Lessons from U.S.-China Trade Relations*

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Abstract

We review theoretical and empirical work on the economic effects of the United States and China trade relations during the last decades. We first discuss the origins of the China shock, its measurement, and present methods used to study its economic effects on different outcomes. We then focus on the recent U.S.-China trade war. We discuss methods used to evaluate its effects, describe its economic effects, and analyze if this increase in trade protectionism reverted the effects of the China shock. The main lessons learned in this review are: (i) the aggregate gains from U.S.-China trade created winners and losers; (ii) China's trade expansion seems not to be the main cause of the decline in U.S. manufacturing employment during the same period; and (iii) the recent trade war generated welfare losses, had small employment effects, and was ineffective in reversing the distributional effects due to the China shock.

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1 Introduction

U.S. trade integration with China has increased since the 1990s. As an illustration, U.S. imports from China as a share of total U.S. imports increased from 3.1 percent in 1990 to 19.2 percent in 2020. Similarly, U.S. exports to China as a share of total U.S. exports increased from 1.3 percent in 1990 to 9.3 percent in 2020. In 2006 China surpassed Mexico as the United States' second-biggest trade partner after Canada. China also increased substantially its exports to the United States as a share of its total exports, growing from 8.3 percent in 1990 to 17.5 percent in 2020.

Together with this increase in trade integration between the United States and China were remarkable changes in observed outcomes such as employment, wages, and prices. Also, during this period, there was a reduction in trade barriers galvanized by China's entry into the World Trade Organization (WTO) in 2000. China also experienced fast growth in manufacturing productivity in the 1990s and 2000s. These two episodes, which the literature calls the China shock, are main determinants behind China's trade expansion and penetration of the U.S. imports market. The China shock has encouraged researchers to develop methodologies to quantify both its differential effects and aggregate effects on manufacturing employment and other economic outcomes. More recently, motivated in part by these developments, U.S.-China relations received backlash that resulted in an unprecedented increase in trade protectionism during the 2018 U.S.-China trade war.

These developments in U.S.-China trade relations have created unique opportunities to revisit important classic questions in the trade literature. What are the aggregate welfare effects of trade integration? What are the distributional effects (i.e., winners and losers) of import competition? Is trade policy an effective way to redistribute aggregate gains and losses from trade? In this review, we describe recent research on U.S.-China trade relations and discuss the main answers the literature has provided to the aforementioned questions.

In Section 2, we discuss the origins of China's trade expansion as analyzed in recent literature. We describe the U.S-China Relations Act of 2000 that granted China permanent normal trade relations (PNTR) status with the United States and paved the way for China to join the WTO in 2001. Because China's trade expansion began prior to 2000, recent literature has also considered China-specific factors like internal reforms that resulted in an increase in China's productivity, particularly in the manufacturing industry, in the 1990s and 2000s. Accordingly, we also discuss alternative ways to measure the China shock and the role of different mechanisms in explaining it.

We present different methods that the literature has used to measure directly and indirectly the different drivers of the China shock. We then present methodologies developed to study the economic effects of import competition, which have been applied to study the effects of the China shock. Some methods are useful to identify relative effects (the effect of more exposed relative to less exposed labor markets), while other methods are more suitable to quantify the aggregate and welfare effects of the China shock. In doing so, we present a simple dynamic spatial general equilibrium model that can be used to study the distributional and aggregate effects of import competition from China across labor markets and over time. We show that the model has a unique equilibrium, and discuss how the model can be extended to study other economic questions.

In Section 3, we describe the aggregate and distributional effects of the China shock on the U.S. economy. Improvements in empirical methods and data availability have allowed recent research to disentangle the effects of China's trade expansion from the effects of other factors (e.g., technological change) on observed allocations such as manufacturing employment, wages, and innovation. The development of quantitative general equilibrium frameworks has also been important for studying the aggregate and distributional welfare general equilibrium effects of the China shock that we discuss in this section.

In Section 4, we discuss the effects of the recent backlash against U.S.-China trade relations; namely, the increase in trade protectionism as a result of the 2018-2019 trade war. We describe recent findings of reduced-form and general equilibrium analyses in the literature. In addition, we take a step back and assess to what extent the recent increase in trade protectionism reversed the distributional effects and the decline in manufacturing employment due to the China shock that we discussed in the previous section.

Ultimately, our review delivers four main lessons based on U.S.-China trade relations: (i) the results of U.S.-China trade integration confirm trade economists' consensus regarding the aggregate gains that come from trade openness; (ii) the aggregate gains from trade are unequally distributed, creating winners and losers; (iii) China's trade expansion is not the main cause of the observed decline in manufacturing employment during the same period; and (iv) the recent trade war generated welfare losses, had very small effects on employment, and was ineffective in reversing the distributional effects and decline in manufacturing employment due to the China shock.

2 Origins of the China shock

China has been one of the fastest-growing countries in the world over the last decades. Today it is the second-largest country in the world in terms of gross domestic product (GDP) and the largest supplier of goods to the world economy. These developments have triggered an increasing interest in possible sources of China's economic growth. Particular attention has been paid to the study of the sources and effects of the growth of Chinese exporters. China's integration into the world's economy, and in particular, its penetration in the U.S. economy, has been remarkable. This export growth performance can be attributed not only to changes in U.S.-China trade policy relations that occurred in 2000 but also to reforms that occurred in the Chinese economy before 2000 and that might have been responsible for the subsequent growth in productivity. The magnitude of the change in trade, and the supply-driven policies of China, have encouraged researchers from different fields to study not only the economic and political effects of this trade integration but also its origins. The premise behind the identification strategy in the literature is that most of China's trade expansion was an exogenous trade shock from the point of view of the U.S. economy, and as a result, the literature has dubbed China's trade expansion "the China shock" or "the China trade shock". In this section we review two important aspects that explain the China shock in the literature: the change in U.S.-China trade policy relations that occurred around 2000, and China's economic reforms prior to 2000 and subsequent productivity growth.

2.1 Pre- and post-accession reforms in China

During the 1990s and far into the 2000s, China underwent a considerable economic transformation. During this time, China experienced fast economic growth, sustained capital accumulation, shifts in the spatial and sectoral relocation of inputs and production, increased urbanization, an increasing role in product markets, investment in human capital, and trade openness. While there is broad consensus that these reforms contributed to China's development and export growth, it is difficult to pinpoint one main source of China's growth. Brandt and Rawski (2008) and Feenstra and Wei (2010) review a series of papers that study the economic impact of many of the reforms that were implemented during this period. We now describe some of these reforms and guide the reader to relevant research.

Although it is difficult to identify which reforms during this period had the largest effects on China's economic growth, research has found that the reallocation of labor (partly due to the relaxation of the Hukou system) and capital across manufacturing firms was an important source of productivity growth. Using firm-level data, Brandt, Van Biesebroeck, and Zhang (2012) find that from 1998 to 2007, the firm-level total factor productivity (TFP) of manufacturing firms grew at an average rate of 2.85 percent when measured using a gross output production function and of 7.96 percent when measured using a value added production function. Hsieh and Klenow (2009), building on Restuccia and Rogerson (2008), find that China's elimination of factor market distortions may have contributed to an increase in TFP of 2 percent per year over 1998–2005. Adamopoulos, Brandt, Leight, and Restuccia (2017), Brandt, Kambourov, and Storesletten (2018), and Caliendo, Parro, and Tsyvinski (2017b) present more recent evidence on the evolution of distortions in China at the firm and sector levels over this period and their impact on TFP as well as the world's economy.

Some of the reforms that might have generated productivity growth started in the 1980s. An example is the creation of special economic zones (SEZs) that allow firms to attract foreign investment, as well as import and export goods at lower costs. Alder, Shao, and Zilibotti (2016) study the spatial economic development effects of place-based industrial policies in China, focusing on the establishment of SEZs. The authors document that in the early 1980s, four cities, Shenzhen, Zhuhai, Shantou, and Xiamen, were given the status of SEZs. By 1984, these four SEZs had attracted 26 percent of China's total foreign direct investment. From 1980 to 1984, Shenzhen grew at an annual rate of 54 percent[1]. The study uses variation across cities and years in the establish-

[1]See Zeng (2011) for more information on the implications of these SEZs for the functioning of the local labor,

ment of different types of SEZs to estimate the effects of SEZs on China's economic development. The authors find that the industrial policies in China affected physical capital accumulation, TFP, and human capital investments. They also find that the SEZs had positive spillover effects on neighboring regions.

Starting in the 1990s, the Chinese government introduced several factors and product market reforms that may have also contributed to the China trade shock (Naughton 2007 provides a comprehensive review of China's reforms and the role that they played during this period).

One of these reforms centered on export processing. From 1997 to 2002, export processing represented more than 50 percent of China's total exports (Feenstra and Hanson 2005). This reform was due in part to a change in Chinese policy that newly permitted foreign ownership of export processing plants. Permission for foreign ownership was granted provided firms followed one of two possible regimes. A plant was permitted to either become a pure assembly plant or an import-and-assembly plant. In a pure assembly plant, foreign-owned inputs are processed into finished goods. The foreign owner hires the plant operator to perform this task while continuing to hold ownership over the inputs. In an import-and-assembly plant, the plant imports inputs, processes them, and sells the processed goods to a foreign buyer. Feenstra and Hanson (2005) study the economic effects of this particular contractual form. The authors find that export-processing multinational firms in China split plant ownership and input control with Chinese managers. The most common type of plant (about 60 percent of the existing plants) is one that is under foreign factory ownership but with Chinese control over input purchases. This change in policy increased foreign direct investment in China and led to a reorientation of manufacturing production to export processing.

China's research and development (R&D) intensity (the ratio of R&D expenditures to GDP) grew in the 1990s, reaching 1 percent in 2000 and rising to 1.35 percent by 2004 (see Hu and Jefferson 2008). China became one of the middle-income countries with a relatively large R&D intensity. This increase seems to be partly due to the relaxation of restrictions on the adoption of foreign technology. Hu and Jefferson (2009) document that since the late 1980s, Chinese patent applications have grown at an annual rate of around 20 percent and that the surge in patents has been driven by domestic and foreign patent applications. Changes in Chinese patent law also contributed to this growth. What is puzzling, according to Hu and Jefferson (2009), is that this explosion in patenting has taken place in an environment where intellectual property rights protection is considered weak compared to that of other countries. The authors find that foreign direct investment, institutional changes, and stronger patent protection impacted the patenting decisions of Chinese firms. More recently, using data not only on R&D expenditures and patent applications but also on receipts and citations, Wei, Xie, and Zhang (2017) show that the Chinese economy has become increasingly innovative over the last decades. The authors argue that expanding markets is one of the drivers of China's growth in innovation. They also find evidence of the misallocation of resources in innovation

capital, and land markets, as well as local transportation and technology.

activities, mostly due to state-owned enterprises obtaining subsidies. Yet the study shows that of all firms, it is private firms that conduct the most innovative activities in China during this period.

During the 1990s, state-owned enterprises mostly comprised the manufacturing sector in China. However, as the economy started growing, the private sector expanded. By the mid-2000s, more than 80 percent of state-owned firms were either defunct or privatized. These findings are documented in Hsieh and Song (2015) and Bai, Hsieh, and Song (2019).

One of the puzzles of China's growth experience is the coexistence of China's high growth rate and increased foreign surplus. Song, Storesletten, and Zilibotti (2011) find that one way to explain China's growth performance from 1990 to 2007 involves understanding the imperfections of China's financial market and its impact on domestic savings. They argue that more productive firms resorted to internal savings for financing due to financial frictions. The authors provide empirical evidence that Chinese private firms relied mostly on self-financing and received limited funding from banks. Such savings could have been sufficiently large to the point that the highly productive firms outgrew the less productive firms (the ones that had more access to credit). The downsizing of the less efficient, financially integrated firms, meant that a growing share of domestic savings was invested in foreign assets and in turn created a foreign surplus.

The above discussion suggests that not one but several economic reforms explain China's export performance. We now discuss how trade policy might have also influenced China's export growth.

2.2 Changes in U.S.-China trade policy

The 2000s witnessed a shift in U.S. trade policy towards China. By the end of 1999, the United States had granted China the status of a permanent trading partner. In 2001, China joined the WTO. In the following subsections, we discuss each of these changes in trade policy between the United States and China.

2.2.1 Changes in U.S. trade policy towards China

In the Trade Act of 1974, the United States designated China a non-market economy. Consequently, China was subject to higher import tariffs than those the United States imposed on members of the WTO. In 1980, under the Jackson-Vanik waiver provision, the U.S. Congress conditionally granted China normal trade relation (NTR) status (i.e., most-favored-nation [MFN] status in the WTO). Every year Congress had to renew the status. In 1989, following the Tiananmen Square protests, U.S. legislators began to question the yearly status renewal. While the status was renewed every year, there was some uncertainty over the outcome. In 2001, after a decade of negotiations, China joined the WTO. China's entry into the WTO meant that the United States had to apply, and commit to applying, MFN tariffs to China. In anticipation, by the end of 1999, the U.S. Senate had granted China permanent status as an NTR (PNTR status). The conferral of PNTR status is considered to be one of the drivers of China's trade expansion. While this change in U.S. trade policy had no effect on actual tariff rates applied by the United States to China, it reduced uncertainty in U.S.-China trade policy. As a result, it might explain part of China's export growth. Researchers have used this change in policy to analyze how a reduction in trade policy uncertainty impacts employment in the manufacturing sector and other economic outcomes.

Pierce and Schott (2016) and Handley and Limao (2017) use this change in policy to measure the effects of China's trade expansion on the U.S. economy. These studies measure the unexpected change in uncertainty by computing the "NTR gap". The gap is constructed as the difference between the non-NTR tariff rates to which tariffs would have risen if annual renewal had failed and the NTR tariff rates that were locked in by PNTR status. To give an idea of the magnitude of the gap, Handley and Limao (2017) document that in 2000, the average U.S. PNTR/MFN tariff applied to China was 4 percent, while the tariff that the United States would have applied to China if it had not had PNTR status would have been on average 31 percent. Importantly, such a measure of uncertainty presents considerable variation across industries. This variation has allowed researchers to use the gap to measure the impact of U.S.-China trade policy uncertainty on several economic outcomes. In particular, as discussed later, it has allowed researchers to estimate the differential effects of the change in policy; namely, the impact on employment in industries that had larger changes in the NTR gap relative to ones that had smaller changes in the gap. Relatedly, Handley and Limao (2022) present a conceptual framework to study such trade policy uncertainty events. The literature considers PNTR one of the causes, though not the main cause, of the China shock. For instance, Handley and Limao (2017) attribute one-third of the growth in Chinese exports to the United States from 2000 to 2005 to the reduction in trade policy uncertainty following the conferral of PNTR status to China.

2.2.2 China's accession to WTO

In 2001 China became the 143rd member state of the WTO. The process of accession had started years before, and it required China to commit to changing several aspects of its foreign and domestic policy, like reducing import tariffs, eliminating domestic and export subsidies, and export licensing.[2] Broadly three aspects of the accession affected China's trade expansion.

First, while most members of the WTO were already applying MFN tariffs to China, the accession reduced the uncertainty of any particular country increasing import tariffs applied to Chinese goods (similar to the reduction in uncertainty that occurred after the United States committed to giving China PNTR). This change gave members of the WTO the opportunity to import goods from China at lower costs than before (see Branstetter and Lardy 2008).

Second, China cut its import tariffs by half in the years after it joined the WTO. During the transition period prior to China's accession, tariffs had been falling gradually. In 1982, the average tariff rate was 56 percent. The tariffs were then reduced to 43 percent in 1985 where they remained until 1992. Subsequently, tariffs fell by two-thirds (see Lardy 2002 for more information on tariff changes during this period). Similarly, China's weighted (and simple) average import tariff rates on

[2]See http://acdb.wto.org/ and https://www.wto.org/english/news_e/pres01_e/pr243_e.htm for more details.

manufacturing goods fell from 13.24 percent (16.23 percent) in 2000 to 5.72 percent (8.71 percent) in 2008.[3]

Finally, quotas on exports of Chinese textiles and clothing were eliminated when China joined the WTO and also in subsequent years. Under the Multi-fiber Arrangement (MFA) and its successor, the Agreement on Textiles and Clothing (ATC), the United States, European Union, and Canada established quotas on the import of textiles from many countries, including China. In 1994, during the Uruguay Round, these countries committed to eliminating quotas on textiles and clothing in four phases. Phases I and II took place in 1995 and 1998, respectively, and resulted in the joint elimination of 33 percent of the quotas. With its entry into the WTO, China started in Phase II in 2001, which led to an increase in textile exports to the United States and Europe. Phase III took place in 2002, and it resulted in the elimination of 18 percent of the remaining quotas. Phase IV took place in 2005 and eliminated the remaining 39 percent. Due to these trade policy changes, China's total textile and clothing export quantities to the United States increased 39 percent in 2005, and exports of the set of goods whose quotas were relaxed that year increased 270 percent (Khandelwal, Schott, and Wei 2013).

Accession to the WTO was a turning point in China's foreign policy. Chinese exports grew after this change in policy. How much of Chinese export and productivity growth from 2000 to 2008 can be attributed to each of the particular aspects of the change in policy? How much can it be attributed to aspects not associated with the accession? Several studies have attempted to decompose the impact of each of the different aspects of the change in Chinese trade policy on China's exports and on the rest of the world.

Yu (2015) finds that both input and output tariff reductions contributed to at least 14.5 percent of the growth in aggregate productivity in China. In a related study, Hu and Liu (2014) find that in the five years following China's entry into the WTO, the TFP for Chinese manufacturing firms increased annually by a rate of 0.94 percent. Focusing on the period from 2000 to 2006, Brandt and Morrow (2017) find that China's falling input tariffs caused a shift from processing to ordinary trade. In fact, they find that falling input tariffs explain about 80 percent of the observed average increase in the share of ordinary trade in exports at the industry-province level. Brandt, Van Biesebroeck, Wang, and Zhang (2017) show evidence of an increase in productivity as a result of the decline in input tariffs in China.

Regarding Chinese firms' trade performance, Feng, Li, and Swenson (2016) find that the year China entered the WTO, manufacturing firms' imports of intermediate inputs grew at a rate of 58.3 percent and manufacturing exports grew by 47.7 percent. In addition, the firms that increased their imports of intermediate inputs were the ones that expanded the volume and scope of their manufacturing exports. Access to cheaper imported intermediate inputs also seems to have helped private Chinese manufacturing firms, especially R&D-intensive ones, to upgrade and increase the range of products they produce. Manova and Zhang (2012) present several stylized facts about

[3] These figures were obtained from the World Integrated Trade Solution database.

how Chinese firms upgraded their product mixes after the accession. Feng, Li, and Swenson (2016) find that the imports of intermediate inputs from higher-income G-7 countries also seem to have facilitated firm exports to higher-income G-7 markets. Manova and Yu (2017) show that in response to the exogenous elimination of the MFA quota on textiles and clothes, Chinese firms allocated resources and activities across products with higher perceived quality and that the product quality ladder seems to have mattered for firms' export dynamics.[4] The elimination of the MFA quota had effects not only on export growth but also on the allocation of resources across firms. Khandelwal, Schott, and Wei (2013) study the effects of quota removal and find that the exogenous change in quotas translated to a surge in export volumes mostly driven by a net entry of firms.

We now discuss how the literature has used China's trade policy and productivity changes to develop measures of the China shock that have been used to study its economic effects.

3 Measuring the China shock and its economic effects

Manufacturing sector employment in the United States has been falling steadily since the 1960s. From 2000 to 2008, the period of the China shock, manufacturing sector employment fell even more rapidly. Research studying the economic consequences of the China shock on the U.S. economy (e.g., Autor, Dorn, and Hanson 2013, Acemoglu, Autor, Dorn, Hanson, and Price 2016, Pierce and Schott 2016, Caliendo, Dvorkin, and Parro 2019, among many others that we describe in this section) find that a part of the employment loss in manufacturing was a consequence of China's trade expansion, which itself was due to either changes in trade policy or changes in productivity in China. We now describe how the China shock has been measured and the methods used to quantify the economic effects of the shock. After doing so, we present the findings regarding the shock's economic effects on the U.S. economy.

3.1 Measurement

As we described in the previous section, China's growth in exports may be due in part to changes in trade policy and economic reforms that led to productivity growth. Accordingly, researchers studying the economic effects of the China shock on the U.S. economy have focused on measuring the shock indirectly (using shift-share designs) or directly (using measures of changes in trade policy). We describe each of these measurements of the China shock in turn.

The growth in U.S. imports from China after 2000 may have been a consequence of the China shock and/or changes in the U.S. demand for Chinese goods. In order to capture the component of U.S. imports growth that is due only to China, Autor, Dorn, and Hanson (2013) instrument the growth in U.S. imports from China with imports from China made by other high-income economies.

[4] Related findings in other contexts, which show that export product prices increase as a function of the destination country's GDP per capita, are presented in Bastos and Silva (2010), Gorg, Halpern, and Murakozy (2017), and Martin (2012).

The assumption is that there is a common component that explains the growth in Chinese imports by high-income countries that is a result of China's internal supply factors and falling global trade barriers. The identification restriction is that import demand shocks in high-income countries are not the main cause of China's export growth.[5]

Autor, Dorn, and Hanson (2013) study the effects of the China shock on the U.S. economy by building a measure of how U.S. local labor markets are exposed to the China shock. The measure they present is derived from a first-order approximation to a gravity model of international trade. In particular, the change in U.S. imports from China per worker in labor market c and at time t denoted by $\Delta IPW_{US,c,t}$, is calculated as

$$\Delta IPW_{US,c,t} = \sum_j \frac{L_{c,j,t}}{L_{US,j,t}} \frac{\Delta M_{US,j,t,t'}}{L_{c,t}}, \tag{1}$$

where $L_{c,j,t}$ is the employment in labor market c, sector j, at time t; $L_{US,j,t}$ is the total U.S. employment in sector j at time t; $L_{c,t}$ is the total employment in labor market c at time t; and $\Delta M_{US,j,t,t'}$ is the change in U.S. imports from China in industry j from period t to t'. In order to determine which component of $\Delta IPW_{US,c,t}$ is due to the China shock, Autor, Dorn, and Hanson (2013) construct a non-U.S. exposure measure denoted by

$$\Delta IPW_{other,c,t} = \sum_j \frac{L_{c,j,t-10}}{L_{US,j,t-10}} \frac{\Delta M_{other,j,t,t'}}{L_{c,t-10}}, \tag{2}$$

where $\Delta M_{US,j,t,t'}$ is replaced by $\Delta M_{other,j,t,t'}$, the growth of imports from China by other high-income countries, and where the 10-year lags $(t-10)$ in U.S. employment levels across regions and sectors $L_{c,j,t-10}$ are used[6].

Caliendo, Dvorkin, and Parro (2019), inspired by Autor, Dorn, and Hanson (2013)'s instrumental variable strategy, estimate the aggregate sectoral changes in imports by the United States from China in industry j from 2000 to 2007 due to the China shock by running a regression between the change in U.S. imports on the change in imports by other economies. In particular, let $\Delta M_{US,j,00,07}$ denote the change in imports from China by the United States in industry j, and let $\Delta M_{other,j,00,07}$ denote the growth in imports from China by other high-income countries. In order to determine the component of $\Delta M_{USj,00,07}$ that is a consequence of changes in the Chinese economy, the authors run the following specification:

$$\Delta M_{US,j,00,07} = a_1 + a_2 \Delta M_{other,j,00,07} + u_j.$$

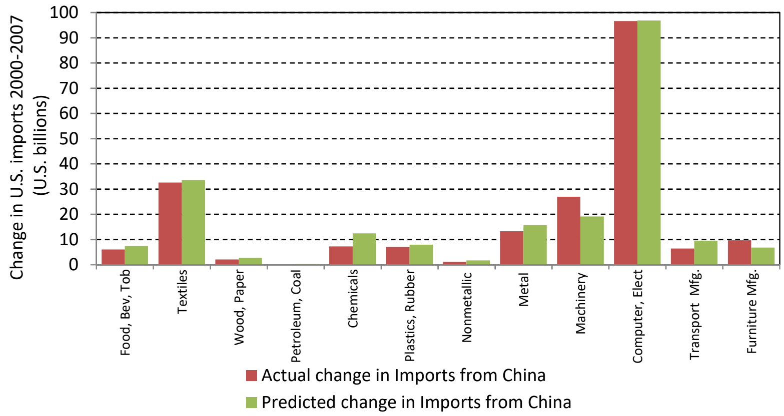
Figure 1 presents the actual and predicted changes in imports from China by the United States from 2000 to 2007. As we can see in the figure, there is variation across sectors, but textiles and

[5]See Autor, Dorn, and Hanson (2016) and Redding (2022) for a more detailed discussion of the measure of the China shock and its identification restrictions.

[6]Autor, Dorn, and Hanson (2013) use eight other high-income countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

computer electronics are the two sectors with the greatest exposure to the China shock.

Figure 1: Actual and predicted changes in imports from China by the United States (2000–2007)



Note: The figure presents the actual changes in U.S. manufacturing imports from China and the predicted changes in manufacturing imports from China using the Autor, Dorn, and Hanson (2013) instrumental variable strategy for the period 2000–2007. See Caliendo, Dvorkin, and Parro (2019).

Caliendo, Dvorkin, and Parro (2019) then propose a method to measure the changes in fundamentals in China that can explain these predicted changes. The authors use the predicted imports from the reduced-form specification previously described as a moment that a structural model can target to obtain the changes in fundamentals in China that deliver the same predicted changes in imports. Caliendo, Dvorkin, and Parro (2019) estimate the changes in TFP in the manufacturing sectors in China to target these moments. The idea of using moments derived from reduced-form estimation to target the change in fundamentals has been used in other studies and is becoming increasingly popular in the literature. For example, Galle, Rodríguez-Clare, and Yi (2021) use a structural model and obtain the changes in fundamental TFP in China that match predicted changes in U.S. expenditure shares from China. With access to more detailed data, future researchers could use this method to measure the shock at a more granular level.

Another approach in the literature is to use NTR gaps. The gaps represent the difference between the tariffs that would have risen if annual renewal had failed and the NTR tariff rates that were locked in by PNTR. Concretely, let j index an industry; then the NTR gap is defined as

$$NTR\,Gap_j = Non\;NTR\,Rate_j - NTR\,Rate_j. \tag{3}$$

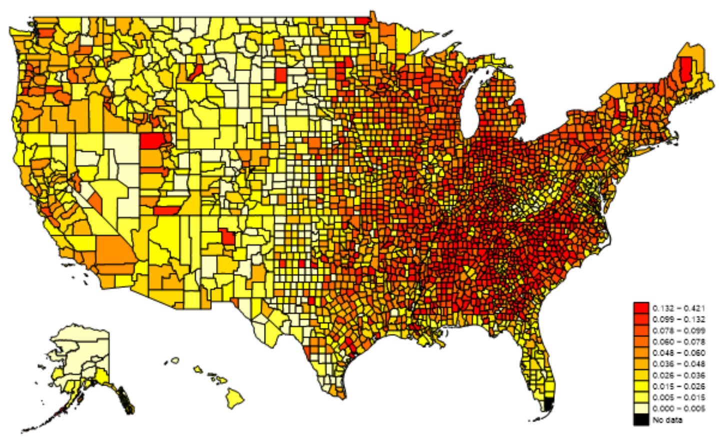
The idea behind this measure is that the variation in gap rates across industries can be used to identify the variation in exposure to the change in policy. The prior is that industries with larger gaps are likely to be more affected by the change in U.S. trade policy. Pierce and Schott (2016) calculate the gap using tariff-line (HS8) data from Feenstra, Romalis, and Schott (2002) for 1999, the year before PNTR. The gap for industry j is the mean across tariff lines in industry j. To give an idea of the magnitude, the mean gap across industries is of the order of 0.32 percentage points with a standard deviation of 0.15.

The $NTR\, Gap_j$ measures heterogeneous trade policy changes across sectors. However, since sectoral economic activity is unevenly distributed across space, one can also use this source of variation to obtain a measure of exposure to the trade shock at the regional level. Building on a shift-share analysis, Pierce and Schott (2020) propose a measure of NTR gap exposure at the regional level using as "shifters" the sectoral NTR gaps and as "shares" the industry-wise employment shares in counties. In particular, defining $NTR\, Gap_c$ by the NTR gap for county c and the employment share of industry j in country c by L_{jc}/L_c leads to

$$NTR\, Gap_c = \sum_j \left(\frac{L_{jc}}{L_c} \right) NTR\, Gap_j. \tag{4}$$

Figure 2 presents the $NTR\, Gap_c$ across space, as computed by Pierce and Schott (2020), using the employment share in 1990, 10 years before PNTR status. Note that the figure presents the percentiles of the distribution of the gaps.

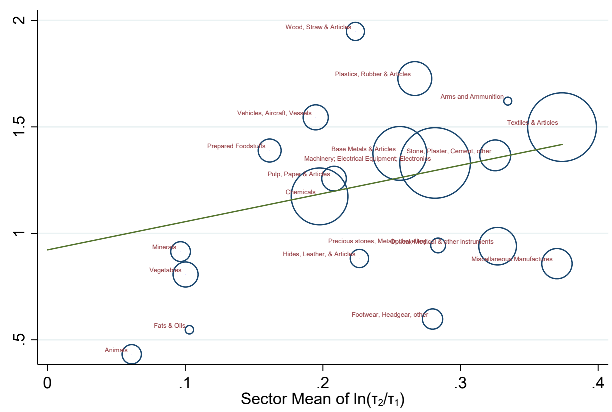
Figure 2: Distribution of $NTR\, Gap_c$ across counties



Note: The figure presents measures of the $NTR\, Gap_c$ at the county level using employment shares in 1990. The different color/grey scales represent percentiles. See Pierce and Schott (2020).

Handley and Limao (2017) compute NTR gaps in a slightly different way using different data. The authors measure the initial uncertainty as the log ratio, $ln(\tau_2/\tau_1)$, where τ_2 denotes the duty rates for countries that do not have NTR status with the United States and τ_1 are the MFN tariffs in 2000 using HS-6 industries and data from the World Bank. The minimum ratio (τ_2/τ_1) in their sample is 1.14, the maximum is 1.42, and the average is 1.33. They show that the variation in the mean of initial uncertainty in tariffs across industries is correlated with sector-level Chinese export growth from 2000 to 2005.

Figure 3: Chinese change in ln exports (Δln) from 2000–2005 versus initial uncertainty



Note: The figure presents measures of mean initial uncertainty $ln(\tau_2/\tau_1)$ versus the change in Chinese exports. The values of τ_2 are the duty rates for countries that do not have NTR status with the United States, and τ_1 are the MFN tariffs in 2000 using HS-6 industries and data from the World Bank. See Handley and Limao (2017).

Figure 3 presents the findings of Handley and Limao (2017). On average, sectors facing relatively higher initial tariff uncertainty also experienced faster export growth. Handley and Limao (2017) make clear that this is a correlation, which raises questions about how to identify causal effects and how to quantify the effects of trade policy uncertainty. To do so, the authors propose a theory-consistent measure of uncertainty, finding that the implied probability of revoking NTR tariffs before China's WTO accession was around 13 percent. According to their estimates, such a change in uncertainty generated export effects equivalent to a permanent tariff increase of 5 percentage points.

Finally, it is important to emphasize again that the NTR gap is a second moment shock (to uncertainty) with no actual change in the first moment (to the level of trade protection). In that way, it is different from the first moment effect of the measure of the China shock as in Autor, Dorn, and Hanson (2013).

3.2 Quantifying the economic effects

In this section we describe different approaches in the literature to measuring the aggregate and distributional effects of the China shock. In particular, we describe methodologies to compute the aggregate welfare effects, discuss difference-in-difference methodologies that shed light on the differential effects between regions more and less exposed to the China shock, and describe quantitative frameworks that allow researchers to study the general equilibrium effects of the shock.

3.2.1 Aggregate gains from U.S.-China trade integration

A macro approach to measuring the gains from bilateral trade openness entails using a one-sector gravity model such as a perfectly competitive Armington model, the Eaton and Kortum (2002) model, or a monopolistic competitive model, as in Krugman (1980) or Melitz (2003). Using any of these frameworks, one can derive a gravity equation of trade that takes the form of

$$\lambda_{in} = \frac{A_n (\kappa_{in} x_n)^{-\theta}}{\sum_{h=1}^{N} A_h (\kappa_{ih} x_h)^{-\theta}}, \tag{5}$$

where i, n, h index countries, λ_{in} is the bilateral expenditure of goods of country i in goods from country n, A_n represents a set of country n characteristics that makes country n more attractive to source goods from relative to other countries (depending on the model this might be a function of fundamental TFP, country size, fixed costs, etc.), κ_{in} represents the bilateral cost to ship goods from n to i, x_n is the unit cost to produce a good in country n, and θ is the trade elasticity (that determines how changes to trade costs impact trade flows). Arkolakis, Costinot, and Rodríguez-Clare (2012) show that there is a sufficient-statistic formula to compute the gains from trade in a variety of trade models satisfying certain macro-level restrictions (one of such restrictions is that the model delivers a gravity equation structure like (5). In particular, the real consumption in a given country i, denoted by W_i, can be computed as

$$W_i = (\lambda_{ii})^{-1/\gamma_i \theta} (A_i)^{1/\gamma_i \theta}, \tag{6}$$

where λ_{ii} is the domestic expenditure share and γ_i is the share of value added in output[7].

In autarky, $\lambda_{ii} = 1$. Therefore, the observed λ_{ii} at a given moment in time, together with the trade elasticity and the value-added shares, is sufficient to compute the gains from going from autarky to the observed level of trade openness, keeping the level of fundamentals, A_i, constant. We now show that we can use the sufficient statistic to measure the aggregate gains from trade openness over a period of time and decompose the fraction of those gains that is a consequence of trading directly with a particular trading partner.

Taking the total differential of (6), we approximate the change in real consumption as

$$\hat{W}_i = \frac{1}{\theta \gamma_i} \sum_{n \neq i} \frac{\lambda_{in}}{\lambda_{ii}} \hat{\lambda}_{in} + \frac{1}{\theta \gamma_i} \hat{A}_i,$$

where the "hat" notation for variable x means $\hat{x} = dln(x)$. Here we use $\sum_{n \neq i} \lambda_{in} + \lambda_{ii} = 1$. Therefore, we can decompose the gains from trade openness as

$$\hat{GT}_i = \frac{1}{\gamma_i \theta} \sum_{n \neq i} \frac{\lambda_{in}}{\lambda_{ii}} \hat{\lambda}_{in}.$$

We can use this simple accounting formula to provide a quantification of the aggregate welfare

[7] A simple way to obtain this expression is as follows. In a model with intermediate goods and a Cobb-Douglas production function, $x_i = (w_i)^{\gamma_i} (P_i)^{1-\gamma_i}$, where P_i is the price of intermediate goods given by $P_i = \left(\sum_{n=1}^{N} A_n (\kappa_{in} x_n)^{-\theta}\right)^{-1/\theta}$. It follows that the expenditure on domestic goods is given by $\lambda_{ii} = A_i \left(\frac{w_i}{P_i}\right)^{-\theta\gamma_i}$. Solving for per capita real income $W_i \equiv \frac{w_i}{P_i}$ can be done by inverting the equation to obtain the sufficient statistic.

effects of U.S.-China trade integration over the last decades. Using data for the World Input-Output Database (WIOD) from 1995–2011, we compute the overall gains from trade and the contribution of each trading partner. Table 1 presents our decomposition. In the first column, we can see that the United States has experienced aggregate gains from trade of about 3.4 percent, and the gains from trade in China are even larger, at about 4.6 percent. Even more interesting, in the second and third columns we can see China's contribution to the United States' gains from trade openness and the contribution of the United States to China's gains. Our decomposition shows that China accounts for about 17.2 percent of the aggregate U.S. gains from trade, while U.S. trade integration with respect to the rest of the world accounts for the remaining 82.8 percent. Meanwhile, the United States explains about 9.8 percent of China's aggregate gains from trade and the rest of the world accounts for the remaining 90.2 percent.

Table 1: Aggregate gains from U.S.-China trade (1995–2011, percent)

	Total gains	Contribution of trading partner (China, United States)	Contribution of the rest of the world
United States	3.39%	17.21%	82.79%
China	4.58%	9.79%	90.21%

Note: This table uses data from WIOD from 1995–2011. See Timmer, Dietzenbacher, Los, Stehrer, and Vries (2015).

The main takeaway of this exercise is that U.S.-China trade integration during the China shock resulted in aggregate welfare gains for both countries. Aggregate gains from trade are widely agreed upon by trade economists, and the increased trade integration between the United States and China over the last 20 years has allowed researchers to confirm this view with the decomposition presented. Far less consensus exists among trade economists with respect to the distributional consequences of trade integration (i.e., who gains more or less) and the extent to which trade policy is effective at redistributing aggregate gains from trade. We discuss research on these aspects in the following sections.

3.2.2 Difference-in-difference specifications to measure distributional effects

Shift-share analysis has emerged as a suitable econometric framework for measuring the effects of import competition on labor market outcomes. Creamer (1943) is among the early adopters of the method, using it as an accounting exercise to predict regional growth in employment and the regional effects of changes to economic policies. This method, also known as the Bartik instrument after Bartik (1991), has been used widely in the labor, trade, migration, and development literature after Blanchard and Katz (1992) popularized it.

Autor, Dorn, and Hanson (2013) use this method to measure the impact of the China shock on economic outcomes. In particular, the study regresses the local import exposure on a local labor market outcome of interest. Denote the change in the manufacturing sector employment share of local labor market c by $\Delta L_{c,t}$. Then the regression specification is given by

$$\Delta L_{c,t} = \alpha_t + \beta_1 \Delta IPW_{US,c,t} + X'_{ct}\beta_2 + e_{ct}, \tag{7}$$

where α_t are time dummies and X_{ct} presents a set of controls (e.g., start-of-decade labor force, demographic composition). The variable $\Delta IPW_{US,c,t}$ is the import exposure of the labor market previously defined in (1).

One concern with this specification is that the change in import exposure is not exogenous; it may have changed as a consequence of the China shock or as a consequence of changes in local demand for imported goods from China. Recall that Autor, Dorn, and Hanson (2013) suggest instrumenting local import exposure $\Delta IPW_{US,c,t}$ with imports by other countries. The first-stage regression regresses $\Delta IPW_{US,c,t}$ on $\Delta IPW_{other,c,t}$ with time dummies and a set of controls, where $\Delta IPW_{other,c,t}$ is given by (2). This first-stage regression yields the predicted import exposure that is subsequently used in (7) to measure the reduced-form distributional effects of the China shock.

A specification like (7) is considered a shift-share design because it quantifies the effects of the shifter (i.e., the change in U.S. manufacturing imports from China) on local employment by using the weight of manufacturing sector employment within each labor market as a proxy to determine the share that the shifter has on each labor market (i.e., local exposure).

Recent studies have discussed the interpretation of the estimates in Bartik econometric specifications and the exogeneity of either the shifters (see Adao, Kolesar, and Morales 2019, and Borusyak, Hull, and Jaravel 2018) or the shares (see Goldsmith-Pinkham, Sorkin, and Swift 2020). Since the econometric specification is a difference-in-difference regression, it can only identify the relative effects of import competition between labor markets with different levels of exposure to the China shock. It cannot be used to learn about aggregate employment effects or changes in the level of employment in each labor market as a consequence of the China shock. Redding (2022) and Caliendo and Parro (2022) provide further discussion of the interpretation and theoretical foundations of the Bartik regression.

Using difference-in-difference specifications to measure the impact of the China shock on economic and non-economic outcomes has become a popular method of analysis. Researchers have also used a shift-share design in which NTR gaps (4) function as shifters to study the differential impact of the change in trade policy between the United States and China on regional outcomes (see Pierce and Schott 2020).

Pierce and Schott (2016) use a difference-in-difference specification to study whether employment losses in industries with higher NTR gaps (first difference) are larger after the imposition of PNTR (second difference). This methodology allows the authors to use the variation across industries in NTR gaps to determine the differential effects across industries. The specification is given by

$$\ln(EMP_{jt}) = \theta PostPNTR_t \times NTR\ Gap_j + PostPNTR_t \times X_j' \gamma + X_{jt}' \lambda + \delta_t + \delta_j + \alpha + e_{jt}.$$

The dependent variable is the log level of employment in a given industry at a given moment in time, and the difference-in-difference term is $NTR\,Gap_j$ interacted with an indicator of the post-PNTR period (from 2001 forward). The regression also includes a post-PNTR dummy variable, time-invariant industry characteristics, and various control variables and fixed effects. One can account for the impact of the trade shock by also incorporating input-output linkages between domestic industries. To do so, the study computes plant-level upstream and downstream NTR gaps using sectoral information on input-output tables from the Bureau of Economic Analysis.

3.2.3 Quantifying general equilibrium effects

Recent quantitative trade literature has developed tractable general equilibrium models to study the effects of trade on workers and firms at the aggregate, sectoral, and regional levels. The mechanisms emphasized in these quantitative frameworks, as well as the access to more and better data and the new techniques developed to take the models to the data, have made such frameworks an easy and important empirical tool of analysis. We refer the reader to Redding and Rossi-Hansberg (2017), Redding (2022), Caliendo and Parro (2022), and McLaren (2017) for reviews of quantitative static and dynamic spatial, geography, and trade models that can be applied to quantify the general equilibrium effects of import competition.

To study the general equilibrium effects of the China shock, Caliendo, Dvorkin, and Parro (2019) develop a dynamic spatial general equilibrium model that can be taken to the data at the level of a local labor market. The quantitative model combines elements of Eaton and Kortum (2002), Artuc, Chaudhuri, and McLaren (2010), Caliendo and Parro (2015), and Caliendo, Parro, Rossi-Hansberg, and Sarte (2017a). We now briefly describe the equilibrium conditions of the model.

There are N different geographical areas indexed by i and n. Depending on the question and the level of aggregation of the analysis, a geographical area can be a local labor market (e.g., county, commuting zone, or state) or a country. Workers in i supply labor, obtain wage $w_{i,t}$, and consume goods with price $P_{i,t}$. In each i goods are produced with a constant returns to scale technology.

Following Eaton and Kortum (2002), goods are traded subject to trade costs and the expenditure share on goods across different n satisfies a gravity representation as in (5). In particular,

$$\lambda_{in,t} = \frac{A_n \left(\kappa_{in} w_{n,t}\right)^{-\theta}}{\left(P_{i,t}\right)^{-\theta}}, \tag{8}$$

where A_n is interpreted as fundamental TFP and the price index is given by

$$P_{i,t} = \left(\sum_{n=1}^{N} A_n \left(\kappa_{in} w_{n,t} \right)^{-\theta} \right)^{-1/\theta}. \tag{9}$$

The local labor market clearing condition is given by

$$w_{i,t} L_{i,t} = \sum_{n=1}^{N} \lambda_{ni,t} w_{n,t} L_{n,t}. \tag{10}$$

The supply of labor in each labor market evolves over time. In particular, workers maximize the present discounted value of their utility by deciding at each moment in time where to supply labor and how much to consume. This decision is affected by idiosyncratic amenity shocks, and by mobility frictions of moving from labor markets i to labor market n, given by m_{in}. Assuming that the idiosyncratic shocks are *i.i.d.* realizations from a *Gumbel* Type I distribution, the value of a representative worker in location i at time t, $v_{i,t}$, is given by

$$v_{i,t} = log \left(w_{i,t} / P_{i,t} \right) + \nu log \left(\sum_{n=1}^{N} exp \left(\beta v_{n,t+1} - m_{in} \right)^{1/\nu} \right), \tag{11}$$

where β is the discount factor and ν is the dispersion of the amenity shocks. By $\mu_{in,t}$ we denote the fraction of workers that moves from location i to location n, given by

$$\mu_{in,t} = \frac{exp \left(\beta v_{n,t+1} - m_{in} \right)^{1/\nu}}{\sum_{h=1}^{N} exp \left(\beta v_{h,t+1} - m_{ih} \right)^{1/\nu}}. \tag{12}$$

Using this gross-flow equation, we observe that the labor supply in i evolves according to

$$L_{i,t+1} = \sum_{n=1}^{N} \mu_{ni,t} L_{n,t}. \tag{13}$$

We now define the general equilibrium of the model.

Equilibrium of the dynamic spatial general equilibrium model. *Given an initial distribution of labor* $\{L_{i,0}\}_{i=1}^{N}$, *fundamentals* $\{A_i, \kappa_{in}\}_{i=1,n=1}^{N,N}$, *discount factor* β, *and elasticities* θ *and* ν, *a sequential competitive equilibrium of the dynamic spatial model is characterized by a sequence of factor prices* $\left\{w_{i,t}\right\}_{i=1,t=0}^{N,\infty}$, *prices* $\left\{P_{i,t}\right\}_{i=1,t=0}^{N,\infty}$, *trade shares* $\{\lambda_{in,t}\}_{i=1,n=1,t=0}^{N,N,\infty}$, *value functions* $\left\{v_{i,t}\right\}_{i=1,t=0}^{N,\infty}$, *migration flows* $\left\{\mu_{in,t}\right\}_{i=1,n=1,t=0}^{N,N,\infty}$, *and labor allocations* $\left\{L_{i,t}\right\}_{i=1,t=0}^{N,\infty}$ *that satisfy equilibrium conditions (8); (9); (10); (11); (12); (13) for all regions* i *and at time* t.

This framework can be used to study how a sequence of shocks to trade costs κ_{in}, migration costs m_{in}, and TFP A_n impact labor supply, trade flows, wages, prices, and migration flows across geography and over time. To study the effects of the China shock on the U.S. economy, Caliendo, Dvorkin, and Parro (2019) incorporate into the model intermediate goods, 22 tradable and non-tradable sectors at each labor market, input-output linkages, local fixed capital structures, labor force participation, non-employment, social-security disability insurance (SSDI), regional and aggregate trade imbalances, and 38 countries and a rest of the world. The authors show how to take the model to the data at a detailed geographic level and study the effects of the China shock across 1,250 U.S. labor markets. The authors also develop a method to compute the model that can be used to study the effects of changes in fundamentals and/or trade and migration policy without imposing that the economy is at the steady state in the initial period. In this way, the framework takes into account pre-trends in the data. More recently, Kleinman, Liu, and Redding (2021) extend the framework in Caliendo, Dvorkin, and Parro (2019) by incorporating endogenous capital accumulation. Rodríguez-Clare, Ulate, and Vasquez (2020) introduce downward nominal wage rigidity in a framework in the spirit of Caliendo, Dvorkin, and Parro (2019) to show how to rationalize, through the lens of the model, the changes in unemployment and non-employment due to the China shock uncovered in Autor, Dorn, and Hanson (2013).

Finally, Kleinman, Liu, and Redding (2021) show that there exists a unique steady-state spatial distribution of economic activity (up to a choice of units) of the dynamic spatial model and that the equilibrium is independent of the initial allocations. The study also provides conditions on elasticities such that even under the presence of agglomeration forces there is a unique spatial equilibrium. We follow Kleinman, Liu, and Redding (2021)'s proof, and in Section A of the supplemental appendix we show that there exists a unique steady-state equilibrium in the aforementioned dynamic spatial model. The next proposition presents the result, where the line above the variables represents their steady state values.

Proposition 1. *Given the set of time-invariant fundamentals $\left\{\bar{A}_i, \bar{\kappa}_{in}\right\}_{i=1,n=1}^{N,N}$, discount factor β, and elasticities θ and ν, there exists a unique (up to a choice of units) steady-state equilibrium prices $\left\{\bar{w}_i, \bar{P}_i\right\}_{i=1}^{N}$, values $\left\{\bar{v}_i\right\}_{i=1}^{N}$, and allocations $\left\{\bar{\lambda}_{in}, \bar{L}_i, \bar{\mu}_{in}\right\}_{i=1,n=1}^{N,N}$ of the dynamic spatial general equilibrium model.*

There is also a strand of fast-growing literature using assignment models to study the effects of import competition (see Lee 2016, Burstein, Morales, and Vogel 2019, Adao 2016, Kim and Vogel 2021, and Galle, Rodríguez-Clare, and Yi 2021). In particular, Kim and Vogel (2021) develop a framework to analyze the impact of trade shocks on several labor market adjustment margins. The study considers a static assignment model of trade with many sectors and heterogeneous labor groups. The model also includes worker-firm matching frictions and direct search. The authors solve for a small open economy in an environment where for a given labor group, the probability of finding a job is common across sectors.

The study shows that one can measure the changes in labor group g's outcomes (e.g., the probability of a worker obtaining employment E_g, average wages per hour of work W_g, hours worked per employee H_g, and expected utility U_g) using

$$dlnK_g = \left(\rho_g^K/\iota_g\right) dln\Phi_g - \rho_g^K dlnP_g,$$

where $K \in \{E, W, H, U\}$ is the outcome of interest, ι_g and ρ_g^K are functions of structural elasticities, $dln\Phi_g$ is the trade shock measured from the production side, and $dlnP_g$ is a consumption-side trade shock measured with a pre-shock income-weighted average of sectoral price changes (the weights are given by the share of income group g earned in sector s).

We have described a set of tools used in the literature to quantify the differential and general equilibrium effects of import competition on economic outcomes. These tools set the stage for the review of economic lessons learned from the China shock that we perform in the next subsection.

3.3 Lessons from the China trade shock: Economic effects

We now review research on the economic effects of the China shock. As we discussed before, researchers have used different methodologies to measure the China shock and quantify the impact of the shock. The main economic outcome studied is the effect on manufacturing employment in the United States, either across subsectors or across geographical areas. We first discuss the economic effects on manufacturing employment and present the economic effects on other outcomes such as employment in other sectors, migration, prices, wages, and welfare. We refer the reader to Autor, Dorn, and Hanson (2016), Fort, Pierce, and Schott (2018), Helpman (2018), Muendler (2017), and Redding (2022) for further descriptions of the methodologies used to measure and quantify the effects of the China shock on different economic outcomes.

3.3.1 Effects on manufacturing employment

Plants, firms, industries, and locations that are more exposed to import competition might be more likely to reduce employment than those that are less exposed. Still, aggregate employment in the sector could go up or down.

Autor, Dorn, and Hanson (2013) study the impact of the China shock on manufacturing employment across commuting zones (CZs)[8]. They find that local labor markets (CZs) that were more exposed to the China shock experienced a larger decline in the manufacturing employment share of the working-age population relative to labor markets less exposed. In particular, a \$1,000 increase in per-worker import exposure over 10 years in the most exposed CZ reduced manufacturing employment per working-age population by 0.596 percentage points more than it did in the least exposed CZ. To put this number in perspective, suppose that the least exposed CZ was not affected by the China shock. The actual import exposure increased by \$1,839 per worker between 2000 and 2007, which implies that U.S. manufacturing employment per population fell by 1.1 percentage

[8] The measure of a CZ was developed by Tolbert and Sizer (1996) using county-level commuting data from the 1990 U.S. Census. Their analysis covers 722 CZs, including metropolitan and rural areas.

points during this period, or approximately 55 percent of the observed decline in manufacturing employment during the period. As we described before, to obtain these results, the authors run a regression between predicted (instrumented) import penetration per worker $\Delta IPW_{US,j,t}$ on the change in employment, and add several controls, see (7). The methodology used in the study is a difference-in-difference regression that can identify only the relative effects; namely, the effects of the most exposed CZ relative to the least exposed CZ. In subsequent work, Autor, Dorn, and Hanson (2021) find that even when the China shock plateaued in 2010, differential impacts of import competition on manufacturing employment and income per capita in relatively more trade-exposed U.S. CZs persisted through 2019.

Caliendo, Dvorkin, and Parro (2019) quantify the general equilibrium effects of the China trade shock through the lens of a dynamic structural model like the one described in the previous section. They measure the China shock using Autor, Dorn, and Hanson (2013)'s empirical moments. The study quantifies the effects at the local labor market, defined as a sector in a state in the United States, taking into account all the direct and indirect linkages across labor markets. Namely, the study takes into account that the China shock can affect employment in a sector indirectly via the exposure of the shock on supply chains (input-output linkages), trade in goods, and changes in labor supply and spatial mobility. The authors use data on production, employment, trade, sectoral linkages, and migration flows for the period from 2000 to 2007 for more than 1,000 labor markets across the United States and 38 countries and a rest of the world. The study also proposes a methodology to take a dynamic spatial model with international trade to the data and shows how to use the framework to study and quantify the effects of import competition across labor markets.

The study finds that increased Chinese import competition reduced the aggregate manufacturing employment share by 0.36 percentage points, or about 0.55 million manufacturing jobs. This decline in manufacturing employment due to the China shock represents about 16 percent of the observed decline in manufacturing employment from 2000 to 2007. A quarter of this decline can be attributed to the computer and electronics industry, followed by the furniture, textiles, metal, and machinery industries, each contributing between 10 to 15 percent of the total decline. Other sectors such as food, beverage, and tobacco experience small employment effects, as they are less exposed to China and benefit from cheaper intermediate goods. In addition, the unequal distribution of U.S. economic activity across space, combined with its differential sectoral exposure to China, implies that the impact of import competition from China on manufacturing employment varies across regions. Accordingly, the authors find that states more exposed to import competition from China lose more employment in manufacturing than those less exposed. For instance, California alone accounted for 20 percent of all employment in the computer and electronics industry in 2000. For comparison, the state with the next-largest share of employment in this industry is Texas with 8 percent; all other states had less than 2 percent each. As a result, California contributed the most to the overall decline in manufacturing employment (about 9 percent), followed by Texas.

Pierce and Schott (2016) study how the United States' granting of NTR status to China impacted manufacturing employment. Using a difference-in-difference specification, they find that industries with larger NTR gap reductions experienced a 0.47 larger reduction in employment relative to the industry with the smallest NTR gap reduction. In particular, moving an industry from an NTR gap at the 25th percentile (0.23) to the 75th percentile (0.40) of the observed distribution increases the relative loss of manufacturing employment by $-0.47 \times (0.40 - 0.23) = -0.08$ log points.

Handley and Limao (2017) find that the United States' granting of NTR status to China explains one-third of the growth in exports of China to the United States in 2000–2005. In particular, Chinese export growth was higher in industries with higher initial trade policy uncertainty. The authors quantify the effect of the increase in imports from China due to the change in uncertainty on the share of manufacturing employment in the U.S. economy using a structural model. They estimate that the reduction in trade policy uncertainty in 2000–2005 reduced manufacturing employment by 1.2 log points, or about a third of the observed reduction during this period (3.3 log points).

Acemoglu, Autor, Dorn, Hanson, and Price (2016) complement the analysis of Autor, Dorn, and Hanson (2013) by performing an industry-level analysis (rather than labor market-level) and by considering a longer period, 1991–2011. The study uses the same identification strategy as Autor, Dorn, and Hanson (2013) but at the industry level. The study measures the direct effects on manufacturing sector employment, taking into account the indirect effects via input-output linkages. The authors find that compared to the previous decade (1990–1999), during the decade of the China shock (2000–2011) industries more exposed to Chinese import competition experienced larger losses in industry employment.

These findings show that the effects of the China shock on U.S. manufacturing employment are economically relevant. Still, looking at the effects on employment in the manufacturing industry, and the relative effects in particular, provides only a partial account of the economic effects of trade shocks. We turn to discuss what we have learned about the effects of the China trade shock on employment in non-manufacturing industries and on other economic outcomes.

3.3.2 Effects on non-manufacturing employment

Imports of cheaper intermediate goods can expand production and employment in indirectly exposed import competing sectors like non-manufacturing industries through the input-output structure of the economy. The China shock has allowed researchers to quantify these indirect employment effects. Consistent with the aforementioned intuition, Caliendo, Dvorkin, and Parro (2019) find that the decline in manufacturing employment due to the China shock led to an increase in employment in other industries such as construction, wholesale and retail, and services. Similarly, Dix-Carneiro, Pessoa, Reyes-Heroles, and Traiberman 2021 find that the decline in manufacturing employment due to the China shock was rapidly accommodated by the creation of jobs in services and agriculture.

Autor, Dorn, and Hanson (2013) also look at the effects on working-age population employed in the non-manufacturing sector and find negative but non-significant relative effects. Bloom, Kurmann, Handley, and Luck (2019) use confidential administrative micro-data from the Longitudinal Business Database of the U.S. Census Bureau and find that the China shock had a positive effect on U.S. service-sector jobs. The study finds that this effect is especially strong in higher human capital geographical areas. The estimation strategy adopted in the study is the same as the one used by Autor, Dorn, and Hanson (2013).

Feenstra, Ma, and Xu (2019) study how import and export exposure affected employment in the U.S. economy across the manufacturing and non-manufacturing sectors. The identification strategy is the same as the one used by Autor, Dorn, and Hanson (2013) but applied to import and export exposure per worker. The authors find an employment reduction in the most, relative to the least import-exposed industries and an employment increase in the most, relative to the least export-exposed sectors. In a related study, Feenstra and Sasahara (2018), using aggregate global input-output data, find that U.S. exports may have created demand for new jobs, primarily in the service sector. Fort, Pierce, and Schott (2018) present evidence that U.S. manufacturing firms increased their number of establishments in non-manufacturing industries and employed more non-manufacturing workers after the China shock.

3.3.3 Spatial labor mobility

Workers displaced in labor markets more exposed to import competition can relocate to other labor markets either by switching firms or industries or migrating to other regions, a process of adjustment that can take time due to mobility frictions.

Using the same strategy to identify the China shock as in Autor, Dorn, and Hanson (2013) but using data on some individual workers over time, Autor, Dorn, Hanson, and Song (2014) find small geographic migration responses to the China shock.

In contrast, Greenland, Lopresti, and McHenry (2019), using several data sets and different empirical methodologies (both the identification specification in Autor, Dorn, and Hanson 2013 and that of Pierce and Schott 2016), document that the local labor markets more exposed to Chinese import competition experienced a reduction in population growth. Furthermore, the mobility response was primarily driven by youth, males, and the less educated. The study is the first to document the response of U.S. internal migration to rising import competition from China across local labor markets. Importantly, the authors also find that the effects occur over a period of seven to ten years, which highlights the role of labor mobility frictions. When looking at China, it seems that workers adjust faster by moving across space. For example, Facchini, Liu, Mayda, and Zhou (2019) use a similar approach to Greenland, Lopresti, and McHenry (2019) to explain migration patterns in China after 2000. The study finds strong evidence of migration from rural to urban areas where firms experienced greater exports from declines in trade policy uncertainty, an effect that is most pronounced for skilled labor. Understanding more generally the conditions under which we expect important population response to local labor market shocks is a promising area of future research.[9]

3.3.4 Effects on innovation

The effects of import competition on innovation and product differentiation documented in the literature are very mixed. Using the aforementioned measure of the China shock, researchers have arrived at different results depending on the measures of innovation used and the time considered. Most studies conducted in the United States have conflicting results, while studies using European data show more consistently positive effects on innovation. We now describe some of these studies and refer to Shu and Steinwender (2019) for a more comprehensive review of the recent literature on the effects of import competition on innovation.

Autor, Dorn, Hanson, Pisano, and Shu (2020b) and Xu and Gong (2017) study the effects of the China shock on U.S. firms' research and development (R&D) expenditures. The studies find that the China shock had a negative effect on the R&D spending of the most exposed firms relative to the least exposed firms and that the effect seems to be driven by those firms with relatively weak initial innovation performance. These results contrast with the ones on the impact of the China shock on the European economy. In particular, Bloom, Draca, and Van Reenen (2015) find that from 2000 to 2007, import competition from Chinese firms accounted for almost 15 percent of the increase in patenting, information technology spending, and productivity in European countries. These results hold when looking at the effects of the elimination of textile quotas under the ATC (preceded by the MFA).

Autor, Dorn, Hanson, Pisano, and Shu (2020b) and Chakravorty, Liu, and Tang (2017) report contrasting findings regarding the impact of Chinese import competition on U.S. firms' patenting. Using data on U.S. patents granted between 1990 and 2006, Chakravorty, Liu, and Tang (2017) find non-significant effects of Chinese import competition on patent count and positive effects on citation-weight patents. Autor, Dorn, Hanson, Pisano, and Shu (2020b) find negative effects on both measures using patents granted between 1975 and 2013.[10]

3.3.5 Effects on welfare

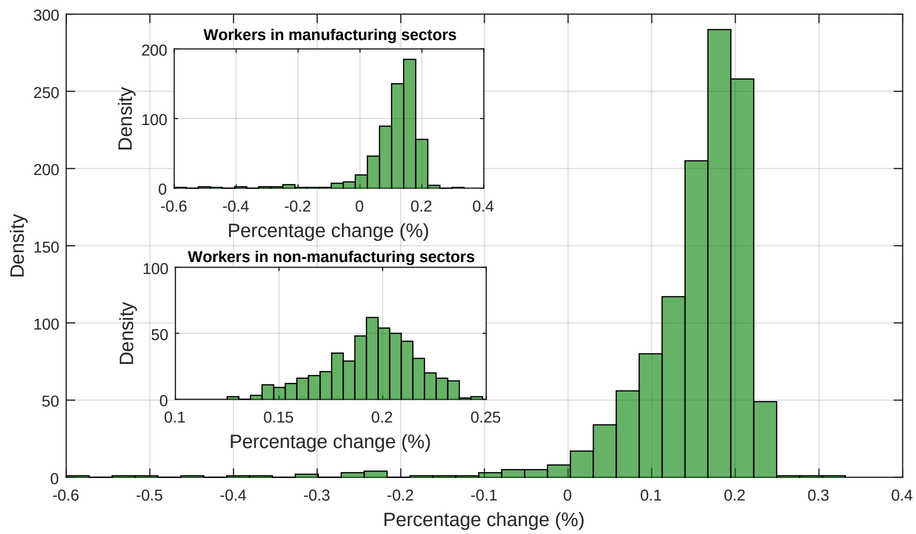
Using the framework described before, Caliendo, Dvorkin, and Parro (2019) find that U.S. aggregate welfare increased by 0.2 percent due to China's import penetration growth. Figure 4 presents a histogram with the changes in welfare across U.S. labor markets computed by Caliendo, Dvorkin, and Parro (2019). It shows that the aggregate change in welfare masks heterogeneity in welfare

[9] In other historical episodes, literature has also found big migration responses to change in economic and political opportunities. For example, Stephan, Redding, and Zylberberg (2021) find evidence of substantial population movements in response to the local labor market shock of the grain invasion in the late-19th century.

[10] In a different line of research, Eriksson, Russ, Shambaugh, and Xu (2021) find that activity in industries more exposed to the China shock moved from high-innovation areas to low-education areas over the 20th century, highlighting another aspect of the heterogenous effects of local labor market shocks.

effects across different labor markets; changes in welfare range from a decline of about 0.8 percent to an increase of 1 percent. The authors also find that welfare effects are more dispersed across labor markets that produce manufacturing goods than those that produce non-manufacturing goods, as manufacturing industries have more differential exposure to import competition from China. In addition, labor markets that produce service goods gain from the China shock, and welfare tends to be higher in those labor markets than in the manufacturing sectors. Intuitively, labor markets that produce non-manufacturing goods do not suffer the direct adverse effects of increased competition from China and at the same time benefit from access to cheaper intermediate manufacturing inputs from China. Across space, labor markets located in states that trade more with the rest of the U.S. economy and purchase materials from sectors in which Chinese productivity increased more tend to have larger welfare gains.

Figure 4: Welfare effects of the China shock across U.S. labor markets (percent)



Note: The central figure presents the change in welfare across all labor markets, and for workers in manufacturing sectors (top-left panel) and for workers in non-manufacturing sectors (bottom-left panel) as a consequence of the China shock. The percentage change in welfare is measured in terms of consumption equivalent variation. Source: Caliendo, Dvorkin, and Parro (2019).

Migration costs are also important for understanding the differences between the welfare effects of the China shock in the short run and those in the long run. In the short run, migration costs prevent workers in the labor markets most negatively affected by the China shock from relocating to other labor markets. Therefore, real wages fall where labor market conditions worsen. In the long run, workers are able to relocate to industries or states with higher labor demand and real wages, a process that takes time. As a result, the authors find that while in the long run only about 4 percent of the labor markets experience welfare losses, real wages drop in about 47 percent of all labor markets when the China shock hits the U.S. economy.

Galle, Rodríguez-Clare, and Yi (2021) also quantify the general equilibrium effects of the China trade shock using a structural model and following Caliendo, Dvorkin, and Parro (2019)'s strategy for measuring the China shock. The authors combine a multi-industry quantitative international trade model with a Roy model to study how the China trade shock impacted the sorting of workers across local labor markets. The study is performed at the CZ level and finds very heterogeneous welfare effects. In particular, the authors find that a modest but non-negligible number of groups representing 15.9 percent of the population suffer welfare losses and that those losses can be up to five times as great as the average gains. The authors find that in the aggregate, the China shock increases U.S. welfare by 0.22 percent.

Kim and Vogel (2020) quantify the welfare effects of China's trade growth using the change in PNTR status. The study finds that granting China PNTR lowers the welfare of a CZ at the 90th percentile of exposure by 3.1 percentage points relative to a CZ at the 10th percentile. They find that around 65 percent of this effect is due to changes in unemployment status[11].

3.3.6 Other effects

On labor force participation and unemployment, Autor, Dorn, and Hanson (2013) find that the China shock raised the fraction of unemployed and out of the labor force households by 0.22 and 0.55 percentage points, respectively, in the regions more impacted by trade exposure relative to those less exposed. The authors also find that the China shock increased the use of SSDI and other transfers in relatively more exposed CZs. Caliendo, Dvorkin, and Parro (2019) extend their dynamic spatial framework to study the role of SSDI during the China shock and find that the disability program amplified the decline in manufacturing employment by about 0.03 percentage points; that is, about 50,000 additional manufacturing jobs were lost due to the disability program. The authors also find an increase in the non-employment rate in the long run. Finally, the authors find that the effects of the disability program on manufacturing employment tend to be larger in regions that are more concentrated in the manufacturing sector and where it is more difficult for workers to relocate to other industries.

In terms of the effect of import competition on entrepreneurship, Aslan and Kumar (2021), using the industry-specific NTR gaps as well as their log changes, find negative aggregate employment effects in the short run but positive productivity effects in non-tradable sectors in the long run. The study finds that business creation is significantly lower in regions with higher NTR gap exposure relative to those regions that are less exposed. Their results show a statistically and economically significant negative effect of import competition on net entrepreneurial entry. At the same time, the study finds positive spillover effects of import competition on entrepreneurship in non-tradable industries.

[11] Other studies have also quantified the aggregate welfare effects of China's productivity growth over the period of the China shock using static multi-sector models. Hsieh and Ossa (2016), for instance, find that China's productivity growth between 1995 and 2007 generated small gains for the United States. Similar results are reported by di Giovanni, Levchenko, and Zhang (2014) using a related approach.

Regarding effects on prices, Amiti, Dai, Feenstra, and Romalis (2020) find that following China's entry into the WTO, between 2000 and 2006 the price index in the median manufacturing industry was 8.0 percent lower than the price index of an industry that was not directly exposed to China's trade reforms. They find that the largest contribution to these effects came from lower input tariffs in China. The authors also find that the reduction in tariff uncertainty contributed to this effect.

Using the same identification strategy as in Autor, Dorn, and Hanson (2013), Xu, Ma, and Feenstra (2019) find that the employment effect of the China shock was magnified through the housing market; namely, if housing prices had not responded to the China shock at all, then the total employment effect of import exposure from China would have been reduced by more than half.

Other research has also studied alternative mechanisms by which import competition from China impacted U.S. export performance. Using a quantitative trade model, Breinlich, Leromain, Novy, and Sampson (2022) find that while PNTR increased aggregate U.S. exports relative to GDP due to lower input costs, exports declined in the most exposed industries because of export destruction effect (i.e., reduction in domestic production). On aggregate, the authors find that the United States and China both gain from PNTR but the gains are larger for China.

The findings of the distributional effects of the China shock are economically relevant and have influenced U.S.-China trade relations. Rodrik (2021) reviews a series of studies that empirically estimate the effect of increased import competition from China on the attitude towards globalization and on political outcomes. As an example, Autor, Dorn, Hanson, and Majlesi (2020a) find that import competition from China contributes to a shift to the right in media-viewing habits and political beliefs, more competitive Congressional elections, greater polarization in the ideological orientation of campaign contributors, and net gains in the number of conservative Republican representatives. Broz, Frieden, and Weymouth (2021) provide a broader overview of the political backlash associated with regional economic decline and deindustrialization linked in turn to globalization. In the next section, we discuss the effects of the backlash against U.S.-China trade relations that resulted in the 2018–2019 trade war between the two countries.[12]

4 Backlash against U.S.-China trade relations: The 2018–2019 trade war

Although protectionist measures have been imposed throughout U.S. history, the recent trade war between the United States and its main trading partners is somewhat unprecedented in terms of the scope and magnitude of tariff changes.[13] In 2018, the United States raised the tariffs applied to a few large import items such as washing machines, solar panels, steel, and aluminum. With

[12] Another paper that explores quantitatively the political economy impact of the China trade shocks is Kleinman, Liu, and Redding (2020). Relatedly, Brunnermeier, Doshi, and James (2018) draw parallels between the China shock and the rise of Germany as a trading nation in the early 20th century.

[13] Irwin (2017) presents a comprehensive review of the history of U.S. trade policy.

few exceptions, these tariff increases were applied indiscriminately across origin countries at a range from 10 to 50 percent. Subsequently, the United States largely targeted China, raising tariffs on thousands of products from China, targeting roughly $350 billion of imports from China. In response to these tariff increases, China retaliated over several tariff waves, targeting about $100 billion of U.S. exports (see Amiti, Redding, and Weinstein 2019 and Fajgelbaum, Goldberg, Kennedy, and Khandelwal 2019 for additional empirical facts).

The trade war resulted in the United States imposing tariffs (on China and other trade partners) on 17.6 percent of its 2017 imports, or about 2.6 percent of its GDP, with average tariffs increasing from 3.7 percent to 25.8 percent. Trade partners retaliated on 8.7 percent of 2017 exports, or about 1 percent of U.S. GDP, with average tariffs rising from 7.7 percent to 20.8 percent. China raised tariffs on about 11 percent of its imports, and about 18 percent of their exports were targeted by the United States. This trade war affected transactions equivalent to about 5.5 percent of China's GDP (Fajgelbaum and Khandelwal 2021). The two parties signed an agreement to halt further tariff escalations in January 2020, but the existing tariffs remain in place as of the publication of this review.

The magnitude of the trade war, together with the recent emergence of detailed cross-country trade and tariff data, has prompted quantitative research on the effects of trade protectionism driven by this trade war. In what follows we review the economic impacts of the U.S-China trade war. This section complements the analysis performed in Caliendo and Parro (2022) and the review by Fajgelbaum and Khandelwal (2021) on the same topic. The section also complements the review by Handley and Limao (2022) on the economic effects of trade policy uncertainty.

4.1 Difference-in-difference specifications

Using monthly U.S. Census data collected from 2017 to 2018 on import quantities and values at the HTS10-country level, Amiti, Redding, and Weinstein (2019) estimate the effects of the trade war on U.S. prices and quantities. The authors find that the tariff changes were almost entirely passed through to domestic prices, leaving relative export prices unchanged. This result might be surprising for a large economy like that of the United States, but it is corroborated by similar estimates made using different methodologies in Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) and Cavallo, Gopinath, Neiman, and Tang (2021).

Using micro-data from the Bureau of Labor Statistics collected at the border and at retailers, Cavallo, Gopinath, Neiman, and Tang (2021) document that the increase in U.S. import tariffs was almost fully passed through to total prices paid by importers, suggesting that the incidence of tariffs has fallen on U.S. consumers. Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) use Census data as in Amiti, Redding, and Weinstein (2019) but follow a different methodology to find evidence of the effects of the trade war on U.S. prices. The authors estimate a U.S. demand system that accommodates substitution across imported varieties, across imported products, and between imported and domestic products within a sector, and they combine this demand system with foreign export supply curves for each variety. Similar to the findings of Amiti, Redding, and Weinstein (2019), their results are suggestive of a perfectly elastic export supply curve. In line with these results, Flaaen, Hortacsu, and Tintelnot (2020) estimate a high tariff pass-through to retail prices for washing machines.

These studies' finding of the complete pass-through of tariffs to duty-inclusive import prices does not imply that the United States is a small open economy that is not able to affect its terms of trade. One possible interpretation is that a complete pass-through is a short-run effect, as relative prices may change over longer horizons. In addition, the fact that the relative price of imports remains the same does not imply that the relative price of imports to exports is unchanged. For instance, changes in the level of exports to the United States may still be associated with a change in the U.S. wage relative to the wage in all countries, a terms of trade effect that would differentiate out in reduced-form regressions. Fajgelbaum and Khandelwal (2021) discuss these and other potential explanations for the complete pass-through results, stressing that more research in this area is necessary to uncover the relevant mechanisms.

Recent studies have also used the 2018–2019 U.S. import tariff increase to learn about the effects of the change in trade policy taking into account supply chain linkages. The starting point is the large increase in trade in intermediate goods that has led to the globalization of value chains (see, for example, Johnson and Noguera 2012 and Antràs and Chor 2022). Consequently, the incidence of a tariff increase may be larger because tariffs affect the input of goods that are used for the production of goods that are later exported. Handley, Kamal, and Monarch (2020) find that firms that were impacted by the change in tariffs accounted for 84 percent of U.S. exports and represent 65 percent of manufacturing employment. In addition, the effect of the change in policy costs an average of $900 per worker in new duties. Flaaen and Pierce (2019) find evidence that the import protection received by U.S. manufacturing industries that were more exposed to tariff increases was offset by larger negative effects from rising input costs and retaliatory tariffs.

Difference-in-difference specifications in the literature have been valuable in providing evidence of the differential effects of the trade war on prices and other outcomes for firms more exposed to the changes in tariffs relative to less exposed firms. However, general equilibrium analysis is required in order to understand and quantify the welfare consequences of the trade war and to recover the level effects on different relevant outcomes. We now proceed to evaluate the general equilibrium effects of the trade war.

4.2 General equilibrium analysis of the U.S.-China trade war

Substantial progress in the development of tractable quantitative frameworks for trade policy analysis, increase in detailed data availability, and advances in computational methods have resulted in recent literature that provides estimates of the general equilibrium effects of the trade war.

Recent frontier quantitative frameworks contain a variety of building blocks in terms of production structure, preferences, number and type of sectors (i.e., tradable and non-tradable), market structure, economic geography, source (or absence) of dynamics, treatment of trade deficits, and the mobility of goods and people. Caliendo and Parro (2022) provide a review of recent quantitative frameworks for trade policy analysis.

In this section, we study the general equilibrium effects of the recent trade war between the United States and China through the lens of the dynamic spatial general equilibrium trade framework that we described in Section 3.2.3. We extend this framework to include the role of trade policy.

It is important to emphasize that this dynamic framework, with its dynamic labor-market decisions, mobility frictions, input-output linkages, and geography, captures three relevant margins for the quantification of the effects of trade policy documented in the empirical literature: (i) the importance of global value chains in shaping the effects of trade policy (e.g., Antràs and Chor 2022); (ii) empirical evidence of the distributional effects of trade policy across space (e.g., Topalova 2010, Kovak 2013); and (iii) the persistent effects of trade policy (e.g., Dix-Carneiro and Kovak 2017).

To incorporate the role of trade policy, we assume that trade between countries is subject to trade frictions that goods produced in sector j face when shipped from n to i, modeled as "iceberg" trade costs, denoted by κ^j_{in}, where $\kappa^j_{in} \geq 1$. In addition, we assume that countries face ad-valorem import tariffs, where τ^j_{in} denotes one plus the ad-valorem tariff that country i applies to n in sector j. Trade flows across regions in a country are not subject to import tariffs; namely, $\tau^j_{in} = 1$ for all i and n that belong to the same country. Hence, the bilateral trade share in each sector is given by

$$\lambda^j_{in} = \frac{A^j_n \left[\tau^j_{in} \kappa^j_{in} x^j_n\right]^{-\theta^j}}{\sum_{h=1}^{N} A^j_h \left[\tau^j_{ih} \kappa^j_{ih} x^j_h\right]^{-\theta^j}}. \tag{14}$$

In addition, we assume that workers receive income from their factor rewards, and as a result, their labor mobility decisions are not distorted by other sources of external income. Tariff revenue, given by $TR_i \equiv \sum_{j=1}^{J} \sum_{n=1}^{N} [\tau^j_{in} - 1] \lambda^j_{in} \frac{X^j_i}{\tau^j_{in}}$, is lump-sum redistributed to the same location and is used to purchase local goods, where X^j_i is the total expenditure in country i and sector j. See Caliendo and Parro (2022) for a detailed description of the dynamic spatial model for trade policy analysis that we use to quantify the general equilibrium effects of the recent trade war.

4.3 Effects of the 2018–2019 trade war

In Caliendo and Parro (2022) we take the dynamic spatial model to a world of 43 countries and a rest of the world, 50 U.S. states, and 22 industries, including tradable and non-tradable sectors. The framework also considers transitions across both U.S. states and industries, and between employment and non-employment. We measured welfare as the change in consumption equivalent of households in each region and sector, which takes into account not only the changes in current real wages each period but also the option value of moving to other locations (e.g., Artuc, Chaudhuri, and McLaren 2010, Caliendo, Dvorkin, and Parro 2019).

We find that aggregate U.S. households' welfare declines 0.1 percent due to the trade war. We also find significant distributional effects on welfare across space. Most states are worse off, with Alabama being the hardest hit, while a few states in the south such as Texas, Oklahoma, Arkansas, and New Mexico, as well as Washington, Idaho, and Oregon in the northeast, are slightly better off. Crucially, we find persistent effects of the trade war on employment and wages across locations, in line with the empirical evidence previously described.

Caliendo and Parro (2022) present results under different versions of the framework. In a static framework with spatial immobility, the authors find that U.S. aggregate real wages decline by 0.16 percent as a consequence of the trade war while real income also declines by around 0.14 percent. Real wages decline in all the U.S. states, but the effects are very heterogeneous across space. With free labor mobility, the aggregate effects on real wages and real income are very similar to those of the model with no regional mobility. One feature of the model that might explain similar results with and without regional mobility is the absence of transition costs in static frameworks. In addition, it is important to emphasize that one main difference between the changes in real wages and the changes in consumption equivalent described in the previous paragraph is the option value of migration, which is an important component of welfare. The welfare results show that heterogeneity in mobility frictions and transitional dynamics cannot be ignored when quantifying the distributional effects of changes in trade policy.

Importantly, while some states that suffer relatively large declines in real wages have high exposure to the changes in tariffs in the manufacturing sectors (measured as import penetration), the correlation between each state's direct exposure to the tariff changes and the effects on real wages is not high, which highlights the importance of input-output linkages as well as general equilibrium effects in the quantification of trade policy changes.

Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) compute the effects of the trade war through the lens of a static spatial framework with labor, fixed factors, and input-output linkages. Their analysis is performed at the county level under the assumption that labor cannot move across sectors or locations; it also takes foreign wages as exogenous. They similarly find a small decline in U.S. aggregate real wages and large spatial heterogeneity. The authors also find evidence that U.S. import protection was biased toward products made in electorally competitive counties, as measured by the counties' 2016 presidential vote shares. More recently, Santacreu, Sposi, and Zhang (2021) also find heterogeneous effects of U.S. tariff increases across states through the lens of a spatial model with labor immobility.

Finally, it is important to emphasize that the welfare effects of the trade war in the United States are importantly shaped by the retaliatory tariffs applied by trading partners, as found in Caliendo and Parro (2022), Caliendo and Parro (2020), and Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019).

Waugh (2019) studies the consumption effects of the U.S.-China trade war across U.S. counties using detailed high-frequency data for the universe of new auto sales at the county level. The author finds that counties relatively more exposed to the retaliatory tariffs from China experienced a 3.8 percentage point decline in consumption growth. In addition, the fall in consumption corresponds with a decline in both tradable and retail employment.

Amiti, Kong, and Weinstein (2021) embed a firm-level specific factors model in an asset pricing model and find that the U.S.-China trade war increased consumption uncertainty, and resulted in large declines in U.S. stock prices, expected cash flows, and expected productivity. The authors also find that the decline in expected consumption reduced U.S. welfare significantly.

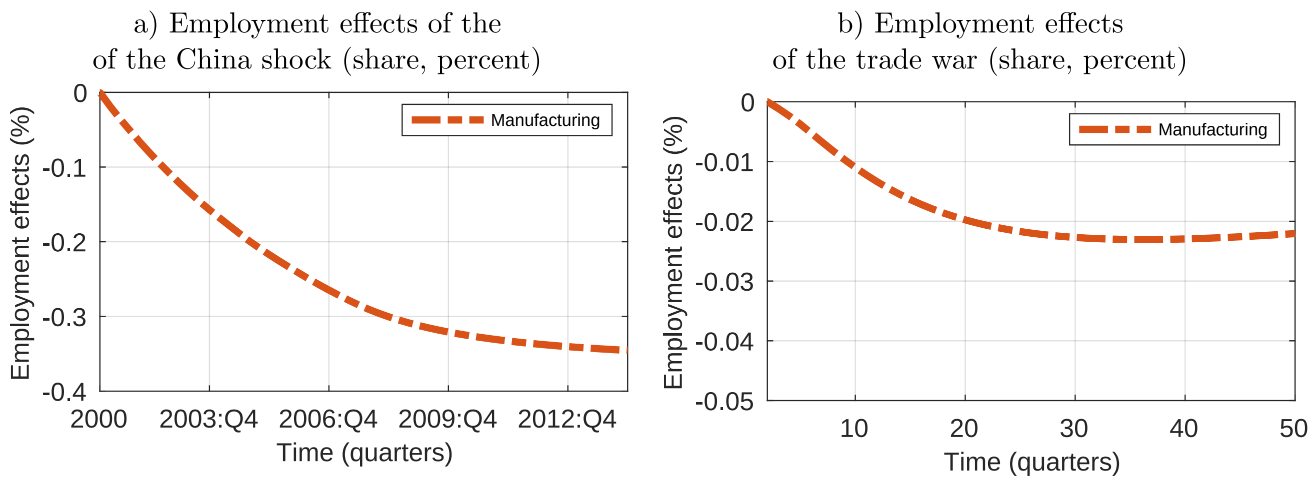
In terms of trade effects, Caliendo and Parro (2022) find aggregate manufacturing imports declined by 6.5 percent and manufacturing exports by about 8 percent as a result of the trade war. Trade effects are very heterogeneous across sectors; for instance, sectors such as the metal and computer and electronics industries experienced large declines in imports while the import declines in other industries such as food, beverage and tobacco, textiles, and transport were much smaller. The same degree of heterogeneity can be seen in the impact on sectoral exports. This sectoral heterogeneity is shaped not only by the size of the tariff change in a given industry but also by sectoral trade elasticities and sectoral linkages.

5 Has the 2018 trade war reversed the distributional effects of the China shock?

We previously noted that the backlash against U.S.-China trade relations that resulted in the recent trade war was motivated in part by the distributional effects of the China trade shock and in particular the employment losses in the manufacturing sector. In this section, we study to what extent the trade war reversed the distributional effects of the China shock across U.S. labor markets. To do so, we compare the general equilibrium employment and welfare effects of the China trade shock with the effects of the trade war computed through the lens of the dynamic spatial trade policy model described in the previous section.

Focusing on the employment effects in the manufacturing sector, Figure 5, Panels A and B depict the effects of the China shock and the trade war on manufacturing employment share respectively. The China shock resulted in a decline in the share of manufacturing employment of 0.36 percentage points. As we can see in Panel B, the full trade war did not reverse this decline; in fact, we find a small decline in the manufacturing employment share of about 0.03 percentage points as a consequence of the trade war. Therefore, the trade war made the manufacturing employment share even smaller. This finding of a decline in manufacturing employment from the trade war is in line with Flaaen and Pierce (2019), who find that the U.S. manufacturing industries more exposed to the tariff increases experienced relative reductions in employment mostly due to the increase in the cost of intermediate inputs.

Figure 5: Manufacturing employment effects



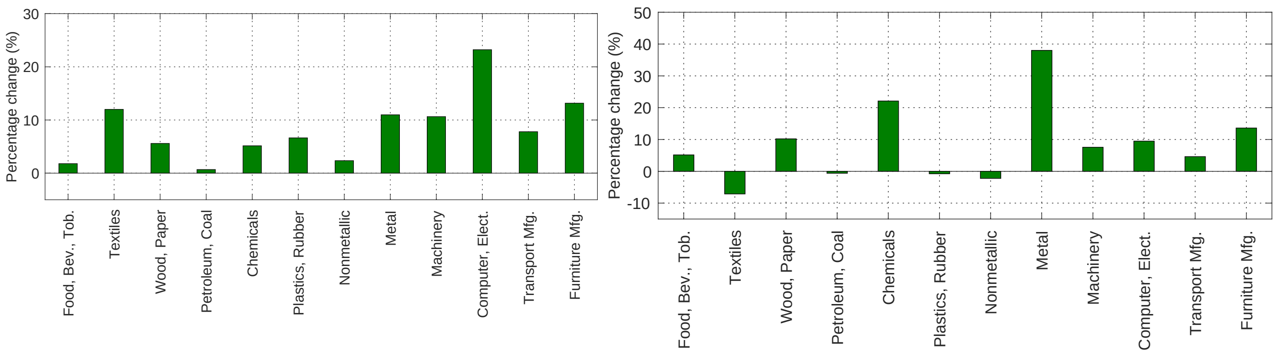
Note: The figures present the change in the manufacturing employment share as a consequence of the China shock (Panel A) and as a consequence of the trade war (Panel B). The effects of the China shock are obtained from Caliendo, Dvorkin, and Parro (2019).

In Figure 6, we present the employment effects across manufacturing industries. In particular, the figure displays the contribution of each industry to the aggregate effects in manufacturing employment illustrated in the previous figure. As before, Panel A presents the employment effects of the China shock, and Panel B displays the effects of the trade war. Comparing the sectoral effects across the manufacturing industry, we can see that only a handful of industries that experienced employment losses due to the China shock, gained employment as a consequence of the trade war; namely, the textile, petroleum, plastic, and non-metallic industries. Among them, the textile industry is the largest winner of the trade war in terms of manufacturing employment. The textile industry is also one of the top three industries that contributed the most to the decline in manufacturing employment as a consequence of the China shock. We also observe that industries like the computers and electronics and furniture industries, which explained almost 40 percent of the decline in manufacturing employment from the China shock, also experienced employment declines as a consequence of the trade war.

Figure 6: Sectoral contributions to manufacturing employment effects

a) Sectoral contributions to the employment effects of the China shock (percent)

b) Sectoral contributions to the employment effects of the trade war (percent)



Note: The figures present the sectoral contributions to the change in the manufacturing employment share as a consequence of the China shock (Panel A) and as a consequence of the trade war (Panel B). The sectoral contributions of the China shock are obtained from Caliendo, Dvorkin, and Parro (2019).

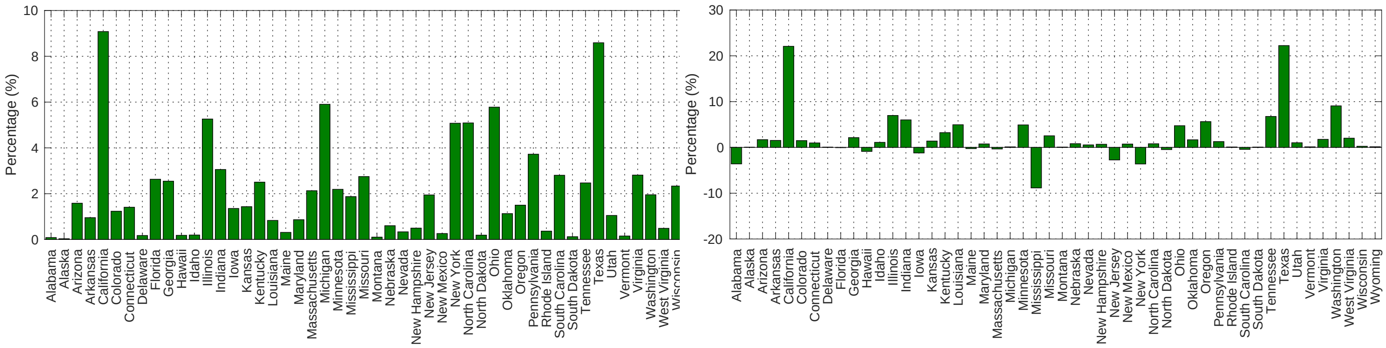
In Figure 7, we present the regional contributions to the aggregate effects on the U.S. manufacturing employment share. Comparing the regional contributions to the decline in manufacturing employment from the China shock in Panel A and from the trade war in Panel B, we see that the states that lost employment during the China shock but gained manufacturing employment during the trade war are Alabama, Florida, Hawaii, Iowa, Maine, Massachusetts, Mississippi, New Jersey, New York, North Dakota, and South Carolina. Among them, the largest winner in terms of manufacturing employment is Mississippi. However, the manufacturing employment gains of the trade war are modest. We also observe that the states that contributed the most to the decline in manufacturing employment as a consequence of the China shock, namely California and Texas, also experienced declines in manufacturing employment during the trade war.

The main takeaways from this analysis of the employment effects are that the trade war was ineffective in reversing the decline in manufacturing employment due to the China shock. Moreover, only a handful of industries and states experienced manufacturing employment gains during the trade war, and those employment gains were very modest.

Figure 7: Regional contributions to manufacturing employment effects

a) Regional contributions to the employment effects of the China shock (percent)

b) Regional contributions to the employment effects of the trade war (percent)



Note: The figures present the regional contributions to the change in the manufacturing employment share as a consequence of the China shock (Panel A) and as a consequence of the trade war (Panel B). The regional contributions of the China shock are obtained from Caliendo, Dvorkin, and Parro (2019).

Figure 8 displays the employment effects across U.S. manufacturing labor markets. Panel A displays the differential employment effects of the China shock. The left-hand side of the figure presents the effects for each labor market over time, and the right-hand side of the figure presents a histogram with the effects after 60 quarters. Panel B shows the effects of the trade war. In both cases, we can see that the employment effects take time to materialize and that they plateau after several quarters. In addition, by comparing the histograms of both figures, we observe that in the case of the China shock, these effects across labor markets are more dispersed than they are in the case of the trade war.

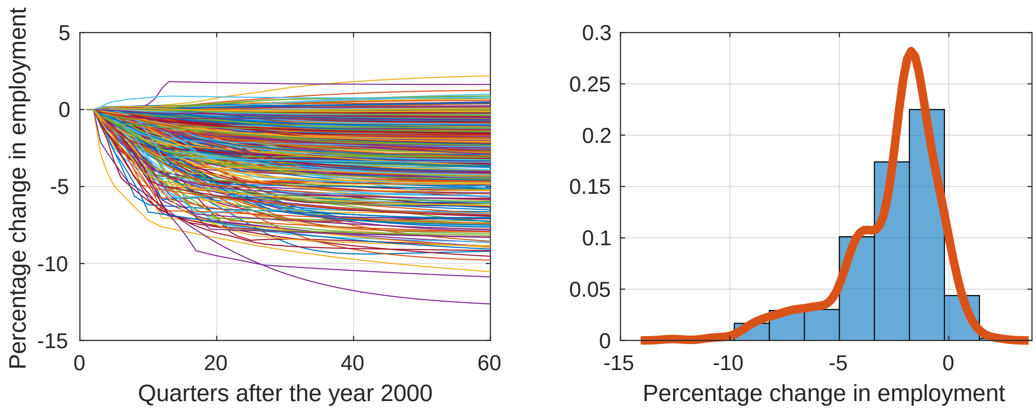
What was the welfare cost of these employment effects of the trade war across U.S. labor markets? We turn to compare the welfare effects of the China shock and the trade war. To make the effects comparable, we look at the change in consumption equivalent of U.S. households.[14] In terms of aggregate welfare effects, Table 2 shows that while the China shock resulted in welfare gains of 0.2 percent for U.S. households, the trade war resulted in welfare losses of 0.1 percent. Figure 9 presents scatter plots of the welfare effects of the China shock and the welfare effects of the trade war. Panel A displays the welfare effects across U.S. states, and Panel B presents the welfare effects across U.S. labor markets. Starting with Panel A, we can see that there is little correlation between the welfare effects of the China shock and the welfare effects of the trade war across U.S. states. In fact, among the states that experience smaller than average welfare gains from the China shock, only two states, Oregon and Texas, experience welfare gains from the trade

[14]See Caliendo, Dvorkin, and Parro (2019) for the derivation of the change in consumption equivalent in the dynamic spatial framework presented in Section 3.2.3. In the case of the trade war, we assume that tariff revenues in each location are spent on local goods but are not part of household income. This way migration decisions are not shaped arbitrarily by tariff revenues, but revenues still exert general equilibrium effects on real wages through the changes in local expenditures.

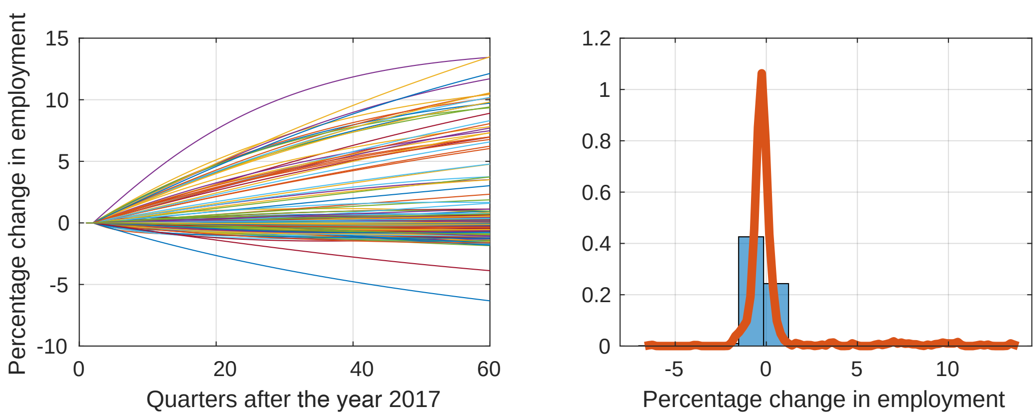
war.

Figure 8: Differential employment effects across manufacturing labor markets

a) Differential employment effects
of the China shock (percent)



b) Differential employment effects
of the trade war (percent)



Note: The figures present the differential employment effects across manufacturing labor markets after 60 quarters due to the China shock (Panel A) and as a consequence of the trade war (Panel B). The effects are the percentage change in employment, calculated as $100{*}(L_t^{\text{with}s}/L_t^{\text{without}s} - 1)$ where s = (china shock, trade war).

Even more striking is the comparison of the welfare effects across U.S. labor markets in Panel B. We can see very little correlation between the welfare effects across labor markets from the China shock and from the trade war. Note that even though the aggregate welfare effects of the trade war are small, they are masked by a large dispersion in welfare effects across U.S. labor markets. One might think that this dispersion in the welfare effects of the trade war redistributed gains to the labor markets that lost with the China shock, but this is clearly not the case. In fact, the southwest quadrant of the figure reflects that only four labor markets that lost with the China shock experience welfare gains with the trade war: the non-metallic industry in Louisiana, the metal industry in Maine, the wood and paper industry in New Mexico, and the transport equipment industry in West Virginia.

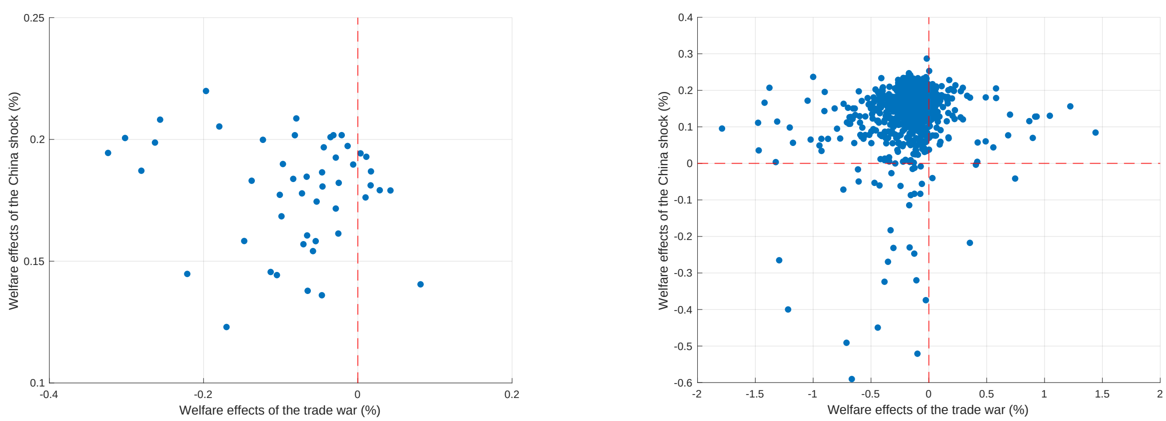
Table 2: Aggregate welfare effects (percent)

	U.S. welfare effects
China shock	0.2%
Trade war	-0.1%

Note: The table presents the aggregate welfare effects for U.S. households, measured as the change in consumption equivalent.

Figure 9: Welfare effects from the China shock and from the trade war

a) Welfare effects across U.S. states (percent) b) Welfare effects across U.S. labor markets (percent)



Note: In the figure, Panel A presents a scatter plot of the welfare effects across U.S. states, measured as the change in consumption equivalent, as a consequence of the China shock and as a consequence of the trade war. Panel B presents an analogous scatter plot of the welfare effects across U.S. labor markets. In Panel B, about 2.5 percent of outlier labor markets are dropped.

6 Lessons from U.S.-China trade relations

The evolution of the U.S.-China trade relations over the last couple of decades has resulted in several remarkable changes to trade policy and observed outcomes such as employment and wages. Together these changes have resulted in China's trade expansion and penetration in U.S. imports. At the same time, the U.S. economy experienced a substantial decline in manufacturing employment.

Motivated in part by these developments, there was an important increase in trade protectionism during the recent U.S.-China trade war.

The various changes to trade integration between the United States and China, together with the recent advances in the trade literature, have allowed researchers to revisit classic questions. What are the aggregate welfare effects of trade integration? What are the distributional effects (i.e., winners and losers) of import competition? Is trade policy an effective way to redistribute aggregate gains and losses from trade?

This review of recent research offers four main lessons learned from U.S.-China trade relations over the last decades: (i) the U.S.-China trade integration confirms trade economists' consensus regarding the aggregate gains from trade for both trading partners; (ii) the aggregate gains from trade are unequally distributed, creating winners and losers; (iii) China's trade expansion is not the main cause of the observed decline in manufacturing employment during the same period; and (iv) the recent trade war generated welfare losses, very small effects on employment, and was ineffective in reversing the distributional effects and decline in manufacturing employment due to the China shock.

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Supplemental Appendix: Lessons from U.S.-China Trade Relations, Annual Review of Economics

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A Appendix: Proof of Uniqueness

Proposition 1. *Given the steady-state fundamentals $\left\{\bar{A}_i, \bar{\kappa}_{in}\right\}_{i=1,n=1}^{N,N}$, discount factor β, and elasticities θ and ν, there exists a unique (up to a choice of units) steady-state equilibrium prices $\left\{\bar{w}_i, \bar{P}_i\right\}_{i=1}^{N}$, values $\left\{\bar{v}_i\right\}_{i=1}^{N}$, and allocations $\left\{\bar{\lambda}_{in}, \bar{L}_i, \bar{\mu}_{in}\right\}_{i=1,n=1}^{N,N}$ of the dynamic general equilibrium model.*

We first write the equilibrium conditions at the steady state. A steady state is an equilibrium of the economy in which given a set of time-invariant fundamentals $\left\{\bar{A}_i, \bar{\kappa}_{in}\right\}_{i=1,n=1}^{N,N}$, prices and allocations stay constant over time for all t. The steady state solves the following system of equilibrium equations:

$$\bar{P}_i = \left(\sum_{n=1}^{N} \bar{A}_n \left(\bar{\kappa}_{in}\bar{w}_n\right)^{-\theta}\right)^{-1/\theta}, \tag{1}$$

$$\bar{w}_i\bar{L}_i = \sum_{n=1}^{N} \frac{\bar{A}_i \left(\bar{\kappa}_{ni}\bar{w}_i\right)^{-\theta}}{\left(\bar{P}_n\right)^{-\theta}} \bar{w}_n\bar{L}_n, \tag{2}$$

$$\bar{L}_i = \sum_{n=1}^{N} \frac{exp\left(\beta\bar{v}_i - \bar{m}_{ni}\right)^{1/\nu}}{\sum_{h=1}^{N} exp\left(\beta\bar{v}_h - \bar{m}_{nh}\right)^{1/\nu}} \bar{L}_n, \tag{3}$$

$$\bar{v}_i = log\left(\bar{w}_i/\bar{P}_i\right) + \nu log\left(\sum_{n=1}^{N} exp\left(\beta\bar{v}_n - \bar{m}_{in}\right)^{1/\nu}\right). \tag{4}$$

Following Kleinman, Liu, and Redding (2021), we simplify these equilibrium conditions using the following change of variables:

$$\tilde{T}_{in} \equiv \bar{A}_n \left(\bar{\kappa}_{in}\right)^{-\theta}, \quad \tilde{m}_{in} \equiv exp\left(\bar{m}_{in}\right)^{-1/\nu},$$
$$\phi_i = \sum_{n=1}^{N} exp\left(\beta\bar{v}_n - \bar{m}_{in}\right)^{1/\nu},$$

to obtain a system of equations at the steady state in terms of the variables $\{\bar{P}_i, \bar{w}_i, \bar{L}_i, \phi_i\}$:

$$\left(\bar{P}_i\right)^{-\theta} = \sum_{n=1}^{N} \tilde{T}_{in} \left(\bar{w}_n\right)^{-\theta}, \tag{5}$$

$$\bar{L}_i\left(\bar{w}_i\right)^{1+\theta}=\sum_{n=1}^{N}\tilde{T}_{ni}\bar{w}_n\left(\bar{P}_n\right)^{\theta}\bar{L}_n, \tag{6}$$

$$\bar{L}_i\left(\bar{w}_i/\bar{P}_i\right)^{-\beta/\nu}\phi_i^{-\beta}=\sum_{n=1}^{N}\tilde{m}_{ni}\phi_n^{-1}\bar{L}_n, \tag{7}$$

$$\phi_i=\sum_{n=1}^{N}\tilde{m}_{in}\left(\bar{w}_n/\bar{P}_n\right)^{\beta/\nu}\phi_n^{\beta}, \tag{8}$$

where to derive the last two equilibrium conditions we use the definition of ϕ_i and note that $exp\left(\frac{\beta}{\nu}\bar{v}_i\right)=\left(\bar{w}_i/\bar{P}_i\right)^{\beta/\nu}\left(\sum_{n=1}^{N}\tilde{m}_{in}exp\left(\frac{\beta}{\nu}\bar{v}_n\right)\right)^{\beta}$. It follows that $exp\left(\frac{\beta}{\nu}\bar{v}_i\right)=\left(\bar{w}_i/\bar{P}_i\right)^{\beta/\nu}\phi_i^{\beta}$. Combining this last expression with the definition of $\tilde{m}_{in}$, we can write $exp\left(\frac{\beta}{\nu}\bar{v}_i\right)=\left(\bar{w}_i/\bar{P}_i\right)^{\beta/\nu}\left(\sum_{n=1}^{N}\tilde{m}_{in}exp\left(\frac{\beta}{\nu}\bar{v}_n\right)\right)^{\beta}$ as (8). As in Kleinman, Liu, and Redding (2021) we can write the matrix Λ and Γ representing the exponents of $\{\bar{P}_i,\bar{w}_i,\bar{L}_i,\phi_i\}$ on the left-hand side and right-hand side of the system of equations given by

$$\Lambda=\begin{bmatrix}-\theta & 0 & 0 & 0\\ 0 & 1+\theta & 1 & 0\\ \beta/\nu & -\beta/\nu & 1 & -\beta\\ 0 & 0 & 0 & 1\end{bmatrix},\quad \Gamma=\begin{bmatrix}0 & -\theta & 0 & 0\\ \theta & 1 & 1 & 0\\ 0 & 0 & 1 & -1\\ -\beta/\nu & \beta/\nu & 0 & \beta\end{bmatrix}.$$

Kleinman, Liu, and Redding (2021) follow the arguments in Allen, Arkolakis, and Li (2020) and define the matrix $A=\Gamma\Lambda^{-1}$. They show that if the spectral radius of A is equal to one ($\rho\left(A\right)=1$) and if A is invertible, then the solution must be unique up-to-scale. Note that the matrix Λ and Γ are identical to the ones in Kleinman, Liu, and Redding (2021) in the case of $\mu=1$ in their model (no capital). Given this, we simply show that the largest eigenvalue of A is one and that A is invertible. First note that A is given by

$$A=\frac{1}{\beta+\nu\left(1+\theta\right)}\begin{bmatrix}\beta & -\theta\nu & \theta\nu & \beta\theta\nu\\ -\nu\left(1+\theta\right) & \beta+\nu & \theta\nu & \beta\theta\nu\\ \left(1+\theta\right)\beta/\theta & \beta & \nu\left(1+\theta\right) & -\left(1-\beta\right)\nu\left(1+\theta\right)-\beta\\ \left(1+\theta\right)\beta/\theta & \beta & -\beta & \beta\nu\left(1+\theta\right)\end{bmatrix}.$$

Denote each eigenvalue of A by x_i. Note that A has two eigenvalues equal to 1 and the other two eigenvalues are the solution to the following quadratic equation:

$$\left(\beta+\nu(1+\theta)\right)x^2+\nu(\theta(1-\beta)-\beta)x-\beta(1+\theta\nu)=0,$$

or

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ \frac{-b+\sqrt{b^2-4ac}}{2a} \\ \frac{-b-\sqrt{b^2-4ac}}{2a} \end{bmatrix},$$

where $a = (\beta + \nu(1+\theta))$, $b = \nu(\theta(1-\beta) - \beta)$, and $c = -\beta(1+\theta\nu)$. Then in order for the spectral radius of A to be 1, it has to be that $|x_3|$ and $|x_4|<1$. For this to be the case, we need to show that $|-b \pm \sqrt{b^2-4ac}| < 2a$. There are different cases to consider. First note that $b^2 - 4ac > 0$. Now we consider each possible case in turn. If $-b + \sqrt{b^2-4ac} > 0$, then we need to show that $-b+\sqrt{b^2-4ac} < 2a \Rightarrow 0 < (2a+b)^{\mathbf{2}} - (b^{\mathbf{2}} - 4ac)$. Note that $a+b+c = \nu(1+2\theta)(1-\beta) > 0$ and that $(2a+b)^2 - b^2 + 4ac = 4a^2 + 4ab + 4ac = 4a\,(a+b+c) > 0$. Now if $-b+\sqrt{b^2-4ac} < 0$, then we need to show that $b - \sqrt{b^2-4ac} < 2a \Rightarrow 0 < 2a - b$, but note that $2a - b = 2\beta + 2\nu + \theta\nu + \beta\nu + \theta\beta\nu > 0$. Now $-b - \sqrt{b^2-4ac} > 0$ is not possible. To see this, notice that if $b > 0$ then $-b - \sqrt{b^2-4ac} < 0$ since $\sqrt{b^2-4ac} > 0$. If $b < 0$ for $-b - \sqrt{b^2-4ac} > 0$ we need that $-b > \sqrt{b^2-4ac} \Rightarrow 4ac > 0$, which is not possible since we have $a > 0$, $c < 0$. Hence, it has to be that $-b - \sqrt{b^2-4ac} < 0$. Finally, if $-b - \sqrt{b^2-4ac} < 0$, then we need to show that $b + \sqrt{b^2-4ac} < 2a \Rightarrow 0 < (2a-b)^{\mathbf{2}} - (b^{\mathbf{2}} - 4ac)$, but note that since $a - b + c = \nu(\beta+1) > 0$, then $(2a-b)^2 - b^2 + 4ac = 4a\,(a-b+c) > 0$. As a result, the spectral radius of A is equal to 1, and the steady-state solution must be unique up-to-scale. Following Kleinman, Liu, and Redding (2021), we normalize the total population size, $\sum_{i=1}^{N} L_{i,t} = \bar{L}$ and income, $\sum_{i=1}^{N} w_{i,t}L_{i,t} = \bar{w}\bar{L}$, as in Alvarez and Lucas (2007).