	US	Western Europe	China	US	Western Europe	China
Resource-rich						
Australia	1.97	1.26	0.53	0.61	0.98	1.04
Brazil	2.08	1.30	0.46	0.53	0.70	0.74
High-tech intensive						
Japan	0.68	0.37	0.20	1.60	2.35	2.28
South Korea	1.53	0.61	0.36	0.86	1.28	1.09
Taiwan	0.99	0.48	0.18	2.82	3.70	2.93
United States	1.00	0.68	0.34	1.00	1.38	1.48
Western Europe	1.38	1.00	0.46	0.68	1.00	0.93
China	1.48	0.93	1.00	0.34	0.46	1.00

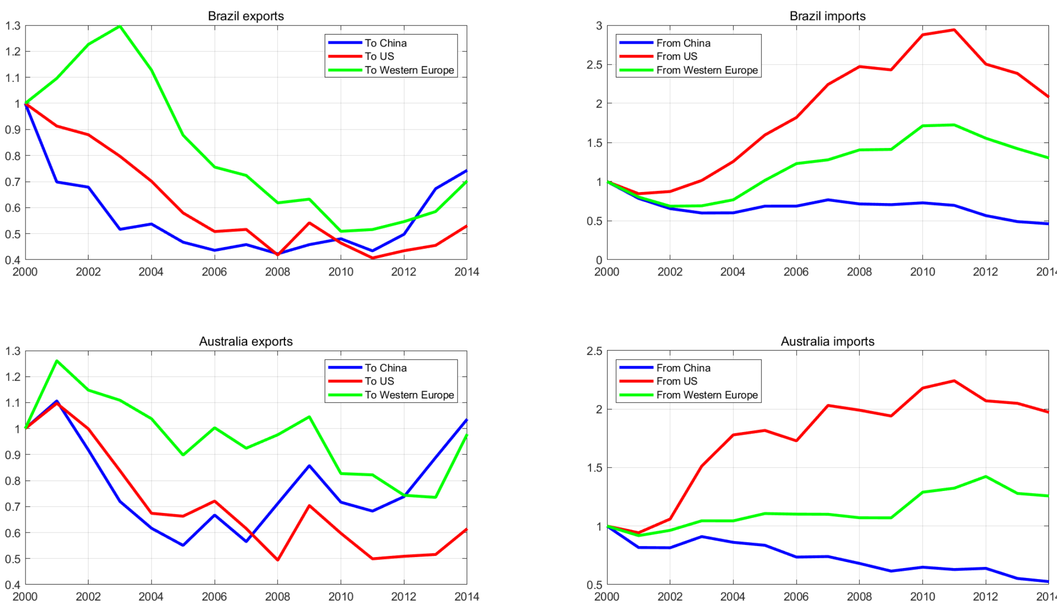
Notes: Same as in Table 9.

differential import costs, with costs decreasing only for China. In the case of Brazil, there is some external evidence supporting the differential import costs from difference source countries. First, at the general level, Brazil has been a relatively closed economy with comparatively high tariffs (Estevao and Alcaraz (2018)). Although there was a wave of trade liberalization in the early 1990s, Brazil reversed course in the early 2000s, introducing several non-tariff barriers and taxing numerous imports, notably capital goods (Estevao and Alcaraz (2018)). Second, as detailed in Dix-Carneiro (2019), Brazil protectionists policies are implemented with differential rates across products.[13] For example, Brazil imposes relatively high tariffs on imports on high-tech manufacturing sectors (automobiles, automotive parts, information technology and electronics, chemicals, industrial machinery, steel). In addition, it imposes both automatic and non-automatic import licensing requirements, with lack of information regarding the requirements for approval of non-automatic import license applications (Representative (2024)). Last, there is evidence that the Brazilian government emphasized diplomatic and economic relationships with other developing countries during the period 2003-2015, particularly with China. During Lula's first presidency in Brazil (2003-2010), economic relationships with China were strengthened in the context of the commodity boom of the 2000s, while bilateral relationships with other key trading partners, including the US and the European Union, were constrained Estevao and Alcaraz (2018). We explore the implications of Brazil's higher import costs from the US and Western Europe, as well as other local fundamentals in Section 5.

A second interesting pattern from Table 10 is that the trade cost of exporting high-tech goods to China and to Western Europe increased between 2000 and 2014 for all HTEs in our sub-sample, notably for Japan and Taiwan. Exporting high-tech goods to the US became more expensive for Japan and Taiwan. At the same time, China faced lower exporting costs of high-tech goods to both the US and Western Europe. Finally, the trade costs of importing high-tech goods from China and Western Europe fell in the sub-sample of HTEs, while imports from the US faced higher costs in China and South Korea. To provide an interpretation of these results, Figure 2 displays the full evolution of high-tech bilateral export costs for China, Japan, the US and Western Europe, and Figure 3 portrays the corresponding high-tech import costs. The patterns in Figure 2 are remarkable: exporting costs of high-tech manufacturing goods from China to Japan, Korea, Taiwan, the US and Western Europe became lower since 2000, very much consistent with China's entry to WTO. A similar pattern holds for Western Europe, except that export costs to China show an upward trend after 2007. In sharp contrast, export costs in Japan tend to rise overall, perhaps with the exception of exporting to Taiwan. The overall rising exporting costs in Japan is consistent the evidence from

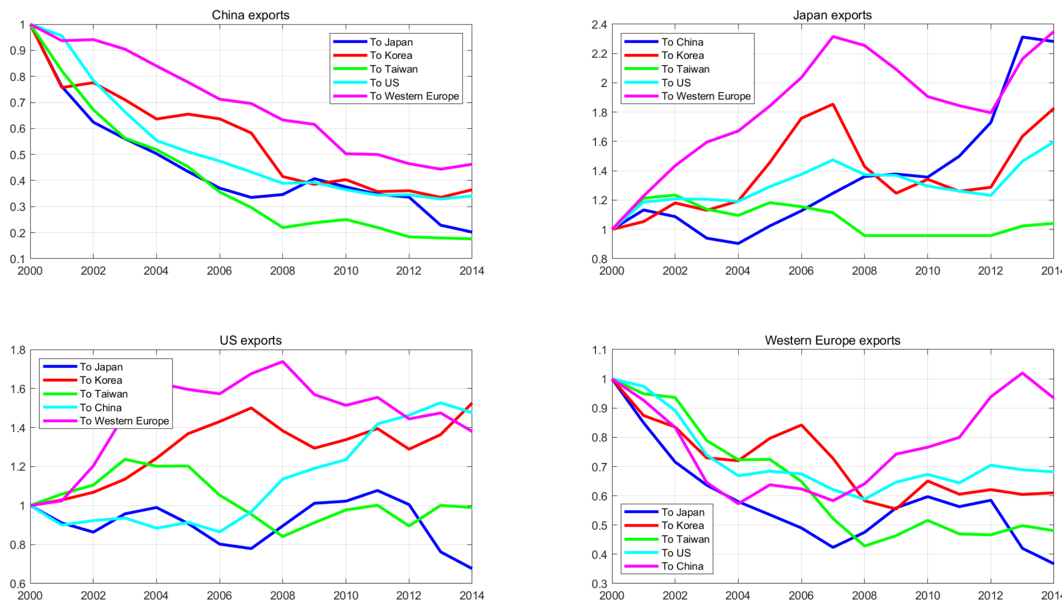
[13]According to Dix-Carneiro (2019), "although Brazil went through a major liberalization episode in the 1990s, it remains a relatively protected economy, with import tariffs across sectors averaging 10.4 percent" (p. 144). There are also substantial tariff differences across sectors: "The twenty-fifth percentile of the distribution of 2010 import tariffs is 5.3 percent, and the seventy-fifth percentile is 13.9 percent, with sectors being protected with over 30 percent tariffs (clothing and footwear" (p. 144).

Figure 1: High-Tech Bilateral Trade Costs for Resource-Rich Economies (relative to 2000)



Notes: Same as in Table 9.

Figure 2: High-Tech Bilateral Export Costs Relative to 2000



Notes: Same as in Table 9.

Amiti and Weinstein (2011) that trade finance is partially responsible for this –using 1987-1999 data they establish a causal link between the declining health of banks and the export growth of the manufacturing firms they serve. There is evidence that the weak bank health in Japan from the "lost decade" of the 1990s persisted into the 2000s and well into the 2007-2009 Great Recession (Correa and Davies (2008)).

Figure 3 also displays interesting patterns for high-tech import costs. Notice that some of the patterns in this figure are mirror image of those in Figure 2, as the bilateral import costs of one country correspond to the export costs of the other country. In the case of China, while imports of high-tech goods from HTEs became generally lower between 2000 and 2006-2008, there is a clear reversal thereafter, with these costs climbing for all source countries, and relatively more for Taiwan and Japan. In the case of Japan, the cost of importing high-tech goods falls, except for imports from Taiwan. For the US, it became cheaper over time to import high-tech goods, expect for imports from Taiwan and Japan. Finally, for Western Europe falling import costs for high-tech goods are only observed for imports from China.

Although we cannot disentangle the variety of factors behind the patterns in Figure 3, the timing of some of the patterns suggest some potentially plausible explanations. For example, the rising import trade costs in China after 2006 coincides with the implementation of industrial poli-

Figure 3: High-Tech Bilateral Import Costs Relative to 2000

Notes: Same as in Table 9.

cies that emphasized domestic production. These policies were established through the National Medium- and Long-Term Science and Technology Development Plan (2006-2020), which identifies innovation as the new national strategy. This plan highlights the strengthening of innovation capabilities as the strategic foundation for science and technology development, as well as the core of industrial restructuring and transformation of growth models. As mentioned, the implementation of this development plan accelerated during the Great Recession. An attempt was made to start implementation of all its projects by 2009, resulting in a significant flow of resources into industrial policy in China (Naughton (2021)). In a book chapter, Li, Yu and Yu (2022) provide the most recent and comprehensive data on non-tariff barriers in China from 2000 to 2016. As they indicate, while average tariffs in China declined from 16% in 2000 to 8% in 2006, they remained stable until 2016. On the other hand, non-tariff barrier measures have become more important over time, with the share of products subject to these barriers increasing substantially in 2000-2006, and continuing to raise until 2016, when 92% of product lines were subject to some form of non-tariff measure. Li, Yu and Yu (2022) also indicate that the majority of non-tariff barriers in China apply bilaterally or to a group of countries, rather than unilaterally to all countries. Although due to the scarcity of comparable non-tariff barriers data there is limited research on their effects on trade, the evidence from Li, Yu and Yu (2022) is at least suggestive of the increasing importing costs in China since

2006.

The increasing exporting costs Taiwan faces in shipping goods to China, the US, Japan and Western Europe is another remarkable pattern in Figure 3. One of the potential factors explaining this trend might be Taiwan's inability to participate in major regional trade agreements, which results in higher tariffs and trade barriers when exporting to other countries (Hammond-Chambers and Danielsson-Murphy (2007), and Morrison (2019)).

4.3.4 Global Portfolio Shares

As explained above, we model trade imbalances by constructing a global portfolio where each country contributes a fraction ρ_{it} of their GDP and receives a common return B_t, which is distributed proportional to the country's GDP. Since our calibration strategy automatically matches NX_{it} from (13), and using the data moments we construct GDP from (14), we can then compute the static portfolio return B_t from (7) and fraction ρ_{it} for each country by matching the ratio of net exports to GDP from (6). Notice that to exactly match this ratio, we also automatically match GDP in the data for each country during 2000-2014. Although we model trade imbalances in a static manner using an approach similar to Caliendo, Dvorkin and Parro (2019), under the counterfactuals changes in these imbalances will be driven by changes in GDP and the corresponding changes in the return B_t.

Table 11 reports our the static global portfolio shares we obtain for 2014. As seen in the table, the portfolio share is correlated with the ratio of net exports to GDP, which we use as the relevant data moment. Taiwan is the largest contributor to the global portfolio in 2014, reflecting the highest trade surplus among the reported sub-sample in the table. Taiwan is followed by South Korea and then China. The US contributes the least, having the largest trade deficit as a share of GDP.

4.4 Time-Varying Fundamentals from Dynamic Equations

In this section we explain how we use data on investment and capital to compute the model's full transitional path to the steady state, which allows us to back-out the following time-varying fundamentals: A_{it} and T_{it}^k. As in Eaton et al. (2016), in computing the model's transition we assume that all fundamentals remain at the 2014 level in subsequent periods, so that capital accumulation is the only factor driving the dynamics after 2014.

4.4.1 Investment Efficiency

We use two dynamic model equations to solve for the full transition to the steady state: the law of motion of capital and the Euler equation. In addition, we use two types of data moments: first, aggregate investment $P_{it}^x X_{it}$ for 2000-2014; and second, an initial capital stock for each country in

Table 11: Global Portfolio Shares - 2014

	Net exports % GDP (2014)	Portfolio share (%, 2014)
Resource-rich economies		
Australia	-0.9	47.4
Brazil	-2.1	46.2
High-tech intensive economies		
Japan	-1.5	46.8
South Korea	9.0	57.3
Taiwan	13.4	61.7
United States	-2.7	45.6
Western Europe	4.8	53.1
China	4.9	53.2

Notes: Net exports as a share of GDP are obtained from the World Input-Output Database. The global portfolio shares, which correspond to the fraction of GDP each country contributes to the global portfolio, are calibrated for the model to exactly match net exports as a share of GDP.

2000 ($K_{i,2000}$). We use the 2013 release of the WIOD to obtain information on the real capital stock in 2000 in each country, which is not available in the 2016 release. Using the model and the data moments, we back out investment efficiency A_{it} to exactly match aggregate investment spending $P^x_{it}X_{it}$ for each country and for 2000-2014. Specifically, given $K_{i,2000}$, we guess $A_{i,2000}$ and iterate forward using the capital accumulation equation in (2) as follows

$$K_{i,2001} = (1-\delta)K_{i,2000} + A_{i,2000}X^{\lambda}_{i,2000}K^{1-\lambda}_{i,2000}$$

where investment $X_{i,2000}$ is computed from

$$X_{i,2000} = \frac{P^x_{i,2000}X_{i,2000}}{P^x_{i,2000}} = \frac{P^x_{i,2000}X_{i,2000}}{\prod_k (P^k_{i,2000}/\omega^k_{i,2000})^{\omega^k_{i,2000}}},$$

and where $P^x_{i,2000}$ is a model-based measure from (11). The full transition for K_{it} can be computed iterating forward on the Euler equation in (12), which does not require knowing the full sequence of $A_{i,t}$ but only a guess on $A_{i,2000}$. In using (12), $r_{i,t+1}$ can be computed using

$$r_{it}K_{it} = \sum_k \alpha^k_i \varphi^k_i P^k_{it} Y^k_{it}. \tag{17}$$

Table 12: Investment Efficiency

	Investment % GDP				Investment efficiency (relative to 2000)		
	2000	2007	2009	2014	2007	2009	2014
Resource-rich economies							
Australia	23.2	29.1	27.5	26.9	1.25	1.23	1.26
Brazil	18.0	19.3	18.9	21.1	1.01	0.92	0.79
High-tech intensive economies							
Japan	25.6	22.1	19.5	21.6	0.97	0.94	1.00
South Korea	31.5	29.4	24.4	25.0	0.97	0.91	1.01
Taiwan	25.2	21.1	18.0	19.3	0.75	0.69	0.65
United States	22.8	21.4	17.5	19.3	0.92	0.84	0.88
Western Europe	22.5	22.2	18.9	18.9	0.93	0.83	0.86
China	33.3	36.3	42.4	40.0	1.16	1.40	1.29

Notes: Investment spending as a fraction of GDP is computed from the World Input-Output Database. Investment efficiency is computed from the model equations to exactly match investment spending as a fraction of GDP, which requires computing the model's full transition to the steady state.

Last, the initial guess for $A_{i,2000}$ is updated by solving the model's full transition from 2000 to the final steady state, adjusting the guess until aggregate investment spending $P_{it}^{x}X_{it}$ in the data for 2000-2014 is exactly matched for each country or region.

Table 12 reports the ratio of our calibrated investment efficiency in 2014 relative to 2000 for a sub-sample of economies. To illustrate the ways in which investment efficiency captures turning points, we also report the 2007 and 2009 values relative to 2000, which mark the Great Recession. As seen in the table, investment efficiency increased in China and Australia between 2000 and 2014, while it remained roughly constant in Japan and Korea, and decreased in Brazil, Taiwan, the US, and Western Europe. For example, China's investment efficiency was 1.29 times larger in 2014 relative to 2000, while in the US it fell by 12% during this period. Among RREs, Australia did notably better, multiplying investment efficiency by 1.26, while there was a 21% fall in Brazil.

The calibrated A_{it} captures well the dip in output almost all countries experienced in 2009, as well as the fact that China was among the few countries that grew during the Great Recession. In fact, China's investment efficiency was 1.4 times larger in 2009 relative to 2000, which altogether indicates that in China's investment efficiency peaked in 2009 and then decreased since then. These results are consistent with Eaton et al. (2016), who also document the 2009 collapse in investment efficiency in the US, Western Europe, Japan and Korea, while it increased in China. Finally, notice how the calibrated A_{it} correlates well with the observed changes in the investment-to-GDP ratio, a data moment also reported in Table 12. Between 2000 and 2014 this ratio increased only in Brazil, China and Australia, while it decreased everywhere else, implying an overall positive correlation between investment efficiency and the investment share of GDP.

4.4.2 Sectoral Productivities

Sectoral productivities are backed-out from

$$T_{it}^{k} = \gamma^{\theta} \pi_{iit}^{k} \left(\frac{u_{it}^{k}}{P_{it}^{k}} \right)^{\theta},$$

which follows from (10) and where the unit costs u_{it}^{k} are given by (8). Sectoral productivity in country i is then proportional to the home trade share π_{iit}^{k} and to the unit-cost to price ratio. Everything else equal, a higher home trade share implies a higher measured productivity T_{it}^{k} as otherwise the country would be buying the good from another country. In addition, if wages and unit costs are growing faster than prices, everything else equal this would imply higher measured productivity.

Notice that obtaining T_{it}^{k} requires computing u_{it}^{k}, which depends on r_{it}, K_{it}, so that it requires computing the model's full transition to the steady state. It also requires computing wages, which can be derived from data moments using the following equation

$$w_{it} L_{it} = \sum_{k} (1 - \alpha_{i}^{k}) \varphi_{i}^{k} P_{it}^{k} Y_{it}^{k}.$$

Table 13 reports the calibrated sectoral productivities T_{it}^{k} in 2014 relative to 2000 levels by country/ region and sector.[14] Among the economies reported in the table, Brazil exhibits the highest productivity growth in the primary sector, while Taiwan's high-tech productivity growth is the largest, followed by China. In fact, except for Australia, all economies exhibit productivity growth in the high-tech sector during 2000-2014. While among RREs, Brazil's sectoral productivity in all sectors exhibits more dynamism, productivity in the primary and low-tech manufacturing sectors declined in some of the HTEs (Japan, South Korea and the US). Finally, except for Brazil, Taiwan and the US, the productivity in the service sector remained mostly stagnant among the sub-sample of countries in Table 13.

[14]Since production functions in our model are different across sectors and countries, productivity levels are not comparable across countries and we cannot directly compute relative sectoral productivities. However, we can comment on relative productivity growth rates as displayed in Figure 8. In Section 5 we include as a robustness exercise a calibration in which production functions differ across sectors but not across countries, making productivity levels comparable within sectors. This robustness exercise confirms that relatively speaking, Brazil has higher productivity than China in primary goods, and lower productivity in manufacturing goods.

Table 13: Calibrated Sectoral Productivity
(2014 relative to 2000 levels)

	Primary	Low-tech	High-tech	Services
Resource-rich economies				
Australia	0.94	0.86	0.94	0.84
Brazil	1.22	1.68	1.68	1.73
High-tech intensive economies				
Japan	0.38	0.71	1.10	0.92
South Korea	0.58	0.67	1.21	0.97
Taiwan	1.18	1.00	2.64	1.57
United States	0.67	0.86	1.33	1.2
Western Europe	0.88	0.94	1.21	1.07
China	1.18	1.60	2.35	0.99

Notes: Obtaining sectoral productivities requires computing the model's full transition to the steady state. Productivity by sector and country is obtained from the model equations using data on home trade shares, wages and prices, as well as the rental rate of capital implied from the full dynamics of the capital stock.

5 Counterfactuals

In this section we use the calibrated model to perform a counterfactual analysis. The spirit of our counterfactual exercises is diagnostic, in the sense that they quantify the relative importance of different fundamentals in generating the observed dynamics in 2000-2014 for the 16 WIOD countries/ regions. We include three sets of counterfactuals. The first one focuses on the China's fundamentals, where one at time we set trade costs, sectoral productivity and investment efficiency back to 2000 levels. These counterfactuals isolate the effect of the China shock on both RREs and HTEs, providing specific information on the relative importance of trade costs with China and sectoral Chinese productivity growth on the macroeconomic outcomes in other countries. The second type of counterfactuals is designed to understand the drivers of China's rise, where we compare the role of global forces, like trade costs and productivity growth in countries other than China, versus the role of China's local fundamentals. Finally, the third type of counterfactual seeks to understand the relative importance of local factors versus the China shock in developing RREs. As noted before, during the 2000-2014 commodity boom, there was an intensification of the comparative advantage of these countries in primary goods, reverting some of their export diversification gains. What it is not clear is the role local factors may have played on these outcomes in the absence of the China shock. We illustrate this type of counterfactual for the case of Brazil, a developing RRE.

5.1 China Shock

This section summarizes the main outcomes of counterfactuals regarding China-related fundamentals. We group the results by outcome, focusing first on trade, then on macroeconomic variables, and finally on welfare.

5.1.1 Trade Outcomes

Bilateral Trade Paralleling the motivating facts presented in Section 2, we first report on bilateral exports to China under China-related fundamentals. Table 14 compares the share of total exports from a sub-sample of economies that go to China under the 2014 benchmark and the following six China-related fundamentals: (1) trade costs (both import and export) in China remain at the 2000 level; (2) productivity in all sectors in China remains at the 2000 level; (3) investment efficiency in China remains at the 2000 level; (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level (counterfactuals (1), (2) and (3) together); (5) import trade costs in China remain at the 2000 level; (6) export trade costs in China remain at the 2000 level. Notice that each of these counterfactuals is implemented one at a time.

Several insights can be highlighted from Table 14. First, column (4) shows that in the absence of the China shock, RREs would have exported a very small share total exports to China in 2014: Australia's exports to China would have been 3%, instead of the 27% in the data, with the corresponding figures for Brazil of 1% and 15%. In contrast, the response among HTEs is asymmetric, with some of them exporting more to China while other less. For example, in the absence of the China shock, Taiwan would have exported to China 51% of its total exports in 2014, instead of the 32% in the data. Similarly, Japan would have exported 19% instead of 16%. On the other hand, Korea would have exported 9% instead of 24%, the US 2% instead of 6%, and Western Europe 2% instead of 8%.

Our quantitative model allows us to further unpack these results, as the China shock counterfactual combines trade costs, sectoral productivities and investment efficiency. The first insight from this unpacking exercise is that, as seen in column (2), sectoral productivity growth in China matters for exports from RREs, while it does not for exports from HTEs –the share of exports from Australia and Brazil to China would have been half in 2014, had China's sectoral productivity remained at the 2000 level. These results suggest the importance of China's productivity growth in generating the 2000-2014 commodity boom. Second, what seems to matter most for HTEs are trade costs, as seen in column (1), where the results are again asymmetric among HTEs, paralleling those in column (4). This suggests that even with China's strong productivity growth observed during 2000-2014, if trade costs with China had been held at the 2000 level, Japan and Taiwan

Table 14: Exports to China under Counterfactual Scenarios on China's Fundamentals (% of total exports)

	Benchmark		Counterfactuals on China's fundamentals - 2014					
	2000	2014	(1)	(2)	(3)	(4)	(5)	(6)
Resource-rich economies								
Australia	5	27	8	14	24	4	17	13
Brazil	3	15	2	8	13	1	5	7
High-tech intensive economies								
Japan	6	16	24	15	15	19	42	7
South Korea	10	24	11	23	23	9	23	12
Taiwan	13	32	57	31	30	51	77	16
United States	1	6	3	4	5	2	7	2
Western Europe	2	8	3	7	7	2	6	3

Notes: Benchmark bilateral export shares to China in 2000 and 2014 exactly match the data. Counterfactual figures are reported for 2014. Counterfactual scenarios are as follows: (1) Trade costs (both import and export) in China remain at the 2000 level; (2) Productivity in all sectors in China remains at the 2000 level; (3) Investment efficiency in China remains at the 2000 level; (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level (counterfactuals (1), (2) and (3) together); (5) Import trade costs in China remain at the 2000 level; (6) Export trade costs in China remain at the 2000 level.

would have exported a larger share of their total exports to China. In contrast, South Korea and the US would have exported less.

We can use the model to unpack even more the role of trade costs with China during 2000-2014. We explore the separate role of export and import costs in China in columns (5) and (6) of Table 14. Under the counterfactual in column (5) we set only imports costs in China back to 2000 levels and find that exports from economies like Japan, Taiwan, and the US would have been higher in 2014 –for example, the share of Japan's exports to China would have been 42%, instead of 16%, and the share of Taiwan 77%, instead of 32%. This is consistent with the increasing bilateral import costs in China from these countries between 2000 and 2014, as reported in Table 10. In contrast, exports from South Korea and the US to China are mostly unaffected by Chinese import costs, hinting at potentially selective degrees of protectionism among HTEs.

The implementation of policies supporting capital-intensive sectors in China, which started in 1998 and were accelerated during the 2008 financial crisis in the form of expansionary fiscal stimulus, may have reduced exporting costs. China's entry to the WTO in 2001 also contributed to these lower export costs. This is in fact what we found in Table 10. Under the counterfactual in column (6) we set only exports costs in China back to 2000 levels and find that exports from both RREs and HTEs in 2014 would have been about half as in the data. This counterfactual underscores income effects in China –had China faced the higher export costs of 2000 through 2014, income had been lower in China, decreasing China's import demand from all goods from other countries. We conclude that while China's productivity growth and decreasing export costs were the most important factors generating larger exports from RREs to China during 2000-2014, increasing import costs in China hindered exports from some HTEs (e.g., Japan and Taiwan) to China.

Turning now to bilateral imports from China, Table 15 reports more symmetric effects of the China shock among RREs and HTEs than those found for exports to China. As reported in column (4), in the absence of the China shock, imports from China in 2014 would have been much lower across the board. Even among HTEs, where we found asymmetric effects of the China shock on exports to China, this is not the case for imports from China. If anything, column (5) suggests that if import costs in China had remained at their lower 2000 levels, all HTEs would have imported even more from China in 2014 than they did in the data. This suggest the importance of income effects among HTEs: first, had HTEs been able to export more to China, they would have also been able to import more from China. Second, had China faced lower import costs, there would have been a more efficient allocation of factors across sectors, endogenously increasing TFP, income, and their ability to purchase more goods from HTEs. Interestingly, columns (4) and (6) are almost identical in Table 15, suggesting a potentially powerful effect of Chinese economic policies in decreasing export costs in China, making China competitive, and generating larger imports from China among RREs and HTEs. In sum, these results highlight the feedback income effect loops among HTEs economies through intra-industry trade.

Export and Import Composition We now examine the effects of the China shock on the sectoral composition of trade. Table 16 reports the overall share of total exports accounted for by the primary and high-tech manufacturing sectors, as well as the share of these exports that are shipped to China under the 2014 benchmark (data) and the China shock counterfactual. Some interesting observations emerge. First, even without the China shock, the overall share of primary good exports in RREs in 2014 would have still been substantial: 51% in Australia and 32% in Brazil. Having said this, without the China shock countries like Brazil would have achieved some export diversification, increasing the share of overall high-tech exports from 16 to 20%. In the case of HTEs, in the absence of the China shock overall high-tech exports would have increased for almost all of them, notably Taiwan from 59 to 66%, Japan from 59 to 62%, and the US from 33 to 36%, capturing the increased competition in the global high-tech manufacturing market from China's economic rise. Interestingly, South Korea is atypical among HTEs, with overall high-tech exports decreasing in the absence of the China shock, hinting at the importance of China's market for this country.

The effects of the China shock on the share of imports of high-tech goods by RREs and HTEs was much more uniform than that for exports. As shown in Table 17, in the absence of the China shock, the overall share of high-tech imports would have fallen in 2014 for both RREs and HTEs,

Table 15: Imports from China under Counterfactual Scenarios on China's Fundamentals
(% of total imports)

	Benchmark		Counterfactuals on China's fundamentals - 2014					
	2000	2014	(1)	(2)	(3)	(4)	(5)	(6)
Resource-rich economies								
Australia	5	16	16	11	15	11	20	13
Brazil	1	12	5	7	11	3	15	4
High-tech intensive economies								
Japan	9	19	4	13	18	3	23	3
South Korea	6	18	11	13	17	8	22	9
Taiwan	3	16	2	10	15	1	20	1
United States	4	14	6	9	13	3	17	5
Western Europe	4	13	7	9	11	4	15	6

Notes: Benchmark bilateral import shares from China in 2000 and 2014 exactly match the data. Counterfactual figures are reported for 2014. Counterfactual scenarios are as follows: (1) Trade costs (both import and export) in China remain at the 2000 level; (2) Productivity in all sectors in China remains at the 2000 level; (3) Investment efficiency in China remains at the 2000 level; (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level (counterfactuals (1), (2) and (3) together); (5) Import trade costs in China remain at the 2000 level; (6) Export trade costs in China remain at the 2000 level.

Table 16: Primary and High-Tech Manufacturing Exports under China Shock Counterfactual
(% of total exports)

	Benchmark - 2014				China shock counterfactual - 2014			
	Total		To China		Total		To China	
	P	H	P	H	P	H	P	H
Resource-rich economies								
Australia	57	4	20	0	51	6	2	0
Brazil	39	16	11	0	32	20	0	0
High-tech intensive economies								
Japan	8	59	1	12	7	62	0	15
South Korea	5	63	1	18	6	61	1	6
Taiwan	5	59	1	27	6	66	3	41
United States	7	33	1	3	6	36	0	2
Western Europe	6	37	0	4	6	38	0	1

Notes: P denotes primary and H high-tech manufacturing. Benchmark export shares in 2014 exactly match the data. Counterfactual figures are reported for 2014. Under the China shock counterfactual, China's trade costs (exports and imports), sectoral productivities, and investment efficiency remain at the 2000 level.

Table 17: Primary and High-Tech Manufacturing Imports under China Shock Counterfactual (% of total imports)

	Benchmark - 2014				China shock counterfactual - 2014			
	Total		From China		Total		From China	
	P	H	P	H	P	H	P	H
Resource-rich economies								
Australia	12	38	1	8	12	37	1	2
Brazil	12	43	1	8	13	41	1	2
High-tech intensive economies								
Japan	33	29	1	11	37	25	1	1
South Korea	31	33	2	10	34	29	2	2
Taiwan	22	43	2	12	22	42	0	1
United States	16	41	0	9	18	39	0	1
Western Europe	13	31	0	7	14	29	0	2

Notes: P denotes primary and H high-tech manufacturing. Benchmark import shares in 2014 exactly match the data. Counterfactual figures are reported for 2014. Under the China shock counterfactual, China's trade costs (exports and imports), sectoral productivities, and investment efficiency remain at the 2000 level.

with all of them importing very little from China. The fact that the overall share of high-tech imports falls in the absence of the China shock suggests a reallocation towards home production of high-tech goods. In addition, the more-than-proportional fall of high-tech imports from China indicates a shift to importing from other relatively less productive HTEs. These are the channels by which China's economic rise might have affected investment and capital accumulation in RREs and HTEs. Not only high-tech goods are highly tradable, but as discussed before in Table 5, they represent about one third of investment spending. We explore these macroeconomic effects next.

5.1.2 Macroeconomic Outcomes

In this section we focus on the effect of China's fundamentals on investment and capital accumulation. As mentioned, China's rise in the global capital goods market may have provided other countries with access to cheaper capital goods, encouraging capital accumulation. Our dynamic model allows us to evaluate this short-term and long-term macroeconomic effects. We evaluate short-term effects by comparing outcomes in year 2014 under the counterfactual and the benchmark (data). Recall that time-varying fundamentals remain unchanged after 2014, the last year of our calibration period, so that all dynamic changes after 2014 are fully driven by capital accumulation. Long-term effects are computed comparing the steady state in the counterfactual relative to the benchmark model.

Table 18: Investment under Counterfactuals
(counterfactual relative to benchmark)

	Investment in high-tech goods				Total investment			
	Short-term (2014)		Long-term (steady state)		Short-term (2014)		Long-term (steady state)	
	(4)	(5)	(4)	(5)	(4)	(5)	(4)	(5)
Resource-rich economies								
Australia	0.87	1.01	0.69	1.00	0.95	1.00	0.84	0.99
Brazil	0.96	1.00	0.84	0.98	0.98	1.00	0.89	0.98
High-tech intensive economies								
Japan	0.94	1.07	0.85	1.15	0.98	1.05	0.92	1.10
South Korea	0.92	1.01	0.85	1.02	0.96	1.00	0.91	1.01
Taiwan	0.99	1.41	0.87	1.69	1.02	1.31	0.95	1.53
United States	0.95	1.01	0.87	1.02	0.98	1.01	0.94	1.01
Western Europe	0.96	1.01	0.89	1.02	0.99	1.00	0.95	1.01
China	0.27	1.12	0.15	1.10	0.32	1.07	0.18	1.06

Notes: Both investment in high-tech goods and total investment are quantity measures. Counterfactual scenarios are as is Table 14 as follows: (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level; and (5) Import trade costs in China remain at the 2000 level. Short-term effects are computed comparing year 2014 under the counterfactual relative to the benchmark. Long-term effects are computed comparing the steady state under the counterfactual relative to the benchmark.

Table 18 reports investment in high-tech goods and total investment in the counterfactual relative to the benchmark, both in the short and long terms. The table includes the China shock counterfactual and also the case when only import costs in China are set back to 2000 levels. In the absence of the China shock, which is marked as (4) on the table, investment in high-tech goods as well as total investment fall both in the short and long terms. In the long run, the fall is larger for the investment in high-tech goods than for total investment —we find high-tech good investment quantities to be 11 and 31% less across countries other than China. The corresponding drops in total quantities invested are between 5 and 16%. These effects are overall larger among RREs than HTEs, highlighting a positive effect of China's rise on investment in RREs.

Another interesting finding from Table 18 is that under the counterfactual where only import costs in China are set back to 2000 levels, shown in columns marked with (5), all HTEs countries would have invested more overall and in high-tech goods. This finding highlights the adverse effect from the higher costs of importing high-tech goods from HTEs into China during 2000-2014. Larger effects are seen for Japan and Taiwan.

Table 19 complements Table 18, reporting on similar effects on the price of investment relative to consumption goods, and the capital stock. In the absence of the China shock, the relative price

Table 19: Relative Price of Investment and Capital Stock under Counterfactuals
(counterfactual relative to benchmark)

	Relative price investment				Capital			
	Short-term (2014)		Long-term (steady state)		Short-term (2014)		Long-term (steady state)	
	(4)	(5)	(4)	(5)	(4)	(5)	(4)	(5)
Resource-rich economies								
Australia	1.02	1.00	1.06	1.00	0.99	0.99	0.84	0.99
Brazil	1.01	1.00	1.03	1.01	1.00	1.00	0.89	0.98
High-tech intensive economies								
Japan	1.02	0.99	1.04	0.97	1.00	1.00	0.92	1.10
South Korea	1.02	1.00	1.03	1.00	0.99	0.99	0.91	1.01
Taiwan	1.02	0.95	1.06	0.93	1.01	1.04	0.94	1.54
United States	1.01	1.00	1.03	1.00	1.00	1.00	0.93	1.01
Western Europe	1.01	1.00	1.02	1.00	1.00	1.00	0.95	1.01
China	1.23	0.98	1.25	0.99	0.45	1.00	0.12	1.06

Notes: Capital is a quantity measure. Price of investment is relative to the price of consumption. Counterfactual scenarios are as is Table 14 as follows: (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level; and (5) Import trade costs in China remain at the 2000 level. Short-term effects are computed comparing year 2014 under the counterfactual relative to the benchmark. Long-term effects are computed comparing the steady state under the counterfactual relative to the benchmark.

of investment goods would have been higher, a key channel affecting capital accumulation. While the relative price of investment increases between 1 and 2% in the short run, the increase ranges between 2 and 6% in the long run. These effects are bigger in China, 23 and 25%, since under the China shock counterfactual sectoral productivities are set back to 2000, directly affecting prices. In the case of the capital stock, short-term effects of the China shock are generally smaller than those on investment due to capital adjustment costs, the need for investment to offset depreciation, and the relatively small size of investment compared to capital. Effects on the capital stock are larger in the long in the run –in the absence of the China shock, capital would be between 5 and 16% lower across countries other than China. As in the case of investment, the effects are larger for RREs. Finally, it is notable from column (5) how the higher costs of exporting high-tech goods to China in 2014 relative to 2000 have affected capital accumulation in HTEs –have these costs remained at the lower 2000 level, Japan's capital would be 10% in the long run, and Taiwan's 54% higher.

In sum, the results in this section underscore the importance of the dynamic effects captured in our model. We find that in the absence of the China shock, there would have been detrimental effects on investment in the short run, and even a larger impact on investment and the capital stock in the long run. The impact of the China shock on capital accumulation is particularly large among

RREs. As initially hypothesized, these economies experienced an intensification of comparative advantage in primary products, but their capital accumulation overall benefited from China's rapid productivity growth in high-tech manufacturing. Last, HTEs would have benefited even more if the costs of importing high-tech goods in China had not increased relative to 2000.

The macroeconomic outcomes reported in this section evoke a more general discussion on the global effects of industrial policies. These global effects appear to be asymmetric. Countries like Brazil actively promote and protect infant high-tech industries, with positive results on high-tech productivity growth between 2000 and 2014, but not large enough relative to HTEs. Not being a large player in the global high-tech manufacturing market, any negative effects from protective tariffs in Brazil are born internally. But things are different among HTEs, especially with the rapid transformation of China in the global trade of high-tech goods. The effects of industrial policy in China, particularly if they involve protection in the form of higher import costs of the sort we found after 2006, are not just born internally, but spillover to other HTEs. There is then a trade-off –for the world as a whole, industrial policy in China that promotes higher productivity growth and lower prices of tradable goods is beneficial, but when protectionism is part of this policy, the negative effects extend to HTEs. This is when intra-industry trade may potentially result in trade tensions of the sort that have been observed since 2018.

5.1.3 Welfare

We now turn to welfare effects. Although as expected, promoting trade is welfare-enhancing while discouraging trade reduces welfare, our analysis allows us to distinguish welfare effects in the short and long terms. In addition, since we compute the full model transition, we can also report on welfare effects accounting for the transitional period. Welfare results are reported in Table 20, where we report the China shock counterfactual as well as the scenario when only Chinese's import tariffs are set back to the 2000 level. As seen on the table, without the China shock, there would have been welfare losses everywhere, although of varying magnitudes. Although short-term losses would have been much lower than those in the long-term (steady state), when we take into account the full transition and the steady state, the losses are in between. This result highlights the importance of the dynamic adjustments that occur in general equilibrium in a multi-sector multi-country model, and that lessen the welfare effects in a counterfactual where the China shock would not have occurred.

Another insight from Table 20 is that in the absence of the China shock, welfare losses would have been relatively larger for the RREs, although South Korea is the only HTE with even larger losses. As pointed out before, China appears to be a particularly important market for South Korea. Last, under the counterfactual where only the import costs in China are set to 2000 levels,

Table 20: Welfare under the Counterfactuals
(percentage consumption equivalent)

	Short-term effects (2000-2014)		Long-term effects (steady state)		Effects including the transition	
	(4)	(5)	(4)	(5)	(4)	(5)
Resource-rich economies						
Australia	-0.89	-0.13	-11.93	-0.49	-3.32	-0.12
Brazil	-0.68	-0.09	-9.99	-1.75	-2.14	-0.32
High-tech intensive economies						
Japan	-0.57	0.39	-6.30	6.77	-1.69	2.00
South Korea	-1.44	0.27	-8.07	1.56	-3.28	0.61
Taiwan	-0.25	3.89	-4.27	40.81	-0.49	13.54
United States	-0.57	0.02	-5.68	0.71	-1.63	0.16
Western Europe	-0.59	-0.02	-5.47	0.57	-1.65	0.09
China	-24.31	-0.17	-77.20	5.22	-50.58	2.60

Notes: Counterfactual scenarios are as is Table 14 as follows: (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level; and 5) Import trade costs in China remain at the 2000 level. Short-term effects are computed comparing the 2000-2014 period under the counterfactual relative to the benchmark. Long-term effects are computed comparing the steady state under the counterfactual relative to the benchmark. The effects including the transition compare the full 2000 to steady-state transition under the counterfactual and the benchmark.

we find that there would have been welfare gains for all HTEs, and losses for all RREs. Consistent with other results described above, the welfare gains would have been particularly large for Taiwan, followed by Japan, with these effects tracing back to the higher import costs of high-tech goods in China in 2014 relative to 2000.

5.2 The Drivers of China's Economic Rise

The previous section focused on the effect of China's rise on trade and capital accumulation in other countries. In this section we use our quantitative model to shed light on the factors that drove China's economic rise. This analysis is similar in spirit to Brandt and Lim (2024), who explore the drivers of China's exports from 2000 to 2013 using customs and firm-level Chinese data. To explore the drivers of China's economic rise in our model, we perform two types of counterfactuals. First, we explore the role of global factors on China's rise by setting some fundamentals back to the 2000 level for all countries except China, including trade costs, productivity in high-tech, and productivity in all sectors. Second, we compare the effects of global fundamentals with those of local China fundamentals by setting these back to the 2000 level, one at a time. As we now show, global fundamentals matter relatively more for China's high-tech trade than for investment and capital

Table 21: High-Tech Manufacturing Trade Shares in China
Global versus Local Fundamentals in China

	Import share high-tech (% total)		Export share high-tech (% total)	
	2000	2014	2000	2014
Benchmark	54	44	34	50
Global fundamentals				
Trade costs	54	51	34	39
High-tech productivity	54	32	34	61
All sectoral productivities	54	32	34	60
China's fundamentals				
Trade costs	54	54	34	39
High-tech productivity	54	65	34	26
Sectoral productivities	54	62	34	31
Investment efficiency	55	44	34	49
China shock	55	70	34	23

Notes: Under the counterfactuals on global fundamentals, values are set back to 2000 for all countries except China. Under the China shock counterfactual, China's trade costs (exports and imports), sectoral productivities, and investment efficiency are set back to 2000 levels. The China shock sets back all of these (trade costs, sectoral productivities, investment efficiency) to 2000 levels.

accumulation in China. Local China fundamentals matter for both trade and capital accumulation.

Table 21 compares the effect of global and local fundamentals on the share of high-tech imports and exports in China. Other than the benchmark on the first row, each of the other rows corresponds to a counterfactual, with the top section reporting on global fundamentals, and the bottom section on local China fundamentals. The first observation from the table is that global counterfactuals have quantitatively large effects. For example, if productivity in all countries other than China had remained at the level of 2000, the share of high-tech goods in China's imports in 2014 would have fallen from the observed 44% to 32%. The opposite would have occurred with the share of high-tech goods in China's exports, which would have increased from 50% to 60%. Without productivity growth everywhere else, the economic rise of China would have featured an even stronger export concentration in high-tech goods. Local factors in China matter as well. For example, if sectoral productivities would have remained at the 2000 level in China, the share of high-tech good imports in 2014 would have been 62% (instead of 44%), and that of exports would have been 31% (instead of 50%). These findings parallel those of Brandt and Lim (2024), who also find foreign demand and factor productivity growth in China to be the main drivers of Chinese exports during 2000-2013.

Using our model we can expand the analysis in Brandt and Lim (2024) by comparing the effect of global and local fundamentals on investment and capital in China. Table 22 reports these results

Table 22: Investment and Capital in China
(change under counterfactual relative to change in benchmark)

	Investment		Capital	
	2014	steady state	2014	steady state
Global fundamentals				
Trade costs	0.94	0.95	0.94	0.96
High-tech productivity	0.99	1.00	0.99	1.00
All sectoral productivities	0.99	0.99	0.99	0.96
China's fundamentals				
Trade costs	0.97	0.97	0.96	0.97
High-tech productivity	0.61	0.53	0.82	0.55
Sectoral productivities	0.31	0.26	0.64	0.29
Investment efficiency	0.69	0.59	0.57	0.38
China shock	0.17	0.14	0.35	0.11

Notes: Same as in Table 21. Column marked 2014 reports the change between 2014 and 2000 under the counterfactual, relative to the change between 2014 and 2000 under the benchmark. Similarly, column marked steady state reports the change between the steady state and 2000 under the counterfactual relative to that change in the benchmark.

for the short-term and the long-term. In the case of this table, the column marked 2014 reports the change between 2014 and 2000 under the counterfactual, relative to the change between 2014 and 2000 under the benchmark (short-term effect). Similarly, column marked steady state reports the change between the steady state and 2000 under the counterfactual relative to that change in the benchmark (long-term effect). Notice that in this case, numbers closer to one indicate a lower explanatory power of the fundamental, as the change in under the counterfactual is not very different than in the benchmark. As seen in the table, when it comes to macroeconomic outcomes, local China fundamentals are quantitatively more important than global fundamentals. For example, if productivity in all countries other than China had remained at the level of 2000, the change in investment between 2014 and 2000 would have been almost identical to that in the benchmark, indicating a low explanatory power. In contrast, China's sectoral productivity growth and investment efficiency have the largest effects on fostering investment and capital accumulation in China, both in the short and long terms. For example, if China's sectoral productivity had not grown since 2000, the change in investment between 2014 and 2000 would only have been 31% of the change observed in the data. Similarly, if China's investment efficiency had remained at the lower levels of 2000, the change in investment between 2014 and 2000 would have been 69% of the change observed in the data.

In fact, in the absence of the China shock, i.e., if trade costs, sectoral productivities and investment efficiency in China had remained at the levels of 2000, the change in investment between 2014 and 2000 would only have been 17% of the change observed in the data, suggesting a strong effect of local fundamentals on local macroeconomic outcomes. The long-term effects for capital are even higher – in the absence of the China shock, the change in capital between the steady state and 2000 would have been 11% of the change in the benchmark.[15]

5.3 Local versus Global Factors in Developing Countries

In this section we use our quantitative model to compare the effects of the China shock with the effect of local fundamentals in developing countries. To illustrate this comparison more precisely, we focus here in the case of Brazil, a RRE that had also developed a high-tech manufacturing base by 2000. As we documented above, Brazil experienced a large demand for primary goods from China since 2000, which reverted some of the export diversification achieved in high-tech manufacturing. On the other hand, Brazil's investment in high-tech goods and overall capital accumulation was enhanced by the China shock. But when it comes to policy implications, a comparison of these external effects with the evolution of local fundamentals becomes important. What would be local factors governments in developing countries could promote to enhance welfare in the new global context created by China's economic rise?

To answer this question we perform counterfactuals on local Brazilian fundamentals (investment efficiency and sectoral productivities) and trade-related fundamentals (import trade costs) by setting them back one at a time to their 2000 levels. We compare some of the 2014 (short-run) outcomes of these counterfactuals with a situation where the China shock does not occur. These are reported in Table 23, which suggest the following main insights. First, regarding export diversification, the China shock plays a non-trivial role in the short-run. In the 2014 benchmark (data), primary goods were 39% of exports and high-tech goods 16% –without the China shock these would have been 32% and 20% respectively, allowing for some export diversification. Having said this, local sectoral productivity increases in Brazil also shape comparative advantage –there was positive productivity growth in all sectors in Brazil between 2000 and 2014. Without productivity growth in low and high-tech manufacturing, the share of primary exports in Brazil would have been 45% and 42% in 2014 respectively. Results are asymmetric for the share of high-tech exports –without low-tech productivity this share would have been higher (18% instead of 16% in the data), but without high-tech productivity it would have been lower (12% instead of 16%). Without high-tech productivity growth Brazil imports more of these goods, producing and exporting less. These results indicate that although the China shock has adverse effects on trade diversification in Brazil, local productivity growth is key to counteract this external shock. Policies aimed at encouraging local productivity are essential.

[15] Notice that our model does not take into account productivity spillovers across countries. If some of China's local productivity growth was the result of global spillovers, our accounting attributes this to local, not to global productivity.

Table 23: Short-Run Outcomes in Brazil under Counterfactuals
China Shock versus Local Fundamentals in Brazil

	Trade shares (% of total)			Investment	Welfare
	Export shares		Import share	(counterfactual over benchmark)	(% consumption equivalent)
	P	H	H		
Benchmark	39	16	43	-	-
China's fundamentals					
China Shock	32	20	41	0.98	-0.68
Brazil's fundamentals					
Import trade costs	39	17	50	1.07	0.97
Investment efficiency	39	16	44	1.24	0.13
Low-tech productivity	45	18	38	0.71	-2.69
High-tech productivity	42	10	53	0.88	-0.46
Service productivity	43	16	38	0.78	-14.81

Notes: P denotes primary and H high-tech manufacturing. Trade shares are reported in percents for the benchmark (first row) and the counterfactuals. The ratio of capital in the counterfactual over benchmark is computed for 2014 (short-run). Consumption equivalent (welfare) in the short-term is computed comparing the 2000-2014 period under the counterfactual relative to the benchmark Under the China shock counterfactual, China's trade costs (exports and imports), sectoral productivities, and investment efficiency remain at the 2000 level. Counterfactual scenarios for Brazil's fundamentals set each of them back to their 2000 levels, one at a time.

Second, in the case of imports of high-tech goods, the China shock plays a role, but local sectoral productivity growth has quantitatively large effects. In the 2014 benchmark (data), high-tech goods were 41% of imports –without the observed low-tech manufacturing productivity growth in 2000-2014, the share of high-tech imports would have been 38%, and without high-tech productivity growth, it would have been 53% in 2014. These results are driven by the reallocation of factors across sectors in response to sectoral productivity differentials.

Third, regarding investment and capital accumulation, the quantitatively strongest factor is investment efficiency –had Brazil kept the higher investment efficiency levels of 2000, investment would have been 24% higher in 2014 relative to the benchmark (data). Brazilian import trade costs also play role in investment –had Brazil kept the lower import costs of 2000, particularly for high-tech goods, investment in 2014 would have been 7% higher. These results hint at the importance of understanding the decrease in investment efficiency in Brazil, as well as the detrimental effects of high import costs for high-tech goods.

Finally, local fundamentals are quantitatively important for welfare. For example, setting service productivity back to the 2000 lower level would result in a welfare loss of about -15% during 2000-2014 (short run), much larger than -0.7% welfare loss in the absence of the China shock. Interestingly, short-term welfare gains in Brazil would have been observed if import costs were set back to the lower levels of 2000 or if investment efficiency went back to the higher 2000 level –welfare gains would have been 0.97% and 0.13% respectively during 2000-2014. In sum, local policies to reduce import costs and increase investment efficiency in Brazil generate quantitatively larger effects on macroeconomic outcomes and welfare than the China shock.

6 Robustness Analysis

In this section we check the robustness of our main insights. For this purpose we calibrate models under three alternative assumptions: first, following Ravikumar, Santacreu and Sposi (2019) we consider the case where the capital adjustment cost is lower by setting $\lambda = 0.76$ rather than the 0.55 of our benchmark calibration. Second, we consider a model with a higher trade elasticity with $\theta = 3$ rather than $\theta = 2$ as in the benchmark calibration.[16] Finally, we assume that although the production functions vary by sector, they do not vary across countries, which is the case considered in Levchenko and Zhang (2016), and a common assumption in the literature. For this purpose, we construct capital shares α^k, value added shares ϕ^k, and intermediate shares μ^{kj}, by averaging the

[16] The trade literature considers even larger trade elasticities in the order of $\theta = 4$ or $\theta = 8$. However, it is not possible to exactly match data moments such as sectoral gross output during 2000-2014 in our model for $\theta > 3$ due to the number of instances where trade costs violate a model constraint and become larger than one. Papers using larger values for θ do not pursue the calibration strategy of backing-out time-varying fundamentals by exactly matching data moments as in Eaton et al. (2016), and as we do here.

Table 24: Time-Varying Fundamentals under Alternative Calibrations

	High-tech manufacturing productivity				Investment efficiency			
	Benchmark	(A)	(B)	(C)	Benchmark	(A)	(B)	(C)
Resource-rich								
Australia	0.94	1.08	1.00	1.10	1.26	0.94	1.26	0.94
Brazil	1.68	1.79	1.39	1.48	0.79	0.60	0.86	0.90
High-tech intensive								
Japan	1.10	1.19	1.26	1.18	1.00	0.89	1.00	0.93
South Korea	1.21	1.50	1.36	1.95	1.01	0.85	1.01	0.71
Taiwan	2.64	2.87	3.74	3.36	0.65	0.52	0.65	0.57
United States	1.33	1.46	1.60	1.39	0.88	0.78	0.88	0.83
Western Europe	1.21	1.32	1.39	1.29	0.86	0.75	0.86	0.76
China	2.35	3.03	3.45	3.66	1.29	0.72	1.29	0.83

Notes: Alternative calibration scenarios are as follows: (A) model with lower capital adjustment costs set to $\lambda = 0.76$; (B) model with higher trade elasticity $\theta = 3$; (C) model where production functions vary across sectors but not across countries. All alternative calibration scenarios fit the same 2000-2014 data moments as in the benchmark calibration. Results are reported as high-tech productivity and investment efficiency in 2014 relative to 2000.

corresponding values across countries for each sector. For all of these alternative assumptions we calibrate the model to exactly match the same data moments during 2000-2014 as in the benchmark calibration.

Table 24 reports two of the key time-varying fundamentals in the benchmark and alternative calibrations: high-tech manufacturing productivity and investment efficiency in 2014 relative to 2000. Columns are marked (A) through (C) to represent the three alternative assumptions respectively –lower adjustment cost, higher trade elasticity, and same production functions across countries but not across sectors. Although there are some quantitative differences across these scenarios, some of the main qualitative patterns from the benchmark calibration remain. For example, China and Taiwan stand out with higher high-tech productivity growth, and Australia has the lowest. Across all calibrations investment efficiency in 2014 relative to 2000 falls for Brazil, Taiwan, the US and Western Europe. There are some differences in the investment efficiency for Australia, Japan, South Korea and China. For these countries, the investment efficiency under the benchmark calibration is most similar to that of the model with higher trade elasticity reported in column (B). In addition, the investment efficiency of the model with lower adjustment costs in column (A) is similar to the model with the same production function across countries in column (C). For example, investment efficiency increase in China under the benchmark calibration and column (B), while it decreases between 2000 and 2014 in columns (A) and (C). The question is whether these variations affect the main insights from the counterfactuals, which we examine next.

Table 25: Long-Run Capital under Alternative Calibrations and Counterfactuals

	(4) China shock				(5) Import costs in China			
	Benchmark	(A)	(B)	(C)	Benchmark	(A)	(B)	(C)
Resource-rich								
Australia	0.84	0.89	0.85	0.89	0.99	1.00	1.02	1.01
Brazil	0.89	0.93	0.91	0.94	0.98	0.99	0.98	0.99
High-tech intensive								
Japan	0.92	0.94	0.94	0.93	1.10	1.07	1.13	1.10
South Korea	0.91	0.93	0.96	0.92	1.01	1.01	1.01	1.02
Taiwan	0.94	0.97	1.05	0.96	1.54	1.44	1.74	1.47
United States	0.93	0.96	0.95	0.94	1.01	1.01	1.02	1.01
Western Europe	0.95	0.97	0.96	0.95	1.01	1.01	1.01	1.01
China	0.12	0.33	0.12	0.26	1.06	1.08	1.07	1.06

Notes: Alternative calibration scenarios are as follows: (A) model with lower capital adjustment costs set to $\lambda = 0.76$; (B) model with higher trade elasticity $\theta = 3$; (C) model where production functions vary across sectors but not across countries. Counterfactual scenarios are as is Table 14 as follows: (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level; and (5) Import trade costs in China remain at the 2000 level. The table reports the ratio of steady-state capital in the counterfactual relative to steady state in the benchmark.

We now show that despite some differences in the time-varying fundamentals backed-out across calibrations, the macroeconomic outcomes under the counterfactuals are overall similar. Table 25 illustrates this point for the case of capital, where we report the steady state in the counterfactual relative to the benchmark, and consider two counterfactuals: the China shock, where we set trade costs, sectoral productivity, and investment efficiency in China back to 2000 levels (counterfactual 4 in other tables above); and the scenario where only import costs in China are set back to 2000 levels (counterfactual 5). As we find under the benchmark calibration, without the China shock, long-run capital would be lower everywhere. In addition, if import costs in China were set back to 2000 levels, capital would be higher everywhere, notably for Japan and Taiwan, except for Brazil.

Finally, Table 26 reports long-run welfare across alternative calibrations for the same two counterfactuals. Again here, the overall results are similar –without the China shock, there would be welfare losses everywhere. In contrast, if import costs in China were set back to 2000 levels, there would be welfare gains everywhere, except for Brazil. Although for some countries like Australia results vary across calibrations for the latter counterfactual, by in large our main insights are robust under alternative calibration scenarios.

Table 26: Long-Run Welfare under Alternative Calibrations and Counterfactuals

	(4) China shock				(5) Import costs in China			
	Benchmark	(A)	(B)	(C)	Benchmark	(A)	(B)	(C)
Resource-rich								
Australia	-11.9	-7.8	-11.1	-8.8	-0.5	0.1	1.0	0.3
Brazil	-9.9	-6.5	-8.9	-5.7	-1.7	-0.7	-1.6	-0.5
High-tech intensive								
Japan	-6.3	-4.2	-4.6	-5.6	6.7	5.3	8.7	6.8
South Korea	-8.0	-6.4	-5.4	-9.0	1.5	1.3	1.9	1.9
Taiwan	-4.2	-2.7	2.5	-4.9	40.8	32.5	56.6	41.9
United States	-5.6	-3.8	-4.8	-5.4	0.7	0.5	0.9	0.7
Western Europe	-5.4	-3.7	-4.7	-5.2	0.5	0.4	0.8	0.5
China	-77.2	-73.1	-77.1	-79.0	5.2	6.9	5.3	5.1

Notes: Alternative calibration scenarios are as follows: (A) model with lower capital adjustment costs set to $\lambda = 0.76$; (B) model with higher trade elasticity $\theta = 3$; (C) model where production functions vary across sectors but not across countries. Counterfactual scenarios are as is Table 14 as follows: (4) China shock counterfactual, i.e., China's trade costs, sectoral productivities and investment efficiency remain at the 2000 level; and (5) Import trade costs in China remain at the 2000 level. The table reports the ratio of steady-state capital in the counterfactual relative to steady state in the benchmark. The table reports percentage consumption equivalent computations for the steady state in the counterfactual and benchmark.

7 Concluding Comments

The China shock has been extensively studied. What has received less attention is the gradual ascent of China in the global trade of high-tech manufacturing goods since 2000 and how this rise may have affected capital accumulation. Our paper fills this gap.

We document that while between 2000 and 2014 China lost comparative advantage in low-tech manufacturing, it increased it in high-tech manufacturing goods. China's transformation from a low-tech manufacturing exporter to a high-tech exporter has the potential of affecting capital accumulation around the world. For one, high-tech manufacturing goods account for a large share of imports in RREs, which constitutes a channel by which investment and capital accumulation might be affected. We also document that HTEs such Japan, South Korea, Taiwan and Western Europe, increased their revealed comparative advantage in high-tech manufacturing goods between 2000 and 2014 as well, although to a much lesser extent than China. The increases in high-tech productivity in HTEs interact with the changing trade costs since 2000 to shape intra-industry trade in high-tech goods among HTEs and capital accumulation.

One of the main insights we take away from our analysis is that China's transformation to a high-tech exporter has a positive effect on the imports of high-tech manufacturing goods, investment, and capital in HTEs, and an even larger positive effect in RREs. This effect on RREs holds despite the intensification of their comparative advantage in primary goods, the associated decrease in export diversification, and the acceleration of deindustrialization trends. Having said this, the welfare gains from the China shock in RREs are smaller than those from local improvements in investment efficiency and productivity. From the policy perspective, these findings suggest the importance of further research on how to enhance investment efficiency and local productivity.

Our analysis highlights the value of dynamic trade models with capital accumulation. High-tech manufacturing goods are highly tradable and represent an important share of investment spending, about a third of the total. This creates a clear link between trade and the opportunity to foster transitional growth through capital accumulation. Using our dynamic model we find important differences in the short-term and long-term macroeconomic and welfare effects, making it fruitful to integrate trade within dynamic macroeconomic models (e.g., as in Eaton et al. (2016), Ravikumar, Santacreu and Sposi (2019)).

Another important insight from our analysis is that the increasing trade costs of importing high-tech manufacturing goods in China during 2006-2014 created negative effects for HTEs, which diminished capital accumulation and gains from trade. From this perspective, it is not surprising to see the rising tensions between China and HTEs since at least 2018, resulting in some radical changes in trade policies. As data beyond 2014 becomes available, future research could explore the consequences of these latest trends for macroeconomics outcomes and welfare.

References

Amiti, M., and D. E. Weinstein. 2011. "Exports and Financial Shocks." *The Quarterly Journal of Economics*, 126(4): 1841–1877.

Autor, David H, David Dorn, and Gordon H Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–2168.

Brandt, Loren, and Kevin Lim. 2024. "Opening up in the 21st century: A quantitative accounting of Chinese export growth." *Journal of International Economics*, 150: 103895.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro. 2019. "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica*, 87(3): 741–835.

Chen, Kaiji, and Tao Zha. 2024. "China's Macroeconomic Development: The Role of Gradual Reforms." *NBER Working Paper 31395*.

Cooper, Russell, and John Haltiwanger. 2006. "On the Nature of Capital Adjustment Costs." *Review of Economic Studies, 73: 611-633*.

Correa, Ricardo, and Sally Davies. 2008. "Implications of the Health of the Japanese Banking Sectorfor the Effectiveness of Monetary Policy." Federal Reserve Board.

di Giovanni, Julian, Andrei A. Levchenko, and Jing Zhang. 2014. "The Global Welfare Impact of China: Trade Integration and Technological Change." *American Economic Journal: Macroeconomics*, 6(3): 153–183.

Dix-Carneiro, Rafael. 2019. "Meeting Globalization Challenges." , ed. Luis Catao and Maurice Obstfeld, Chapter Trade and Labor Market Adjustment: Recent Research on Brazil, 143–153. Princeton University Press.

Dix-Carneiro, Rafael, and Brian Kovak. 2023. "Globalization and Inequality in Latin America." *NBER Working Paper 31459*.

Dix-Carneiro, Rafael, and Sharon Traiberman. 2023. "Globalization, trade imbalances and inequality." *Journal of Monetary Economics*, 133: 48–72.

Eaton, Jonathan, and Samuel Kortum. 2001. "Trade in capital goods." *European Economic Review*, 45(7): 1195–1235.

Eaton, Jonathan, Samuel Kortum, Brent Neiman, and John Romalis. 2016. "Trade and the Global Recession." *American Economic Review*, 106(11): 3401–3438.

Estevao, Marcelo, and Fernando Coppe Alcaraz. 2018. "Brazil: Boom, Bust, and the Road to Recovery." , ed. Alberto Spilimbergo and Krishna Srinivasan, Chapter Brazil in the New World Economic Order, 95–110. International Monetary Fund.

Hammond-Chambers, Rupert, and Lotta Danielsson-Murphy. 2007. "US-China Trade: Implications of the US-Asia-Pacific Trade and Investment Trends." US Taiwan Business Council.

Hanson, Gordon. 2020. "Who Will Fill China's Shoes? The Global Evolution of Labor-Intensive Manufacturing." *NBER Working Paper 28313*.

Hanson, Gordon H. 2012. "The Rise of Middle Kingdoms: Emerging Economies in Global Trade." *Journal of Economic Perspectives*, 26(2): 41–64.

Koopman, Robert, Zhi Wang, and Shang-Jin Wei. 2014. "Tracing Value-Added and Double Counting in Gross Exports." *American Economic Review*, 104(2): 459–494.

Levchenko, Andrei A., and Jing Zhang. 2016. "The evolution of comparative advantage: Measurement and welfare implications." *Journal of Monetary Economics*, 78: 96–111.

Li, Mingchong, Miaojie Yu, and Zhihong Yu. 2022. "Non-tariff Measures: Australia, China, India, Japan, New Zealand, and Republic of Korea." , ed. Lili Yan Ing, Denise Penello Rial and Rizqy Anandhika, Chapter An Anatomy of China Non-tariff Measures, 43–58. Economic Research Institute for ASEAN and East Asia.

Michael Sposi, Kei-Mu Yi, and Jing Zhang. 2024. "Deindustrialization and Industry Polarization." *NBER Working Paper 29483*.

Morrison, Wayne. 2019. "US-Taiwan Trade Relations." Congressional Research Service.

Mutreja, Piyusha, B. Ravikumar, and Michael Sposi. 2018. "Capital goods trade, relative prices, and economic development." *Review of Economic Dynamics*, 27: 101–122.

Naughton, Barry. 2021. *The Rise of China's Industrial Policy: 1978 to 2020.* Universidad Nacional Autonoma de Mexico.

Ravikumar, B., Ana Maria Santacreu, and Michael Sposi. 2019. "Capital accumulation and dynamic gains from trade." *Journal of International Economics*, 119: 93–110.

Representative, United States Trade. 2024. "National Trade Estimate Report on Foreign Trade Barriers." Office of the United States Trade Representative.

Rodrik, Dani. 2015. "Premature deindustrialization." *Journal of Economic Growth*, 21(1): 1–33.

Sposi, Michael. 2019. "Evolving comparative advantage, sectoral linkages, and structural change." *Journal of Monetary Economics*, 103: 75–87.

Xing, Yuqing. 2012. "The People's Republic of China's High-Tech Exports: Myth and Reality." *Asian Development Bank Institute Working Paper Series No. 357.*