Decomposing the China Shock: Direct and Upstream Effects in the United States and Germany[1]

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Abstract: This paper analyzes and contrasts the impact of increased global trade with China on the US and Germany during the "China shock" period from 2000 to 2014. We introduce novel decompositions of overall output and labor market effects into direct effects and indirect effects operating upstream from focal industries, while further distinguishing between domestic and international channels. To construct counterfactuals in which Chinese trade flows remain at their 2000 levels, we employ a computable general equilibrium (CGE) model. We find that in both the US and Germany, upstream effects raise output and more than offset the direct effects of increased Chinese trade. Further decomposing upstream effects into domestic and international components, we show that both are quantitatively important in both countries, particularly in manufacturing, with domestic upstream effects playing a central role for service industries. Labor demand responses are highly heterogeneous across worker types: male manufacturing workers experience disproportionately negative effects in the US, while comparable workers see gains in Germany. At the same time, upstream linkages generate absolute increases in labor demand for service workers in both countries.

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1. Introduction

The integration of China and other middle- and lower-income countries into the global economy had profound effects on advanced economies in the early 21st century. This is most prominently illustrated by the United States, where a large literature, following the seminal contribution of Autor et al. (2013), has documented substantial negative impacts of increased imports on manufacturing workers and on regional labor markets heavily exposed to Chinese competition.[3] While the empirical literature has primarily focused on the direct effects of trade shocks, it has yet to fully explore the indirect effects transmitted through domestic and international upstream linkages.

In this paper, we examine the direct *and* indirect effects of China's expansion of imports and exports, focusing on the contrasting experiences of the United States and Germany between 2000 and 2014, two economies that responded very differently to China's rise (see, e.g., Dauth et al. (2014)). Using a computable general equilibrium (CGE) model adapted from Caliendo and Parro (2015) and Caliendo et al. (2019), we construct counterfactual scenarios in which trade with China remained at its 2000 level. Within this framework, we develop a novel decomposition of the overall impact of increased Chinese trade on output and labor market outcomes along three key dimensions: (1) indirect (i.e., upstream) vs. direct supply chain effects, (2) effects from final vs. intermediate goods, and (3) international vs. domestic shifts in production.

We define direct effects as the combined changes in production within industries that experience altered trade flows, encompassing both increased import competition and expanded

[3] See for instance Autor et al. (2014), Acemoglu et al. (2016), Autor et al. (2020) and Autor et al. (2021) for related works by the same authors (with additional co-authors). For other works studying the US case, see Pierce and Schott (2016), Caliendo et al. (2019), Borusyak and Jaravel (2021), Feenstra and Sasahara (2018) and Feenstra et al. (2019), among others. Dauth et al. (2014), Dauth et al. (2017), and Dauth et al. (2021) cover the effects of opening up to the East on German labor markets.

export opportunities. Because our framework captures the net impact of all trade changes with China simultaneously, these two channels are jointly reflected in our trade effects. Indirect effects, on the other hand, arise from induced changes upstream in the production network, both domestically and internationally, as in Antràs et al. (2012). For example, increased German automobile exports to China directly affect the German automobile industry and indirectly boost production in upstream sectors, such as the German machine tools industry, through greater domestic demand. Moreover, when third countries increase exports to China using German machine tools, these international upstream effects feed back into German production. In fact, as we show below, for German machine tools, over two-thirds of upstream production effects stem from third-country trade with China. Analyses that focus solely on imports overlook these upstream effects, and even studies using general equilibrium models often restrict their attention to domestic linkages, missing the international dimension of upstream effects that our framework captures.

We use data from the World Input-Output Database (WIOD; Timmer et al. (2015)) to construct counterfactual scenarios in which Chinese productivity and consumption are held constant at their 2000 levels. We adapt the computable general equilibrium framework of Caliendo et al. (2019), expanding sectoral coverage from 22 to 55 and incorporating the full global input-output network. To maintain tractability, we abstract from within-country regional variation and the dynamic migration decisions central to their framework, focusing instead on international production linkages. We solve the model using "dynamic hat algebra", expressing all variables in time differences relative to a baseline, allowing us to compute counterfactual equilibria without estimating levels of underlying fundamentals such as productivity or trade costs. We utilize a leave-one-out type identification strategy to generate counterfactual productivity and consumption

in the absence of the China shock. We refer to differences between actual and counterfactual equilibrium values as the effect of China's global integration. This framework accounts for the full general equilibrium response across multiple channels: direct import competition and export expansion, input-output linkages, price and cost changes, and the reallocation of factors across industries. Our main contributions relative to existing work are threefold: we develop novel decompositions separating direct from upstream effects and domestic from international channels; we explicitly model the full matrix of international input-output linkages rather than focusing primarily on domestic production networks; and we provide cross-country comparisons that reveal how differences in global value chain integration shape the labor market consequences of trade shocks, highlighting in particular the underappreciated role of service industries, which we show are affected by trade primarily through upstream linkages, and have largely been ignored in the existing literature.

We find that increased integration with China from 2000 to 2014 led to a nearly 3% increase in aggregate output in Germany, while the overall effect in the United States was only marginally positive.[4] In both countries, a large share of the gains is attributed to upstream effects. Consistent with earlier findings (e.g., Autor et al. (2013); Acemoglu et al. (2016)), we demonstrate that the direct impact of trade with China reduced manufacturing output in the U.S., concentrating losses that disproportionately affected manufacturing-intensive communities in the Southeast and Midwest. However, these negative direct effects were offset by indirect upstream effects, driven by global changes in production that increased U.S. and foreign exports to, and imports from,

[4] In the model introduced in Section 2, as in Caliendo et al. and similar structural gravity trade models, productivity growth in China is isomorphic to a decline in origin-specific trade costs from China, in terms of its effects on U.S. outcomes. Likewise, growth in Chinese consumption is isomorphic to a reduction in destination-specific trade costs. Throughout, we refer to both changes collectively as "increased integration" with China.

China. Thus, while the net impact of China trade on U.S. output over this period was slightly positive, the costs were highly concentrated, reinforcing the conclusions of Autor et al. (2013) that the China Shock produced diffuse benefits but concentrated harms.

In contrast, both the direct and indirect effects of increased trade with China boosted output in Germany. Disaggregating our results reveals striking cross-country differences: while U.S. manufacturing workers experienced loses in demand relative to workers in other sectors, their German counterparts saw relative gains. These sectoral differences in output translated into heterogeneous labor demand effects across worker types, varying by gender and the task content of occupations.

The contrasting outcomes in Germany and the U.S. are partly driven by Germany's stronger export orientation. However, Germany's deeper integration into global production networks also amplifies the indirect effects of trade. These include both domestic upstream effects, captured in single-country input-output analyses, and international upstream effects, which require multi-country data and are often overlooked. We find that these international upstream effects account for 30% of total trade-induced output effects in Germany and 35% in the U.S. While Germany's deeper integration into global supply chains produces larger absolute upstream effects, the international share is somewhat higher for the U.S. because its direct trade effects are smaller, making international upstream channels proportionally more prominent.

Within the manufacturing sector, the role of international linkages is even more pronounced: they account for 65% of all indirect effects in Germany and 49% in the U.S. In contrast, domestic indirect effects are especially important for service industries. While often ignored in trade studies, services contribute significantly to the production of traded goods and experience trade effects primarily through their role as inputs in global value chains (see Breinlich and Magli (2024) on

trade in services and Ariu et al. (2019) on the colocation of tradable goods and services, though neither investigates the upstream dimension as we do here). Indeed, we find that the aggregate impact of trade is shared about equally between goods-producing and service industries (for Germany, about 1.5% and 1.3% of total output, respectively; for the US, 0.3% and 0.4%). Because services comprise a larger share of overall output, the proportional impact is smaller, but not negligible (for Germany, about 7.5% and 1.8% of sectoral output, respectively; for the US, 3% and 0.5%).[5] These findings challenge the conventional view that trade shocks are confined to manufacturing. In aggregate, the China shock generated output gains in services of roughly comparable magnitude to those in goods-producing sectors—approximately 1.3% of total output in Germany and 0.4% in the United States—channeled almost entirely through upstream production linkages rather than direct trade. Service industries are critical inputs throughout global value chains, yet are rarely considered "exposed" to trade. Our decomposition highlights the broad reach of globalization: while the direct effects of trade are concentrated in goods-producing sectors, indirect production linkages transmit trade shocks across the entire economy, demonstrating that the labor market consequences of globalization extend far beyond the factory floor.

Because trade affects industries differently, its impact on workers varies both across and within countries. In the United States and Germany, the structure of trade with China resulted in divergent outcomes for different types of workers. In the U.S., trade has disproportionately harmed male manufacturing workers, a pattern well-documented by Autor et al. (2014), Pierce and Schott (2016), Caliendo et al. (2019), and Borusyak and Jaravel (2021), among others. In contrast, similar

[5] The role of services in trade may not be immediately apparent. Still, it becomes clearer when one considers the broad range of 'soft' inputs—such as transportation, administrative support, legal services, marketing, and sales—that are integral to modern production. These service inputs form essential links in global value chains, shaping how trade shocks ripple through the broader economy.

groups in Germany experienced increases in labor demand, both in absolute and relative terms, due to growing trade with China. This is due to stronger direct and indirect export growth in Germany, driven by Chinese economic growth. Meanwhile, workers in service sectors—who are typically less directly exposed to globalization—experienced the opposite pattern relative to manufacturing workers: *relative* gains in labor demand in the U.S., and *relative* losses in Germany. These cross-country differences reflect the nature of trade integration and the mechanisms through which trade affects the labor market.[6]

The asymmetry between direct and indirect effects has implications beyond measurement. Direct effects—such as job losses from import competition or gains from export growth—are immediate, concentrated, and readily attributable to trade. Workers and communities experiencing these shocks can identify their cause. Indirect effects, by contrast, are diffuse and harder to trace: a machinist in Ohio whose job depends on supplying parts to a German automaker exporting to China is unlikely to connect her employment to Chinese demand. This asymmetry in salience may help explain why public attitudes toward globalization have soured even when aggregate outcomes are positive, a pattern documented in the growing literature linking trade exposure to political outcomes (e.g., Autor et al. (2020); Colantone and Stanig (2018a), (2018b)). Our findings suggest that the benefits of trade integration are more widely shared than commonly perceived, but that these benefits flow through channels that are largely invisible to those who receive them.[7]

[6] Service workers experience positive effects from trade in absolute terms in both countries, primarily through supply chain (indirect) channels. However, in Germany, manufacturing workers benefit substantially from large positive direct effects of trade, whereas in the U.S., these direct effects are negative. As a result, service workers see relative gains compared to manufacturing workers in the U.S., but relative losses in Germany.

[7] See Autor et al. (2020), Grossman and Helpman (2021), di Tella and Rodrik (2020), and Feigenbaum and Hall (2015) for recent evidence on the effects of globalization on US political outcomes, and Dippel et al. (2018), Colantone and Stanig (2018a), Colantone and Stanig (2018b), Malgouyres (2017), Aksoy et al. (2018) and Gennaioli and Tabellini (2019) for recent evidence from across Europe.

Through input-output analysis and a novel decomposition of trade effects, along direct versus indirect channels, final versus intermediate goods, and domestic versus international production, we reinforce prior findings (e.g., Autor et al. (2013); Dauth et al. (2014)) that demonstrate significant cross-country variation in the impact of globalization. At the same time, we offer new evidence on how these effects propagate through supply chains and manifest in labor markets.

Our paper provides essential context on production networks to the growing literature on the labor market effects of trade, including work by Autor et al. (2013), Pierce and Schott (2016), Dix-Carneiro and Kovak (2017), Caliendo et al. (2019), and others. We also build on studies that incorporate export growth and input-output linkages, such as Dauth et al. (2014), Acemoglu et al. (2016), Wang et al. (2018), Feenstra and Sasahara (2018), and Feenstra et al. (2019), by incorporating international input-output effects and providing detailed decompositions of trade's impact on both production and labor outcomes. Importantly, our cross-country approach highlights differences in the magnitude and distribution of these effects across national contexts.[8]

We add to the literature by highlighting the importance of supply chain effects and the distinction between final and intermediate goods - dimensions that are often overlooked, with some notable exceptions (e.g., Wang et al. (2018); Feenstra and Sasahara (2018)). For example, in the U.S., we find that most of the impact of trade with China arises not from direct import competition but from upstream production network effects linked to international trade. These indirect effects

[8] Our approach is complementary to but differs from Aghion et al. (2024), who decompose the China shock into output and input supply components at the firm level. While their framework captures direct and downstream effects, ours focuses on upstream production linkages across countries at the industry level. Other recent works relating trade and labor market outcomes include Autor et al. (2014), Autor et al. (2021), Dix-Carneiro and Kovak (2019), Pavcnik (2017), Kondo (2018), Galle et al. (2022), Burstein et al. (2020), Burstein and Vogel (2017), Adao et al. (2019), Adao et al. (2020), Helm (2020), Keller and Utar (2016), Borrs and Knauth (2021), Lin et al. (2018), Borusyak and Jaravel (2021), and Costa et al. (2019).

fully offset the negative direct shocks of Chinese import penetration. In Germany, by contrast, they amplify already-positive direct effects.

2. Methodology

We begin by introducing the paper's core notation, including an "upstreamness" measure adapted from Antràs et al. (2012) that captures an industry's or country's position along the global supply chain. Next, we outline the counterfactual scenarios in which trade with China is fixed at its 2000 level and describe how we compute the resulting output changes by comparing actual outcomes to their counterfactual analogues. Building on this framework, we introduce a set of novel decompositions that attribute output changes to direct versus upstream effects, differentiate between final and intermediate goods, and isolate the roles of domestic versus foreign downstream production. We outline the main ideas in the text and provide detailed discussions of each item in the Appendix.

2.1 Setup

Total production in year *t*, country *i*, and industry *r* is given by:

$$(1) \qquad y_t^{(i,r)} = \sum_j d_t^{(i,r),j} + \sum_{j,s} x_t^{(i,r),(j,s)},$$

where $d_t^{(i,r),j}$ are final goods produced in year *t*, country *i*, industry *r,* bought by consumers in country *j*. Moreover, $x_t^{(i,r),(j,s)}$ are intermediate goods produced in year *t*, country *i*, industry *r,* which are used as inputs by industry *s* in country *j*. Define the ratio $a_t^{(i,r),(j,s)} = \frac{x_t^{(i,r),(j,s)}}{y_t^{(j,s)}}$, which measures inputs from country *i*, industry *r* used to produce one unit of output in country *j,* industry *s*, i.e., the amount of input from one industry required to produce a single unit of output in another industry. These measures can be constructed annually for the period 2000–2014 using global input-output trade data, such as that provided by the World Input-Output Database (see next section).

By expressing the relevant terms in matrix form, and assuming standard regularity conditions (see e.g. Antràs and Chor (2022)), the relationship among them can be restated as follows (see Appendix Section A.1 for details):

$$(2) \qquad \boldsymbol{Y_t} = (\boldsymbol{I} - \boldsymbol{A_t})^{-1}\boldsymbol{D_t} = \sum_{n=0}^{\infty} \boldsymbol{A_t^n D_t} = \boldsymbol{D_t} + \boldsymbol{A_t D_t} + \boldsymbol{A_t^2 D_t} + \boldsymbol{A_t^3 D_t} + \cdots$$

where A_t is the matrix of input-output coefficients $a_t^{(i,r),(j,s)}$. The first equality in equation (2) describes country-industry production flows using the standard Leontief Matrix, extended to incorporate international linkages. It expresses total production (stacked in the vector Y_t) as a linear function of final demand $\boldsymbol{D_t}$ and the Leontief inverse $(\mathbf{I} - \mathbf{A}_\mathrm{t})^{-1}$, which captures the total output required at each stage of production to deliver one unit of final output in each industry. The second equality breaks this total production down into its constituent production stages. Specifically, it shows that output in any industry, $y_t^{i,r}$, consists of final goods produced directly for consumption, intermediates from that industry used to make final goods, intermediates used to produce other intermediates that eventually become final goods, and so on.

2.2 Counterfactual trade flows and the output effects of trade using a CGE model

We define the "output effect of trade" as the difference between observed and counterfactual production for each country-industry pair, $y_t^{(i,r)}$-$\tilde{y}_t^{(i,r)}$, where the counterfactual (denoted by "~") reflects a scenario without post-2000 changes in trade flows with China. This effect can be decomposed into two components: a direct effect, capturing the immediate impact of trade changes on production, and an indirect (or "upstream") effect, reflecting changes in the production of inputs used to produce traded goods and services, including the higher-order inputs used to produce those inputs, and so on throughout the supply chain.

2.2.1 Constructing Counterfactuals

To construct counterfactuals, we adapt the framework of Caliendo et al. (2019) by developing a multi-country, multi-sector computable general equilibrium (CGE) model that captures the full network effects of China's trade integration on global production and labor markets. This approach builds on a growing literature that uses quantitative trade models for counterfactual analysis, including the foundational work of Caliendo and Parro (2015) on the trade and welfare effects of NAFTA. The model is specifically designed to disentangle trade effects along key dimensions: direct versus indirect (upstream) channels, final versus intermediate goods, and domestic versus international production linkages.

We modify the original framework in several important ways to better suit our research question. First, we eliminate the regional (cross-state) structure within the United States, while expanding sectoral detail from 22 to 55 sectors. Second, we abstract from interregional labor mobility and instead focus on sectoral reallocation within countries. Most critically, we incorporate international input-output linkages to capture global value chain dynamics.

The most substantial simplification involves removing the subnational regional structure that is central to Caliendo et al.'s model. While their model includes N-1 countries with one region and one country with R regions, creating (N-1+R)×J distinct labor markets, we treat each country as a single unit, reducing the dimensionality from (N-1+R)×J to N×J country-sector labor markets. This change has broad implications throughout the model. Variables defined at the location-sector level *(n,r,j)* are now defined at the country-sector level *(n,j)*: regional productivity terms A_t^{nrj} become national-sectoral terms A_t^{nj}; regional factor endowments H^{nrj} are replaced by country-level endowments H^{nj}, and interregional trade costs $\kappa_t^{nrj,irk}$ are collapsed into international trade

costs $\kappa_t^{nj,ij}$. Similarly, regional wage variation w_t^{nrj} is replaced by sectoral wage variation within countries w_t^{nj}.

A second major simplification involves eliminating the complex migration dynamics that are central to the original framework. In Caliendo et al. (2019), forward-looking households make dynamic discrete-choice migration decisions across labor markets. We set international migration costs to infinity and focus on sectoral reallocation within countries. This allows us to eliminate the dynamic programming problem associated with migration decisions, the system of difference equations governing the evolution of labor distribution, and the associated migration cost parameters and value functions for location utility.

While the above framework substantially reduces model complexity, we introduce two key extensions. First, we expand the sectoral dimension to capture heterogeneous exposure to China across industries and to model input-output linkages in global value chains more accurately. Specifically, we increase the number of sectors from 22 to 55, following the WIOD classification. This richer sectoral structure allows us to represent inter-industry relationships more precisely. Our second major extension involves explicitly modelling global input-output networks in which intermediate goods flow across borders at each production stage. While the original framework of Caliendo et al. (2019) includes international trade in intermediates, its emphasis lies primarily on the transmission of shocks through domestic production networks. We extend this by treating international flows symmetrically and fully incorporating the global production structure. Implementing this requires constructing the full 2035×2035 matrix of international input-output coefficients from WIOD data. Appendix A.2 provides a detailed description of these model extensions.

Our main object of analysis is the production impact of resetting Chinese productivity and trade costs to their levels in the year 2000. We begin by calibrating the model to the observed global economy in 2000, recovering a full set of structural parameters: productivities, trade costs, and preferences. We then construct a counterfactual scenario in which China's productivity and consumption remain fixed at 2000 levels. The model solves for the resulting counterfactual equilibrium by determining prices and allocations that satisfy four key conditions: global goods-market clearing, country-level factor-market clearing, trade-flow consistency with imposed constraints, and zero-profit conditions across sectors. The difference between observed and counterfactual production, $\boldsymbol{Y_t - \widetilde{Y}_t}$, defines our measure of the output effect of China's trade integration.

A key advantage of the CGE framework we employ is that it can be solved using the "dynamic hat algebra" approach developed by Caliendo et al. (2019), building on the "exact hat algebra" methodology introduced by Dekle et al. (2007) and extended by Arkolakis et al. (2012). This method expresses all equilibrium conditions in terms of proportional changes (ratios of counterfactual to observed values) rather than levels. By doing so, we can compute counterfactual equilibria without estimating the levels of underlying fundamentals such as productivities, trade costs, or preference parameters.

To implement this approach, we require two categories of inputs: (i) observable data that map directly into the model's equilibrium conditions, and (ii) a small set of structural elasticity parameters. The observable data comes primarily from the World Input-Output Database (WIOD, 2016 release). These include bilateral trade flows for both final and intermediate goods, disaggregated by sector and country pair; gross output by country and sector; input-output coefficients capturing the share of each sector's output used as intermediate inputs by every other

sector (both domestically and internationally); value-added shares by country and sector; and employment by country and sector. These data directly determine the model's equilibrium shares (trade shares, expenditure shares, and factor income shares), which serve as sufficient statistics for the underlying fundamentals given our functional form assumptions.

The key structural parameters required are sector-specific trade elasticities, θ_j, which govern the responsiveness of trade flows to changes in relative costs. We draw our trade elasticity estimates from the existing literature (specifically, adapted from Fontagné et al. (2022)), allowing full coverage of a larger set of sectors. These elasticities vary substantially across sectors, reflecting differences in product differentiation and the intensity of competition. Values range from approximately 2 for highly differentiated goods to over 10 for more homogeneous commodities, consistent with estimates in Caliendo and Parro (2015), Simonovska and Waugh (2014), and the meta-analysis in Head and Mayer (2014).

Our counterfactual exercise identifies the effect of China's trade integration by comparing two scenarios. In the baseline scenario, fundamentals (productivity and trade costs) evolve as observed in the data from 2000 to 2014. In the counterfactual scenario, we hold Chinese productivity and consumption fixed at their 2000 levels while allowing all other countries' fundamentals to evolve as observed. Our identification strategy employs a leave-one-out regression approach to estimate trade flow responses to foreign supply and demand shocks. From this, we derive sector-specific elasticity estimates, which we then utilize to predict counterfactual trade flows under the scenario where China's supply and demand growth is shut down, holding third-country fundamentals at their observed values. The difference between these two equilibrium paths identifies the causal effect of China's integration on production and employment outcomes. Formally, we solve for counterfactual prices and quantities that satisfy goods-market clearing in

each country-sector, factor-market clearing in each country, balanced trade (subject to observed deficits), and zero-profit conditions for firms.

This approach captures the full general equilibrium consequences of the China shock. It accounts for direct effects, through changes in import competition and export opportunities, as well as indirect effects, through shifts in intermediate input costs and availability. Because these effects reflect both import and exports channels jointly, a positive direct effect for a given industry indicates that export gains outweigh import losses, while a negative direct effect indicates the reverse. It also incorporates price adjustments that equilibrate markets and factor reallocation across industries within countries. Compared to reduced-form methods, the CGE framework offers several advantages: rather than focusing solely on import penetration or export growth, it captures the global network effects of trade integration, including how China's trade with third countries propagates through international supply chains to affect domestic production. This framework provides detailed predictions of changes in production and trade flows due to increased trade integration, which we further decompose in the next section to allocate output changes more granularly.

2.3 Decomposing Output Effects

Figure 1: Decomposing the Trade Effect

We extend the existing literature (as reviewed in Antràs and Chor (2022)) by decomposing the output effects described above into direct and supply chain (or "upstream") components. Leveraging the stage-by-stage construction of output introduced earlier, we break down the total effects into contributions from changes in trade flows of both final and intermediate goods. This decomposition, visualized in Figure 1, highlights how trade integration affects production not only through immediate channels but also through cascading effects along global value chains:

Direct Effects of Final Outputs: $\boldsymbol{D_t - \widetilde{D}_t}$

Upstream Effects of Final Outputs: $\sum_{n=1}^{\infty} \frac{\mathbf{1}}{\mathbf{2}} \left(\boldsymbol{A_t^n + \widetilde{A}_t^n}\right)\left(\boldsymbol{D_t - \widetilde{D}_t}\right)$

Direct Effects of Intermediate Outputs: $\sum_{n=0}^{\infty} \frac{\mathbf{1}}{\mathbf{2}} \left(\boldsymbol{A_t - \widetilde{A}_t}\right)\left(\boldsymbol{A_t^n + \widetilde{A}_t^n}\right)\boldsymbol{\bar{D}_t}$

Upstream Effects of Intermediate Outputs: $\sum_{n=0}^{\infty} \frac{\mathbf{1}}{\mathbf{2}} \left(\boldsymbol{A_t + \widetilde{A}_t}\right)\left(\boldsymbol{A_t^n - \widetilde{A}_t^n}\right)\boldsymbol{\bar{D}_t}$

This decomposition not only quantifies the total effect of trade changes but also reveals where within the production structure those effects originate. Specifically, it breaks down the total output effect, $\mathbf{Y}_t - \widetilde{\mathbf{Y}}_t$, into four components, where $\mathbf{D_t}, \widetilde{\mathbf{D}}_t$, $\mathbf{A_t}$ and $\widetilde{\mathbf{A}}_t$ are as defined as above, and $\bar{\mathbf{D}}_t$ is the average of the observed and counterfactual final goods vectors[9]. The underlying intuition for these components is straightforward in most cases. The direct effect of final goods trade is simply the difference in final goods consumption between the observed and counterfactual worlds. The direct effect of intermediate goods reflects the difference, at each production stage, in the intermediates produced to satisfy observed versus counterfactual demand. The upstream effect of final goods captures the cumulative intermediates required to produce the observed final goods vector, relative to those required under the counterfactual. The upstream effect of intermediate goods is more complex: it reflects the full recursive chain of inputs required to support the observed

[9] $\bar{\mathbf{D}}_t$ can alternatively be set equal to either the respective observed or counterfactual vectors, with offsetting bases for different effects such that the sum is equal to the total change in output. However, results are largely unaffected. Similar results hold when substituting either $\mathbf{A_t}$ or $\widetilde{\mathbf{A}}_t$ alone for the stage mean coefficient matrix $\frac{1}{2}(\mathbf{A}_t^n + \widetilde{\mathbf{A}}_t^n)$. Conceptually, when calculating effects higher in the supply chain, results would change depending on whether lower-stage output is as observed or as in the counterfactual. To be parsimonious, we use the mean of the observed and counterfactual values. Results are not substantially different when either the observed or counterfactual is taken as the 'base'.

use of intermediates, rather than the counterfactual, isolating changes driven solely by intermediate trade flows[10].

Importantly, increased exports in a given industry do not only raise production and labor demand within that industry (the direct effect); they also generate ripple effects upstream, raising demand for inputs from supplier industries, and further upstream from their suppliers, and so on along the production network. This decomposition thus sheds light on the mechanisms through which trade integration reshapes production. As we show below, for the countries in our sample, the upstream effects of trade integration generally outweigh the direct effects, highlighting the importance of accounting for production linkages when assessing the impact of trade shocks.

We extend the decomposition further by distinguishing between production for domestic and international markets, separately for both intermediate and final goods. For the direct effect of final goods trade, we calculate two components: the difference between observed and counterfactual exports (capturing production for international markets), and the difference between observed and counterfactual domestic consumption (capturing production for home markets).

To decompose the upstream effects of final goods and the direct and upstream effects of intermediate goods, we construct two submatrices from the factual input-output matrix A: a block-diagonal matrix $A_{i,i}$ containing domestic input-output coefficients, and its complement $A_{-(i,i)}$, containing all cross-border (international) coefficients. Corresponding block diagonal matrix matrix $\tilde{A}_{(i,i)}$ and complement $\tilde{A}_{-(i,i)}$ are built from the counterfactual input-output matrix $\tilde{A}$, which are in turn utilized along with $A_{i,i}$ and $A_{-(i,i)}$ to construct the stage mean coefficient matrices $\bar{A}_{(\boldsymbol{i},\boldsymbol{i})}$ and $\bar{A}_{-(\boldsymbol{i},\boldsymbol{i})}$. We then replace the relevant leading matrices in the decomposition expressions above with their domestic or international counterparts. This allows us to trace how production is

[10] For further details and representations in matrix form, see appendix section A.3.

allocated, either to domestic consumption or to international markets, at each stage of the production process. In other words, we compute distinct measures of domestic and international production for each of the four output effects introduced above[11]:

	Domestic	*International*
Direct Effects of Final Outputs:	$\boldsymbol{D}_{(i,i)} - \widetilde{\boldsymbol{D}}_{(i,i)}$	$\boldsymbol{D}_{-(i,i)} - \widetilde{\boldsymbol{D}}_{-(i,i)}$
Upstream Effects of Final Outputs:	$\sum_{n=0}^{\infty} \overline{\boldsymbol{A}}^{\boldsymbol{n}}_{(i,i)}(\boldsymbol{D} - \widetilde{\boldsymbol{D}})$	$\sum_{n=0}^{\infty} \overline{\boldsymbol{A}}^{\boldsymbol{n}}_{-(i,i)}(\boldsymbol{D} - \widetilde{\boldsymbol{D}})$
Direct Effects of Intermediate Outputs:	$\sum_{n=0}^{\infty}\left(\boldsymbol{A}_{(i,i)} - \widetilde{\boldsymbol{A}}_{(i,i)}\right)\overline{\boldsymbol{A}}^{\boldsymbol{n}}\overline{\boldsymbol{D}}$	$\sum_{n=0}^{\infty}\left(\boldsymbol{A}_{-(i,i)} - \widetilde{\boldsymbol{A}}_{-(i,i)}\right)\overline{\boldsymbol{A}}^{\boldsymbol{n}}\overline{\boldsymbol{D}}$
Upstream Effects of Intermediate Outputs:	$\sum_{n=0}^{\infty} \overline{\boldsymbol{A}}_{(i,i)}\left(\boldsymbol{A}^{\boldsymbol{n}} - \widetilde{\boldsymbol{A}}^{n}\right)\overline{\boldsymbol{D}}$	$\sum_{n=0}^{\infty} \overline{\boldsymbol{A}}_{-(i,i)}\left(\boldsymbol{A}^{\boldsymbol{n}} - \widetilde{\boldsymbol{A}}^{n}\right)\overline{\boldsymbol{D}}$

The sum of all eight components described above exactly equals the total output effect, $\mathbf{Y}_t - \widetilde{\mathbf{Y}}_t$. As we show later (Figure 5), it is crucial to distinguish between domestic and export production when evaluating the impact of trade shocks. While upstream effects are often presumed to operate entirely within national borders, our decomposition reveals that this assumption is misleading. In an input-output setting, cross-border linkages matter, even at higher production stages, underscoring the importance of accounting for international propagation in global value chains.[12]

Following Johnson and Noguera (2012), we assess the impact of trade on value-added rather than gross output by pre-multiplying our output changes by a vector of value-added shares in gross production. Specifically, we use the average value-added share observed over the full sample period, calculated at the country-industry level. The value-added effect of trade is then given by:

[11] Matrix representations are provided in appendix section A.3.

[12] Consider for instance increased German intermediate exports to British manufacturers who sell to China, or US exports to Chinese manufacturers who then assemble and ship final products back to the United States, etc.

$$\Delta \mathbf{V} = \overline{\mathbf{V}/\mathbf{Y}}\,(\mathbf{I} - \mathbf{A}_t)^{-1}\mathbf{D}_t - \overline{\mathbf{V}/\mathbf{Y}}\left(\mathbf{I} - \widetilde{\mathbf{A}}_t\right)^{-1}\widetilde{\mathbf{D}}_t \quad (3)$$

where $\overline{\mathbf{V}/\mathbf{Y}}$ denotes the vector of average value-added shares. All other output effect measures discussed above can be analogously defined in value-added terms. Focusing on value-added rather than gross output is essential when examining changes in labor demands, which we turn to in the next section.

2.4 Trade and the Demand for Labor

We adopt a straightforward procedure to convert changes in output due to changes in trade into changes in demand for different types of labor. Within the CGE framework, labor demand is directly linked to output through market-clearing conditions. Specifically, the change in labor demand due to trade is computed by applying a diagonal matrix of employment shares, $\mathbf{\Lambda}_t = diag\left(\lambda_t^{(i,r)}\right)$, where $\lambda_t^{(i,r)}$ is the labor share of country *i* in industry *r*, to the value-added output changes described earlier:

$$\boldsymbol{L}_t = \boldsymbol{\Lambda}_t \overline{\boldsymbol{V}/\boldsymbol{Y}}\,(\boldsymbol{I} - \boldsymbol{A}_t)^{-1}\boldsymbol{D}_t - \boldsymbol{\Lambda}_t \overline{\boldsymbol{V}/\boldsymbol{Y}}\left(\boldsymbol{I} - \widetilde{\boldsymbol{A}}_t\right)^{-1}\widetilde{\boldsymbol{D}}_t \quad (4)$$

At the industry level, the labor demand effect is $l_t^{i,r} = \lambda_t^{i,r}\Delta v_t^{(i,r)}$. Summing over all industries gives the total change in labor demand for country i:

$$l_t^i = \sum\nolimits_r \lambda_t^{i,r}\Delta v_t^{(i,r)} \quad (5)$$

To assess labor demand changes relative to labor supply, we normalize by total domestic labor input, measured in efficiency units per country and year.

Whereas prior studies have often stopped at aggregate labor demand effects, we extend this analysis by examining how trade affects different types of workers. Building on earlier work (e.g., Katz and Murphy (1992); Wood (1995); Borjas et al. (1997)), we disaggregate labor demand by worker type g (gender, task content of occupation), leveraging variation in industry-level labor

composition and the heterogeneity of trade effects across industries. Specifically, we compute the change in labor demand for worker type g in industry r and country i as:

$$l_{t,g}^{i,r} = s_g^{i,r} l_t^{i,r} \quad \text{and} \quad l_{t,g}^{i} = \sum_r s_g^{i,r} l_t^{i,r}$$

where $s_g^{i,r}$ is the share of efficiency units of worker type g in industry r, measured in the base year (2000). Differences in trade-induced labor demand by type arise due to both the distribution of worker types across industries and the variation in output responses to trade.

These measures allow us to express the change in demand for type g labor as a share of total labor demand in year t. To capture relative demand, we normalize these values and subtract overall labor demand:

$$(6) \qquad RD_{t,g}^{i} = \frac{1}{s_g^i} \sum_r s_g^{i,r} l_t^{i,r} - l_t^i$$

This relative demand measure captures how the demand for labor of type g in country *i* compares to overall labor demand. It is constructed such that $\sum_g s_g^i \cdot rd_{t,g}^i = 0$, which ensures that relative increases in demand for some worker types are offset by decreases for others, facilitating direct comparison across groups.

While this measure highlights relative shifts, it is equally important to account for absolute changes in labor demand. Just as we decomposed output changes into direct and upstream components, we apply a similar decomposition to labor demand, using the change in value-added $\Delta v_t^{(i,r)}$ to trace whether labor demand changes originate directly from trade shocks or indirectly through upstream linkages in the production network. This approach enables us to determine whether the increased demand for a particular worker type stems from trade-induced expansion within their own industry or from shifts further up the value chain, including in foreign industries that rely on inputs from the worker's sector. To our knowledge, this is one of the first attempts to

decompose the labor market effects of trade by both worker type and the channel of effect (direct vs. upstream).

3. Data

3.1 World Input-Output Database (WIOD)

To estimate the output effects of trade, we use the 2016 release of WIOD, which provides annual data from 2000 to 2014 across 56 sectors in 43 countries, plus a "Rest of World" aggregate. We collapse some countries into this aggregate to better align with other data used, resulting in 37 countries plus this aggregate. For each country-sector pair, total output is disaggregated into: (i) final goods delivered to one of the 38 destinations, or (ii) intermediate inputs used in any of the 2,464 country-sector combinations. This results in over 6 million yearly production flows. Value-added is calculated as the difference between gross output and total inputs, expressed as a share of output. We assume value-added shares are constant across usage types (intermediate vs. final). WIOD data is used to assess: (i) the initial industrial structure by country, (ii) trade flow changes driven by China's rise, and (iii) their impact on production and employment.

To enhance sectoral detail for the United States, we draw on the 2012 U.S. Bureau of Economic Analysis (BEA) Input-Output table. This allows us to proportionally disaggregate WIOD flows into 393 U.S. industries, enabling more granular inference. Importantly, our results are robust to using or omitting this refinement.

3.2 CGE Model Inputs

Key structural parameters for the CGE model are also drawn from WIOD. These include bilateral trade flows for both final and intermediate goods (by sector and country), gross output, input-output coefficients, value-added shares, and trade balances. Productivity parameters are calibrated

from gross output, while trade elasticities are taken from the literature, specifically, adapted from the product-level trade elasticities from Fontagné et al. (2022).

3.3 Labor Market Data

For labor market outcomes, we use administrative microdata for Germany and survey data for the U.S., covering 2000–2014.

For Germany, we use the Sample of Integrated Labour Market Biographies (SIAB), a 2% sample of social security records, covering roughly 80% of the workforce. Workers' five-digit WZ industry codes are matched to WIOD's two-digit sectors. Task assignments are based on occupations, using data from Dengler et al. (2014).

For the United States, we use the American Community Survey (approx. 1.5 million households annually) and the 2000 Census. Workers are matched to WIOD sectors using custom concordances, and tasks are assigned following Autor and Dorn (2013). Skill groups are defined analogously: low-skilled (no high school diploma), medium-skilled (high school but no four-year degree), and high-skilled (four-year college degree or more).

4. Changes in Trade, Production, and Labor Market Structure

4.1 Changes in Global Trade Flows

The "China Shock" unfolded in markedly different ways for Germany and the United States. Both countries experienced sharp increases in imports from China, primarily in manufactured goods (see Table 1). From 2000 to 2014, German imports from China rose by 520%, while U.S. imports increased by 407% over the same period. However, the export side tells a different story. In the U.S., export growth to China was just one-third the rate of import growth. In contrast, German exports to China grew even faster than its imports, by a factor of roughly 1.5 (see column Δ, Panel "Total").

In absolute terms, the divergence is equally striking. Between 2000 and 2014, U.S. exports to China increased by $72 billion per year, while German exports rose by $84 billion. Yet the growth in U.S. imports dwarfed that of Germany: U.S. imports from China expanded by $210 billion, compared to $56 billion for Germany.

Table 1: Changes in Imports and Exports From/To China

Beyond aggregate values, Germany and the U.S. also differed in the structure of their trade. As shown in Table A-1, about 43% (4,612/10,750) of Germany's imports from China in 2000 were used as intermediate inputs, compared to just 29% for the U.S. This suggests that Germany was more integrated into global production networks and thus better positioned to benefit from China's growing role in international supply chains. For a highly integrated economy like Germany, increased availability of intermediate inputs from China may have enhanced competitiveness and productivity.

In contrast, the U.S., with a larger domestic market and a more self-contained production system, was arguably less well positioned to benefit from China's integration. Instead, many U.S. producers faced direct competition from Chinese imports, particularly in final goods markets. The U.S. manufacturing base in 2000 was concentrated in industries producing final consumer goods such as automobiles, furniture, textiles, and electronics, which faced direct competition from Chinese exports, rather than in capital goods and intermediate inputs, where Germany specialized.

4.2 Upstreamness and Global Production

One way to assess a country's integration into global value chains is to examine its average position along the supply chain, i.e., how "upstream" or "downstream" its output is. We adopt the upstreamness measure introduced by Antràs et al. (2012) and extend it by decomposing total

production into separate upstreamness measures for domestic, exported, and imported goods. See Appendix Section A.4 for technical details on how these measures are constructed.

Figure 2 presents the average production stage for imports, exports, domestic production, and total production for China, Eastern Europe, the United States, and Germany, along with the evolution of these measures over time. Clear cross-country differences emerge. Chinese production is positioned far upstream: on average, Chinese goods pass through two additional production stages before reaching final consumption. This upstreamness has generally increased over time, save for Chinese exports, which are further downstream, suggesting China's role as a "finishing factory" that assembles upstream imports into final or near-final goods for export.

Figure 2: Upstreamness of Countries' Outputs by Type

In the U.S., imports and exports are moderately upstream, averaging between second- and third-stage inputs by 2014. However, total, and especially domestic, production is much closer to final consumption and shows little change over time. This reflects the service-heavy structure of the U.S. economy, where industries typically require fewer inputs and sell directly to consumers. The trend toward services has muted the effects of global supply chain lengthening on average upstreamness. This does not imply that services are insulated from trade shocks; as we show in Section 5, services experience substantial indirect effects through their role as inputs to traded goods sectors.

Germany, in contrast, occupies a more upstream position than the U.S. across all production flows. German imports are located further up the supply chain (2.45 average production stages in 2000, see Table 2) than both domestic production (1.98) and exports (2.21), a gap that has widened over time: Table 2 shows that German imports reached 2.64 average production stages by 2014, vs 2.07 and 2.40 for domestic and exported production. This structure suggests that Germany was

well-positioned to substitute for or complement domestic inputs with imported ones, making it more responsive to the rise of China and more competitive in export-oriented manufacturing. The U.S., by comparison, was less able to adapt in this way. Table 2 shows that overall US production moved slightly down the supply chain from 2000 to 2014 (from 1.82 to 1.80 average stages of production). This was driven entirely by domestic production, suggesting that any changes in the nature of imported and exported production (both of which moved slightly upstream) had little impact on the US's overall positioning in global supply chains.

Table 2: German and US upstreamness measures over time

4.3 Labor Market Demographics

One of the core motivations behind recent research on globalization and labor markets is the widespread decline in manufacturing employment across advanced economies. Table 3 summarizes key changes in labor market demographics in Germany and the United States between 2000 and 2014, distinguishing between males and females, and reporting numbers for primaries, manufacturing, and services.

Table 3: Levels and Changes in Sectoral Gender Composition, US and Germany

The most striking difference between the two labor markets is Germany's much larger manufacturing sector: in 2000, manufacturing employed nearly twice the share of the workforce in Germany compared to the U.S. Although manufacturing employment declined in both countries from 2000 to 2014, the scale and composition of that decline differed. In 2000, manufacturing employed 18.6% of male and 10.5% of female workers in the U.S., compared to 31.8% and 15.5% in Germany. By 2014, manufacturing employment had fallen by similar magnitudes in absolute terms: 4.1 and 3.5 percentage points for men and women in the U.S. versus 3.8 and 3.1 percentage points in Germany. However, given the U.S.'s smaller manufacturing base, these declines represent

much sharper relative contractions: a 21.5% decline for U.S. men versus 11.6% in Germany, and a 33.3% decline for U.S. women versus 20.1% in Germany. In both countries, these manufacturing losses were fully offset by employment gains in the service sector. This shift may reflect structural changes associated with global supply chain integration, including increased use of imported intermediate inputs and domestic outsourcing (see Goldschmidt and Schmieder (2017)).

5. Direct and Indirect Effects of Trade

5.1 Changes in Output Due to Changes in Trade

Figure 3 illustrates how trade with China between 2000 and 2014 reshaped output across industries in the US and Germany. Using the decomposition approach introduced in Section 2, we distinguish between direct trade effects and upstream (indirect) impacts.[13] The figures highlight striking contrasts between the US and Germany.

The clearest divergence emerges in the manufacturing sector, as shown by the grey-shaded area in the graph. German manufacturers experienced strong output growth, benefiting not only from direct export demand but also from upstream linkages with other expanding sectors. In terms of magnitude, the German machinery and automobile industries stand out, posting the largest output increases directly linked to trade expansion. By contrast, US manufacturing, particularly in computers, electronics, and optical products, suffered sharp declines in output, driven almost entirely by direct trade effects.

Figure 3: Changes in Output due to Trade by Country and Effect Type, 2014

Beyond manufacturing, direct trade effects are modest. Yet, an important and often underappreciated driver of output growth lies in upstream service industries. As Figure 3 shows,

[13] For ease of exposition, we omit the decomposition into international vs. domestic and final vs. intermediate goods, as well as the more detailed U.S. industry classifications from the BEA data.

output effects in services are driven almost entirely by upstream linkages rather than direct trade: service industries experience negligible direct effects but substantial indirect gains as inputs into expanding manufacturing and other traded sectors. Although services are not traded heavily themselves, they serve as critical inputs into the production of traded goods[14]. This dimension is often overlooked in conventional trade analyses, but our findings suggest that ignoring it would significantly understate the actual impact of trade.

Figure 4 traces annual sector-level effects. In Germany, the gains from trade have expanded steadily over time, driven by growth in both the manufacturing and service sectors. However, the sources of these gains diverge: Germany's trade surplus with China translated into sizable direct effects in manufacturing, while other sectors saw little direct benefit. Nearly all output gains in Germany's service sector stemmed from upstream linkages, a pattern clearly depicted in the final panel of Figure 4.

Figure 4: Change in Observed Output due to Trade, by Country, Sector, and Effect Type

In the United States, the impact of trade on output is an order of magnitude smaller than in Germany when measured relative to each country's total output. As in Germany, direct trade effects on output in the services and primary sectors remain small, while some negative direct effects are seen in the manufacturing industry. However, all three broad sectors, services, primaries, and manufacturing, experience upstream gains[15]. Focusing solely on direct effects would therefore obscure much of the story. While global integration has, at times, led to contractions in industries facing direct import competition, its broader effects are predominantly positive in both countries. Most of these changes occurred before the brief dip in trade during the

[14] For example, WIOD data shows that services account for 32.7% of the input value in Germany's machinery industry and 35.9% in its automotive sector, the two largest export industries in Germany.
[15] One can think of the US exporting inputs to e.g. Japan, which are then utilized to produce goods for export to China.

Great Recession. Trade flows then rebounded rapidly, returning to pre-crisis levels and subsequently stabilizing.

Importantly, upstream effects are not limited to increased production of intermediate goods and services for domestic use. Figure 5 breaks down the total change in upstream production in Germany and the United States by sector and destination. In both countries, upstream effects are positive and driven by two distinct channels: rising demand for intermediate inputs by domestic firms and growing export demand for inputs used by foreign producers. Domestic upstream effects in services reflect not only direct input demand from manufacturing but also services supplied upstream of other expanding sectors, whose own output grows through upstream linkages. This helps explain why domestic upstream service effects are positive even in the U.S., where the direct manufacturing effect is negative. In Germany's machinery and equipment sector, for instance, only one-third of the production increase linked to upstream effects is attributable to direct German trade flows, such as increased car exports to China involving domestic machine tools. The remaining two-thirds result from third-country trade linkages: for example, UK car exports to China that rely on German machinery, or Chinese electronics exports to Australia that incorporate US software.

These positive upstream effects from both domestic and international trade flows span the manufacturing and services industries (and, to a lesser extent, the primary sector), with overall impacts relatively small. A notable feature of Figure 5 is the prominence of service sectors in upstream effects: services account for a substantial share of the upstream gains in both countries, with the bulk channeled through domestic linkages. This contrasts with manufacturing, where export-oriented production of inputs accounts for a larger share of total upstream effects, as expected given its greater tradability. For services, however, domestic upstream channels

dominate, reflecting their role as locally supplied inputs throughout the production network. An exception is the United States, where changes in upstream service exports play a relatively larger role than in Germany, consistent with the US's comparative advantage in tradable business services.

While some existing studies on the China trade shock do incorporate input-output linkages (e.g., Acemoglu et al. (2016), who focused primarily on the negative direct and downstream effects of Chinese import competition in the US, rather than upstream production linkages; or Dauth et al. (2014) for Germany), they typically focus on domestic production channels, and on downstream rather than upstream linkages. Our decomposition reveals that this perspective overlooks a crucial aspect of the picture: the international dimension of upstream effects, which significantly contributes to the observed changes in output.

Figure 5: Decomposition of Upstream Effects into Domestic and International Components

5.2 German vs. US Positioning in Global Supply Chains

The preceding results highlight a clear pattern: Germany benefited more than the United States in output terms from increased globalization over this period. This divergence stems largely from Germany’s deeper integration into global production networks, both before 2000 and increasingly thereafter. One helpful way to assess a country's integration into global value chains is to examine its average position in the production process. That is, whether its output tends to lie “upstream” (early in the chain) or “downstream” (closer to final consumption). We adopt the upstreamness measures developed by Antràs et al. (2012) and extend them as before (section 4.2, Appendix Section A.4).

As illustrated in Figure 2, Chinese total and domestic production, as well as imports, are notably upstream. In contrast, Chinese exports are positioned further downstream, reflecting China's role as a "finishing factory," assembling imported intermediates into final or near-final goods for export. Key intermediate imports include electronic components, machinery parts, and processed materials from Japan, South Korea, Taiwan, and Germany (see WIOD data).

German production lies further upstream than US production, suggesting that German goods tend to pass through about 0.2 more stages before reaching the final consumer. This pattern reflects two features of German production: first, a concentration in industries that lie higher up the value chain, and second, a greater reliance on trade. Germany both exports a larger share of its output and uses more imported intermediates than the US.

Figure 6 shows that integration with China amplified this trend between 2000 and 2014, as evidenced by a more pronounced increase in the upstreamness of Germany's total production (solid blue line) than in the US. The figure also illustrates a general rise in the number of production stages used for both imports and exports in both countries, driven by shifts in the composition of traded goods and the growing complexity of supply chains. This trend affected the US and Germany in broadly similar ways.

Figure 6: Changes in Upstream Measures due to Global Integration

However, a larger divergence between the two countries is observed in the evolution of total and domestic production. Compared to a counterfactual scenario without integration with China, domestic production in Germany became increasingly more 'upstream' over this period, while domestic production in the United States remained largely unchanged in its position along the value chain. This shift illustrates how Germany's deeper integration with global trading partners pulled its domestic production into longer, multi-national production networks, whereas

US producers did not fundamentally alter their production structures. For example, a German auto parts supplier may sell to a domestic car manufacturer, who then assembles the vehicle for export, thus embedding even "domestic" production within a broader global value chain.

5.3 The Labor Demand Effects of Changes in Trade

We now translate the output effects documented above into labor market outcomes. Using the methodology described in Section 2, we convert changes in sectoral production into implied changes in labor demand, disaggregated by worker characteristics including gender, and task content of occupation. Figure 7 presents estimates (constructed as described in Section 2) of changes in labor demand resulting from trade in Germany and the United States. A first point to note is the order of magnitude: overall, the labor-demand effect of trade with China has been about 10 times larger in Germany than in the United States, closely mirroring the output patterns documented earlier.

Figure 7: Change in Labor Demand, by Country, Group and Effect Type

Tables 4 and 5 contain these labor demand effects for the year 2014 in percentage and absolute terms, respectively. We estimate that trade integration with China increased total labor demand in Germany by approximately 775,000 FTEs between 2000 and 2014, equivalent to 2.8% of the German labor force (Table 4, Total row; Table 5, Total row). This effect decomposes into two channels: direct effects from changes in bilateral trade flows account for roughly 207,726 (181105+26621) FTEs (0.9% of the labor force), while upstream effects contribute an additional 567,751 FTEs (1.9% of the labor force). Notably, upstream effects account for more than two-thirds of the total labor demand gain, underscoring the importance of supply chain linkages in transmitting the benefits of trade integration.

Table 4: Labor Demand Effects, % of Labor Force

Table 5: Labor Demand Effects, FTEs

For the United States, the total labor demand effect is considerably more modest: approximately 246,000 FTEs, or 0.2% of the labor force. Total direct effects (Final+Intermediate) are slightly negative (-100,000, -0.08%), while all of the positive US labor demand effect operates through upstream channels, which contribute 363,000 FTEs. This pattern suggests that while the net direct effect of trade with China, reflecting both increased import competition and direct export demand, was modestly negative for US labor demand, these losses were more than offset by gains from US value-added embodied in goods produced elsewhere in global supply chains. In proportional terms, Germany's labor demand effect (2.8% of the labor force) is over ten times larger than that of the United States (0.21%), closely mirroring the output patterns documented in Section 5.

Tables 4 and 5 also reveal important heterogeneity across demographic groups. In Germany, male workers experience significantly larger increases in labor demand than female workers: 3.1% of the male labor force versus 1.9% of the female labor force (Table 4). In absolute terms, this translates to 535,000 FTEs for men compared to 240,000 FTEs for women (Table 5). This gap reflects underlying patterns in sectoral employment: as discussed in Section 4, male workers are disproportionately concentrated in manufacturing, particularly in trade-intensive industries such as machinery and automobiles, whereas female workers are more likely to be employed in services. Since Germany's manufacturing sector expanded due to trade with China (Figure 4), this has driven the observed gender disparity. Workers in routine-intensive occupations experienced the largest gains in Germany (3.4% of the labor force, or 419,000 FTEs), followed by abstract task workers (2.4%, 216,000 FTEs) and manual task workers (1.9%, 140,000 FTEs). This pattern differs markedly from the US, where routine workers have often been identified as the most

adversely affected group. While heterogeneity across groups is less pronounced in the US, given the smaller overall effect, the pattern of negative direct effects combined with positive upstream effects is consistent across most demographic categories (Table 5).

Our results are broadly consistent with findings in the existing literature. For example, Dauth et al. (2014) estimate that Germany's integration with Eastern Europe and China created approximately 442,000 jobs between 1988 and 2008. In comparison, we find that increased integration with China alone generated direct labor demand for 207,000 FTEs between 2000 and 2014 (Table 5, sum of Direct Effects columns). The key distinction in our analysis is the inclusion of upstream effects, which more than triple the total impact to 775,000 FTEs. Importantly, these gains are not solely the result of bilateral trade between Germany and China; approximately two-thirds arise from increased trade between China and third countries that rely on German intermediate inputs (see Figure 5).

For the United States, most existing studies focus exclusively on import competition. Acemoglu et al. (2016) estimate that imports from China resulted in a total loss of 2.0-2.4 million US jobs between 1999 and 2011. Autor et al. (2013) find substantial negative effects on local labor markets exposed to Chinese import competition. In contrast, Feenstra and Sasahara (2018), covering 1995-2011, estimate that export growth generated 6.6 million jobs while imports led to losses of 2.0 million jobs, for a net gain of 4.6 million.

Our estimates are more modest than Feenstra and Sasahara's (2018) net figures. This difference likely reflects two features of our approach. First, our general equilibrium framework jointly models import and export changes, accounting for the fact that some export gains may substitute for domestic production rather than representing net additions. Second, Feenstra and Sasahara's accounting framework sums direct and indirect effects without modelling the price

adjustments and factor reallocation that dampen the total impact in a general equilibrium setting. Despite these differences in methodology and magnitude, both approaches point to the importance of looking beyond import competition alone. We find a total labor demand effect of approximately 246,000 FTEs (Table 5), with small, negative direct effects and all gains operating through upstream channels. This suggests that while direct import competition has displaced workers in exposed industries, these losses were offset by US value-added embodied in goods produced elsewhere, either Chinese goods destined for other markets or third-country goods using US inputs.

Caliendo et al. (2019) find that increased trade with China reduced U.S. manufacturing employment by approximately 0.55 million workers between 2000 and 2007, with aggregate welfare gains of 0.2% despite concentrated losses in exposed regions. These aggregate welfare gains are of a similar magnitude to our estimated changes in labor demands. However, some differences between our approaches merit attention. Caliendo et al. (2019) focus on the 2000–2007 period, while we extend through 2014 (though effects are relatively minor from 2007 onwards). Additionally, Caliendo et al. (2019) emphasize welfare and migration responses, while we focus on decomposing production and labor demand effects along direct versus upstream channels. Our finding that upstream effects largely offset direct negative effects in the U.S. complements CDP's result that general equilibrium adjustments substantially moderate the aggregate impact of the China shock, though the channels differ: they emphasize labor reallocation across regions and sectors, while we highlight international production linkages. The magnitudes are broadly consistent: both studies find that the aggregate U.S. impact is small relative to the concentrated losses in directly exposed industries, though our emphasis on upstream international linkages provides a different mechanism for understanding how these effects propagate through the economy.

In the Appendix, we briefly present a more direct comparison of our exposure measures with standard import-penetration measures, in the style of Autor et al. (2013). While our direct exposure metric correlates strongly with ADH-type measures, our upstream exposure measure is largely orthogonal to theirs (see Figure 8). This suggests that our framework captures dimensions of trade exposure, particularly indirect and international upstream linkages, that are not captured in traditional import-focused approaches (see Appendix Section A.6 for further details).

Figure 8: Commuting Zone Level Import Penetration vs Exposure Measures

6. Discussion and Conclusions

This paper analyzes both the direct and indirect effects of China's expanding trade by comparing the markedly different experiences of the United States and Germany from 2000 to 2014. Building on a computable general equilibrium (CGE) framework adapted from Caliendo and Parro (2015) and Caliendo et al. (2019), we simulate counterfactual scenarios in which trade with China remained at its 2000 level. Within this setting, we propose a new decomposition of the total impact of rising Chinese trade on output and labor market outcomes along three key dimensions: (1) direct versus indirect (upstream) supply chain effects, (2) effects stemming from final versus intermediate goods, and (3) international versus domestic reallocations of production.

We find that both Germany and the United States substantially increased their imports from China between 2000 and 2014, but only Germany experienced a commensurate rise in exports. Decomposing the total trade effects into direct and upstream components—and further distinguishing between intermediate and final goods, as well as between output destined for export versus domestic use—we show that most of the impact of changing trade patterns on production and labor market outcomes arises not from direct trade flows (import competition or export

expansion), but from upstream effects driven by the broader production linkages created through integration.

For the United States, the positive output and labor demand effects directly due to increased exports only offset a small share of the negative output and labor demand effects associated with the direct increase in imports from China (i.e., the classic 'China Shock'). However, the upstream effects of increased trade, stemming from both domestic exports and foreign production, more than offset the negative direct import-competition effects. In Germany, by contrast, the China shock was already net positive in direct terms for production and labor demand, and the upstream effects are almost twice as large, implying that focusing solely on direct trade effects substantially understates the aggregate impact of growing trade with China.

These patterns are also reflected in labor demand across worker groups. In both countries, the effects of trade vary by gender and task composition. While the overall changes mirror the aggregate production effects, they may also have amplified existing labor market inequalities. In Germany, men experienced significantly larger labor-demand increases than women, while cross-gender effects are muted in the United States. Once again, upstream effects play a central role in shaping these outcomes.

Overall, our results show that tracing effects throughout the production network and decomposing them by type provides valuable additional insights. Moreover, they underscore the importance of country-specific contexts in interpreting global economic shocks. The United States and Germany experienced the "China shock" in fundamentally different ways: while Germany saw strongly positive effects on production and labor demand, the U.S. effects were only marginally positive. This contrast highlights how national economic structures mediate the consequences of global trade integration.

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Tables and Figures

Table 1: Changes in Imports and Exports From/To China

Table 1: Changes in Imports and Exports From/To China

			Manufacturing				Total			
		Type	2000	2014	Δ	%	2000	2014	Δ	%
China	*Germany*	*Imports*	8,747	56,053	47,306	541%	10,750	66,647	55,896	520%
		Exports	7,143	76,671	69,528	973%	8,619	92,590	83,971	974%
	USA	*Imports*	48,013	251,332	203,319	423%	51,575	261,655	210,079	407%
		Exports	10,327	52,844	42,517	412%	12,469	84,416	71,947	577%

Note: All values taken from the World Input-Output Table, in millions of 2000 US dollars. Total includes primaries, manufacturing, and services industries.

Table 2: German and US upstreamness measures over time

Table 2: German and US upstreamness measures over time

	Germany			United States		
Upstreamness Measure:	2000	2014	Δ	2000	2014	Δ
Total	1.94	2.06	0.12	1.82	1.80	-0.02
Domestic	1.98	2.07	0.10	1.84	1.80	-0.04
Exports	2.21	2.40	0.19	2.34	2.59	0.25
Imports	2.45	2.64	0.19	2.20	2.41	0.21

Note: Upstreamness measures (the average stage of production for goods of each type) are calculated from WIOD for the years 2000 and 2014. Constructed as indicated in the text. Country-level measures are weighted averages of industry-level averages within each country. Total follows the procedure in Antràs et al. (2012), $\boldsymbol{US}_{Total} = [\boldsymbol{I}-\boldsymbol{A}]^{-1}\boldsymbol{1}$. *Domestic, exports and imports are defined as in text and Appendix A.4 as weighted averages of the following:*

$\boldsymbol{US}^{(i,r)}_{Domestic} = [\boldsymbol{D}_{dom}+\boldsymbol{A}_{dom}\boldsymbol{Y}+\boldsymbol{A}_{dom}[\boldsymbol{I}-\boldsymbol{A}]^{-1}\boldsymbol{Y}]_{(i,r)} / [\boldsymbol{Y}_{dom}]_{(i,r)}$

$\boldsymbol{US}^{(i,r)}_{Exports} = [\boldsymbol{D}_{exp}+\boldsymbol{A}_{exp}\boldsymbol{Y}+\boldsymbol{A}_{exp}[\boldsymbol{I}-\boldsymbol{A}]^{-1}\boldsymbol{Y}]_{(i,r)} / [\boldsymbol{Y}_{exp}]_{(i,r)}$

$\boldsymbol{US}^{(i,r)}_{Imports} = [\sum_{j\neq i} \boldsymbol{US}_{exp}^{(j,r)} x^{(j,r),(i)}] / [\sum_{j\neq i} x^{(j,r),(i)}]$

Table 3: Levels and Changes in Sectoral Gender Composition, US and Germany

Table 3: Gender Concentrations

Germany						
	2000		2014		Change	
	Male	Female	Male	Female	Male	Female
Primaries	2.6%	1.2%	2.2%	1.0%	-0.4%	-0.2%
Manufacturing	31.8%	15.5%	28.1%	12.4%	-3.8%	-3.1%
Services	65.6%	83.3%	69.7%	86.7%	4.2%	3.3%
USA						
	2000		2014		Change	
	Male	Female	Male	Female	Male	Female
Primaries	2.5%	0.6%	2.9%	0.8%	0.4%	0.1%
Manufacturing	18.6%	10.5%	14.6%	7.0%	-4.1%	-3.5%
Services	78.8%	88.9%	82.5%	92.2%	3.7%	3.4%

Note: Data for Germany is constructed from the Sample of Integrated Labour Market Biographies (SIAB), a 2% sample of social security records. Data for the US come from the American Community Survey and the 2000 census. Percentages capture the share of workers within each gender who work in each of the three respective sectors.

Table 4: Labor Demand Effects, % of Labor Force

Table 4: Labor Demand Effects, Observed vs Counterfactual

		Direct Effects		Upstream Effects		
Country	**Group**	Final	Intermediate	Final	Intermediate	**Total**
Germany	Total	0.754	0.126	1.373	0.502	2.755
	Male	0.900	0.170	1.521	0.559	3.149
	Female	0.430	0.028	1.044	0.377	1.879
	Abstract	0.628	0.086	1.240	0.451	2.406
	Manual	0.444	0.090	1.046	0.367	1.947
	Routine	0.987	0.174	1.619	0.601	3.381

		Direct Effects		Upstream Effects		
Country	**Group**	Final	Intermediate	Final	Intermediate	**Total**
United States	Total	-0.042	-0.039	0.234	0.058	0.216
	Male	-0.036	-0.044	0.273	0.068	0.261
	Female	-0.053	-0.029	0.164	0.040	0.122
	Abstract	-0.038	-0.038	0.228	0.057	0.210
	Manual	-0.012	0.013	0.251	0.072	0.324
	Routine	-0.056	-0.055	0.236	0.055	0.180

Note: The above figures represent the percentage difference (in terms of each group's labor force) between labor demands under the observed vs counterfactual in 2014 vs 2000. Direct effects of final and intermediate goods and the upstream effects of final and intermediate goods are defined as in Table 1, with each output effect converted to a change in labor demand. Gender and task categories are defined as in the text. Output data is constructed primarily from the WIOD, with calculations as in text. German labor data comes from the Sample of Integrated Labour Market Biographies (SIAB), a 2% sample of social security records. Labor data for the US come from the American Community Survey and the 2000 census

Table 5: Labor Demand Effects, Full Time Equivalents

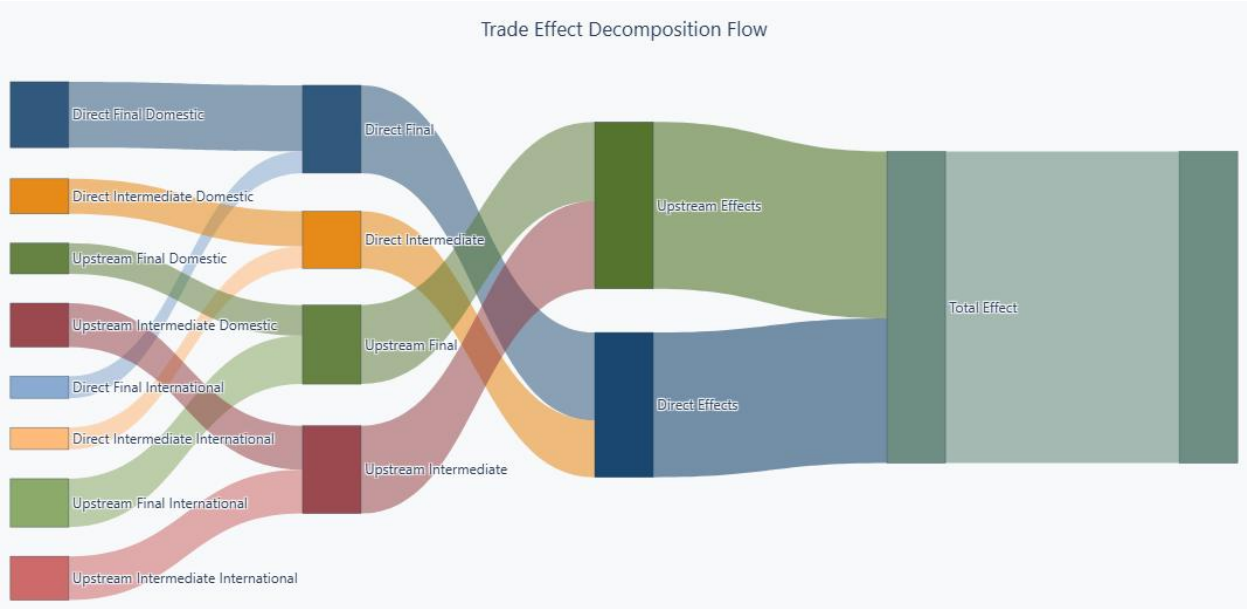
Table 5: Labor Demand Effects, Observed vs Counterfactual

		Direct Effects		Upstream Effects		
Country	**Group**	Final	Intermediate	Final	Intermediate	**Total**
Germany	Total	181105	26621	419016	148735	775478
	Male	133538	25026	277557	99024	535145
	Female	47567	1595	141459	49711	240332
	Abstract	48419	5068	120156	42455	216097
	Manual	24271	4350	83338	28357	140315
	Routine	108416	17204	215522	77923	419065

		Direct Effects		Upstream Effects		
Country	**Group**	Final	Intermediate	Final	Intermediate	**Total**
United States	Total	-63915	-35592	277104	68479	246076
	Male	-27239	-20906	189162	47514	188531
	Female	-36676	-14686	87942	20965	57545
	Abstract	-15046	-9312	102296	26186	104125
	Manual	-4818	3519	45432	13125	57257
	Routine	-44051	-29799	129375	29168	84694

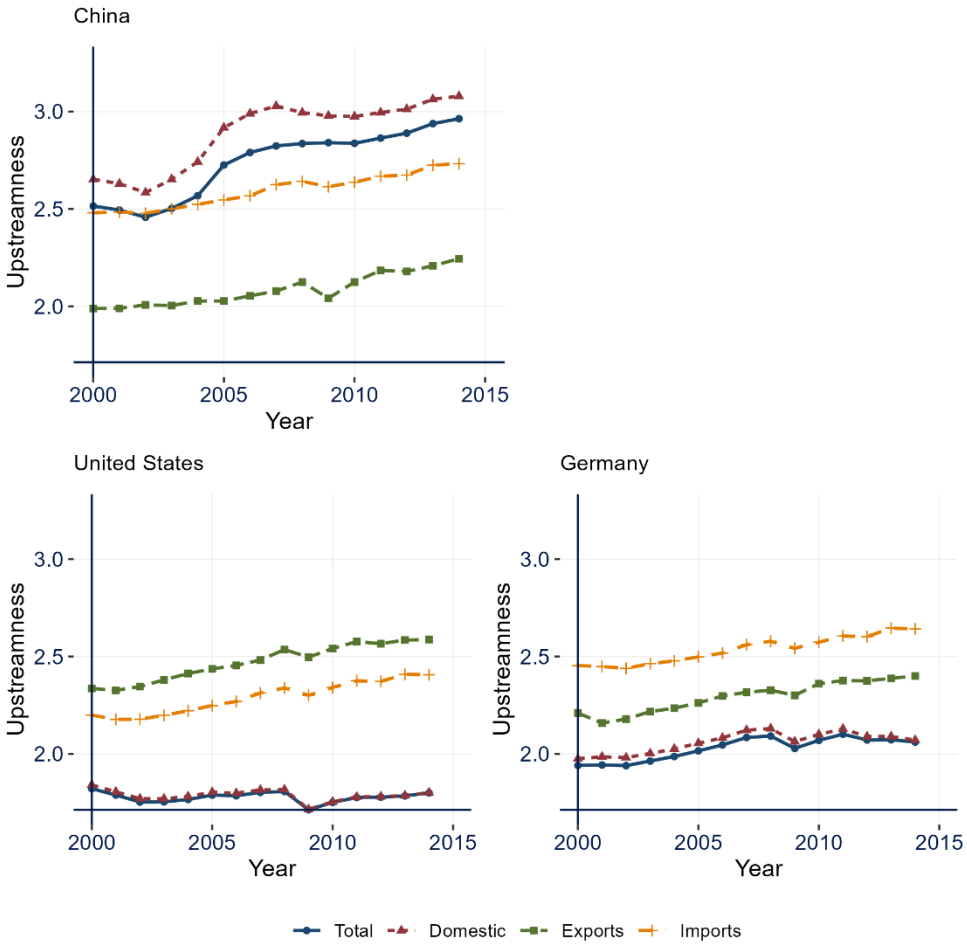
Note: The above figures represent the implied change in labor demand, expressed as full-time equivalent workers, between the observed and counterfactual. Direct effects of final and intermediate goods and the upstream effects of final and intermediate goods are defined as in Table 1, with each output effect converted to a change in FTE labor demand. Gender and task categories are defined as in the text. Output data is constructed primarily from the WIOD, with calculations as in text. German labor data comes from the Sample of Integrated Labour Market Biographies (SIAB), a 2% sample of social security records. Labor data for the US come from the American Community Survey and the 2000 census

Figure 1: Decomposition of Trade Effects



Note: Schematic representation of decomposition of trade effects into direct vs. upstream, final vs. intermediate, and domestic vs. international effects. Sizes not connected to empirical values.

Figure 2: Upstreamness of Countries' Outputs by Type



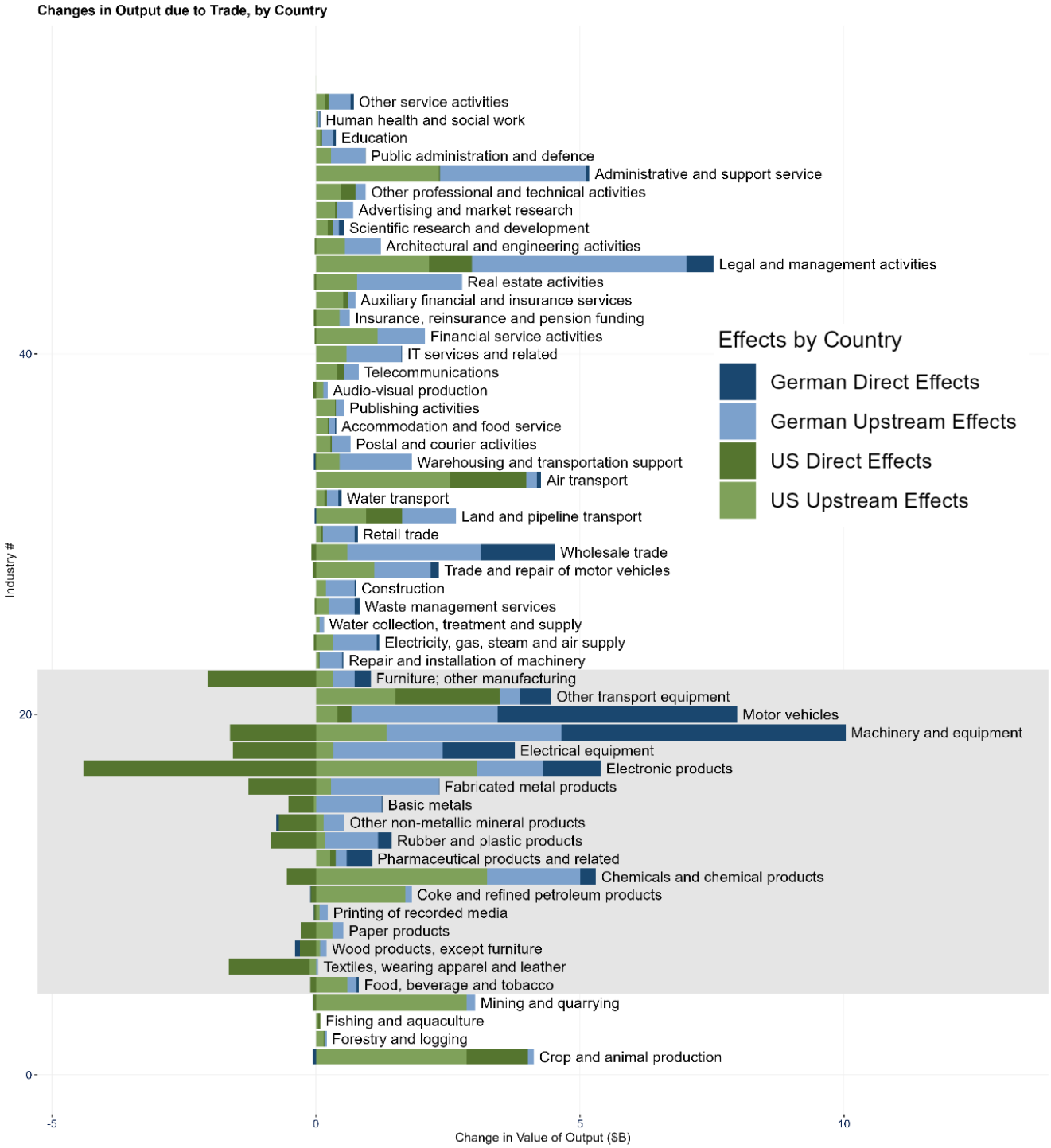
Note: Data from the World Input-Output Database, with results using authors' calculations. Lines measure the weighted-average stage of production of total, domestic, exported and imported production. Total follows the procedure in Antràs et al. (2012), $\boldsymbol{US}_{Total} = \boldsymbol{[I-A]^{-1}I}$*. Domestic, exports and imports are defined as in text and Appendix A.4 as weighted averages of the following:*

$\boldsymbol{US}^{(i,r)}_{Domestic} = [\boldsymbol{D}_{dom} + \boldsymbol{A}_{dom}\boldsymbol{Y} + \boldsymbol{A}_{dom}\boldsymbol{[I-A]^{-1}Y}]_{(i,r)} / [\boldsymbol{Y}_{dom}]_{(i,r)}$

$\boldsymbol{US}^{(i,r)}_{Exports} = [\boldsymbol{D}_{exp} + \boldsymbol{A}_{exp}\boldsymbol{Y} + \boldsymbol{A}_{exp}\boldsymbol{[I-A]^{-1}Y}]_{(i,r)} / [\boldsymbol{Y}_{exp}]_{(i,r)}$

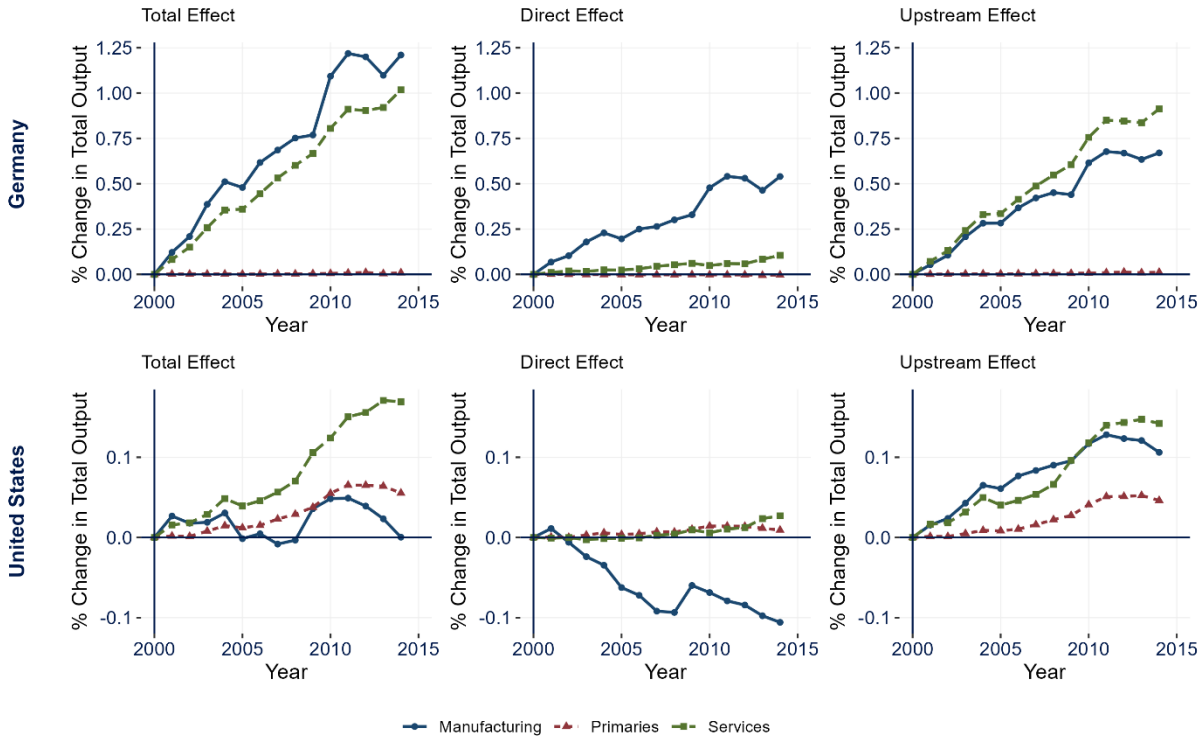
$\boldsymbol{US}^{(i,r)}_{Imports} = [\sum_{j \neq i} \boldsymbol{US}_{exp}^{(j,r)} x^{(j,r),(i)}] / [\sum_{j \neq i} x^{(j,r),(i)}]$

Figure 3: Changes in Output due to Trade, by Country and Effect Type, 2014



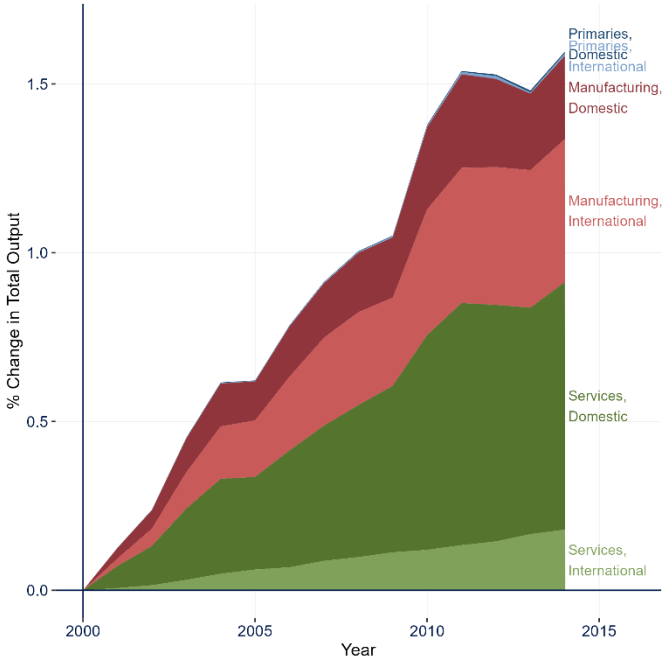
Note: The change in output represents the difference between observed and counterfactual outputs in each industry in 2014, due to both direct and upstream effects. Data sourced from the World Input-Output Database, with results based on the authors' calculations. In the counterfactual scenario, Chinese trade remained at 2000 levels. Refer to appendix tables A.3 and A.4 for detailed output effects per industry. Industry names have been shortened and/or simplified for readability.

Figure 4: Change in Output due to Trade, by Country, Sector, and Effect Type

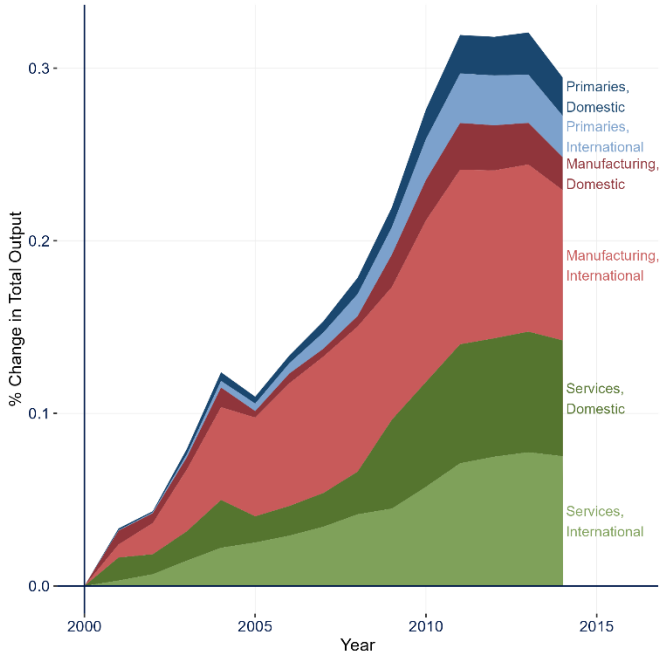


Note: All figures capture the difference between the observed vs counterfactual outputs in each sector, as a percent of observed total output. Data from the World Input-Output Database, with results using authors' calculations. In the counterfactual scenario, Chinese trade stayed at the 2000 level.

Figure 5: Decomposition of Upstream Effects into Domestic and International Components, by Sector



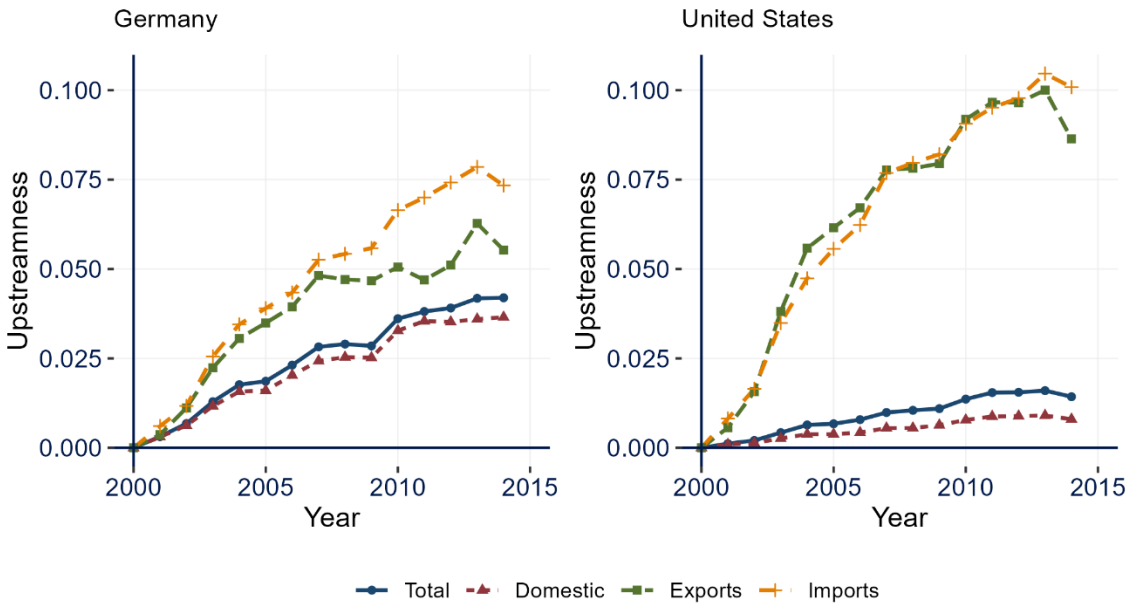
(a) Germany



(b) United States

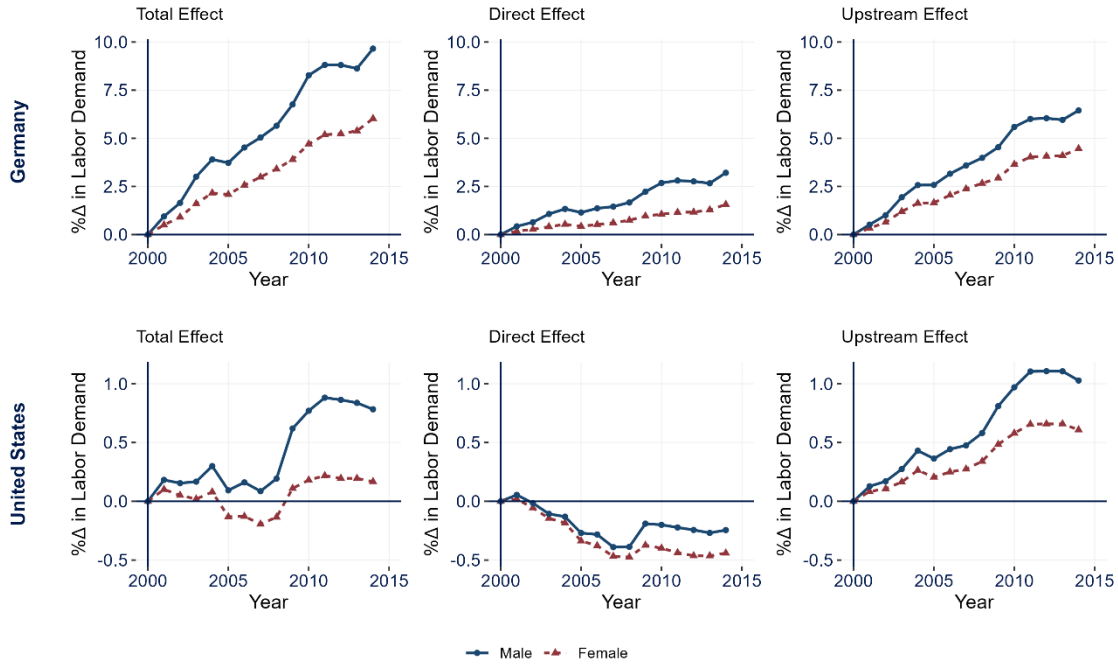
Note: All figures show the difference between observed and counterfactual outputs in each sector attributable to upstream effects, as a percentage of the observed total output. Data from the World Input-Output Database, with results using authors' calculations. In the counterfactual scenario, Chinese trade stayed at the 2000 level. Note different scales on the Y-axis.

Figure 6: Changes in Upstream Measures due to Global Integration



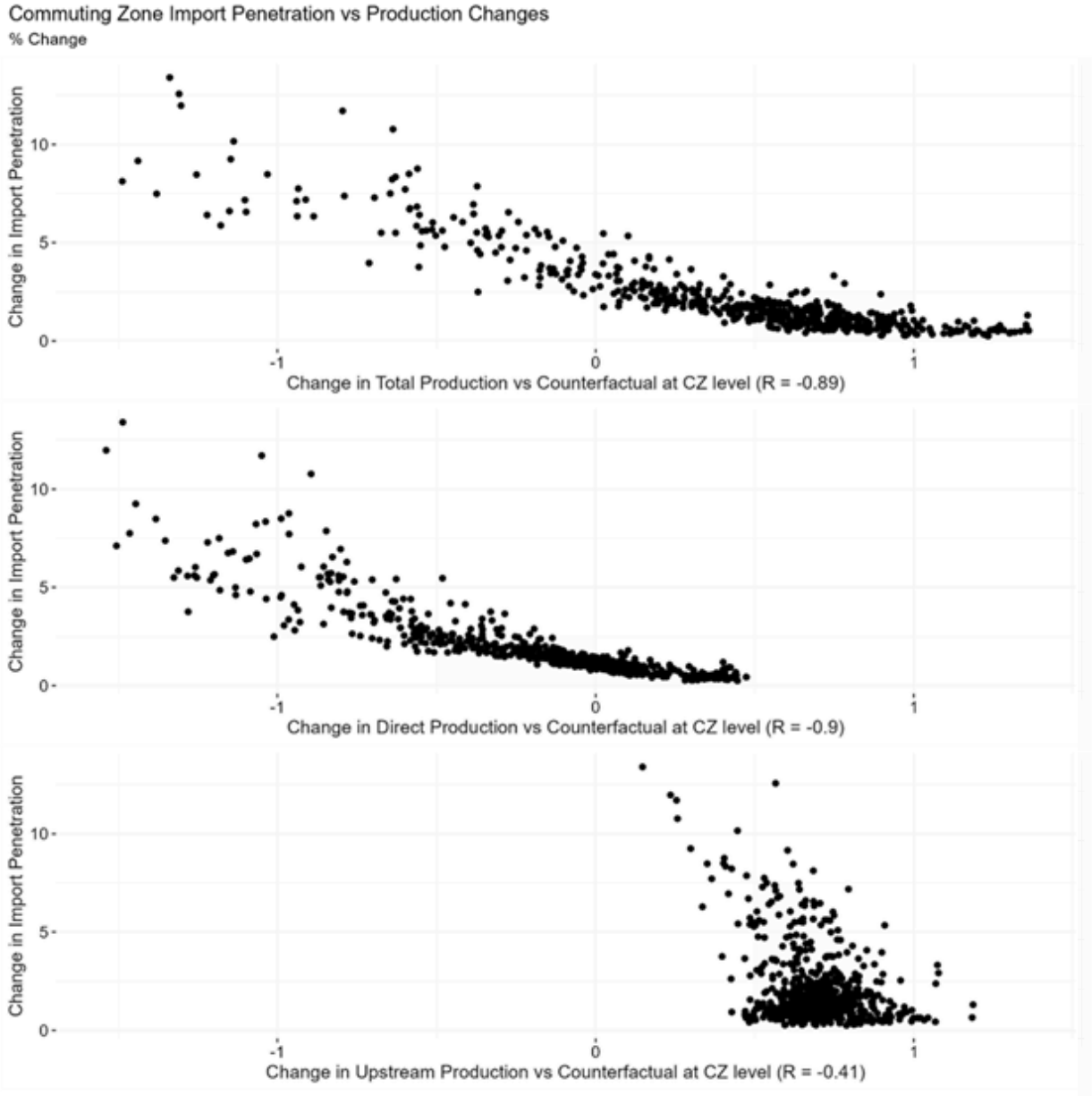
Note: All figures capture the difference between the observed vs counterfactual upstreamness average (see figure 1 for observed values). Data from the World Input-Output Database, with results using authors' calculations. In the counterfactual scenario, Chinese trade stayed at the 2000 level. Lines measure the weighted-average stage of production of total, domestic, exported and imported production. Total follows the procedure in Antràs et al. (2012). Domestic, exports and imports are defined as in Figure 1, text and Appendix A.4, minus analogous terms for counterfactual.

Figure 7: Change in Labor Demand, by Country, Gender, and Effect Type



Note: All figures capture the difference between the observed vs counterfactual labor market demand as a percentage of observed group labor demand. Data from the World Input-Output Database, the German SIAB, and the US ACS and Census, with results using the authors' calculations. Counterfactuals assume China's trade stayed at the 2000 level.

Figure 8: Commuting Zone Level Import Penetration vs Exposure Measures



Note: Exposure measures as defined in the text. Import penetration changes are the commuting zone level exposure to changes in imports, constructed using shift-shares. Further details in the text. Data from the World Input-Output Database and the ACS, with results using authors' calculations. Counterfactuals assume Chinese trade stayed at 2000 level. Values below first or above 99th percentiles excluded.

Appendix

A.1 Input-Output Representations

This section explains some of the basics of the input-output notation and different representations, as demonstrated in equation (2) in the text. We start with the scalar representations of total production, final goods production, and intermediate goods production in each country-industry pair, from equation (1):

$$y_t^{(i,r)} = \sum_j d_t^{(i,r),j} + \sum_{j,s} x_t^{(i,r),(j,s)}$$

That is, total production in a given country-industry pair *(i,r)* is equal to the sum of final goods produced in that country-industry pair for each country *j* (this included production for the domestic market), plus the goods produced which are utilized as inputs by all country-industry pairs *(j,s)* (again, including the given country-industry pair *(i,r)*, if it uses its own production as inputs into production).

We next introduce the Leontief input-output coefficient:

$$a_t^{(i,r),(j,s)} = \frac{x_t^{(i,r),(j,s)}}{y_t^{(j,s)}}$$

This coefficient, bounded between 0 and 1 (else the value of inputs would exceed the value of output), captures the ratio of intermediate goods from industry *(i,r)* that constitute a fraction of the value of total production in the destination industry *(j,s)*. From hereon, we utilize $a_t^{(i,r),(j,s)}$ rather than $x_t^{(i,r),(j,s)}$ throughout, as we can construct some useful Leontief-style matrix relationships between the $y_t^{(i,r)}, d_t^{(i,r),j}$ and $a_t^{(i,r),(j,s)}$'s. First, we define the vectors $\boldsymbol{Y_t}$ and $\boldsymbol{D_t}$ as the stacked (N·S)x1 vectors of the scalar output values $y_t^{(i,r)}$ and $d_t^{(i,r),j}$, i.e.:

$$\boldsymbol{Y_t} = \begin{bmatrix} y_t^{(1,1)} \\ y_t^{(1,2)} \\ \vdots \\ y_t^{(2,1)} \\ \vdots \\ y_t^{(N,S)} \end{bmatrix} \text{ and } \boldsymbol{D_t} = \begin{bmatrix} d_t^{(1,1)} \\ d_t^{(1,2)} \\ \vdots \\ d_t^{(2,1)} \\ \vdots \\ d_t^{(N,S)} \end{bmatrix}$$

Similarly, we can define the (N·S)x(N·S) matrix of input-output coefficients, $\boldsymbol{A_t}$, as:

$$\boldsymbol{A_t} = \begin{bmatrix} a_t^{(1,1),(1,1)} & \cdots & a_t^{(1,1),(N,S)} \\ \vdots & \ddots & \vdots \\ a_t^{(N,S),(1,1)} & \cdots & a_t^{(N,S),(N,S)} \end{bmatrix}$$

We first define the relationship between the above using the traditional Leontief inverse representation, then use it to introduce an equivalent representation via sums over infinite sequences of matrix products. From the definition of the Leontief input-output coefficient, introduced above, note that $a_t^{(i,r),(j,s)} y_t^{(j,s)} = x_t^{(i,r),(j,s)}$. Post-multiplying the coefficient matrix by the vector $\boldsymbol{Y_t}$ thus, it produces the vector of the sum of intermediate goods production by origin industry, which we can call $\boldsymbol{X_t}$ for consistency: $\boldsymbol{A_t Y_t} = \boldsymbol{X_t}$. Therefore, equation (2) can be represented in matrix form as

$$\boldsymbol{Y_t} = \boldsymbol{D_t} + \boldsymbol{X_t} = \boldsymbol{D_t} + \boldsymbol{A_t Y_t}$$

So long as $\boldsymbol{A_t}$ is invertible, it is easy to get to the Leontief inverse representation of $\boldsymbol{Y_t}$:

$$\boldsymbol{Y_t = D_t + A_t Y_t \Longrightarrow Y_t = (I - A_t)^{-1} D_t}$$

This representation is well known in the input-output literature and is utilized throughout our work as well. Somewhat less common, but quite useful for our purposes, is representing the above as the sum of an infinite sequence. While one can use some matrix algebra to go from the latter part of the above to this representation, it is perhaps conceptually easier to proceed from the first part of the equation and use its recursiveness:

$$\boldsymbol{Y_t = D_t + A_t Y_t = D_t + A_t(D_t + A_t Y_t) = D_t + A_t D_t + A^2{}_t D_t + A^3{}_t D_t + \cdots = \sum_{n=0}^{\infty} A_t^n D_t}$$

This holds so long as the sum $\sum_{n=0}^{\infty} \boldsymbol{A_t^n}$ converges, which the input-output coefficient matrix does when its elements have values required of input-output structures[16].

This second representation is perhaps a more direct way of understanding total outputs: they are simply the sum of final goods, plus the intermediate goods used by producers of those final goods, plus the intermediate goods used by producers of the intermediate goods supplied to final goods producers, etc., all the way up the supply chain.

A.2 Model Construction

Our multi-country computable general equilibrium model builds on the theoretical foundations established by Eaton and Kortum (2002) for trade with heterogeneous firms and Caliendo et al. (2019) (hereafter CDP) for dynamic spatial equilibrium. We build off the latter, simplify the CDP model in several key respects while extending it along other dimensions. First, we eliminate the subnational regional structure, treating each country as a single unit rather than modeling N-1 countries with one region plus one country with R regions. This reduces the state space from (N-1+R)×J to N×J country-sector pairs. Second, we abstract from the dynamic migration decisions central to CDP's framework by setting cross-country migration costs to infinity, thereby eliminating the forward-looking discrete-choice migration problem and associated value functions. Third, and importantly, we do not include an explicit utility function in our welfare calculations. CDP model households as maximizing expected lifetime utility with consumption aggregated

[16] Specifically, convergence of $\sum_{n=0}^{\infty} \boldsymbol{A^n}$ requires that $|\lambda_i| < 1$ for all eigenvalues λ_i of $\boldsymbol{A}$. By the definition of our input-output coefficients, the maximal column sum must be less than one (so long as each industry produces more than it utilizes as inputs). Therefore, the absolute value of the largest eigenvalue must be less than one as well, (by e.g. the Perron–Frobenius theorem, or other linear algebra theorems on the spectra of non-negative matrices), so the coefficient matrix converges.

across sectors via Cobb-Douglas preferences. Instead, we trace the output and employment consequences of the China shock without taking a stance on how consumption gains or losses translate into utility. Finally, we extend CDP by expanding sectoral coverage from 22 to 55 sectors and by explicitly incorporating the full 2035×2035 matrix of international input-output coefficients, enabling a richer characterization of global value chain linkages.

Our identification strategy employs a leave-one-out regression approach to estimate trade flow responses to foreign supply and demand shocks, which we then use to calibrate the counterfactual scenarios in our CGE model. Specifically, we estimate sector-specific regressions of the form $\Delta ln\, y_{cjt} = \beta_j^{sup}\, \Delta ln(ForSup_{cjt}) + \beta_j^{dem}\, \Delta ln(ForDem_{cjt}) + \varepsilon_{cjt}$, where y_{cjt} denotes trade flows (imports or exports) for country *c*, sector *j*, and year *t*. The key regressors are constructed using a Bartik-style shift-share design: foreign supply (*ForSup*) captures changes in partner countries' export capacity to country *c* in sector *j*, weighted by base-year bilateral trade shares, while foreign demand (*ForDem*) captures changes in partner countries' import demand from country *c*, similarly weighted. Crucially, we exclude the focal country's own flows when constructing these shift-share instruments, ensuring that the estimated elasticities reflect exogenous variation in foreign market conditions rather than domestic shocks. We then use these sector-specific elasticity estimates to predict counterfactual trade flows under the scenario where China's supply and demand growth is shut down, holding third-country fundamentals at their observed values. This approach anchors our counterfactual exercise in empirically estimated trade responses rather than relying on externally calibrated parameters, while the leave-one-out construction addresses the reflection problem inherent in using aggregate trade flows as instruments.

The identifying assumption underlying this approach is that, absent China's productivity and consumption growth, the rest of the world's fundamentals would have evolved as observed. This assumption is analogous to the parallel trends assumption in difference-in-differences designs: we treat China's growth as the "treatment" and other countries' observed trajectories as the counterfactual. The leave-one-out construction of our shift-share instruments addresses the reflection problem that would arise if we used aggregate trade flows directly as regressors, since a country's own trade with China is mechanically correlated with its domestic shocks. By excluding the focal country when constructing foreign supply and demand measures, we isolate variation in third-country trade patterns that is plausibly exogenous to focal country shocks. The key threat to identification is that China's integration may have induced endogenous responses in other countries' productivity or trade policies; we cannot fully rule out such general equilibrium feedback effects, though their magnitude is likely second-order given the short time horizon of our analysis.

We assume that productivity draws for individual firms follow independent Fréchet distributions, which generates the tractable gravity equation structure central to quantitative trade models. Specifically, if firm efficiency z^{nj} in country n, sector j follows the distribution $F^{nj}(z) = \exp\left(-T^{nj}z^{-\theta_j}\right)$, where T^{nj} is a location-scale parameter and θ_j is the shape parameter, then the resulting trade shares and price indices have closed-form solutions that facilitate computation and estimation.

The Fréchet assumption implies that log-productivity differences across firms within a sector follow a double-exponential distribution, which provides a reasonable approximation to empirical productivity distributions while maintaining analytical tractability. The parameter θ_j plays a crucial role as the trade elasticity, governing how responsive trade flows are to changes in

relative costs. Higher values of θ_j indicate more homogeneous goods where small cost differences lead to large changes in market shares, while lower values suggest more differentiated products where trade patterns are less sensitive to cost variations.

Our production structure assumes constant-returns-to-scale technologies with Cobb-Douglas aggregation across inputs. While this functional form restriction eliminates certain types of complementarity and substitutability effects, it significantly reduces computational burden while preserving the essential general equilibrium channels through which trade shocks propagate. The Cobb-Douglas assumption ensures that expenditure shares across inputs remain constant even as relative prices change, allowing us to calibrate input-output coefficients directly from observed data without estimating substitution elasticities.

The market structure assumes perfect competition across all sectors, eliminating strategic interactions between firms while ensuring that our results reflect technological and trade-cost fundamentals rather than market-power considerations. This assumption is most plausible for sectors producing relatively homogeneous intermediate goods where markup variation is likely to be small. For industries with significant product differentiation or market concentration, our approach may understate the role of strategic considerations in shaping trade patterns.

Formally, the model economy consists of N countries, each specialized in J sectors, with perfect competition in all markets and costless factor mobility within countries but not between them. We denote firm output by *q,* wages by *w*, labor inputs by *l*, rental rates on structures by *r*, and structure inputs by *h*. Following CDP, we use γ to denote value-added shares in production, with ξ representing the share of structures in value-added. Trade costs are denoted by κ, productivity parameters by T (location-scale) and A (TFP), and the trade elasticity by θ. Price indices are denoted P, trade shares by π, intermediate inputs from sector k by M^k and total

expenditure by X. The input-output coefficients $\gamma^{nj,nk}$ capture the share of sector *k* inputs used in sector *j* production in country *n*. Following CDP, we aggregate from firm-level decisions to sectoral outcomes. Each firm with efficiency z^{nj} in country n, sector j solves the cost minimization problem:

$$\min_{l,h,\{M^k\}} w^{nj} l + r^{nj} h + \sum_{k=1}^{J} P^{nk} M^k$$

subject to the production constraint:

$$q = z^{nj} A^{nj} h^{\xi^n \gamma^{nj}} l^{(1-\xi^n)\gamma^{nj}} \prod_{k=1}^{J} (M^k)^{\gamma^{nj,nk}}$$

The first-order conditions for this problem yield linear factor demand functions, reflecting the constant returns to scale assumption. Specifically, the optimal demands are:

$$l^{nj}(z) = \frac{(1-\xi^n)\gamma^{nj} \cdot p^{nj}(z) \cdot q^{nj}(z)}{w^{nj}}$$

$$h^{nj}(z) = \frac{\xi^n \gamma^{nj} \cdot p^{nj}(z) \cdot q^{nj}(z)}{r^{nj}}$$

$$M^{nj,k}(z) = \frac{\gamma^{nj,nk} \cdot p^{nj}(z) \cdot q^{nj}(z)}{P^{nk}}$$

where $p^{nj}(z)$ is the price charged by the firm with efficiency z, determined by the zero-profit condition under perfect competition.

The unit cost function emerges from this optimization as:

$$c^{nj} = B^{nj} \left(\frac{r^{nj}}{\xi^n}\right)^{\xi^n \gamma^{nj}} \left(\frac{w^{nj}}{1-\xi^n}\right)^{(1-\xi^n)\gamma^{nj}} \prod_{k=1}^{J} \left(\frac{P^{nk}}{\gamma^{nj,nk}}\right)^{\gamma^{nj,nk}}$$

where B^{nj} is a constant that depends only on the production function parameters. Under perfect competition, the price of a variety with efficiency z is $p^{nj}(z) = c^{nj}/(zA^{nj})$.

The aggregation from individual varieties to sectoral price indices requires integrating over the distribution of efficiencies and accounting for the trade costs faced by importers. For buyers in country m purchasing sector j goods, the relevant price distribution includes varieties from all countries, adjusted for bilateral trade costs. The resulting price index is:

$$P^{mj} = \Gamma_j \left[\sum_{n=1}^{N} T^{nj} \left(c^{nj} \kappa^{mj,nj} \right)^{-\theta_j} \right]^{-1/\theta_j}$$

where Γ_j is a constant depending on the Fréchet distribution parameters and $\kappa^{mj,nj} \geq 1$ represents the iceberg trade costs for shipping sector j goods from country n to country m.

Trade shares follow from the lowest-cost sourcing behavior of buyers and the properties of the Fréchet distribution. The probability that country n provides the lowest-cost variety for any randomly drawn sector j product in country m is:

$$\pi^{mj,nj} = \frac{T^{nj} \left(c^{nj} \kappa^{mj,nj} \right)^{-\theta_j}}{\sum_{i=1}^{N} T^{ij} (c^{ij} \kappa^{mj,ij})^{-\theta_j}}$$

This share represents both the probability that country n is the lowest-cost supplier for any given variety and the fraction of country m's total expenditure on sector j goods that goes to country n, due to the properties of the Fréchet distribution.

The treatment of trade imbalances follows CDP through a global portfolio mechanism. Each country has a representative agent who owns domestic structures but receives income from a diversified global portfolio of all structures. The portfolio income for country n is ι^n, where $\chi =$

$\sum_{m=1}^{N}\sum_{k=1}^{J} r^{mk}H^{mk}$ is total global structure income and ι^{n} is country n's portfolio share. The trade balance for country n is:

$$TB^{n} = \sum_{k=1}^{J} r^{nk}H^{nk} - \iota^{n}$$

This mechanism allows countries to run persistent current account surpluses or deficits while maintaining general equilibrium consistency, as the portfolio shares can be calibrated to match observed trade imbalances in any base year.

The complete equilibrium system requires simultaneous clearing of all goods markets, all factor markets, and the balance-of-payments constraint. The goods market clearing condition for sector j in country n states that total production must equal the sum of intermediate usage across all sectors and countries plus final consumption:

$$Y^{nj} = \sum_{k=1}^{J}\sum_{m=1}^{N} \gamma^{mk,nj}\pi^{mk,nj}X^{mk} + \alpha_{j}\sum_{m=1}^{N} \pi^{mj,nj}\left[\sum_{k=1}^{J} w^{mk}L^{mk} + \iota^{m}\chi\right]$$

This condition captures both the intermediate goods usage that creates input-output linkages and the final consumption that represents ultimate demand. The first term shows how production in country n, sector j is demanded as an intermediate input in sector k production across all countries m, weighted by the input coefficient $\gamma^{mk,nj}$ and the trade share $\pi^{mk,nj}$. The second term represents final consumption demand, where the consumption bundle weights α_{j} determine sectoral demand patterns and the trade shares $\pi^{mj,nj}$ determine sourcing patterns.

Labor market clearing in each country-sector pair requires that employment equals the derived demand from production:

$$L^{nj} = \frac{(1-\xi^n)\gamma^{nj}}{w^{nj}} \sum_{m=1}^{N} \pi^{mj,nj} X^{mj}$$

This condition shows that employment in country *n*, sector *j* depends on global demand for that country-sector's output, captured by the sum over all destination markets m of trade shares times total expenditures. The employment response to changes in global demand is mediated by the labor share in value added $(1-\xi^n)\gamma^{nj}$ and the wage rate w^{nj}.

Similarly, the market-clearing condition for structures ensures that the fixed factor supply equals derived demand:

$$H^{nj} = \frac{\xi^n \gamma^{nj}}{r^{nj}} \sum_{m=1}^{N} \pi^{mj,nj} X^{mj}$$

The structure rental rates r^{nj} adjust to clear these markets given the fixed supplies H^{nj}.

Our solution method adapts the dynamic hat algebra approach of Caliendo et al. (2019) to our multi-country setting without migration. The key insight is that by expressing all equilibrium conditions in terms of proportional changes (growth rates), we can solve for counterfactual allocations without estimating the levels of fundamentals such as productivities and trade costs.

For any variable y, define the hat operator as $\widehat{y_{t+1}} = y_{t+1}/y_t$, representing the gross growth rate between periods t and t+1. The equilibrium conditions can then be rewritten entirely in terms of these growth rates. For example, the unit cost equation becomes:

$$\widehat{c_{t+1}^{nj}} = \left(\widehat{r_{t+1}^{nj}}\right)^{\xi^n \gamma^{nj}} \left(\widehat{w_{t+1}^{nj}}\right)^{(1-\xi^n)\gamma^{nj}} \prod_{k=1}^{J} \left(\widehat{P_{t+1}^{nk}}\right)^{\gamma^{nj,nk}}$$

The price index equation becomes:

$$\widehat{P_{t+1}^{mj}} = \left[\sum_{n=1}^{N} \pi_t^{mj,nj} \left(\widehat{c_{t+1}^{nj} \kappa_{t+1}^{mj,nj}}\right)^{-\theta_j} \left(\widehat{A_{t+1}^{nj}}\right)^{\theta_j}\right]^{-1/\theta_j}$$

And the trade share evolution follows:

$$\pi_{t+1}^{mj,nj} = \pi_t^{mj,nj} \left(\frac{\widehat{c_{t+1}^{nj} \kappa_{t+1}^{mj,nj}}}{\widehat{P_{t+1}^{mj}}}\right)^{-\theta_j} \left(\widehat{A_{t+1}^{nj}}\right)^{\theta_j}$$

The complete system consists of these hat equations for unit costs, price indices, trade shares, total expenditures, and factor prices. Given an initial allocation and a sequence of changes in fundamentals (productivities and trade costs), this system can be solved recursively to trace out the full dynamic path of the economy.

The key advantage of this approach is that it requires only data on the initial period allocation (employment, trade flows, expenditures) plus information about how fundamentals change over time. We do not need to estimate productivity levels, trade cost levels, or other fundamentals that would typically require complex identification strategies in structural models. The observed allocations in the initial period serve as sufficient statistics for all the underlying fundamentals.

For counterfactual analysis, we compare two sequences: the baseline sequence where fundamentals evolve as they actually did, and a counterfactual sequence where some subset of fundamentals evolve differently. In our application, the counterfactual sets Chinese productivity growth to zero while allowing all other fundamentals to evolve as observed. The difference between these two sequences identifies the causal effect of Chinese productivity growth on all endogenous variables.

A.3 Decomposing Differences in Output

Having defined the direct and upstream effects of changes in final goods and intermediate goods output, we show below that they (as claimed) sum to the total effect of moving from the counterfactual to the observed output vectors, $\boldsymbol{Y} - \widetilde{\boldsymbol{Y}}$:

$$\boldsymbol{Y} - \widetilde{\boldsymbol{Y}} = \sum_{n=0}^{\infty} \boldsymbol{A^n D} - \sum_{n=0}^{\infty} \widetilde{\boldsymbol{A}}^{\boldsymbol{n}} \widetilde{\boldsymbol{D}}$$

$$= \boldsymbol{D} - \widetilde{\boldsymbol{D}} + \sum_{n=1}^{\infty} \boldsymbol{A^n D} - \sum_{n=1}^{\infty} \widetilde{\boldsymbol{A}}^{\boldsymbol{n}} \widetilde{\boldsymbol{D}}$$

$$= (DF) + \frac{1}{2}[\sum_{n=1}^{\infty} (\boldsymbol{A^n} + \widetilde{\boldsymbol{A}}^{\boldsymbol{n}})(\boldsymbol{D} - \widetilde{\boldsymbol{D}}) + \boldsymbol{A^n D} - \widetilde{\boldsymbol{A}}^{\boldsymbol{n}} \widetilde{\boldsymbol{D}} + \boldsymbol{A^n} \widetilde{\boldsymbol{D}} - \widetilde{\boldsymbol{A}}^{\boldsymbol{n}} \boldsymbol{D}]$$

$$= (DF) + (UF) + \frac{1}{4} \sum_{n=1}^{\infty} \left(\boldsymbol{2A^n} - \boldsymbol{2}\widetilde{\boldsymbol{A}}^{\boldsymbol{n}}\right)\left(\boldsymbol{D} + \widetilde{\boldsymbol{D}}\right) + \frac{1}{4} \sum_{n=0}^{\infty} \left(\boldsymbol{A}\widetilde{\boldsymbol{A}}^{\boldsymbol{n}} - \boldsymbol{A}\widetilde{\boldsymbol{A}}^{\boldsymbol{n}} + \widetilde{\boldsymbol{A}}\boldsymbol{A^n} - \widetilde{\boldsymbol{A}}\boldsymbol{A^n}\right)\left(\boldsymbol{D} + \widetilde{\boldsymbol{D}}\right)$$

$$= (DF) + (UF) + \frac{1}{4} \sum_{n=0}^{\infty} (\boldsymbol{A} - \widetilde{\boldsymbol{A}})(\boldsymbol{A^n} + \widetilde{\boldsymbol{A}}^{\boldsymbol{n}})(\boldsymbol{D} + \widetilde{\boldsymbol{D}}) + \frac{1}{4} \sum_{n=0}^{\infty} (\boldsymbol{A} + \widetilde{\boldsymbol{A}})(\boldsymbol{A^n} - \widetilde{\boldsymbol{A}}^{\boldsymbol{n}})(\boldsymbol{D} + \widetilde{\boldsymbol{D}})$$

$$= (DF) + (UF) + (DI) + (UI)$$

A similar matrix form representation is also possible, utilizing the notation introduced above:

$$\boldsymbol{Y} - \widetilde{\boldsymbol{Y}} = \boldsymbol{Y_1} - \boldsymbol{Y_4}$$

$$= \boldsymbol{D} - \widetilde{\boldsymbol{D}} + \boldsymbol{AY_1} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}$$

$$= (DF) + \frac{\boldsymbol{1}}{\boldsymbol{2}}\left[\boldsymbol{AY_1} - \boldsymbol{AY_2} + \widetilde{\boldsymbol{A}}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}\right] + \frac{\boldsymbol{1}}{\boldsymbol{2}}\left[\boldsymbol{AY_1} + \boldsymbol{AY_2} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}\right]$$

$$= (DF) + (UF) + \frac{\boldsymbol{1}}{\boldsymbol{2}}\left[\boldsymbol{AY_1} + \boldsymbol{AY_2} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}\right] \pm \frac{\boldsymbol{1}}{\boldsymbol{4}}\left[\widetilde{\boldsymbol{A}}\boldsymbol{Y_1} + \widetilde{\boldsymbol{A}}\boldsymbol{Y_2} + \boldsymbol{AY_3} + \boldsymbol{AY_4}\right]$$

$$= (DF) + (UF) + \frac{\boldsymbol{1}}{\boldsymbol{4}}\left[\boldsymbol{AY_1} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_1} + \boldsymbol{AY_2} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_2} + \boldsymbol{AY_3} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_3} + \boldsymbol{AY_4} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}\right]$$

$$+ \frac{\boldsymbol{1}}{\boldsymbol{4}}\left[\boldsymbol{AY_1} + \widetilde{\boldsymbol{A}}\boldsymbol{Y_1} + \boldsymbol{AY_2} + \widetilde{\boldsymbol{A}}\boldsymbol{Y_2} - \boldsymbol{AY_3} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_3} - \boldsymbol{AY_4} - \widetilde{\boldsymbol{A}}\boldsymbol{Y_4}\right]$$

$$= (DF) + (UF) + (DI) + (UI)$$

As noted in the text, we can additionally represent the domestic and export components of changes in production due to changes in trade outlined in section 2.3 in a similar matrix form to the above. That is, the four components of changes in domestic production due to trade can be represented as:

$$\boldsymbol{Y_{(i,i)}} - \widetilde{\boldsymbol{Y}}_{(i,i)} =$$

$$= \boldsymbol{D_{(i,i)}} - \widetilde{\boldsymbol{D}}_{(i,i)} + \boldsymbol{A_{(i,i)}Y_1} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}$$

$$= (DF)_{(i,i)} + \tfrac{1}{2}\left[\boldsymbol{A_{(i,i)}Y_1} - \boldsymbol{A_{(i,i)}Y_2} + \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}\right]$$

$$+ \tfrac{1}{2}\left[\boldsymbol{A_{(i,i)}Y_1} + \boldsymbol{A_{(i,i)}Y_2} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}\right]$$

$$= (DF)_{(i,i)} + (UF)_{(i,i)} + \tfrac{1}{2}\left[\boldsymbol{A_{(i,i)}Y_1} + \boldsymbol{A_{(i,i)}Y_2} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_3} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}\right]$$

$$\pm \tfrac{1}{4}\left[\widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_1} + \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_2} + \boldsymbol{A_{(i,i)}Y_3} + \boldsymbol{A_{(i,i)}Y_4}\right]$$

$$= (DF)_{(i,i)} + (UF)_{(i,i)}$$

$$+ \tfrac{1}{4}\left[\boldsymbol{A_{(i,i)}Y_1} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_1} + \boldsymbol{A_{(i,i)}Y_2} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_2} + \boldsymbol{A_{(i,i)}Y_3} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_3} + \boldsymbol{A_{(i,i)}Y_4}\right.$$

$$\left. - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}\right]$$

$$+ \tfrac{1}{4}\left[\boldsymbol{A_{(i,i)}Y_1} + \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_1} + \boldsymbol{A_{(i,i)}Y_2} + \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_2} - \boldsymbol{A_{(i,i)}Y_3} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_3} - \boldsymbol{A_{(i,i)}Y_4} - \widetilde{\boldsymbol{A}}_{(i,i)}\boldsymbol{Y_4}\right]$$

$$= (DF)_{(i,i)} + (UF)_{(i,i)} + (DI)_{(i,i)} + (UI)_{(i,i)}$$

Replacing $\boldsymbol{A_{(i,i)}}$ with $\boldsymbol{A_{-(i,i)}}$ and $\widetilde{\boldsymbol{A}}_{(i,i)}$ with $\widetilde{\boldsymbol{A}}_{-(i,i)}$ results in a similar expression for the change in export production due to changes in trade. We decompose the combined final goods and intermediate goods upstream effects (UF and UI) into their domestic and export components in Figure 4.

A.4 Measuring "Upstreamness"

Following Antràs et al. (2012), we measure "upstreamness" at the country-industry level, and then generate country level measures by taking the weighted average of the industry level measures across each country. The vector of country-industry upstreamness measures of total production is constructed as $US = [I - \boldsymbol{A}]^{-1}\mathbf{1} = \mathbf{1} + \boldsymbol{A}\mathbf{1} + \boldsymbol{A}^2\mathbf{1} + \cdots$, where $\mathbf{1}$ is a unit vector. In this way, the upstreamness measure of a country industry pair is equal to the sum product of the share of output at each stage in the global production chain times the index-value of that stage in the production chain. That is, final output has a weight of 1, the intermediate output used immediately to produce final outputs has a weight of 2, the output used one stage up the production chain to produce that output has a weight of 3, etc. To assess the upstreamness of exported or imported production, some adjustments to the above formula are made.

For exported goods, the upstreamness measure is constructed as:

$$US_{exp}^{(i,r)} = \frac{[\boldsymbol{D}_{exp} + \boldsymbol{A}_{exp}\boldsymbol{Y} + \boldsymbol{A}_{exp}[I - \boldsymbol{A}]^{-1}\boldsymbol{Y}]_{(i,r)}}{[\boldsymbol{Y}_{exp}]_{(i,r)}}$$

Here, $\boldsymbol{D}_{exp}, \boldsymbol{A}_{exp}$ and $\boldsymbol{Y}_{exp}$ are the analogous measures of final demands, input-output ratios and total output, considering only exports. This equation simply takes the equation for total exports, $\boldsymbol{Y}_{exp} = \boldsymbol{D}_{exp} + \boldsymbol{A}_{exp}\boldsymbol{Y}$, i.e. total exports are equal to final exported goods plus exported intermediate goods, and divides each stage by total output to get the share of total output in each industry per stage, before multiplying by the index of that stage. Therefore, the part of the upstreamness measure due to final exports is $\frac{\boldsymbol{D}_{exp}}{\boldsymbol{Y}_{exp}}$, the part due to the second stage $2\frac{\boldsymbol{A}_{exp}\boldsymbol{D}}{\boldsymbol{Y}_{exp}}$, the third stage $3\frac{\boldsymbol{A}_{exp}\boldsymbol{A}\boldsymbol{D}}{\boldsymbol{Y}_{exp}}$, etc. The sum of the part coming from intermediate production can be simplified to $\frac{\boldsymbol{A}_{exp}\boldsymbol{Y} + \boldsymbol{A}_{exp}[I - \boldsymbol{A}]^{-1}\boldsymbol{Y}}{\boldsymbol{Y}_{exp}}$. To see why, note that the numerator can be decomposed as:

$$\boldsymbol{A}_{exp}\boldsymbol{Y} + \boldsymbol{A}_{exp}[I-\boldsymbol{A}]^{-1}\boldsymbol{Y} = \boldsymbol{A}_{exp}(\boldsymbol{Y} + [I-\boldsymbol{A}]^{-1}\boldsymbol{Y})$$

$$= \boldsymbol{A}_{exp}(\boldsymbol{Y} + [I-\boldsymbol{A}]^{-2}\boldsymbol{D})$$

$$= \boldsymbol{A}_{exp}(\boldsymbol{Y} + [I-\boldsymbol{A}]^{-1}(\textstyle\sum_{n=0}^{\infty}\boldsymbol{A}^n\boldsymbol{D}))$$

$$= \boldsymbol{A}_{exp}(\boldsymbol{Y} + (\textstyle\sum_{m=1}^{\infty}\boldsymbol{A}^m(\sum_{n=0}^{\infty}\boldsymbol{A}^n\boldsymbol{D})))$$

$$= \boldsymbol{A}_{exp}(\boldsymbol{Y} + \textstyle\sum_{n=0}^{\infty}\boldsymbol{A}^n\boldsymbol{D} + \sum_{n=1}^{\infty}\boldsymbol{A}^n\boldsymbol{D} + \sum_{n=2}^{\infty}\boldsymbol{A}^n\boldsymbol{D} + \cdots))$$

$$= \boldsymbol{A}_{exp}(\boldsymbol{Y} + \boldsymbol{D} + 2\boldsymbol{A}\boldsymbol{D} + 3\boldsymbol{A}^2\boldsymbol{D} + 4\boldsymbol{A}^3\boldsymbol{D} + \cdots)$$

$$= \boldsymbol{A}_{exp}(2\boldsymbol{D} + 3\boldsymbol{A}\boldsymbol{D} + 4\boldsymbol{A}^2\boldsymbol{D} + 5\boldsymbol{A}^3\boldsymbol{D} + \cdots),$$

which, when multiplied out, recovers the terms in the sequence above.

Since any imported goods must have been exported by a partner country, we take the import measure of upstreamness to be a weighted average of the upstream measures of the exporting country-industry pairs. That is, the vector of average upstreamness of imports is:

$$US_{imp}^{(i,r)} = \sum_{j\neq i}^{J} \frac{US_{exp}^{(j,r)} x^{(j,r),(i)}}{\sum_{j\neq i}^{J} x^{(j,r),(i)}}$$

Lastly, a measure of the upstreamness of domestic production is produced in a similar fashion to the upstreamness measure of exports, i.e.:

$$US_{dom}^{(i,r)} = \frac{[\boldsymbol{D}_{\text{dom}} + \boldsymbol{A}_{dom}\boldsymbol{Y} + \boldsymbol{A}_{dom}[I-\boldsymbol{A}]^{-1}\boldsymbol{Y}]_{(i,r)}}{[\boldsymbol{Y}_{dom}]_{(i,r)}}$$

A.5 Labor Demands by Task Concentration

Figure A-1 decomposes effects by the task content of worker's occupations. Tasks performed within each occupation are assigned to one of "routine", "abstract" or "manual" (following e.g. Autor and Dorn (2013) and Spitz-Oener (2006), among others). We categorize industry-level task content by aggregating across workers within each industry, set using data from our base year 2000.

German workers in occupations that heavily consisted of routine task work see larger increases in labor demands than do those in abstract or manual task-focused occupations. The difference is not insignificant: increased demand for routine-task labor was nearly twice as much as the increase in demand for manual-task labor[17], and 1.5x as much as the increased demand for abstract-task labor, driven by a greater concentration of routine task-focused occupations in manufacturing industries. Task concentration profiles across industries are relatively similar in the US and Germany, but due to the US's output gains in service rather than manufacturing industries, manual (non-routine) task labor sees a relatively larger increase in labor demand when compared to routine-task labor.

Figure A-1 additionally decomposes task-level labor market effects into direct and indirect components. Much of the effects again come through upstream rather than direct effects. The upstream effects on task-labor demands by 2014 are bunched between 0.59%-0.61%, while the direct effects vary from -0.08% for routine workers to 0.14% for manual workers.

Figures A-2 and A-3 further decompose task-level labor demand effects into domestic and international components for Germany and the United States, respectively. In Germany, the striking advantage of routine-task workers is driven almost entirely by the international channel: international effects account for approximately 2.5 percentage points of labor demand growth for routine workers by 2014, compared to roughly 2 percentage points for manual and abstract workers. Within the international channel, direct effects, which reflect Germany's export orientation in routine-intensive manufacturing, are particularly pronounced for routine workers. Domestic effects are more muted and similar across task types, with upstream linkages accounting

[17] Note here that, as in Autor and Dorn (2013), routine tasks consist of both physical (manual) and non-physical routine labor, therefore manual tasks are defined here as solely non-routine manual tasks.

for virtually all domestic gains. In the United States, the domestic channel is uniformly negative across all task types, reflecting the direct impact of import competition on domestically-oriented production. However, international upstream and direct effects are positive for all worker types, partially offsetting domestic losses. Manual-task workers see slightly larger international gains than routine or abstract workers, consistent with the US pattern of output growth concentrated in less trade-exposed service industries rather than manufacturing.

A.6 Regional Analysis

We use the changes in production generated in Section 5 to allocate the effects of the rise and integration of the East across local labor markets in the US. Through the decompositions described earlier, we can further distinguish between direct effects in local labor markets and upstream effects arising indirectly from induced changes in production in downstream industries.

We map commuting zone (CZ) level exposure measures in Figure A-4 (summary statistics in table A-4). Mechanically, we use ACS data to generate labor supplies by industry-commuting zone cell across years. Commuting zone definitions are standardized over available years and match those found in the literature (e.g. Autor and Dorn (2013)). We construct a measure of the CZ level exposure to induced production changes due to changes in trade flows from and to the East as follows:

$$(7) \qquad EXP_{c,t} = 100 * \sum_i \frac{L_{i,c,00}}{L_{c,00}} \cdot \Delta y_{i,t}$$

where $\frac{L_{i,c,00}}{L_{c,00}}$ is the industry *i* share of labor supply CZ *c* in the base year and $\Delta y_{i,t}$ is the total, direct or upstream effect (as a percentage of total production) in industry *i*, year *t*. This is structurally similar to the exposure measure of Autor et al. (2021), but with the replacement of the change in imports measure with our estimated changes in production. This allows us to differentiate between total, direct, and upstream effects at the regional level.

Figure A-4 demonstrates the substantial variation in the geographic incidence of production effects due to changes in trade flows with the East. The direct effects were felt most strongly throughout the upper South. This aligns with Autor et al. (2021), who document the exposure of manufacturing industries to increased imports from China and other competitors in these regions. There is some evidence that Great Plains states saw production increases directly due to changes in trade, likely driven by increased petroleum production and exports during this period. Meanwhile, the upstream effects of trade changes are dispersed, with no broad regions seeing losses but a few seeing significantly higher gains than others.

We generate CZ-level import exposure measures analogous to those of Acemoglu et al. (2016) and Autor et al. (2021) by replacing our generated effects from equation (7) with industry-level changes in imports from China $\Delta m_{i,t}$, as follows:

$$(8) \qquad IP_{c,t} = 100 * \sum_i \frac{L_{i,c,00}}{L_{c,00}} \cdot \Delta m_{i,t}$$

We then compare our exposure measures from equation (7) with these import exposure measures in Figure 8As seen there, our measures of CZ-level total and direct effects are strongly and negatively correlated with these CZ-level import-competition measures (correlation coefficient r = -0.89 and -0.90, respectively), as expected. However, our measure of upstream effects is not strongly correlated with the Autor et al. (2013) style measures (r = -0.41). This suggests that while our direct effects are picking up much of the 'China Shock,' our upstream effects are not, rather capturing changes in trade mediated through other avenues. In large part, as shown by the significant proportion of upstream effects due to international rather than domestic changes in trade flows, these must be coming from re-exports or third-country exports.

We next assess the effects of local exposure rates on labor market outcomes by regressing the CZ-level manufacturing and non-manufacturing employment-to-population ratios on changes

in the total, direct, and upstream exposure measures. We build off prior work, such as Autor et al. (2013), by taking our industry-level measures of total, direct, and upstream effects and allocating them regionally using shift-share instruments. Crucially, however, our exposure measures capture positive direct or upstream production effects and therefore are directionally different from those often used to study import competition (imports being typically explicitly or implicitly modelled as a negative production shock). Whereas more exposed industries in e.g., Autor et al. (2013) and Autor et al. (2021) saw larger import competition, more exposed industries in our work are those that saw greater production demand due to changes in trade (the direct component of which would manifest as exports minus imports). Table A-5 largely reinforces the findings of Autor et al. (2013) and subsequent work: we find that higher exposure leads to higher manufacturing employment (columns 1-3). Controlling for initial manufacturing concentration significantly mediates but does not remove this finding (columns 4-6)

The pattern is markedly different for non-manufacturing workers (Table A-6). Here we see that higher exposure led to a *decrease* in non-manufacturing employment (-0.770, column 4). One potential interpretation is that greater direct import exposure (negative exposure value in our context) led to workers switching from manufacturing to service work, an interpretation Autor et al. (2013) also posit. What is interesting in our context is that for both manufacturing and non-manufacturing employment rates, we see positive effects on the upstream exposure variable (column 6, 0.743 for non-manufacturing, 0.313 for manufacturing). That is, indirect positive exposure to changes in trade flows through production networks led to higher employment-to-population rates, whereas the direct effects largely cancelled out across manufacturing and non-manufacturing workers. However, due to the intrinsically more dispersed nature of upstream vs direct effects, there is not enough variation across commuting zones for results to be significant

(see the map in Figure A-4 for an empirical example of this dispersion in our context: while direct effects are much more variable across commuting zones, upstream effects are naturally more evenly dispersed).

A.7 Appendix Tables

Table A - 1: Changes in Imports and Exports with China (Million USD (2000))

Table A-1: Changes in Imports and Exports From/To China

		Manufacturing			Other			Total		
	Type	2000	2014	Δ	2000	2014	Δ	2000	2014	Δ
Germany	Imports	8,747	56,053	47,306	2,003	10,594	8,591	10,750	66,647	55,896
	Intermediates	*2,802*	*21,988*	*19,187*	*1,810*	*9,526*	*7,716*	*4,612*	*31,514*	*26,903*
	Exports	7,143	76,671	69,528	1,476	15,918	14,443	8,619	92,590	83,971
	Intermediates	*3,713*	*33,287*	*29,574*	*963*	*9,888*	*8,924*	*4,676*	*43,174*	*38,498*
	Net	1,604	-20,618	-22,222	528	-5,324	-5,852	2,131	-25,943	-28,074
	Intermediates	*-911*	*-11,298*	*-10,387*	*847*	*-362*	*-1,209*	*-64*	*-11,660*	*-11,596*
USA	Imports	48,013	251,332	203,319	3,562	10,322	6,760	51,575	261,655	210,079
	Intermediates	*12,116*	*91,749*	*79,633*	*2,634*	*6,372*	*3,738*	*14,750*	*98,122*	*83,372*
	Exports	10,327	52,844	42,517	2,142	31,572	29,430	12,469	84,416	71,947
	Intermediates	*5,354*	*23,397*	*18,043*	*1,566*	*26,666*	*25,101*	*6,920*	*50,063*	*43,143*
	Net	37,686	198,488	160,802	1,420	-21,250	-22,670	39,106	177,238	138,132
	Intermediates	*6,762*	*68,353*	*61,591*	*1,068*	*-20,294*	*-21,362*	*7,830*	*48,059*	*40,228*

Note: All values taken from the World Input-Output Table, in millions of 2000 US dollars. "Intermediates" refer to flows of intermediate goods; all other figures are sums of these intermediate flows and final goods. "Other" covers the primary and service sectors.

Table A - 2: Changes in German Output by Industry due to Changes in Trade Flows

Table A-2: Changes in German Output by Industry from 2000 to 2014 due to Trade, Across Counterfactuals

	Industry Description	Output	Δ	%	ΔA1	%A1	ΔA2	%A2
1	Machinery and equipment n.e.c.	92.2	18.5	20%	12.6	14%	15.7	17%
2	Motor vehicles, trailers and semi-trailers	93.2	15.7	17%	10.5	11%	13.2	14%
3	Wholesale trade, except of motor vehicles	116.8	11.4	10%	4.8	4%	8.0	7%
4	Chemicals and chemical products	45.0	8.8	20%	4.9	11%	7.4	16%
5	Legal, accounting, head office and management consultancy activities	78.5	9.1	12%	4.4	6%	6.8	9%
6	Electrical equipment	40.4	7.0	17%	3.2	8%	6.2	15%
7	Administrative and support service activities	127.6	8.6	7%	2.6	2%	5.4	4%
8	Computer, electronic and optical products	31.1	4.5	14%	0.6	2%	4.8	15%
9	Fabricated metal products, except machinery and equipment	52.5	6.3	12%	2.8	5%	4.7	9%
10	Real estate activities	285.6	6.4	2%	1.7	1%	3.5	1%
11	Basic metals	24.1	4.7	19%	1.5	6%	3.4	14%
12	Rubber and plastic products	27.7	4.2	15%	1.8	6%	3.3	12%
13	Electricity, gas, steam and air conditioning supply	54.6	3.6	7%	1.1	2%	2.1	4%
14	Information technology services and related	67.3	3.5	5%	0.7	1%	2.0	3%
15	Financial service activities, except insurance and pension funding	73.6	3.1	4%	0.7	1%	1.7	2%
16	Warehousing and support activities for transportation	47.1	3.6	8%	-0.1	0%	1.7	4%
17	Basic pharmaceutical products and pharmaceutical preparations	23.2	1.8	8%	1.1	5%	1.6	7%
18	Architectural and engineering activities; technical testing and analysis	38.2	2.5	7%	0.7	2%	1.6	4%
19	Food products, beverages and tobacco products	45.7	2.6	6%	0.9	2%	1.5	3%
20	Other transport equipment	14.1	1.5	11%	1.0	7%	1.4	10%
21	Furniture; other manufacturing	22.0	1.9	8%	-0.1	0%	1.4	6%
22	Textiles, wearing apparel and leather products	7.2	1.4	19%	0.3	5%	1.3	18%
23	Public administration and defence; compulsory social security	169.9	3.0	2%	0.5	0%	1.3	1%
24	Waste management services	22.0	1.9	9%	0.5	2%	1.2	6%
25	Paper and paper products	11.3	1.5	13%	0.6	6%	1.1	10%
26	Wholesale and retail trade and repair of motor vehicles	40.7	2.4	6%	0.3	1%	1.1	3%
27	Construction	117.9	3.4	3%	0.4	0%	1.0	1%
28	Repair and installation of machinery and equipment	14.7	1.4	9%	0.4	2%	0.8	6%
29	Other non-metallic mineral products	16.9	1.3	8%	0.4	2%	0.8	5%
30	Other service activities	99.1	1.6	2%	0.4	0%	0.8	1%
31	Printing and reproduction of recorded media	8.5	1.1	13%	0.6	8%	0.8	9%
32	Advertising and market research	12.8	1.1	9%	0.4	3%	0.8	6%
33	Postal and courier activities	15.4	1.0	6%	0.3	2%	0.6	4%
34	Other professional, scientific and technical activities; veterinary activities	12.4	0.9	7%	0.3	2%	0.5	4%
35	Telecommunications	28.7	1.0	3%	0.2	1%	0.5	2%
36	Crop and animal production, hunting and related service activities	18.7	1.2	6%	-0.1	0%	0.5	3%
37	Mining and quarrying	4.3	0.9	21%	-2.7	-62%	0.5	11%
38	Water transport	9.3	0.7	8%	0.0	0%	0.4	5%
39	Education	123.0	1.1	1%	0.3	0%	0.4	0%
40	Land transport and transport via pipelines	47.4	2.0	4%	-1.2	-3%	0.4	1%
41	Publishing activities	14.6	0.6	4%	0.2	1%	0.4	2%
42	Air transport	6.4	0.5	8%	0.3	4%	0.3	5%
43	Accommodation and food service activities	41.0	0.7	2%	0.2	1%	0.3	1%
44	Insurance, reinsurance and pension funding	26.0	0.6	2%	0.1	0%	0.3	1%
45	Activities auxiliary to financial services and insurance activities	16.0	0.5	3%	0.1	0%	0.2	2%
46	Audio-visual production and related	16.2	0.4	2%	0.1	1%	0.2	1%
47	Scientific research and development	20.2	0.5	2%	0.1	1%	0.2	1%
48	Water collection, treatment and supply	5.7	0.2	4%	0.0	1%	0.1	2%
49	Wood and wood products, except furniture	7.2	0.4	5%	-0.2	-3%	0.1	1%
50	Human health and social work activities	195.8	1.3	1%	0.0	0%	0.1	0%
51	Fishing and aquaculture	0.2	0.0	2%	0.0	-2%	0.0	1%
52	Household activities and production	7.5	0.0	0%	0.0	0%	0.0	0%
53	Retail trade, except of motor vehicles	89.3	1.2	1%	-0.9	-1%	0.0	0%
54	Forestry and logging	2.6	0.0	1%	-0.2	-8%	-0.1	-4%
55	Coke and refined petroleum products	7.0	0.5	8%	-1.9	-28%	-1.1	-16%

Note: All values in billions of 2000 US dollars. Sourced from the World Input-Output Table using authors' calculations with counterfactuals as defined above. Ranks are according to net changes in output value under counterfactual 2. Δ1 indicates the net change in output value due to counterfactual 1, % the percent change in output for the same counterfactual.

Table A - 3: Changes in US Output by Industry due to Changes in Trade Flows

Table A-3: Changes in US by Industry from 2000 to 2014 due to Trade, Across Counterfactuals

	Industry Description	Output	Δ	%	ΔA1	%A1	ΔA2	%A2
1	Administrative and support service activities	523.3	6.9	1%	-1.1	0%	3.1	1%
2	Crop and animal production, hunting and related service activities	135.8	6.1	4%	3.4	3%	4.0	3%
3	Legal, accounting, head office and management consultancy activities	424.3	5.8	2%	0.3	0%	3.2	1%
4	Mining and quarrying	310.2	5.5	2%	-0.6	0%	1.8	1%
5	Public administration and defence; compulsory social security	1639.1	5.0	1%	-0.3	0%	0.4	0%
6	Air transport	68.8	4.9	7%	3.5	5%	4.1	6%
7	Other transport equipment	105.1	4.8	4%	1.8	1%	3.8	2%
8	Chemicals and chemical products	195.3	4.6	3%	-0.2	0%	3.2	2%
9	Wholesale and retail trade and repair of motor vehicles	368.8	3.7	1%	-1.3	0%	1.2	0%
10	Construction	502.1	3.2	1%	-0.1	0%	0.2	0%
11	Financial service activities, except insurance and pension funding	389.5	3.2	1%	-1.2	0%	1.2	0%
12	Land transport and transport via pipelines	144.4	3.1	5%	0.7	2%	1.8	4%
13	Real estate activities	1456.1	2.9	0%	-0.4	0%	0.8	0%
14	Telecommunications	251.7	2.8	1%	0.3	0%	0.9	0%
15	Wholesale trade, except of motor vehicles	604.4	2.5	0%	-3.2	-1%	0.6	0%
16	Motor vehicles, trailers and semi-trailers	111.6	2.2	2%	-0.2	-1%	0.9	1%
17	Information technology services and related	240.6	2.1	1%	-0.4	0%	0.7	0%
18	Coke and refined petroleum products	154.3	2.0	1%	-1.2	-2%	0.4	0%
19	Human health and social work activities	947.5	1.9	0%	0.0	0%	0.0	0%
20	Architectural and engineering activities; technical testing and analysis	187.9	1.9	1%	-0.5	0%	0.6	0%
21	Other service activities	330.1	1.5	0%	-0.1	0%	0.3	0%
22	Food products, beverages and tobacco products	211.3	1.4	1%	0.0	0%	0.4	0%
23	Activities auxiliary to financial services and insurance activities	188.6	1.4	1%	0.0	0%	0.7	0%
24	Other professional, scientific and technical activities; veterinary activities	70.4	1.3	1%	0.4	0%	0.8	0%
25	Audio-visual production and related	130.5	1.2	1%	0.1	0%	0.3	0%
26	Accommodation and food service activities	369.1	1.2	0%	-0.1	0%	0.3	0%
27	Publishing activities	146.0	1.2	1%	-0.1	0%	0.5	0%
28	Insurance, reinsurance and pension funding	364.5	1.2	0%	-0.4	0%	0.4	0%
29	Advertising and market research	112.9	1.1	1%	-0.2	0%	0.5	0%
30	Warehousing and support activities for transportation	64.4	1.1	2%	-0.1	0%	0.5	1%
31	Retail trade, except of motor vehicles	630.3	1.0	1%	-0.2	0%	0.0	0%
32	Electricity, gas, steam and air conditioning supply	172.3	0.9	1%	-0.4	0%	0.3	0%
33	Scientific research and development	103.4	0.9	1%	-0.1	0%	0.3	0%
34	Basic pharmaceutical products and pharmaceutical preparations	45.5	0.9	1%	0.0	0%	0.5	1%
35	Postal and courier activities	39.0	0.8	2%	0.2	0%	0.5	1%
36	Machinery and equipment n.e.c.	131.7	0.8	0%	-2.8	-3%	0.1	0%
37	Waste management services	38.8	0.7	2%	-0.3	-1%	0.2	0%
38	Water transport	25.2	0.5	3%	-0.1	0%	0.2	2%
39	Education	144.4	0.5	0%	0.0	0%	0.1	0%
40	Paper and paper products	46.7	0.5	1%	-0.5	-1%	0.0	0%
41	Repair and installation of machinery and equipment	37.7	0.3	1%	-0.1	0%	0.1	0%
42	Forestry and logging	6.6	0.3	4%	0.1	1%	0.1	2%
43	Printing and reproduction of recorded media	26.2	0.2	0%	-0.1	-1%	0.1	0%
44	Water collection, treatment and supply	6.8	0.2	2%	0.0	0%	0.1	1%
45	Fishing and aquaculture	4.2	0.1	4%	0.1	2%	0.1	2%
46	Household activities and production	9.5	0.0	1%	0.0	0%	0.0	0%
47	Wood and wood products, except furniture	22.1	0.0	-1%	-0.5	-3%	-0.3	-1%
48	Other non-metallic mineral products	39.9	-0.3	-1%	-1.0	-3%	-0.5	-1%
49	Basic metals	53.7	-0.4	-1%	-2.4	-5%	-0.6	-2%
50	Rubber and plastic products	56.7	-0.5	-1%	-1.8	-4%	-0.7	-2%
51	Fabricated metal products, except machinery and equipment	109.1	-1.0	-1%	-2.9	-3%	-0.9	-1%
52	Furniture; other manufacturing	78.2	-1.2	-2%	-3.3	-5%	-1.7	-3%
53	Textiles, wearing apparel and leather products	28.5	-2.0	-7%	-7.1	-24%	-1.5	-5%
54	Electrical equipment	43.8	-3.0	-10%	-3.8	-12%	-1.2	-4%
55	Computer, electronic and optical products	164.8	-12.1	-7%	-10.5	-6%	-0.9	0%

Note: All values in billions of 2000 US dollars. Sourced from the World Input-Output Table using authors' calculations with counterfactuals as defined above. Ranks are according to net changes in output value under counterfactual 2. Δ1 indicates the net change in output value due to counterfactual 1, % the percent change in output for the same counterfactual.

Table A - 4: Commuting Zone Exposure, Summary Statistics

	Total Effect	Direct Effect	Upstream Effect
Minimum	-1.2543	-1.2543	0.1474
25th Percentile	0.2491	-0.4258	0.6228
Median	0.6203	-0.0771	0.7055
Mean	0.5205	-0.1678	0.7103
75th Percentile	0.8626	0.1323	0.7927
Max	1.2543	0.4733	1.186
SD	0.5424	0.4452	0.1372

Note: Summary statistics of total, direct and upstream effects in the United States at the commuting zone level. Output data constructed from WIOD data. Labor data from ACS and 2000 and 2010 census. Measures constructed as in text (Appendix Section A.6).

Table A - 4: US Local Labor Market Regression - Manufacturing Employment / Population Ratio

Table A-5: US Local Labor Market Regression - Manufacturing Employment / Population Ratio

	Dependent Variable					
	Change in Manufacturing Employment / Population Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Local Total	2.908***			0.983***		
	(0.323)			(0.188)		
Local Direct		3.333***	3.360***		1.101***	1.035***
		(0.352)	(0.341)		(0.206)	(0.206)
Local Upstream			−0.586			0.743
			(1.448)			(0.747)
Manuf. Concentration*				−0.227***	−0.223***	−0.225***
				(0.017)	(0.019)	(0.019)
Constant	−0.039***	−0.018***	−0.014	0.029	0.033	0.030
	(0.002)	(0.001)	(0.009)	(0.038)	(0.039)	(0.037)
Num. Obs.	722	722	722	722	722	722

Note: *p<0.1, **p<0.05, ***p<0.01

**Regression run on United States commuting zones. Manuf. Concentration refers to CZ level industrial concentration in manufacturing in 2000, with additional controls for female-, routine-task-, migrant-, college- and non-white shares, along with age group controls and census divisions. Local total, direct and upstream exposure measures as defined in text section 5.4. Regressions weighted by CZ share of working age population in 2000. Standard Errors clustered at state level.*

Table A - 5: US Local Labor Market Regression – Non-Manufacturing Employment / Population Ratio

Table A-6: US Local Labor Market Regression - Non-Manufacturing Employment / Population Ratio

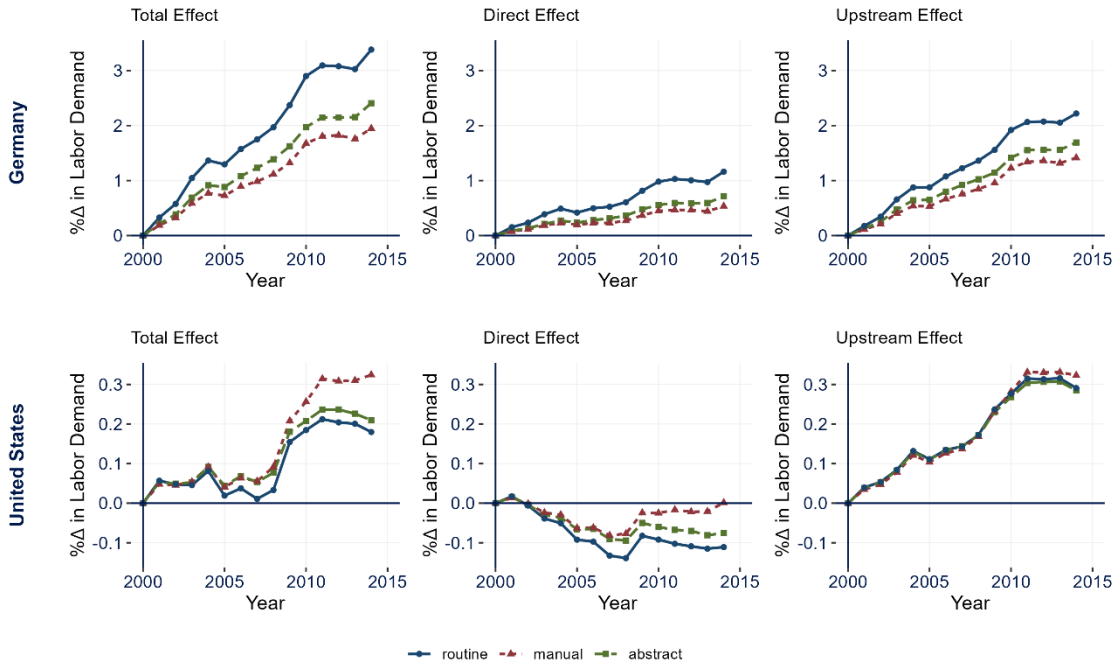
	Dependent Variable					
	Change in Non-Manufacturing Employment / Population Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Local Total	−1.540***			−0.770*		
	(0.408)			(0.351)		
Local Direct		−1.866***	−1.936***		−0.978*	−1.006*
		(0.469)	(0.489)		(0.404)	(0.413)
Local Upstream			1.533			0.313
			(2.489)			(1.089)
Manuf. Concentration*				0.061	0.052	0.051
				(0.038)	(0.040)	(0.041)
Constant	0.024***	0.013***	0.003	−0.172**	−0.176**	−0.177**
	(0.004)	(0.003)	(0.018)	(0.060)	(0.060)	(0.063)
Num. Obs.	722	722	722	722	722	722

Note: *p<0.1, **p<0.05, ***p<0.01

**Regression run on United States commuting zones. Manuf. Concentration refers to CZ level industrial concentration in manufacturing in 2000, with additional controls for female-, routine-task-, migrant-, college- and non-white shares, along with age group controls and census divisions. Local total, direct and upstream exposure measures as defined in text section 5.4. Regressions weighted by CZ share of working age population in 2000. Standard Errors clustered at state level.*

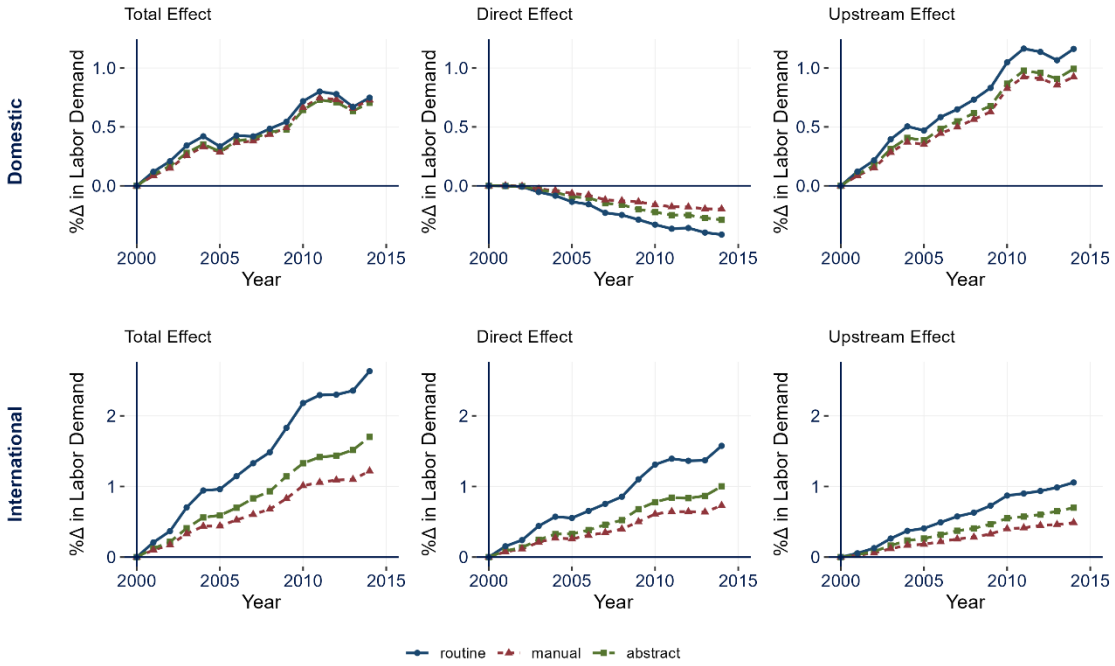
A.8 Appendix Figures

Figure A-1: Change in Labor Demand, by Country, Task Type; Total, Direct and Upstream Effects



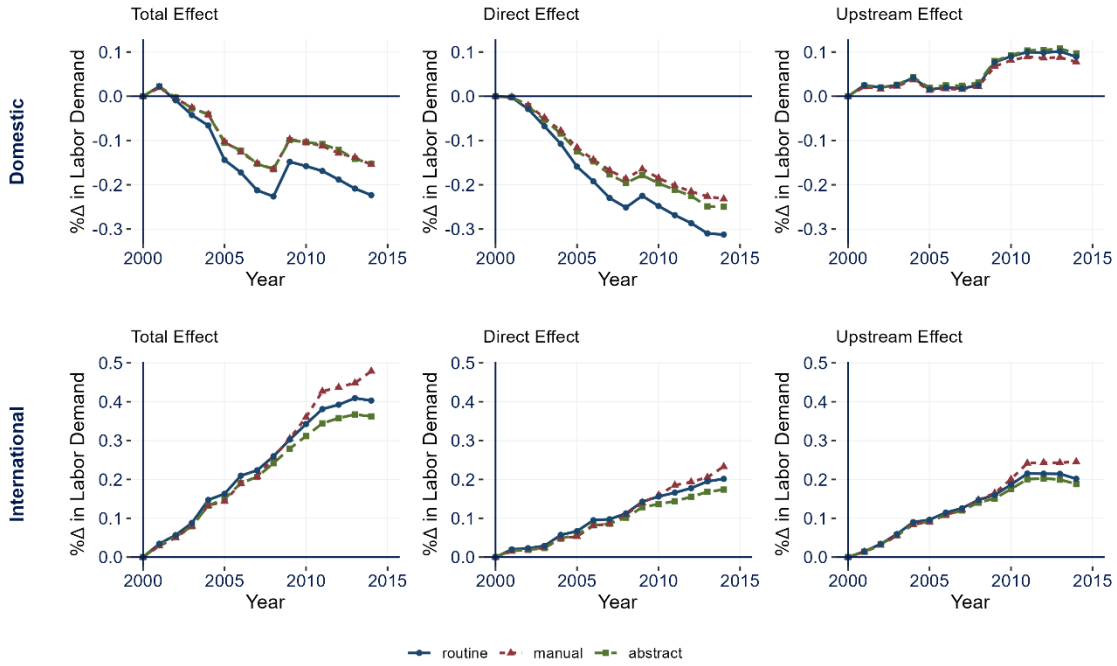
Note: All figures capture the difference between the observed vs counterfactual labor market demand as a percentage of observed group labor demand. Data from the World Input-Output Database, German SIAB, and US ACS and Census, with results using the authors' calculations. Counterfactuals assume China's trade stayed at the 2000 level.

Figure A-2: Change in Labor Demand, by Domestic vs. International, Group; Total, Direct and Upstream Effects, Germany



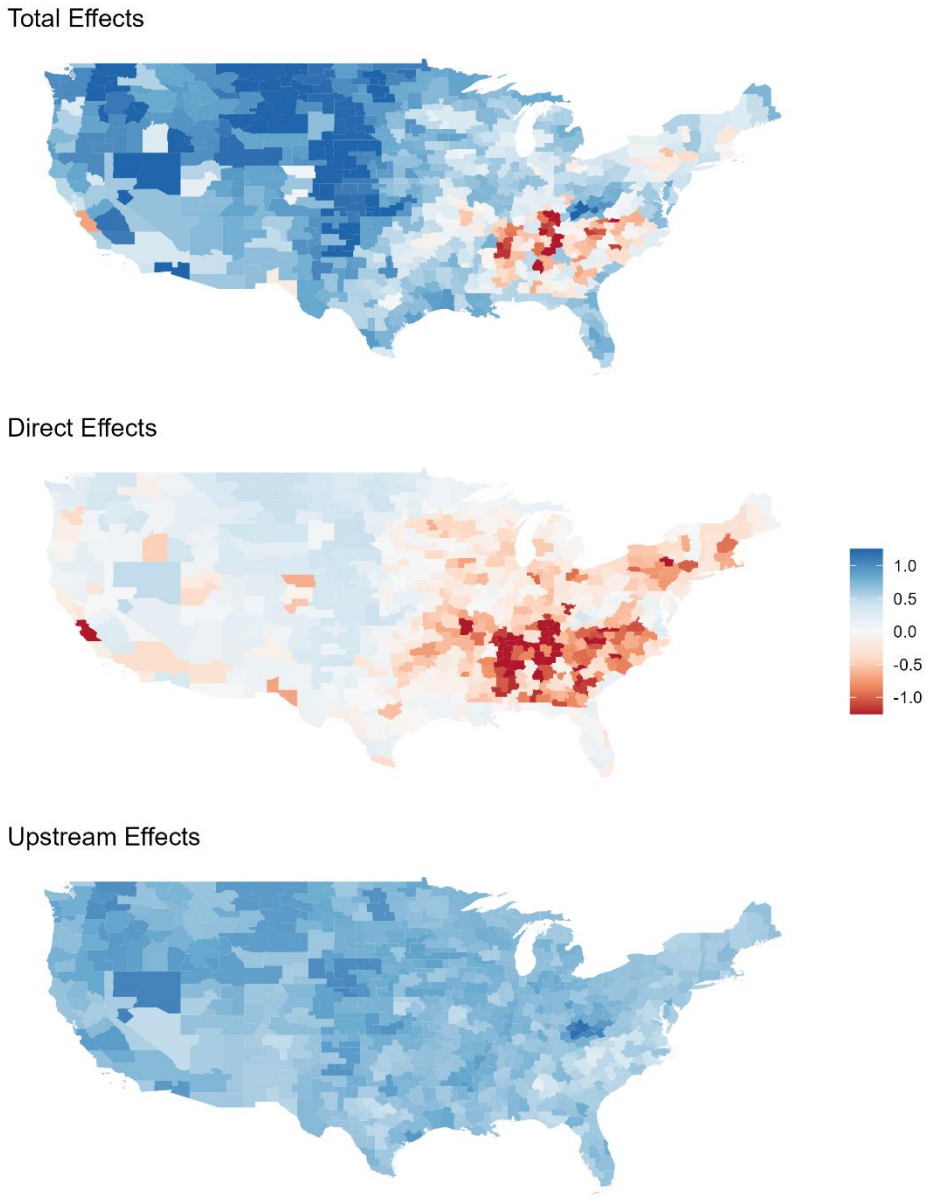
Note: All figures capture the difference between the observed vs counterfactual labor market demand as a percentage of observed group labor demand, decomposed into domestic and international effects. Data from the World Input-Output Database and the German SIAB, with results using the authors' calculations. Counterfactuals assume China's trade stayed at the 2000 level.

Figure A-3: Change in Labor Demand, by Domestic vs. International, Group; Total, Direct and Upstream Effects, United States



Note: All figures capture the difference between the observed vs counterfactual labor market demand as a percentage of observed group labor demand, decomposed into domestic and international effects. Data from the World Input-Output Database and the US ACS and Census, with results using the authors' calculations. Counterfactuals assume China's trade stayed at the 2000 level.

Figure A-4: US Regional Exposure by Commuting Zone



Note: Measures capture the difference between the observed vs counterfactual labor market demand as a percentage of observed labor demand at the commuting zone level. Further details in the text. Data from the World Input-Output Database, BEA, Census, and the ACS, with results using the authors' calculations. Counterfactuals assume China's trade stayed at the 2000 level. Values truncated below the first and above the 99th percentiles.