What Drives the Labor Market Incidence of Trade Shocks?: An Equilibrium Matching Analysis of China's WTO Accession*

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Abstract

This paper reveals the underappreciated role of labor market competition among imperfectly substitutable workers and non-manufacturing industries in mediating the earnings, welfare, and unemployment incidence of changes in the international trade environment. We merge hundreds of millions of LEHD job match records with firm-level import and export records from the LFTTD and use them to estimate a very large-scale assignment model of the entire U.S. labor market. The model flexibly accommodates frictions from switching regions, industries, trade engagement status, and even particular employers. We construct firm-level estimates of the employment impact of China's WTO entry using exogenous tariff gap variation via four different channels, import and export competition and import and export access, and combine them with the model to evaluate the shock's worker-level incidence. Our results show that the first three channels contribute meaningfully to the shock's overall incidence between 2001 and 2006. Furthermore, even though employment changes in these three channels are concentrated among high-paying multinational firms, labor market competition causes the shock's impact to spread to seemingly unaffected sectors and trickle down the skill ladder, so that entry-level non-traded service workers and initially unemployed job-seekers account for a larger share of earnings and particularly employment losses than has previously been acknowledged.

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1 Introduction

The last twenty years have spawned a growing appreciation of the importance of deeply understanding how changes in the international trade environment affect labor markets, as politicians, business advocates and grassroots organizations have disputed the degree to which globalization and trade agreements should be blamed for increased income inequality, rural and regional poverty, and political polarization. Analyses of potential trade agreements and disputes in the popular media blithely declare labor market "winners" and "losers" based on straightforward and sometimes simplistic economic reasoning.

Yet accurately characterizing the labor market incidence of multifaceted trade agreements and tariff adjustments is an extremely challenging endeavor. In particular, it requires 1) identifying which firms' product demand and costs are most affected, 2) how sensitive their employment demand is to these changes, 3) what kinds of workers such firms tend to hire and retain, and 4) which other workers compete elsewhere with the directly affected workers.

The trade literature has explored several channels by which globalization affects firm profits, including increased domestic competition from foreign imports, cheaper imported intermediate inputs, increased export access in some foreign markets, and increased competition for exports in others. However, most evaluations of globalization's labor market impact focus narrowly on manufacturing job loss due to greater import competition or outsourcing opportunities.

Our paper broadens this focus by constructing and estimating an extremely rich equilibrium assignment model of the U.S. labor market. We use the model to illustrate several overlooked mechanisms that shape the labor market incidence of international trade shocks and quantify their importance in the context of a major change in the trade environment, China's World Trade Organization (WTO) accession (the "China Shock"). The model uses as inputs novel reduced-form estimates of firm-level employment impacts of China's WTO accession across multiple channels and industries and produces equilibrium worker-level impacts on earnings, unemployment, and welfare.

Specifically, we first construct a comprehensive database linking international trade with the labor market by combining establishment-level data from the Longitudinal Business Database (LBD), firm-level trade activity data from the Longitudinal Foreign Trade Transactions Database (LFTTD), and linked employer-employee data from the Longitudinal Employer-Household Dynamics database (LEHD). Next, we run firm-level regressions that combine our data on employment and trade activity from the near universe of U.S. firms with plausibly exogenous shift-share measures of firm-level exposure to China's WTO accession, and use the estimates to characterize how the product and input market channels noted above mediated the China Shock's impact on the firm-level distribution of employment demand. For the import competition channel, we adopt Pierce and Schott (2016) exposure measure based on product-level variation in the size of potential tariff increases whose threat was eliminated by China's WTO entry, while for export access we exploit product-level changes in realized Chinese tariffs.

In addition, we evaluate the labor market importance of two channels receiving less attention. The first, denoted "export competition", highlights the role of increasing competition from Chinese products in foreign export markets in exacerbating the import competition shock. The second, denoted "import access", considers opportunities for employment expansion at existing importers of Chinese products. Here, our trade-linked firm data allows us to extend Pierce and Schott (2016)'s tariff gap approach to measuring exposure by using information on the product mix of individual firms' exports and imports. The granularity of our data also allow us to explore heterogeneity in employment sensitivity to each channel by industry and by how the firm engages with trade (e.g. importing vs. exporting vs. both, arms-length vs. related-party). Introducing such heterogeneity is important because we show that large shares of international goods trade in general and China Shock exposure in particular occurs outside manufacturing and is concentrated among multinational firms.

Our firm-level estimates of the employment impact of the first five years following China's WTO accession generate four main findings. First, the export competition and import access channels cause meaningful employment impacts beyond the well-explored import competition channel. Specifically, we estimate that import competition was indeed responsible for a large reduction in manufacturing employment (646,000 jobs between 2002 and 2006), but increased export competition due to rising Chinese supply to U.S. exports markets substantially reinforced these losses (330,000 jobs lost), while increased import access at firms already importing from China substantially offset them (net 240,000 job gain). We do not find a statistically or economically significant role for increased export access to China between 2002 and 2006.

Second, we find that 69% of the export competition job losses and all of the import access job gains accrue to industries besides manufacturing (which experiences net losses from greater import access), with the Wholesale/Retail sector displaying particular sensitivity to both channels (42% and 76% of national gains/losses, respectively). These findings underscore the need for data with broad industry coverage when evaluating the incidence of trade shocks.

Third, we find that 77% of shock-induced employment net losses and 62% of gains occurred among multinational firms already engaged in importing and exporting with related parties even though these firms account for 15.5% of initial U.S. employment. Fourth, we find that 50% of net employment losses occur among the highest-paying (worker-weighted) quartile of firms, while the lowest-paying quartile of firms experienced net job creation of 50,000 jobs. When combined with the fact that the multinationals have particularly right-skewed pay distributions, this suggests that high-paid workers were more exposed to these firm-level employment changes.

To translate firm-level employment impacts to worker-level incidence, we combine the annual firm-level estimates from 2002 to 2006 with an assignment model to produce counterfactual paths for labor market reallocation and earnings adjustments when one or all of the shock's channels are shut down. Four features of assignment models make them ideally suited for a rich characterization of trade shock incidence.

First, the model's minimal structure places very few restrictions on the functional forms of the forces that collectively determine which workers and firms directly and indirectly compete: worker preferences for alternative firms, their productivity at these firms, and the joint distribution of frictions from switching firms, industries and regions. Our implementation facilitates flexible matching by featuring a large set of worker and firm types defined by combinations of several characteristics, including region, sector, past earnings and trade engagement status. Second, the key parameters governing job matching – mean worker and firm surpluses from matches among alternative worker and firm types – are transparently identified by double differences across worker and firm types of job counts and earnings averages from large contingency tables, combined with a logit distributional assumption on idiosyncratic surplus deviations (Choo and Siow (2006)). The hundreds of millions of job match records in our database facilitate estimation of hundreds of thousands of surplus values without overfitting.

Third, by requiring equilibrium among many types, the model allows labor market competition to shape shock incidence in subtle ways. For example, some worker types whose firms received negative trade shocks may easily find other nearly equivalent jobs, while others may be harmed considerably. Similarly, some worker types at firms seemingly unaffected by trade shocks may be nearly insulated, others may be fairly sensitive due to increased competition with workers at affected firms. Fourth, changes in equilibrium allocations and earnings and welfare distributions from counterfactual labor demand or supply shocks can be computed quickly even at this scale, so that meaningful heterogeneity is not lost to computational feasibility.

Though our equilibrium labor market model is a static model designed to match worker reallocation over a one year horizon, we generate five-year cumulative impacts by initial worker type by simulating equilibrium earnings and allocation adjustments for each of a sequence of five single-year firm-level employment shocks. We link the periods by using counterfactual end-of-year job matches to update the next year's distribution of worker types. This retains secular trends in other determinants of job match surpluses, but assumes that workers and firms are myopic about subsequent increases in China's supply.

The simulations yield five main findings driven by mechanisms that are likely to be relevant for other shocks to the international trade environment. First, despite the substantial firm-level employment adjustments we attribute to greater export competition and import access, we find that increased import competition drives the shock's largest earnings and employment impacts, which are experienced by workers at multinational manufacturing firms. Specifically, the average worker initially employed in such firms is estimated to have lost $4,185 in 2002-2006 earnings, with import competition accounting for $3,393.

The second main finding is that import competition more generally accounts for a disproportionate amount of the worker-level earnings losses relative to its impact on firm-level employment. Thus, research that focuses only on the impact of increased import competition on manufacturing workers may still approximate reasonably well the shock's broader impact for this subpopulation. We construct simulations of simple stylized shocks that reveal four mechanisms that explain why the import competition channel generates more concentrated impacts than other channels. First, the firm-level employment losses from export competition are spread more broadly across industries, so that only a small share of any particular worker type lose their job via this channel. Thus, such workers generally need not compete for substitute jobs with large numbers of displaced workers with similar skills and preferences. Second, while the import access shock is reasonably concentrated within the wholesale/retail sector, it is somewhat offset by a moderate export competition shock to this sector. Third, the gains from job creation are much less concentrated than the losses from job destruction. We show that this asymmetry is entirely driven by the existence of large frictions from switching firms. Essentially, trade-induced job destruction eliminates previously valuable firm-specific experience and forces costly job search for targeted workers, while job creation incurs search/recruiting costs to reallocate workers not previously at the targeted firms, generating less new surplus. More generally, such frictions imply that even employment-neutral shocks still produce net earnings losses. Fourth, reinforcing this asymmetry, the job turnover rate in the wholesale/retail sector (26%) is much lower than in manufacturing (19%), suggesting that the jobs created by expanded import access were disproportionately low surplus jobs that workers left quickly.

Our third main finding is that 36% of total earnings losses, 30% of job-related welfare losses, and 77% of increased full-year unemployment due to the China Shock accrue to workers not initially employed in manufacturing. This finding underscores the importance of incorporating non-manufacturing sectors and multisector labor market competition when assessing worker-level effects of trade shocks. Restricting attention to the import competition channel modestly increases these values, despite the large earnings and job-related welfare losses for the most targeted manufacturing workers and the fact that we impose that the import competition channel only eliminates manufacturing jobs.

Examination of counterfactual job transition patterns reveal the relevant underlying mechanisms. Displaced manufacturing workers seek employment in other sectors that may offer similar job environments (e.g. natural resources/utilities for production workers, professional and business services for management), or may have low training/experience requirements (the low-paid service sector). Greater competition leads workers already seeking jobs in those sectors to further expand their search, causing ripple effects throughout the labor market. Moreover, since large shares of manufacturing workers have considerable training and/or experience, they tend to be able to secure employment elsewhere within a year, albeit with possibly lower earnings. Thus, the shock's net employment loss falls to workers who are either initially unemployed or already working in volatile low-paying service jobs who do not obtain or retain the jobs they would have in the absence of the shock.

Our fourth main finding from the simulations is that despite greater initial employment losses at firms with large shares of high paid workers, shock-induced decreases in equilibrium earnings growth and increases in full-year unemployment were larger for initially low paid and unemployed workers. Within manufacturing, initially high-paid and medium-paid workers are better able to secure remaining manufacturing employment, and when they cannot, they out-compete low-paid workers for jobs in other sectors. Thus, relatively lower paid workers from all sectors are disproportionately vulnerable to trade-induced labor market competition. In addition, other high paid sectors such as health/education/government have educational requirements and occupational amenities that do not make them natural destinations for displaced workers from manufacturing and other sectors with intensive trading activity, thus insulating them from the China Shock and most trade shocks more generally.

Using customized simulations of highly targeted shocks to isolate and evaluate the importance of several reallocation frictions, our fifth finding is that firm-switching frictions and regional mobility frictions particularly drive greater concentration of incidence, but frictions from switching industries and trade engagement still reduce equilibrium incidence dispersion.

This paper contributes most directly to the literature on the labor market incidence of shocks to the international trade environment. One strand of this literature uses reduced-form methods featuring quasi-experimental variation to estimate the impact of trade shocks on manufacturing employment at the firm, sectoral, or regional level. Pioneering papers such as Autor et al. (2013) and Pierce and Schott (2016) emphasize the import competition channel, while later papers highlight the possibility of greater opportunities for exporting and of greater competition in foreign export markets from Chinese imports (see Feenstra et al. (2019) and Dauth et al. (2017)). We adopt Pierce and Schott (2016)'s shift-share tariff gap measure of exposure to import competition, but we allow the impact of exposure to vary by firms' trade engagement and size. Furthermore, we also extend their approach to generate analogous measures for the export competition, import access and export access channels by using data on firms' import and export product mix and history of trade with China. We also contribute by generating these measures for firms in all industries, since non-manufacturing firms account for the majority of international trade value and employment at trading firms. Bloom et al. (2019) also emphasize the importance of including non-manufacturing industries because the industry classification of firms is itself sensitive to changes in the trade environment.

A second strand of the reduced-form literature combines quasi-experimental measures of exposure to either import competition or outsourcing risk with worker-level administrative data to analyze trade shocks' short- and long-run impacts on workers initially in the most exposed firms, industries, or locations (e.g. Autor et al. (2014), Kovak and Morrow (2022), Menezes-Filho and Muendler (2011), Hummels et al. (2014)). These papers generally compare average labor market outcomes for subpopulations of workers in "treated" manufacturing industries or locations with concentrations of such industries to those not directly affected by the relevant change in trade activity. Like us, they find that workers in industries/firms/locations directly exposed to import competition or outsourcing exhibit considerable earnings and employment losses, especially among less educated or initially lower paid workers. However, without a characterization of equilibrium these papers cannot analyze the importance of labor market competition in generating indirect effects on workers outside the targeted firms.

Another part of the literature relies more heavily on theoretical models of trade to provide a broader characterization of the spatial and sectoral redistribution of welfare generated by changes in the trade environment. These papers, including Caliendo et al. (2019), Adao et al. (2019), and Galle et al. (2017), emphasize the importance of spatial mobility frictions and equilibrium price adjustments in the product, land, and labor markets for producing accurate assessments of incidence. While these papers often solve jointly for equilibrium in all three markets, and in some cases consider dynamic adjustments (e.g. Caliendo et al. (2019)), they generally feature simple labor markets with very limited worker heterogeneity. Importantly, both quasi-experimental and model-centric papers focused on spatial reallocation tend to use aggregate employment and earnings data at the location level, which precludes a deeper focus on the underlying labor market competition that drives trade-induced earnings inequality.

A few recent papers combine matched employer-employee data with a theoretical model that permits the simulation of a distribution of welfare impacts from trade shocks. Dix-Carneiro (2014) and Traiberman (2019) estimate dynamic models of labor market adjustment to trade shocks, in which workers have different comparative advantages within different sectors based on both fixed demographic characteristics as well as accumulated overall or occupation-specific experience, while Kim and Lee (2020) use occupational skill measures and a matching framework similar to ours to analyze differential equilibrium impacts of outsourcing by worker skill class. These papers emphasize the role of heterogeneity in comparative advantages for determining which kinds of workers experience the largest losses from increased import competition. We go beyond these papers by allowing surplus from job transitions to depend on whether workers are switching not just industries but also regions and even particular firms within industry-region combinations. In addition, we incorporate heterogeneity in relative job match surpluses across firms featuring different size, average pay, and patterns of trade engagement. This allows us to highlight the role of multinationals, multiple shock channels, and within-industry reallocation in determining labor market winners and losers from trade shocks.

The literature built around general equilibrium models of trade emphasizes the importance of accounting for offsetting increases in labor demand from importers, exporters, multinationals, and downstream buyers of imported inputs. However, because this subliterature focuses on employment and earnings at the industry-location level and even the firm level, it does not explore the degree to which the kinds of firms that prosper in more globalized environments tend to hire different kinds of workers, and the role of interconnected labor markets in distributing shifts in the firm composition of labor demand to the worker level.

Taken together, ours is the only paper that simultaneously 1) combines several channels through which a trade shock affects firm-level labor demand, 2) allows labor demand adjustments to vary by firms' form of trade engagement, and 3) flexibly models the labor market competition among many categories of workers and firms to incorporate the frictions generated by imperfect worker mobility and substitutability. This permits the firm's trade engagement, size, sector, and location to inform the distribution of welfare changes by worker type.

Finally, our paper also contributes to a developing literature on the estimation of assignment models, following Choo and Siow (2006), Menzel (2015), and Galichon and Salanié (2021), among others. In conjunction with Mansfield (2019), we demonstrate how to accommodate missing data on unmatched partners on one side of the market, and we show that solving for stable allocations remains computationally tractable even at a very large scale.

The paper is organized as follows. Section 2 introduces our model. Section 3 describes the data we use. In Section 4 we discuss our approach to measure the China Shock at the firm level and our estimated firm-level employment impacts. Section 5 presents and interprets our worker-level incidence estimates of the China Shock. Finally, Section 6 concludes.

2 An Assignment Model of the Labor Market

In this section, we introduce our assignment model of the labor market. The model is based on the two-sided transferable utility matching environment introduced by Choo and Siow (2006), in which a finite set of discrete types on each side of the market search for a potential partner and a unique stable matching exists that defines the equilibrium allocation. We first consider the firm's human resources problem of which workers to fill a pre-specified set of positions. Then we introduce the worker's job choice problem, define equilibrium, and discuss identification of model parameters. Finally, we consider the construction of counterfactual equilibria and discuss key extensions to the model that are reflected in our empirical work.

In Appendix A1, we show how the human resources problem can be nested within a more complex firm-level profit maximization problem of the kind used in general equilibrium models of international trade. The appendix demonstrates that standard trade models could incorporate considerably more worker heterogeneity in productivity and preferences than they generally do without losing computational tractability. It also introduces the fundamental sources of firm heterogeneity that determine how shocks to the trade environment differentially affect the magnitude and composition of employment among firms: variation in firm total factor productivity and in fixed costs of importing, exporting, and importing/exporting with a related party. We use these insights to motivate how we define firm types in the assignment model.

2.1 The Human Resources Problem

Suppose that the set of positions to fill at firm j has already been determined in an earlier stage (see Appendix A1). Firm j's human resources staff must choose worker types l for each of N_j positions to maximize the workforce's profit contribution, where worker types are defined below as combinations of categories of observed characteristics. Specifically, they solve:

$$\max_{\{\vec{l} \in \mathcal{L}^N\}} \sum_{k=1}^{N_j} \left[\Psi_j(\alpha_{l(k)}^{f(j)} + \tilde{\sigma}_{f(j)} \mu_{l(k)k}) - W_{l(k)}^{f(j)} \right] \tag{1}$$

where we let $l(k)$ denote the worker type chosen to fill position k. Similarly, $f(j)$ denotes the type of firm j, analogously defined below by combinations of firm characteristics. Similarly, $\vec{l} = \{l(1), \ldots, l(N)\}$ defines a vector of worker types chosen to fill the N_j positions, while $\mathcal{L}^N$ is the set of permutations of N_j choices among L worker types. From this point forward, we suppress the dependence of l on k and f on j except where necessary for clarity.

A worker's productivity depends on two components. The systematic part α_l^f captures the mean productivity among type l workers at positions in type f firms. The variation in α_l^f stems from skills or experiences common to all workers of type l that make them more or less productive on average at positions in type f firms. μ_{lk} captures type l workers' productivity deviation at the particular position k from the type combination mean α_l^f. This component captures any firm-specific or even task-specific skills required by position k possessed by type l workers. $\tilde{\sigma}_{f(j)}$ captures the relative importance at type f firms of the idiosyncratic and systematic components in determining each worker type's productivity at position k.

Ψ_j captures the marginal revenue product at firm j of an extra unit of worker productivity. Ψ_j is set in an earlier stage of optimization (also described in Appendix A1), and is treated as exogenous by the human resources staff. Thus, $\Psi_j(\alpha_{l(k)}^{f(j)} + \tilde{\sigma}_f \mu_{l(k)k})$ captures the revenue contribution of a worker of type l in position k when k is treated as the marginal position (as is appropriate when considering possible adjustments to which worker fills the position).

$W_{l(k)}^{f(k)}$ is the annual earnings paid to the worker type $l(k)$ chosen to fill position k for a firm of type f. Each firm is assumed to be a sufficiently small share of each worker type's demand such that the required pay $\{W_l^f\}$ is taken by the firm as given.

Assuming a vanishingly small probability that the same worker maximizes the profit contribution at two positions, one can maximize (1) by separately maximizing the profit contributions of each position and adding together these maximized profit contributions:

$$\max_{\{\vec{l} \in \mathcal{L}^N\}} \sum_{k=1}^{N_j} \left[\Psi_j(\alpha_l^f + \tilde{\sigma_f} \mu_{lk}) - W_l^f \right] \approx \sum_{k=1}^{N_j} \left[\max_{l \in \mathcal{L}} \left[\Psi_j(\alpha_l^f + \tilde{\sigma}_f \mu_{lk}) - W_l^f \right] \right] \equiv \sum_{k=1}^{N_j} \max_{l \in \mathcal{L}} V_{lk} \tag{2}$$

where $V_{lk} \equiv \Psi_j(\alpha_l^f + \tilde{\sigma}_f \mu_{lk}) - W_l^f$ is the marginal profit due to worker type l at position k.

Suppose that μ_{lk} follows an i.i.d. Gumbel distribution across positions k within an (l, f) pair, and that $\Psi_j \approx \Psi_f \ \forall j \in f$. Define $\sigma_f \equiv \Psi_f \tilde{\sigma}_f$. Then the conditional probability that a position at a type f firm chooses a type l worker follows the standard logit formula:

$$P(l|f) = e^{(\Psi_f \alpha_l^f - W_l^f)/\sigma_f} \Bigg/ \sum_{l' \cup 0} e^{(\Psi_f \alpha_{l'}^f - W_{l'}^f)/\sigma_f} \tag{3}$$

where α_0^f and $W_0^f = 0$ capture the firm's value of keeping the position vacant and the accompanying lack of payment. Below we show how to handle missing data on vacant positions.

The composite systematic components of revenue contributions $\{\Psi_f \alpha_l^f\}$ are objects of interest that we seek to identify and estimate, while $\{\sigma_f\}$ will be calibrated (see Section A2.3).

2.2 The Worker's Choice of Position

Consider a worker i who maximizes the utility derived from the worker's choice of job. The worker can potentially match with any position k in the set $\mathcal{K}$ of positions offered by some firm $j \in \mathcal{J}$. Let $U_{if(k)}$ denote the worker's payoff from accepting position k. We impose a symmetric form for $U_{if(k)}$ as for $V_{l(i)k}$ in equation (2):

$$U_{if(k)} = \gamma_{l(i)}^{f(k)} + \sigma_{l(i)}\, \epsilon_i^{f(k)} + W_{l(i)}^{f(k)} \tag{4}$$

$\gamma_{l(i)}^{f(k)}$ captures any non-pecuniary component of the worker's payoff that is common to all type l workers who accept jobs at type f positions, while $\epsilon_i^{f(k)}$ captures the part of the non-pecuniary payoff that is specific to the particular worker. The non-pecuniary components might include the worker's tastes for position k's amenities, or the location of establishment j, or any moving, search or training costs borne by the worker to form the job match and make it productive. For example, $\gamma_{l(i)}^{f(k)}$ might capture that existing workers in the Northeast region prefer positions in the Northeast, while $\epsilon_i^{f(k)}$ might capture worker i's particular taste for working in the Northeast beyond the mean among other Northeast workers who share the other characteristics defining the worker's type. $\sigma_{l(i)}$ captures the relative importance of the systematic vs. idiosyncratic components for the variation in the non-pecuniary payoff, which may vary by the worker's type $l(i)$. $W_{l(i)}^{f(k)}$ captures the annual earnings a worker of type l receives from type f firms.

Given the structure of $U_{if(k)}$, each position within type f generates the same payoff, so the worker's problem can be written as:

$$\max_{f \in \mathcal{F}} \gamma_{l(i)}^{f(k)} + \sigma_{l(i)}\, \epsilon_i^{f(k)} + W_{l(i)}^{f(k)} \tag{5}$$

Analogous to the production side, the systematic components $\{\gamma_{l(i)}^{f(k)}\}$ are objects of interest that we seek to identify and estimate, while the set $\{\sigma_l\}$ is calibrated (Section A2.3). The set $\{\epsilon_i^{f(k)}\}$ is assumed to follow an i.i.d Gumbel distribution across all (i, f) pairs.[1]

These assumptions imply that the conditional probability that a type l worker chooses to accept (or continue) a position of type f is also given by the standard logit formula:[2]

$$P(f|l) = e^{(\gamma_l^f + W_l^f)/\sigma_l} \Big/ \sum_{f' \cup 0} e^{(\gamma_l^{f'} + W_l^{f'})/\sigma_l}. \tag{6}$$

[1]Chiappori et al. (2019) provide simulation evidence that misspecification of the structure of the error component is not very consequential in the Choo and Siow (2006) model.

[2]γ_l^0 and $W_l^0 = 0$ capture the utility and lack of earnings associated with unemployment.

2.3 Labor Market Equilibrium

Define the joint surplus from a job match between worker i and position k as the sum of the worker and firm payoffs:

$$\pi_{ik} = U_{if(k)} + V_{l(i)k} \tag{7}$$

Since the annual earnings W_l^f enter additively in the payoffs U_{if} and V_{lk} and cancel out in the joint surplus, the model is a transferable utility assignment game as defined by Koopmans and Beckmann (1957) and Shapley and Shubik (1972). Shapley and Shubik (1972) show that 1) this game has a unique stable allocation; 2) this allocation is efficient;[3] 3) the allocation is fully determined by the set of joint surpluses $\{\pi_{ik}\}$, as long as one includes payoffs to each agent from remaining single, which we denote $\{U_{i0}\}$ and $\{V_{0k}\}$; and 4) the allocation can be decentralized via a competitive equilibrium using a set of (i,k)-specific market-clearing earnings values.

Without further structure, even data on all job matches cannot identify the full set of joint surpluses $\{\pi_{ik}\}$ that governs the stable matching. Thus, following Choo and Siow (2006), we characterize an aggregated stable equilibrium defined by match counts among type pairs (l,f).

As in Choo and Siow (2006), equations (3) and (6) act as a set of position-type-level demand equations and worker-type-level supply equations, respectively, that can be used to form $L \times F$ conditions that define labor market equilibrium at the aggregate (l,f) level. Let m_l denote the total number of type l workers, and let h_f denote the number of type f positions. Equilibrium requires the number of (l,f) job matches chosen by type l workers to equal the number demanded by type f positions:

$$m_l \frac{e^{(\gamma_l^f + W_l^f)/\sigma_l}}{\sum\limits_{f' \cup 0} e^{(\gamma_l^{f'} + W_l^{f'})/\sigma_l}} = h_f \frac{e^{(\Psi_f \alpha_l^f - W_l^f)/\sigma_f}}{\sum\limits_{l' \cup 0} e^{(\Psi_f \alpha_{l'}^f - W_{l'}^f)/\sigma_f}} \;\; \forall (l,f) \in \mathcal{L} \times \mathcal{F} \tag{8}$$

For now, treat $\{\Psi_f\}$, $\{\alpha_l^f\}$, $\{\gamma_l^f\}$, $\{\sigma_l\}$, $\{\sigma_f\}$, $\{m_l\}$ and $\{h_f\}$ as pre-determined, exogenous parameters. Then the solution to the equations (8) is determined by $L \times F$ earnings values $\{W_l^f\}$. Decker et al. (2013) prove that these equilibrium conditions yield an allocation that is unique and consistent with a stable matching at the individual worker/position level. Choo and Siow (2006) show that when single counts are available on both sides of the market, the $L \times F$ equilibrium conditions can be collapsed to $L + F$ equations governing the equilibrium singles counts by worker and firm type.

2.4 Identification

We next turn to identification of the model parameters. Consider first the taste parameters $\{\gamma_l^f\}$ and the composite revenue parameters $\{\Psi_f \alpha_l^f\}$. Assume that population match frequencies $P(l,f)$, their associated conditional probabilities $\{P(f|l)\}$ and $\{P(l|f)\}$, and mean annual

[3]The efficient allocation is defined as the allocation that maximizes the sum of the payoffs of all workers and positions (including unemployed workers and vacant positions).

earnings $\{W_l^f\}$ are observed for each (l, f) from administrative data combined with data on the level and composition of unemployment. Taking log differences of (6) and (3), respectively, between a chosen firm (worker) type f (l) and a reference type $\tilde{f}$ $(\tilde{l})$ and rearranging yields:

$$\gamma_l^f - \gamma_l^{\tilde{f}} = \sigma_l(\ln P(f|l) - \ln P(\tilde{f}|l)) - W_l^f + W_l^{\tilde{f}} \tag{9}$$

$$\Psi_f(\alpha_l^f - \alpha_{\tilde{l}}^f) = \sigma_f(\ln P(l|f) - \ln P(\tilde{l}|f)) + W_l^f - W_{\tilde{l}}^f \tag{10}$$

Thus, $\{\gamma_l^f\}$ and $\{\Psi_f \alpha_l^f\}$ are identified up to sets of L and F normalizations from a single observed population allocation and associated transfers, given calibration of $\{\sigma_l\}$ and $\{\sigma_f\}$.

Let $\theta_l^f = \Psi_f \alpha_l^f + \gamma_l^f$ capture the mean joint surplus combining the average worker and firm payoffs among matches between worker and firm types l and f. Adding (9) and (10) and taking differences in differences with respect to $\tilde{l}$ and $\tilde{f}$ shows that the set of mean joint surplus diff-in-diffs $\Theta \equiv \{(\theta_l^f - \theta_l^{f'}) - (\theta_{l'}^f - \theta_{l'}^{f'})\ \forall\ (l, f, l', f')\}$ is identified:

$$(\theta_l^f - \theta_{\tilde{l}}^f) - (\theta_l^{\tilde{f}} - \theta_{\tilde{l}}^{\tilde{f}}) = (\sigma_f + \sigma_l)\ln P(l, f) - (\sigma_f + \sigma_{\tilde{l}})\ln P(l', f) - (\sigma_{\tilde{f}} + \sigma_l)\ln P(l, f') + (\sigma_{\tilde{f}} + \sigma_{\tilde{l}})\ln P(l', f') \tag{11}$$

Surplus diff-in-diffs capture comparative advantages in matching among alternative type pairs.

Intuitively, observing that type l workers and f firms match disproportionately frequently with each other compared to other potential partners reveals a comparative advantage based on joint surplus values. Recovering the source of the comparative advantage requires the match-level earnings data used in equations (9) and (10). Specifically, disproportionately high earnings in these matches also compared to l and f's alternative matches suggests that particularly high worker productivity at these firms is the primary source of the comparative advantage, while disproportionately low earnings despite high match rates suggests that l-type workers' strong taste for f's is driving the comparative advantage.

2.5 Counterfactual Equilibria

We consider simulating scenarios in which the taste and productivity parameters $\{\gamma_l^f\}$ and $\{\Psi_f \alpha_l^f\}$ are held fixed but the compositions of supply and demand are shifted from m_l and h_f to alternatives m_l^{CF} and h_f^{CF}. Choo and Siow (2006) and Galichon and Salanié (2021) show that re-solving the equilibrium conditions (8) yields unique counterfactual allocations $P^{CF}(l, f)$ and earnings transfers $W_l^{CF,f}$ for any such scenario. While we only demonstrated identification of the difference sets $\{\gamma_l^f - \gamma_l^{\tilde{f}}\}$ and $\{\Psi_f(\alpha_l^f - \alpha_{\tilde{l}}^f)\}$, note that substituting the term $\gamma_l^f - \gamma_l^{\tilde{f}}$ in for γ_l^f in the conditional choice probabilities appearing in both the numerator and denominator of the equations (8) reveals that the normalization cancels out in each equilibrium condition. The same is true for $\Psi_f \alpha_{\tilde{l}}^f$ in (3). Thus, identification of *relative* preferences and productivities are sufficient to generate unique counterfactual allocations $P^{CF}(l, f)$ and transfers $W_l^{CF,f}$.

We now describe the methodology we develop to overcome a lack of data on unfilled vacancies by firm type. In doing so, we also show how this seeming drawback can be transformed into a feature by facilitating a computationally efficient approach to solving for allocations, earnings, and welfare changes from counterfactual labor supply and demand shocks.

Specifically, while we can observe nonemployed workers in the LEHD ($P(0|l)$), we cannot observe vacancies that are never filled (in contrast to marriage markets where all singles are observed), so we cannot directly implement the Choo and Siow (2006) approach to model simulation. Publicly available JOLTS data on vacancies exist, but not by type f. Furthermore, these data do not focus on positions that are vacant for long enough to characterize them as unmatched. In this and the following subsection, we proceed by assuming that no positions are left vacant at the prevailing earnings levels, so that $P(0|f) = 0 \ \forall \ f$, but we extend the model in appendix A2.4 to endogenize the set of positions to be filled by firm type.[4]

As noted above, Shapley and Shubik (1972) show that the equilibrium allocation solves the social planner's problem of maximizing social surplus. Since this is a linear programming problem, the optimal individual-level allocation also solves the dual problem of minimizing expenditure subject to producing a given social surplus. But given knowledge of the surplus components, the unique solution to the aggregate expenditure minimization problem only requires specifying shadow prices by worker and firm type. These shadow values represent equilibrium mean utilities $\{U_l^*\}$ and mean profit contributions $\{V_f^*\}$.[5] Moreover, Koopmans and Beckmann (1957) show that one can construct the stable allocation with dual problem payoffs from only one side of the market when unmatched agents only exist on one side.

Appendix A2 uses this insight to rewrite worker choice probabilities in terms of identifiable joint surplus components and equilibrium shadow prices, $V_f^{*,CF}$. These alternative formulations, when combined with the (temporary) assumption that all vacancies are filled, can be used to construct a system of F market clearing conditions with F endogenous relative changes in $V_f^{*,CF}$ whose solution yields the counterfactual changes in profit contributions, choice probabilities, and associated allocation. Furthermore, by treating nonemployment as a dummy "firm" type, this approach can be used on the other side of the market to generate $L-1$ equations that yield counterfactual mean utility changes by worker type $\{U_l^{*,CF}\}$ relative to a normalized type, along with the equilibrium allocation.[6] In the results below, we normalize mean utility and earnings changes to 0 for the worker type estimated to be most insulated from the China Shock based on the absence of direct exposure to job loss in their trade status-industry-region combo and minimal indirect exposure based on their baseline distribution of firm type destinations (See Appendix A2). Given the counterfactual allocation, reversing equations (9) and (10) yields the earnings vector $\{W_l^{f,CF}\}$ that supports this equilibrium.

[4]This assumption could be rationalized with relatively high costs of adjusting positions compared to changing workers' composition in current positions. If small or moderate earnings changes do not significantly impact the set of unfilled vacancies, ignoring them is relatively harmless, as they do not affect the allocation of workers.

[5]The insight that I+K prices, when taken as given, are sufficient to guide optimizing agents to an efficient allocation among I*K possible matches is at the core of the first welfare theorem.

[6]The position count h_0 can be inferred after assuming that all vacancies are filled (if $I > K$). Note also that it is this assumption that implies that the optimal allocation is fully determined by relative utilities: one type's utility value can be normalized to 0, and one of the original L equations can be removed.

To develop intuition for this alternative approach to market clearing, conceptualize the U.S. labor market as a single massive first price ascending auction. Each position can potentially bid on any worker, and the position bidding the highest utility wins the worker. Positions' utility bids have a baseline component based on the worker's valuation of the firm's amenities $(\gamma_l^f + \epsilon_i^f)$, but can be adjusted using changes in salary, and workers can set reservation utilities based on their values of unemployment $\gamma_l^0 + \epsilon_i^0$. The auction ends when no position wishes to change its bid for any worker, with the winning utility bids acting as the worker shadow values. The assumed structure of worker and firm payoffs implies that compensation W_l^f will not vary across job matches within worker-type/position-type combinations.

This analogy also reveals that even though workers' tastes affect the baseline utility associated with any firm's bid, any increases in these bids resulting from shock-induced increases in demand for a worker type must take the form of salary increases. Thus, the shock-induced changes in utility we estimate are naturally reflected in mean earnings changes by worker type, making their scale easy to interpret. Estimated mean earnings and utility gains differ because shock-induced reallocations across firm types cause changes in mean amenity quality that are offset by earnings compensating differentials and thus do not affect utility.

Importantly, our approach to address lack of data on vacancies yields substantial computational savings as well. By imposing $P(0|f) = 0$, compute counterfactual equilibria only requires solving a system of $\min\{L, F\}$ equations instead of $L + F$ equations. Thus, whenever singles can be observed on one side of the market and assumed away on the other, one can use a very large type space on a chosen side of the market.[7] Below we use 5,000 worker types but 12,000 firm types, which allows us to model the impact of multifaceted trade shocks much more flexibly than most alternative empirical models that cannot accommodate such heterogeneity.

2.6 Allowing for Additional Heterogeneity: Movers and Stayers

To this point, our assignment model has not distinguished retentions of incumbent workers from new hires of workers of the same type l. However, the joint surplus from maintaining job matches with incumbents is likely to be considerably larger than among new job matches with observationally similar workers. For example, moving, search, and training costs need not be re-paid, firm-specific experience may have made the incumbent worker more productive, and incumbents may have selected the particular firm due to high idiosyncratic tastes ϵ_i^f.

Furthermore, ignoring the difference in mean surplus between incumbents and new hires among (l, f) matches may obscure important asymmetries in the incidence of shocks to the trade environment between positive and negative shocks. This is because expanding production requires the targeted firm type to hire and train new workers, while contracting production requires forfeiting valuable firm-specific experience.

[7] This result could be useful in other contexts, such as student-to-school allocations, where singles are unlikely to exist on one side of the match (e.g. due to truancy laws).

Thus, in our empirical work we distinguish job stayers from movers by introducing an indicator $z_{i,k}$ that equals 1 when i is an incumbent worker at $k's$ establishment and 0 otherwise.[8] Define the transition group $g \equiv g(i,k) = [l(i), f(k), z(i,k)]$. Then we can then represent the mean nonpecuniary worker, firm, and joint surplus payoffs among (l,f) job matches with incumbent indicator z as γ_g, $\Psi_f \alpha_g$, and θ_g, where we have suppressed dependence of g on l, f, z and i and k. The extra payoff from a job retention is identified using the log difference in the frequency of job retentions relative to job swaps within type-pair.

However, note that start-up firms cannot fill positions with stayers, while large firms may have many incumbent workers for several worker types. We incorporate constraints on the supply of incumbent workers in two ways. First, to avoid downward bias in the estimated surplus premium from job retention, we divide our initial estimates of the surplus components for stayer groups ($g(l,f,z)$ where $z = 1$) by an estimate of the probability that there are no incumbent workers.[9] Second, when constructing simulated shocks, we impose that the share of any positive shock-induced job growth accounted for by newly formed establishments equals the chosen firm type's historical share, and restrict that share of newly created positions to only match with non-incumbent workers. This adjustment is necessary to capture the degree to which job creation creates opportunities for outside workers vs. job security for incumbents.

2.7 Model Extensions

Appendix A2.3 presents our procedure for calibrating $\{\sigma_f\}$ and $\{\sigma_l\}$. These parameters govern the importance of the systematic $\{\gamma_g\}$ and $\{\Psi_f \alpha_g\}$ components relative to the idiosyncratic components $\{\epsilon_i^f\}$ and $\{\mu_{lk}\}$ in determining the match-level surpluses π_{ik} that determine the market-clearing allocation. Note that σ is not identified from a single cross-sectional allocation even when one assumes that $\sigma_f = \sigma_l = \sigma \ \forall \ l, f$. Rather, identification of σ requires observing multiple matching markets and imposing restrictions on the relationships among the surplus parameters that govern them. After experimenting unsuccessfully with IV approaches to estimating $\{\sigma_f\}$ and $\{\sigma_l\}$, we chose to calibrate them by selecting an elasticity of substitution from the literature (7.4 from Borjas et al. (2012)) and using the fact that, conditional on $\{\Psi_f \alpha_g\}$, $\{\sigma_f\}$ pins down the firm type's elasticity of substitution among alternative worker types.

Appendix A2.4 demonstrates how to allow the position counts by firm type to endogenously respond to the earnings cost per efficiency unit of labor required by the current labor market. We show how to solve jointly for the number of positions by type h_f and the equilibrium pay by type pair W_l^f via a fixed point algorithm. In practice, comparisons of simple simulated shocks revealed that accounting for endogenous vacancy responses only slightly muted the size

[8] Mourifié et al. (2014) follow a similar approach to model cohabitation in the marriage market. It is straightforward but empirically cumbersome to extend $z_{i,k}$ to have several values for different workers' tenure.

[9] We estimate this probability using the firm-type-specific share of job growth in the LBD due to expansions at existing establishments rather than by new establishments in the three years prior to China's WTO entry.

of employment shocks, and negligibly impacted patterns of worker incidence. Thus, in our China Shock simulations below, we interpret our constructed employment shock as the net change in employment demand after endogenous responses to changes in required wages.

3 Data, Smoothing, and Type Space

We combine several sources of restricted-access and publicly available data from the Census Bureau that provide detailed information on workers, firms, and job matches. The core of our data is the restricted-access Longitudinal Employer-Household Dynamics (LEHD) database, which follows the near universe of workers as they transition between jobs in 25 states, accounting for 60% of U.S. employment (see Vilhuber (2018)).[10] The database reports each workers' earnings by job-quarter along with their establishments' detailed industry codes and locations. It also contains an indicator for whether workers were employed (had positive employee earnings) in any state reporting data in each year, including states outside our 25 state sample. Our final LEHD sample spans 1998-2006 and includes around 70 million workers per year.

We then merge in establishment-level data from the Longitudinal Business Database (LBD) on employment, payroll, location, and firm affiliation for the near universe of establishments across all 50 states (see Jarmin and Miranda (2002)). These data are then merged with firm-level customs records containing values of arms-length and related-party imports and exports from the Longitudinal Firm Trade Transactions Database (LFTTD) (see Kamal and Ouyang (2020)). Our nationwide LBD-LFTTD sample contains on average 4.7 million firms, 6.1 million establishments, and 105 million in total employment per year between 1998 and 2006. We end our sample in 2006 due to changes in how the LFTTD identifies importing firms in 2007. Together, these data sources allow us to estimate a very flexibly parameterized assignment model of the U.S. labor market.

3.1 Assigning Job Matches to Types

In order for changes in the international trade environment to systematically shift employment rates and earnings distributions of particular kinds of workers, firms featuring different trade profiles must hire and retain different types of workers. Otherwise, changes in international product markets would merely cause temporary churn in the labor market.

Thus, we seek to select characteristics to define firm types that capture not only heterogeneity in the nature of their exposure to trade shocks but also heterogeneity in their worker compositions and pay distributions. These in turn are fundamentally determined by the productivity complementarities, job amenities, and recruiting, search and moving costs that determine the surplus components γ_g and $\Psi_f \alpha_g$. We chose to define firm types based on combinations of their trade engagement status, industry, region, and firm size and pay categories.

[10] Approved states in our sample cover all the major U.S. regions and most of U.S. coastline. The national LEHD covers 96% of U.S. employment, with exclusions for federal, farm, and self-employment, among others.

The most central firm characteristic for our analysis is our categorization of the firm's trade engagement. Handley et al. (2021) show that firms engaging in importing only, exporting only, and both importing and exporting in combination each account for large shares of U.S. employment (1.8%, 12.3%, and 32.1% respectively) that vary meaningfully by industry and by region. In a companion paper, Carballo et al. (2023) provide additional statistics showing that importer-only and exporter-only firms and particularly firms engaging in both pay substantially more than non-trading firms, even conditional on industry and firm size. They also show that these firms are more likely to hire workers with previous experience at trading firms.

In addition, Carballo et al. (2023) show that whether trade is done with other firms ("arms-length") or with foreign affiliates within the same firm ("related parties") matters for both firms' exposure to trade shocks and labor market behavior. In particular, multinational firms who both import and export from related parties represent only 0.13% of all U.S. firms, but they account for over 80% of both U.S. total goods imports and exports, and they represent 21% of U.S. total payroll. Furthermore, these multinationals have significantly different hiring and pay patterns: they disproportionately poach high-paid workers and give larger raises.

We include industry categories because shock exposure and pay distributions vary dramatically across industries, while we include regions because geographic differences in industry composition combined with moving and search costs are likely to lead to regional differences in incidence from even a common nationwide shock.[11] Similarly, firms of different size and average pay exhibit very different trade engagement and worker pay distributions and may have lower per-worker search and training costs. In addition, simple theoretical models of trade predict that firm size, like trade engagement, is likely to reflect firm total factor productivity.

In total, we create 4,704 firm types using combinations of the following five characteristics:

1. Trade Engagement (6): the trade engagement of the firm associated with the position's establishment. We consider six trade status categories: non-trading (NT), non-related party importer only (M), non-related party exporter only (X), non-related party importer and exporter (X&M), related party exporter and importer (RP X&M), and related party exporter or related party importer but not both (RP X|M).[12] See Appendix A5.1 for further detail.

2. Industry (7): the industry of the position's establishment. We aggregate 2-digit NAICS sectors into 7 industry categories that group together sectors featuring similar trade engagement and average worker pay distributions so as to preserve the heterogeneity in incidence from trade shocks: construction/natural resources/utilities, manufacturing, wholesale and retail trade, information, finance/real estate/professional and business

[11] For multi-region and/or multi-industry firms, we assign positions to industries and regions by establishment.

[12] To be categorized in a given trade engagement category, a firm needs to have recorded at least $50,000 of trade value in the particular activity in the chosen year. See Appendix A5.1 for more details.

services, leisure/transportation/administration, and education/health/government. See Appendix A5.3 for the exact NAICS mapping.

3. Region (7): the region of the position's establishment. We divide the continental U.S. into 7 regions: Northeast, Midwest, Great Plains, West Coast, Southwest, Deep South, Mid-Atlantic/Appalachia (we exclude Alaska and Hawaii). The mapping from state to region is provided in Appendix A5.2.

4. Firm Size (4): the quartile of the position's firm in the national firm employment distribution, with cutoffs defined so that 25% of employment is in each firm size bin.

5. Firm Average Pay (4): the quartile of the position's firm in the firm average worker earnings distribution, with cutoffs defined so that 25% of employment is in each pay bin.

We define 3,528 worker types based on combinations of the worker's initial (previous year) earnings decile at their dominant job, initial region, and the industry and trade engagement status of their dominant employer.

Earnings decile cutoffs are defined using the distribution of primary job annual earnings among workers in the observation's year, and are based on prorating earnings from full quarters only to ensure that the decile captures a worker's salary rather than the share of the year he/she worked. Including initial earnings categories permits us to evaluate the degree to which the shock contributes to income inequality. We define workers as unemployed in the initial year if their earn less than \$5,000 at their dominant job. For initially unemployed workers, the earnings decile is replaced by one of two unemployed categories, differentiated by age (< 25 or ≥ 25).[13] The region, industry, and trade engagement categories mimic those for firm types. Including these three characteristics in worker type definitions as well allows us to assess the role of worker mobility across categories in shaping the shock's incidence. In addition, Carballo et al. (2023) highlight the role that industry-specific and trade-specific experience play in the composition of new hires, suggesting that they are important determinants of joint surplus.

These type definitions allow each job match (i, k) to be assigned to a transition group $g \equiv g(l(i), f(k), z(i, k))$. Note that each (l, f) combination in which l and f share a region and industry must be divided into two groups based on an indicator $z(i, k)$ for whether the worker's primary job was at position k's establishment in the previous year, so that a group $g = [l, f, z]$ with $z(i, k) = 1$ represents retentions rather than new hires. Thus, each element of $P(g)$ captures the share of all year-to-year worker transitions between dominant (i.e. highest earnings) jobs consisting of workers in a given earnings category, industry, state, and initial firm trading status moving to (or staying at) a position in an establishment from a given state and industry within a firm of a given size, average pay, and trade engagement status.

[13] We chose these categories to distinguish new entrants/recent graduates from workers with meaningful work experience, since employers might treat new and experienced unemployed workers as quite imperfect substitutes.

Our rich type space, which features over 27 million transition groups g, serves two purposes. First, it allows us to impose few restrictions on the U.S. job matching process, ensuring that results are driven mostly by data patterns rather than assumptions. Second, it enables us to explore and reveal overlooked subgroups of worker winners and losers from trade shocks.

3.2 Imputation and Smoothing

Because estimation and simulation of the assignment model requires a complete set of counts at the $g = [l, f, z]$ group level, we implement an imputation procedure (fully described in Appendix A3) to fill gaps in our group-level counts. Broadly speaking, we address missing LEHD data on job matches from 25 states by 1) using LBD employment counts by firm type from all 50 states, 2) multiplying by an industry-specific scaling factor to handle differences in industry coverage between the LEHD and LBD, and 3) distributing these employment counts by type f across g combos using the conditional distribution $P(l, z|f)$ observed in the in-sample LEHD state with the most similar firm type distribution to the chosen state. We then assign locations to unemployed workers and distinguish them from self-employed workers, federally employed workers, and workers exiting the labor force by using the empirical distribution of locations and labor force status among nonemployed workers from several years of the American Community Survey. After completing imputation, we aggregate from states to regions.

Due to the vast number of groups g we consider, there are relatively few observed job matches per group despite using the near universe of U.S. employment. Thus, following Hotz and Miller (1993) and Arcidiacono and Miller (2011), we smooth $\hat{P}(g)$ prior to estimation by replacing each group's value with a kernel-density weighted average of $\hat{P}(g)$ among groups featuring "similar" worker and position characteristics. To prevent excessive smoothing from eroding the estimated heterogeneity among surpluses from matches featuring different worker and position characteristics, we develop a customized smoothing procedure.

The procedure, described in Appendix A4, is based on the intuition that the bulk of the variation in joint surpluses is driven by complementarities between certain subsets of the worker and firm characteristics that define l and f. Specifically, the position's industry and trade engagement are likely to determine which initial industry and trade engagement combinations among potential worker hires will generate the greatest joint surplus, perhaps because industry- and trade engagement-specific experience are key determinants of worker productivity. By contrast, the position's location, firm size, and average pay may be more essential in determining the relative surpluses among worker types featuring different initial location and earnings combinations, since the interaction between these characteristics determine moving and search costs as well as the productivity gains from worker skill. Thus, we preserve the joint distribution of characteristic combinations likely to capture key complementarities, and smooth across subsets of characteristics where such complementarities are unlikely. We then estimate the surplus components $\{\hat{\gamma}_g\}$ and $\{\widehat{\Psi_f \alpha_g}\}$ by replacing $P(g)$ with its smoothed empirical counterpart $\hat{P}^{smooth}(g)$ in equations (9) and (10).

4 Measuring the China Shock at the Firm Level

In order to characterize the distribution of worker-level earnings and employment impacts of the China Shock, we must first generate estimates of how the change in potential tariffs on Chinese products shifted labor demand at the firm-level. Specifically, our assignment model requires as inputs separate vectors of firm type-specific employment changes attributable to China's WTO entry for each of five post-shock years (2002-2006) we consider, denoted $h_{t,f}^{CF}$.

We use national firm-level and establishment-level data from the LBD to generate separate estimates of shock-induced firm-level employment impacts for each of four channels: import competition, import access, export competition, and export access. This allows us to highlight the role played by each channel in shaping the incidence of the China Shock.

Our approach mirrors and extends that of Pierce and Schott (2016): 1) construct a shift-share-based measure to isolate exogenous variation in firm-level exposure to the chosen channel; 2) regress each year's employment growth at the firm level on the firm's exposure measure along with other controls that remove the influence of other correlated shocks to labor demand (including exposure to other channels); 3) collect firm-level predicted values from the regression and aggregate to the firm type level to form the estimated labor demand shock $h_{t,f}^{CF}$.

All our exposure measures defined below imperfectly capture firms' true exposure to these channels, in part because they are designed to minimize the risk of conflating the impact of the China Shock with other contemporaneous labor market trends. Thus, our approach is likely to understate each channel's employment impact. Rather than produce a definitive accounting of the shock's impacts on firm-level employment, our goals are to 1) provide evidence of the importance of overlooked channels, 2) illustrate heterogeneity among firm types in sensitivity to exposure, and 3) provide a reasonable quantification of the overall employment shock to feed into the assignment model to characterize worker-level equilibrium incidence.

4.1 Exposure Measures

Consider first the import competition channel. This channel seeks to isolate employment changes triggered by increased competition for U.S. manufacturers from imported Chinese products in the domestic market. Because we cannot observe the particular products sold by non-exporting domestic firms, here we directly adopt Pierce and Schott (2016)'s exposure measure. Specifically, they measure the product-level gap between the pre-2001 maximum potential U.S. tariff on Chinese imports and the most favored nation tariff guaranteed to WTO members, denoted TG_p, and then average these product-level tariff gaps at the NAICS 4-digit level, $\overline{TG}_n$. Because industry is reported at the establishment level in the LBD, we construct firm-level exposure in year t, denoted IC_{jt}, by weighting each establishment e's associated mean tariff gap by the establishment's share of firm employment in that year.[14]

$$IC_{jt} = \sum_{e \in \mathcal{E}(j)} \frac{N_{et-1}}{N_{jt-1}} \overline{TG}_{n(e,t)} \tag{12}$$

This measure of exposure assumes that investment in Chinese production and exporting capacity in certain sectors had previously been deterred by the threat of tariff increases, and that removing this threat triggered relatively larger increases in Chinese investment, production, and exports to the U.S. in industries whose products initially had higher potential tariffs relative to the WTO tariff. By isolating the tariff gap variation, it seeks to remove other causes of increased Chinese imports that also directly affect employment demand or wages, such as labor supply shifts, automation opportunities, and contemporaneous product demand shocks. We restrict our sample for this channel to all manufacturing firms, so the identifying variation consists of varying intensity of exposure among manufacturing firms as well as comparisons to a control group of manufacturers of products experiencing a zero tariff gap.

We measure firm exposure to export competition in a similar fashion. This channel considers employment changes driven by increased competition faced by U.S. exporting firms in foreign markets due to China's increased production after their WTO entry. Here we exploit our ability to observe each firm's full set of exported products. In particular, we construct firm-level exposure in year t by weighting the tariff gap associated with each exported product p by the product's share of the firm's estimated total revenue in that year:

$$EC_{jt} = \sum_{p} \frac{X_{pjt-1}}{\widehat{Rev}_{jt-1}} TG_p \tag{13}$$

where X_{pjt-1} is the value of firm j's exports of product class p in year $t-1$ and $\widehat{Rev}_{jt-1}$ is firm j's estimated revenue in year $t-1$.[15] Since Chinese competition in foreign markets affects U.S. exporters in many industries, we construct EC_{jt} for all active exporters regardless of industry. Thus, all exporting firms constitute the sample considered for this channel. The identifying variation consists of varying intensity of exposure among exporting firms due to differential reliance for revenue on exports of products with larger tariff gaps, as well as comparisons to a control group of exporters of products with a zero tariff gap.

The product-level tariff gaps in our exposure measure use U.S. tariffs rather than those of the relevant export markets. Erten and Leight (2021) find that Chinese counties whose pre-existing mix of manufacturing output indicated more exposure to U.S. tariff uncertainty reductions experienced greater growth in foreign direct investment, output, and exports. Once

[14] We aggregate across establishments to the firm level because Bloom et al. (2019) show that multi-establishment firms reallocate workers from exposed to non-exposed establishments, so that establishment-level regressions may overstate the net firm-level employment changes associated with shock exposure.

[15] Revenue is observed every five years for each firm in the Economic Census and yearly for a sample of firms in the Annual Surveys. For firms with observed revenue in some year t, we construct revenue in other years t' by multiplying payroll in t' by the revenue-to-payroll ratio in year t and assuming it remains constant. For firms where revenue is never observed, we multiply their payroll by the average revenue-to-payroll ratio for the cell defined by their trade engagement/industry/firm size/firm avg. pay combination.

investment in production capacity had been directed to products facing larger reductions in U.S. guaranteed tariffs, China could also easily expand exports to other countries. Importantly, the authors do not detect a production response to other countries' tariff uncertainty changes.

The import access channel considers the firm-level employment impact for U.S. importers of expanded opportunities to import from China after their WTO entry. We measure firm j's exposure to this channel as the sum of the tariff gaps of the products they imported from China in the previous year, weighted by the products' shares of estimated total costs:

$$IA_{jt} = \sum_p \frac{M_{pjt-1}^{China}}{\widehat{TC}_{jt-1}} TG_{pt} \tag{14}$$

where M_{pjt-1}^{China} captures the value of imports of product p by firm j in year $t-1$ and $\widehat{TC}_{jt-1}$ approximates firm j's total cost using the sum of its total payroll plus total value of imports. This measure assumes that firms' labor demand is likely to be more sensitive to changes in potential tariffs when import spending on the relevant product is a larger share of firm's costs.

Expanded importing opportunities may decrease employment for some firms and increase it for others. Cheaper imports may substitute for inputs produced by the firm's workers, reducing labor demand despite increasing firms' profits. In other cases, Chinese imports may replace more expensive imported inputs, reducing unit cost and creating a scale effect that leads the firm to expand production and employment. Furthermore, for firms specializing in importing (e.g. wholesalers), lower prices and greater availability of Chinese imports may increase demand for their services, causing them to hire more workers to coordinate the importing process.

While in principle any firm could respond to the China shock by expanding imports, our measure of exposure focuses attention on firms that were importing from China in a previous year the particular products whose potential tariff fell. These firms have already paid any fixed costs of coordinating with Chinese exporters of these products (or producing them via a Chinese subsidiary), so they are well positioned to quickly expand imports.

The sample considered for the import access channel consists of all importers in the previous year. The identifying variation stems from varying intensity of exposure among importing firms as well as comparisons to a control group of importers who did not import from China in the previous year as well as importers who imported products with a zero tariff gap.[16]

Finally, our export access channel considers possible employment gains at exporting firms whose products now face lower Chinese tariffs. We measure firm j's exposure to this channel as the average tariff reduction in the products exported to China weighted by those products'

[16] We experimented with other measures of import access. The first assumes that the bulk of fixed costs stems from importing the relevant product, regardless of source country, and measures exposure as the sum of tariff gaps of all products the firm imported in year t, weighted by their import value as a share of total costs. The second assumes that the bulk of fixed costs stem from establishing an importing relationship with China, regardless of product, and measures exposure as firms' imports from China as a share of total costs. Both measures suggested that exposure to import access substantially increased U.S. employment, albeit with some variation in the magnitude.

share of estimated revenue:

$$EA_{jt} = \sum_{p} \frac{X_{pjt-1}^{China}}{\widehat{Rev}_{jt-1}} \Delta\tau_{pt} \tag{15}$$

where X_{pjt-1}^{China} captures the value of firm j's exports of product p to China in year $t-1$ and $\Delta\tau_{pt}$ is the Chinese tariff change between 2000 and year t.[17]

The sample considered for the export access channel consists of all exporters in the previous year. Identifying variation stems from varying intensity of exposure as well as comparisons to control groups of exporters who did not export to China in the previous year as well as exporters to China whose products' tariffs do not change due to China's WTO accession.

4.2 Regression Specification and Predicted Employment Impacts

A generic version of our estimating equation is given by:

$$\begin{aligned} \Delta_t ln(N_{jt}) =& Exposure_{jt}^{c} \times \left[\sum_{e=1}^{6} \beta_e 1(te_{jt-1}=e) + \sum_{i=1}^{7} \delta_i 1(i_{jt-1}=i) + \sum_{s=1}^{4} \gamma_s 1(fs_{jt-1}=s) \right] \\ & + \sum_{c' \neq c} \lambda_{c'} Exposure_{jt}^{c'} + \boldsymbol{\theta}\mathbf{X}_{jt-1} + \mathbf{D}_{jt-1}^{te}\boldsymbol{\omega}^{te} + \mathbf{D}_{jt-1}^{i}\boldsymbol{\omega}^{i} + \mathbf{D}_{jt-1}^{fs \cdot fe}\boldsymbol{\omega}^{fs \cdot fe} \end{aligned} \tag{16}$$

where $\Delta_t ln(N_{jt})$ captures log employment growth in firm j between year $t-1$ and t, and $Exposure_{jt}^{c}$ is the exposure measure for a particular channel c. $1(te_{jt}=e)$, $1(i_{jt}=i)$ and $1(fs_{jt}=s)$ are indicators for firm j's trade engagement category, industry category, and firm size quartile in year t, with $\{\beta_e\}$ $\{\delta_i\}$ and $\{\gamma_s\}$ capturing the degree of differential sensitivity in employment growth to exposure via the chosen channel for firms in particular trade engagement, industry and firm size categories, respectively. These interaction terms exploit the richness in the firm-level LBD by allowing a flexible pattern of heterogeneity in the impact of exposure across firms with different values of the characteristics defining position types.

Because the same firm may be exposed to the China Shock via multiple channels, we control for the other channels' exposure measures $Exposure_{jt}^{c'}$ when estimating each channel's effects. We chose to run separate regressions for each channel primarily in order to transparently select a sample for each channel that includes only treated firms and the relevant control group(s) described above. Non-trading non-manufacturing firms have no exposure to any of our channels, but may not be a valid control group for any of them, since firms select into trading activity partly on the basis of unobserved characteristics such as age and productivity that may predict sensitivity to other contemporaneous shocks. Also, other papers in the literature generally focus on a single channel, so separately estimating employment effects by channel eases comparison between their and our results.

We also include other firm-level characteristics $\mathbf{X}_{jt-1}$ that control for broader trends in

[17] China also implemented a set of tariff reductions in the years leading up to WTO accession (particularly 1997). As a robustness check, we confirm that our results are similar when we use 1996 tariffs as our baseline.

firm growth and trade activity that may be correlated with their exposure: lagged employment growth, lagged total import value, and lagged total export value. $\mathbf{D}^{te}_{jt-1}$, $\mathbf{D}^{i}_{jt-1}$, and $\mathbf{D}^{fs\cdot fe}_{jt-1}$ represent design matrices for each trade engagement category, 4-digit NAICS industry, and unique combination of year-specific national firm size decile and firm average pay decile, with $\boldsymbol{\omega}^{te}$, $\boldsymbol{\omega}^{i}$, and $\boldsymbol{\omega}^{fs\cdot fe}$ capturing the corresponding fixed effects. To reduce sampling error, we pool year t with $t-1$ and $t+1$ when estimating (16), so that coefficients reflect a 3-year moving average. We omit industry fixed effects and industry-specific exposure effect heterogeneity for the import competition channel, since exposure varies at the industry rather than firm level.

We generate each channel's firm-level employment shock by subtracting a counterfactual alternative where the channel's exposure measure equals zero from (16)'s predicted value:

$$Shock^{c}_{jt} = \exp\left(\widehat{\Delta \ln N}_{jt}(Exposure^{c}_{jt} = Exposure^{c}_{j,2000}) - \widehat{\Delta \ln N}_{jt}(Exposure^{c}_{jt} = 0)\right) \times N_{jt} \quad (17)$$

Finally, we aggregate each channel's shock to the firm-type level: $Shock^{c}_{ft} = \sum_{j\in f} Shock^{c}_{jt}$.[18] When evaluating the worker-level impact of the full China WTO shock below, we combine the employment impacts from all four channels:

$$Shock^{Total}_{jt} = Shock^{IC}_{jt} + Shock^{EC}_{jt} + Shock^{IA}_{jt} + Shock^{EA}_{jt} \quad (18)$$

In practice, we do not find a statistically or economically significant role for the export access channel, so we omit it from this total.

4.3 The Distribution of Firm-Level Employment Impacts of the China Shock

This section summarizes key features of the firm-level employment changes attributed to the China Shock. While we report in Table 1 and briefly discuss key regression coefficients, our primary regression specification is necessarily complex in order to flexibly capture multiple sources of heterogeneous treatment effects. Consequently, we focus on characterizing the distribution of predicted values aggregated to the firm type-by-year level via (17), since these are the key inputs to the simulations that characterize the China Shock's worker-level incidence. To this end, Table 2 summarizes employment changes based on using the moving average versions of specification (16) to construct annual firm-level shock measures for each $t \in [2002, 2006]$.

Finding #1: The Export Competition and Import Access Channels Substantially Exacerbate and Offset the Employment Losses from Import Competition

The first panel of Table 2 reports the nationwide employment change attributed to the China Shock by channel and year. Despite intentionally narrow exposure measures, we find that the overall shock is large: 729,000 jobs lost over five years. We confirm the literature's finding that the import competition channel is dominant ($\sim 650,000$ net jobs lost) and relatively stable between 2002 and 2006. However, our estimates reveal substantial additional job destruction from greater export competition ($\sim 330,000$ net jobs lost) and sizeable net job creation due to

[18] The LBD measures employment in March each year, while the LEHD includes any employee that registered earnings in any quarter. This causes employment reported by the LEHD to exceed that of the LBD. To match the scale of the LEHD job counts, we rescale our estimated shock by the ratio of LEHD to LBD employment.

expanded import access ($\sim 240,000$ net jobs) that the other two channels mask.

These results are supported by Panel B of Table 1, which reports coefficients on each channel's exposure measure from simplified regressions featuring homogeneous effects. They show that greater exposure to elimination of the tariff gap statistically significantly reduced firm employment growth via the import competition and export competition channels and raised growth via the import access channel. Relative to a non-exposed firm, mean exposure to import competition and export competition predicts 1.24% and 0.24% employment losses, respectively, while mean import access exposure increases annual growth by 0.15%.[19]

By contrast, greater access to the Chinese domestic market does not generate statistically significant nor economically meaningful changes in firm-level employment growth. There are several possible reasons for this null result. First, the large trade imbalance between the U.S. and China and the relatively small size of China's domestic market during this period suggests that exports from China were far more disruptive than the opportunity to export to China. Second, one sector that might have experienced substantial employment gains via expanded export access, agriculture, is not covered by the LBD. Similarly, rises in exported services in the entertainment and education industries, for example, are not reflected in customs records. Third, it may be that existing experience with exporting to China does not strongly predict which firms are poised to benefit from expanded export access, so that isolating an exogenous component of the variation in export access is more challenging.

Finding #2: In Contrast to Import Competition, Job Losses and Gains via Export Competition and Import Access Generally Occur Outside of Manufacturing

The second panel of Table 2 disaggregates the employment shock by industry and channel. On one hand, we find that net job destruction in manufacturing accounts for all of the U.S. net job destruction induced by the China Shock.[20] On the other hand, we find that the vast majority of both job destruction via export competition and largely offsetting job creation via importing opportunities occurred outside of manufacturing. This highlights the importance of widening the focus to include other industries when analyzing the impact of trade shocks. For the export competition channel, our results show that the wholesale/retail sector experienced the largest net job destruction, losing almost $140,000$ jobs between 2002-2006, while manufacturing firms lost around $100,000$ over the the same period. Export competition also destroyed almost 70,000 jobs in the high-paying service sectors (professional services, financial services and real estate) and caused non-trivial job loss in the information and natural resources/construction/utilities sectors ($\sim 15,000$ and $\sim 8,000$ jobs, respectively).

Job gains from the import access channel were concentrated in the wholesale-retail sector ($\sim 190,000$ net jobs created), so that overall this sector enjoyed shock-induced net job creation

[19] Our estimated impact on firm-level employment of a 1 SD change in import competition exposure is within range of the 2% industry impact that Pierce and Schott (2016) report.

[20] This may partly reflect our inability to measure exposure to import competition outside of manufacturing.

of $53,000$ jobs despite high sensitivity to export competition. Several service sectors outside of wholesale/retail (leisure/administration/transportation, professional services/finance/real estate, and information) collectively accounted for another $\sim 60,000$ of net job creation via the import access channel. Unlike these other sectors, manufacturing firms with greater exposure to expanded import access experienced net job losses, suggesting a stronger role for outsourcing of workers' tasks in this sector, consistent with evidence in the literature.[21] However, the import access channel only accounts for 1.5% of total net job destruction among manufacturing firms. Interestingly, the education/health/government sectors, consisting primarily of white-collar service jobs, were virtually isolated from the firm-level China Shock, with no significant employment changes via any channel.

Finding #3: Multinational Firms Account for the Vast Majority of Each Channel's Shock-Induced Employment Changes

The third panel of Table 2 decomposes the net employment change for each channel by firms' trade engagement status. RP X&M firms dominate all the channels, contributing at least 60% of the aggregate job change in each case despite representing only 20% of U.S. jobs. This reflects the fact that such firms account for 82.3% and 82.5% of U.S. international goods imports and exports, respectively (see Figure A2). For the import competition channel, RP X&M firms represent 47% of the manufacturing employment deemed at-risk but make up 72% of the net job destruction. In contrast, non-trading firms account for 3% of manufacturing job destruction due to import competition but 12% of initial employment. These findings reflect sizable heterogeneity in sensitivity to exposure across trade statuses. For example, the coefficients in Table 1 indicate that the same one SD (0.14%) increase in tariff gap exposure reduces employment growth by 1.8% for RP X&M firms, but only by 0.4% for non-traded firms and negligibly for exclusively arms-length exporters (only 10% of manufacturing employment).

The level of job destruction from export competition also generally increases with the level of trade engagement, with RP X&M firms accounting for over 86% of job loss from this channel. This reflects both greater exposure of more trade-engaged firms as well as greater sensitivity to exposure. For example, within manufacturing, mean exposure among RP X&M firms is nearly three times that for exclusively arms-length exporters. Across industries, a single product RP X&M firm experiencing the mean tariff gap of 32% who generates 10% of revenue from exports is predicted to experience a 1.35% reduction in employment growth, while the same degree of exposure only predicts a 0.52% reduction for an exclusively arms-length exporter. Overall, 40% of job destruction at RP X&M firms stems from the export competition channel, highlighting the sensitivity of these multinational firms to market conditions abroad.

Similarly, we only observe meaningful offsetting job creation via the import access channel if the firm is also involved in exporting, in related parties trade, or both. Our regression results suggest that a RP X&M firm and a $RP\,X|M$ firm exposed to the mean tariff gap on

[21] Recall that such lost employment may reflect lower unit costs, and thus may not indicate declining profits.

imports that account for 10% of total costs are predicted to experience 0.44% and 0.75% faster annual employment growth, while exclusively arms-length importers do not experience any statistically significant change. As discussed above, we do find that some subpopulations of firms, particularly in manufacturing, reduce employment in response to greater import access exposure, which is consistent with greater outsourcing (see Hummels et al. (2018)).

Finding #4: Shock-induced Employment Losses Are Concentrated at High-Paying Firms, while Employment Gains Are Concentrated at Low-Paying Firms

The fourth panel of Table 2 presents firm-level employment changes by channel and firm average pay quartile (employment-weighted). Firms in the top two quartiles account for 82% and 88% of jobs destroyed by the import and export competition channels despite employing 50% of U.S. workers. By contrast, the two lowest paying quartiles account for 77% of jobs created by the import access channel, with the bottom quartile experiencing overall net job creation across all three channels. At first blush, this finding suggests that the shock may have disproportionately targeted high-paid workers while expanding job opportunities for low-paid workers, and thus could in principle reduce income inequality. However, a major goal of the paper is to explore whether labor market competition causes equilibrium worker-level incidence to deviate substantially from what one might predict based on the kinds of workers directly hired by targeted firms. Thus, characterizing the shock's worker-level incidence requires the counterfactual simulations of the assignment model presented in Section 5.

4.3.1 Regional Variation and Robustness Checks

The fifth panel of Table 2, which decomposes the firm-level shock by region, reveals that the shock's impact was fairly broadly across U.S. regions, both by channel and overall. However, the share of job losses experienced by Midwest and Mid-Atlantic/Appalachia regions were 10-20% higher than their initial employment shares, while the Southwest's share of job losses was only 60% as large as its employment share.

We run several robustness exercises to confirm our firm-level findings. First, we estimate the impact of our exposure measures without treatment effect heterogeneity and add additional interaction terms incrementally. Table A1 presents correlations among firm types in the implied shock across specifications using alternative interactions. For each channel, the implied shock for each alternative specification has a correlation of at least .94 with our preferred specification.

We also run regressions that exclude time-varying firm-level controls or feature less granular fixed effects. Additionally, we consider alternative exposure measures, including measuring import competition using Autor et al. (2013)'s approach, constructing the import access index using all imports subject to tariff gaps (not just those from China), using 1996 as a tariff baseline when constructing the export access index, and allowing both the import access and export competition exposure indices to focus only on trade values without incorporating the product-specific tariff gaps. Overall, we find consistent results across specifications featuring different controls, fixed effects, and exposure effect heterogeneity. We do find some instability in the magnitude of effects across alternative exposure measures, but we consistently find strong negative import and export competition shocks, a heterogeneous import opportunity shock that in aggregate is moderately positive, and a trivial export access shock. We selected the more conservative specifications as our preferred ones.

5 The Worker-Level Impact of the China Shock

In this section we describe how we quantify the worker-level incidence of China's accession to the WTO and discuss our main findings. Section 5.1 describes how we combine estimated annual firm-type-level employment shocks between 2002 and 2006 to construct counterfactual paths for the labor market and accompanying summary measures of cumulative worker-level incidence. Section 5.2 presents our simulation results, with emphasis on how labor market competition and the import access and export competition channels generate important trade-induced changes in labor market outcomes for non-manufacturing workers.

5.1 Mapping China's Accession into a Sequence of Assignment Model Shocks

We seek to isolate the labor market impact of China's WTO accession by evaluating a sequence of five single-year counterfactual demand shocks between 2001-2002 and 2005-2006, each of which mimics the form of the static shocks summarized in Section 4.2. Our goal is to approximate how the labor market would have evolved had China not joined the WTO during this period. We summarize our methodology here, and provide further detail in appendix A2.5.

To construct the counterfactual labor market matching for the initial 2001-2002 shock, we first estimate the worker and firm surplus components $\{\gamma_g^{0102}\}$ and $\{\Psi_f^{0102}\alpha_g^{0102}\}$ using realized 2001-2002 job flows/retentions and earnings, following equations (9) and (10), and hold these values fixed when constructing the 2001-2002 counterfactual allocation. This approach implicitly assumes that any evolution in surplus components between the 2000-2001 and 2001-2002 transitions is due to other secular trends in the labor market unrelated to China's WTO entry. Similarly, we hold fixed the observed 2001 composition of worker types, presumed to be predetermined prior to the shock. We then construct the counterfactual number of type f positions, $h_f^{0102,CF}$, by restoring or removing from the observed employment level the part of type f's 2001-2002 employment growth estimated to be eliminated or generated by China's WTO entry in equation (18) in Section 4.2:

$$h_f^{0102,CF} = h_f^{0102} - Shock_{f,0102}^{Total} \tag{19}$$

When isolating the role of a single channel, we replace $Shock_{f,0102}^{Total}$ with $Shock_{f,0102}^{IC}$, $Shock_{f,0102}^{EC}$, or $Shock_{f,0102}^{IA}$. Finally, we assume that the parameters $\{\sigma_l\}$ and $\{\sigma_f\}$ governing elasticities of substitution remain fixed at values estimated using the 1999-2000 and 2000-2001 labor markets.

We then solve the system of equations (40) described in appendix A2.2 to generate the

2001-2002 utility changes and allocation of workers that would have transpired in the absence of China's WTO accession, and use (45) to solve for the corresponding equilibrium earnings changes. To recover the change in worker mobility induced by the first year of the China Shock, we simply subtract the counterfactual allocation from the observed 2001-2002 allocation.

Next, to capture the cumulative nature of the multi-year China Shock, we use our 2001-2002 counterfactual allocation and earnings change distribution to generate the counterfactual worker type distribution for the 2002-2003 simulation, $m_l^{0203,CF}$. This requires calculating the number of workers ending 2002 in each (region, industry, trade engagement) combination who are predicted to have received earnings in the appropriate decile. We assume that the initial distribution of earnings is uniform between the cutoffs defining each earnings category, and use the counterfactual earnings change W_g^{CF} to determine the shares of workers in each transition group who remain in/switch earnings deciles relative to the previous year (see Appendix A2.5).

For t = 2002-03 and each subsequent pair of years, we continue to assume that year-to-year changes in surplus components were induced by other macroeconomic shocks unrelated to China's WTO accession, and set $\gamma_g^{t,CF} = \gamma_g^t$ and $\alpha_g^{t,CF} = \alpha_g^t$, where γ_g^t and α_g^t are estimated via (9) and (10) with smoothed worker allocations during year pair t. Next, note that after the first year of the simulation, the economy is inheriting different distributions of worker types and position types than those observed in the data. Thus, the observed allocation in year pair t no longer serves as a useful comparison for isolating the impact of the China Shock in year t. So we must generate two counterfactual allocations for year t. The first adds the observed change in the distribution of position counts between year pair t and year pair $t-1$, $(h_f^t - h_f^{t-1})$, to the previous year's counterfactual position counts. This creates a composite shock that combines the year t China Shock with any other concurrent shocks to labor demand:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) \tag{20}$$

The second counterfactual then restores jobs by subtracting the (usually negative) estimated China Shock component (e.g. $Shock_{f,0203}^{Total}$) from (18) in section 4:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) - Shock_{f,t}^{Total} \tag{21}$$

For each counterfactual demand shock, we solve for the allocation, utility, and earnings changes using (40) and (45). We then subtract the second counterfactual allocation, utility changes, and earnings changes from their analogues from the first counterfactual. This isolates the impact of year t of the China Shock relative to a baseline in which China had not joined the WTO in any previous year but other concurrent shocks had occurred and continued to occur. We use the second counterfactual's allocation to update the worker and position type distributions for the next year via (57), (20), and (21), and continue in this vein through 2005-2006.

Evaluating the cumulative five-year impact among worker types requires extending the methods for assessing incidence used for our single-period shocks. Note that each period's simulated allocation yields utility and employment changes by worker type and earnings changes by transition group. To track the accumulation of impacts for workers classified by their pre-shock (2001) types, we generate a transition matrix among worker types in adjacent years with elements $P(l^{t+1}|l^t)$ using (60). We then use backward induction to accumulate expected outcomes over multiple years for type l workers in 2001 by using the mean 2005-06 outcomes by 2005-06 worker type (e.g. $E[U_g^{0506}|l^{0506}]$ for utility) as the base case and using the transition probabilities $P(l^{t+1}|l^t)$ to form the induction step (See Appendix A2.5 for the exact formula).

5.2 Results

Finding # 1: Workers at Multinational Manufacturing Firms Experience the Largest Earnings, Employment and Welfare Losses

The rightmost bars in each group of Panel A of Figure 1 display our estimates of the cumulative earnings impact between 2002 and 2006 of China's WTO entry among workers classified by their 2001 sector. In keeping with much of the literature, we see that the average worker in manufacturing in 2001 experiences large cumulative earnings losses over the next five years worth \$4,138 as a result of the China Shock (in 2020 dollars). Average earnings losses in other sectors are generally far smaller, between \$25 and \$600.

Panel A of Figure 2 displays the 5-year earnings incidence of the full (all channels) China Shock by combination of industry and trade engagement category. Workers initially at RP X&M manufacturing firms suffered the largest cumulative earnings loss (\$6,560), far higher than any other trade category, while losses for workers at nontrading manufacturing firms were only about one-eighth as large (\$872). Moreover, outside of manufacturing, the only industry-trade category combinations with earnings losses above \$580 correspond to RP X&M firms. This reflects the finding above that labor demand at large multinational firms was particularly sensitive to the China Shock, in part due to much heavier reliance on international goods trade.

Panel B of Figures 1 and 2 display analogous results to Panel A for money-metric utility rather than earnings. Across both figures, we find that earnings and utility results exhibit extremely similar distributions of impacts across sectors, channels, and trade engagement categories, but that earnings impacts tend to be larger in magnitude than utility impacts. The magnitude differences occur even though the money-metric welfare impacts are scaled as earnings equivalents, since shock-induced adjustments to positions' utility bids for workers take the form of changes in earnings offerings.

This discrepancy is primarily due to the fact that transitions to unemployment remove any earnings, but may cause much smaller utility losses due to welfare/UI benefits and increased leisure. Remaining differences reflect changes in compensating differentials stemming from shock-induced reallocation to jobs with more desirable amenities. These results suggest that the earnings losses from increased import competition identified by the literature may overstate welfare losses. Nonetheless, given the similarity in the distribution of losses and gains for these two outcomes, henceforth we focus our attention on earnings and employment outcomes rather than welfare in order to facilitate comparison with reduced-form findings from the literature that cannot evaluate welfare impacts.

Panel C of Figure 1 displays the impact of the China Shock on annualized unemployment risk between 2002 and 2006, both overall and separately by channel. While workers initially in manufacturing still experience the largest increases in full-year unemployment risk of around 0.25% per year, workers in other sectors generally experience increases around half as large (between 0.05% and 0.16% per-year). These results suggest most displaced manufacturing workers are able to find alternative jobs within a year, so that much of their welfare losses stem from settling for lower wages and less desirable positions.

Panel C of Figure 2 shows that unemployment incidence is far less concentrated among RP X&M firms, with workers from all trade engagement categories in all industries experiencing meaningful increases in their unemployment risk. As we demonstrate below, RP X&M firms in general and manufacturing RP X&M firms in particular employ a greater share of high paid workers whose skills are sufficiently portable that they can outcompete workers for either the remaining jobs at RP X&M firms or jobs at firms with lower levels of trade engagement.

Finding # 2: Import Competition Accounts for a Disproportionate Amount of the Worker-level Earnings Losses Relative to its Impact on Firm-level Employment

The three leftmost bars of Panel A display the 5-year earnings impacts generated by simulated shocks that only add or remove positions that we estimate were created or destroyed by a single channel: import competition, export competition, or import access.[22] The earnings impact of the import competition channel approximates well the China Shock's overall impact, despite the substantial changes in firm-level employment caused by the export competition and import access channels. This finding justifies the narrower focus of pioneering papers by Autor et al. (2013) and Pierce and Schott (2016) on the effects of import competition on manufacturing workers and areas with concentrations of manufacturing employment.

Four explanations contribute to import competition's dominance. First, and most obviously, the other two channels are nearly canceling each other out, since net job creation from expanded import access almost matches net job destruction from increased export competition. For example, these two channels generate larger earnings changes than import competition in the wholesale/retail and information industries, but their positive and negative earnings impacts are nearly offsetting. However, this explanation is insufficient: when the export competition shock and particularly the import access shock are imposed in isolation, they produce earnings impacts that on average are much less than half the magnitude of those produced by import competition, despite creating net employment changes about half as large.

The second explanation is that the import competition shock is concentrated in a single industry, while the other shocks are distributed across several industries.[23] When a large pool

[22]Note that this channel "decomposition" need not sum to the total impact of the China Shock, since the shocks interact with one another in equilibrium when they occur simultaneously.

[23]This partly reflects the restriction that only manufacturing firms are exposed to import competition, which

of workers who are close substitutes for one another (perhaps due to industry-specific skills) are all displaced simultaneously, the glut of supply to the remaining jobs at which they generate large relative surplus substantially erodes earnings for this worker type, while displacement of many small pools of workers from different industries allows most of these workers to find work at an alternative firm where most of their initial job surplus is salvaged.

A third mechanism is asymmetry in the magnitude and concentration of earnings changes between equally-sized positive and negative shocks, which further limited the earnings impact of the import access shock. For example, in wholesale/retail, expanded import access created 191,000 jobs while increased export competition removed 139,000 jobs, but these importing opportunities produced smaller earnings gains than the losses from greater export competition.

We demonstrate this asymmetry directly by running two additional single-period simulations featuring customized labor demand shocks: one that adds 112,000 non-traded manufacturing positions (1% of the U.S. labor force), and one that removes the equivalent number instead. Panels A and B of Figure 3 show that the earnings loss among non-traded manufacturing workers in the first simulation is nearly twice the earnings gain in the second simulation.

This asymmetry in incidence between positive and negative shocks stems from the extra surplus generated when firms retain their existing workers. Because moving, search and training costs have already been paid, incumbent workers generally have far higher expected surplus with their existing employers than equivalent jobs with other employers. Thus, when their jobs are destroyed, they experience considerable welfare losses. By contrast, new hiring caused by positive shocks requires new moving, search, and training costs, and thus creates smaller surplus gains. Furthermore, without firm-specific experience, many worker types may be close substitutes, so idiosyncratic surplus components play a larger role in determining the resulting allocation, and the welfare gains get distributed widely across types.

This interpretation is confirmed by Figure A1, which displays results from simulations that feature the same stylized positive and negative shocks described above but restrict the surplus from incumbents and new hires to be equal conditional on the (l, f) pair: $\theta_l^{f,z} = \theta_l^f \ \forall \ (l, f, z)$. The asymmetry disappears. These results imply that employment reallocation among firms driven by product market competition will generally reduce worker welfare in the short run, even if the growing firm's new positions closely resemble those lost by their competitor. They also imply that temporary shocks generate persistent impacts on labor market outcomes.

Fourth, reinforcing this asymmetry, the job turnover rate in the wholesale/retail sector (26%) is much lower than in manufacturing (19%). This suggests that the jobs created by expanded import access were disproportionately low surplus jobs that offered low quality amenities and/or low pay, and that workers that did take them did not benefit for very long.

Finding # 3: Labor market competition causes substantial dispersion of firm-

is imposed both due to data limitations preventing measurement of import competition exposure outside of manufacturing and a desire to follow the literature to facilitate easy comparison.

level shocks across worker types, particularly for unemployment incidence.

While Finding #1 highlights which types of workers were most affected by the China Shock, focusing on per-worker losses may mislead us about the shock's aggregate burden if the most affected worker types account for small shares of the U.S. labor force. To this end, Figure 4 displays, for each industry and trade engagement category, its 2001 labor force share (black-outlined bars) and the estimated shares of national earnings losses (narrow dark blue bars) and unemployment losses (wide light blue bars) borne by its 2001 workers. The labor force shares remind us that the vast majority of U.S. employment occurs outside of manufacturing, and in either nontrading or RP X&M firms rather than exclusively arms-length traders.

Even though manufacturing accounts for more than 100% of national firm-level net employment losses (Table 2), workers in manufacturing only experience 64% of aggregate earnings losses and a paltry 22.5% of additional years of unemployment. These gaps reflect the role of equilibrium adjustments in spreading the initial shock more broadly. Specifically, displacement of manufacturing workers, combined with redirection of non-manufacturing workers discouraged from seeking jobs in manufacturing, expands labor supply to other industries, lowering their pay levels. In addition, if the number of positions firms seek to fill is fairly inelastic in the short run, less productive workers in these industries may be systematically outcompeted for positions by skilled manufacturing workers, limiting their promotion opportunities and pushing them toward unemployment or less desirable positions elsewhere. An analogous pattern occurs across trade engagement statuses: workers initially at RP X&M firms bear 59% of national earnings losses, despite 82% of firm-level employment loss occurring at such multinationals.

One way to see the power of these equilibrium forces is to note that even combinations of industry and trade category whose firms experience net job growth as a result of the China Shock (see Table 2) still generally feature cumulative earnings and employment losses for their workers. For example, we estimate that the shock increased employment at wholesale/retail X&M firms by 12,500 over five years (1% of their pre-shock total), but workers initially at these firms experience $145 in shock-induced cumulative earnings losses and 0.13% greater unemployment risk per year relative to the most insulated worker type. This is partly due to increased competition for jobs like theirs and reduced opportunities elsewhere. However, it also reflects the fact that many of the workers initially at firms untargeted by the shock naturally move to other firms or sectors that may be increasingly targeted over time. For example, 25.6% of wholesale/retail trade workers leave their jobs each year at baseline. Thus, a greater share of the workforce experiences direct exposure over time, since even declining industries hire many workers due to routine turnover.

We can investigate which types of workers most directly compete with displaced manufacturing workers by considering how the China Shock alters the natural pattern of worker reallocation. Panel A of Figure 5 shows the change in the probability that a worker initially at a nontraded manufacturing firm transitions to a job in each different sector or trade category within manufacturing due to the first year of the shock. Panel B displays the analogous results for workers initially at RP X&M manufacturing firms. The large magnitudes of changes in transition probabilities for RP X&M workers reflects their far greater degree of direct exposure: their firms shed an estimated 181,000 jobs due to the shock in 2002. The results indicate that even the first year of the shock causes 0.75% more of these workers (18,000 extra workers) to transition to the leisure/administration/transportation sector, and causes substantial increased flows to natural resources/utilities and finance/professional services relative to their initial shares of national employment. We also see a sizeable 1.42 percentage point increase in their probability of transition to unemployment. Nonetheless, the ability of a large share of RP X&M manufacturing workers to find alternative jobs in other sectors, albeit at lower pay, explains the much greater dispersion of unemployment incidence than earnings incidence. While a much smaller number of nontrading manufacturing workers are induced to leave, they very disproportionately move to unemployment (0.55 percentage point increase) compared to jobs elsewhere in manufacturing or in other industries, suggesting that these workers, who are more likely to be initially lower paid, face a harder time finding alternative employment.

The increased competition for jobs in the low-paid service industries (leisure/ administration/ transportation) is also reflected in Figure 4, which shows that workers in these industries bear 5.4% of earnings losses and 21.7% of increased unemployment even though firms in these industries are generally not directly targeted by any of the three channels we consider. Workers in the natural resources/utilities sector also bear a much larger share of earnings and unemployment losses than their minuscule share of firm-level job losses would suggest. By contrast, workers in the education/health/government sector are much better insulated from the shock, indicating that workers leaving other industries do not generate sufficient surplus with employers in the education/health/government sector to effectively compete with these workers. These findings corroborates the classic blue collar/white collar intuition that manufacturing workers and professionals are very poor substitutes.

Notably, initially unemployed workers, many of whom would have found jobs faster in the absence of the China Shock, account for 12.3% of all shock-induced full year unemployment spells despite making up 7.5% of the 2001 labor force. They experience a larger increase in per-person unemployment rate (0.22% per year) than any other non-manufacturing sector, despite lacking an initial job for the trade shock to target. Interestingly, we find that a very small share of initially unemployed workers would have taken positions in manufacturing in the absence of the shock. Instead, the shock pushes other initially employed workers to positions in other sectors that frequently hire workers from unemployment, such as the nontrading service sector. Thus, existing long-term unemployed workers act as last resort hires for firms, making their employment status vulnerable even to negative demand shocks targeting firms with workers who are seemingly poor substitutes. That said, the shock does shift the composition of unemployment to more recently separated workers, so that initially unemployed workers comprise a smaller share of end-of-year unemployment than they would in its absence.

Finding # 4: Despite Lesser Exposure of Low-Paying Firms, Lower-Paid Workers Experience Disproportionate Welfare and Particularly Employment Losses

A major advantage of our matched employer-employee data is that it permits analysis of how trade shocks differentially impact workers throughout the earnings distribution. The substantial increases in unemployment risk for workers from the generally low-paying leisure-administration-transportation sectors suggest that an implicit job ladder mediates the labor market incidence of the China Shock. To examine this mechanism, the first four rows of the right panel of Table 3 display the earnings incidence of China's WTO entry by initial earnings category among workers initially in the heavily exposed RP X&M manufacturing sector.

Earnings losses monotonically increase in RP X&M manufacturing workers' initial pay, with those initially in the top two deciles of national pay estimated to have lost $15,921 on average over 5 years relative to the economy's most insulated workers. Furthermore, due to RP X&M manufacturing's high concentration of highly paid workers, these decile 9 and 10 workers account for 21.0% of national earnings losses, considerably more than the bottom five deciles (8.1%). Thus, there is some evidence that the disproportionate job losses among high-paying firms in general and RP X&M firms in particular translate to a greater burden among high-paid workers, at least in the most exposed sector.

Column 2 of Table 3 reports cumulative earnings changes as a percentage of the average pre-shock annual earnings within the earnings category. This exercise suggests that workers in the lower-middle part of the earnings distribution may lose a greater share of baseline earnings than higher paid workers. For example, the shock causes RP X&M manufacturing workers initially in deciles 3-5 to lose 2.6% of baseline earnings per year compared to 1.1% for deciles 9-10. Column 4, which considers employment losses, indicates that increases in unemployment risk also fall monotonically with workers' initial pay for RP X&M manufacturing workers. Specifically, workers initially in deciles 1-2 experience a 0.63% higher unemployment rate per year compared to 0.24% for deciles 9-10. These patterns suggest that more skilled or experienced workers are either able to outcompete less skilled or experienced workers for remaining manufacturing jobs, or that they generate more surplus with firms in other industries.

The earnings and employment results for the non-traded manufacturing sector (columns 6-10) display similar patterns of earnings and employment losses across initial earnings categories. Given that the non-traded manufacturing sector experienced few firm-level employment losses, these patterns suggest that increased competition for jobs from displaced RP X&M workers affects lower-paid and middle-paid workers more strongly than higher-paid workers.

Columns 1-5 and 6-10 of Panel B of Table 3 display the corresponding earnings and employment losses for workers initially within the wholesale/retail sectors at RP X&M and nontrading firms, respectively. Even though the China Shock generated 141,000 net jobs at low-paying wholesale/retail firms, we see only tiny earnings gains and small earnings losses for initially low paid workers at RP X&M and nontrading firms in this sector compared to the least exposed worker types in the U.S., while moderately to highly paid RP X&M workers in particular experience substantial cumulative earnings losses ($2,400 and $8,000 for deciles 6-8 and 9-10, respectively). These patterns are partly explained by the asymmetric impact of job creation (Finding #2) due to smaller surpluses from new hiring compared to retention. Still, one might expect existing low-paid wholesale/retail workers to leverage their experience and an influx of positions seeking their skills to improve their bargaining power or receive a promotion.

However, another more subtle mechanism causing the minimal earnings gains stems from the fact that low paid workers from wholesale/retail generally have particularly low year-to-year job retention rates. For example, in 2001-2002, only 62% of workers from the bottom two national earnings deciles at RP X&M wholesale/retail firms retained the same position as their dominant job, compared with 81% among those in the top two deciles and 92% among education/health/government workers in the top two deciles. This implies that many of the workers who gain a promotion or keep a job they would have lost would have soon moved to higher paying jobs anyway, limiting their earnings gains relative to a counterfactual in which China never joins the WTO. Put simply, greater job security in or expanded access to a low quality job does not improve earnings or utility prospects very much.

Columns 6-10 of rows 12-16 of Table 3 display the earnings and employment losses for the leisure/administration/transportation sector. Though firms in these sectors were minimally exposed to the China Shock, we still see that both percentage earnings losses and increases in unemployment risk decrease monotonically with initial earnings deciles. Notably, while earnings losses are only around $100-200 over 5 years for low paid workers in this sector, they experience non-trivial increases in their unemployment rate (about 0.2% increased risk per year), consistent with their being near the bottom of the economy-wide job ladder. By contrast, columns 6-10 of rows 9-12 report the same outcomes by initial earnings category for workers from education/health/government. Firms in these sectors also experienced very little direct exposure to the China Shock. However, for every initial earnings category, earnings changes are below $120 over five years, and unemployment increases are much smaller than in leisure/administration/transportation, and are truly tiny for the higher paid workers (0.03%). The high-paying jobs in these sectors often require very high levels of specialized education and training. This makes their workers particularly poor substitutes for those displaced by the China Shock, and ensures that they are extremely well insulated from trade shocks.

Finally, Figure 6 displays earnings and unemployment outcomes by initial earnings category after aggregating across all initial industries, trade statuses, and regions. Economywide, earnings losses induced by the China Shock increase with higher initial earnings, but percentage losses are considerably higher for deciles 3-5 and 6-8 than lower or higher earnings levels. In general, initially low and lower-middle paid workers' share of national earnings losses induced by the China Shock exceeds their initial share of national earnings, while the opposite is true for the highest paid workers. Thus, the China Shock contributed to greater earnings inequality, despite the fact that the shock caused net job creation among the lowest-paying employment-weighted quartile of firms, with firm-level employment losses concentrated among the top two quartiles. This counterintuitive result highlights the importance of characterizing equilibrium incidence at the worker level rather than relying on the distribution of firm-level or sector-level reductions in payroll. Interestingly, the opposite holds for unemployment: increases are larger for lower and middle-paid workers, but such workers had much higher baseline rates of transition to unemployment, so the China Shock actually made the composition of unemployment risk among initial earnings categories less regressive than it would have been.

Finding #5: Several Sources of Joint Surplus Heterogeneity Govern Labor Market Competition and Shape the Equilibrium Incidence of Labor Demand Shocks

The patterns of equilibrium incidence just discussed are shaped by an implicit tapestry of frictions associated with changing firms, industries, regions, and even firm trade status.[24] To better gauge the relative strength of these different sources of frictions, we reconsider simple stylized simulations introduced earlier that destroy 112,000 jobs, or 1% of U.S. workforce, in a single year among selected subpopulations of firms.

Panel A of Figure 3 shows results from a simulation in which all 112,000 jobs are removed from non-trading manufacturing firms, and are distributed across different firm size/avg. pay/region categories using the empirical conditional distribution of non-trading manufacturing employment. We see that workers initially in the targeted nontrading manufacturing sector experience by far the largest earnings losses ($1,109), suggesting that firm-level switching costs are quite large. Recall that we confirmed the importance of firm-level switching costs in Figure A1 by showing that these losses shrink dramatically when we restrict the surplus from within-firm type job switchers to be the same as firm stayers.

Panel A of Figure 3 also shows that workers initially at manufacturing firms with other trade statuses are all more harmed by the shock than workers from any other industry. This confirms a smaller but substantial role for industry-switching frictions, perhaps driven by limited portability of skills outside manufacturing. Among workers from other industries, natural resources/construction/utilities workers seem to be the closest competitors, while those from education/health/government are the most insulated, in line with the China Shock results.

Within manufacturing, the size of earnings losses arguably declines with the degree or intensity of trade engagement, with the largest losses occurring among workers whose firms are engaged in either arms-length importing or arms-length exporting, followed by those at $X\&M$, $RP\,X|M$, and finally RP X&M firms. Panel C of Figure 3 shows that removing the same number of jobs from RP X&M manufacturing firms instead reverses this ordering, with

[24]These frictions include search costs, moving costs, imperfect skill portability, and tastes for work amenities.

workers at non-trading firms relatively less affected. These results suggest that highly trade-engaged firms may be less inclined to hire workers at non-trading firms, though this relationship may be driven by other firm characteristics correlated with trade engagement.

To gauge the importance of regional mobility frictions, we alter our stylized simulation so that all of the destruction of non-trading manufacturing jobs occurs exclusively in the Midwest region. Results are displayed in the bottom panel of Table 4. Creating such a concentrated pool of similarly located and skilled workers causes enormous losses for the targeted nontraded manufacturing workers of over $5,000 per worker. Furthermore, workers at firms with other trading status categories within Midwestern manufacturing now experience quite large average losses of $574, while workers from other industries within the Midwest experience average losses of $395 dollars. In addition, losses for nontraded manufacturing workers in the great plains and mid-Atlantic/Appalachia regions (which border the Midwest) are about $200 and $150 respectively, while losses for their more distant counterparts on the West Coast and Northeast are only $18 and $22. The fact that regionally concentrated shocks generate such regionally concentrated impacts, even outside targeted industries, suggests quite large regional mobility frictions.

The first row of the first panel of Table 4 shows that the regional differences in firm-level loss do translate to regional differences in per-worker earnings losses: we find that the Midwest and Mid-Atlantic/Appalachia ("Upper South") regions suffered the largest per-worker earnings losses ($1,044 and $1,039), while the Southwest and West Coast regions were the most insulated ($394 and $563). The first row of the second panel of Table 4 shows the corresponding impacts of the shock on per-year unemployment. While the regional pattern is fairly similar, we find relative larger unemployment impacts in the Deep South. This is partly due to the fact that the Deep South lost the largest share of initial manufacturing employment among regions.

Interestingly, the regional rankings of per-worker losses vary substantially across industries for both outcomes, though the eastern half of the country tends to have larger per-worker earnings losses and unemployment increases in almost every industry. The regional rankings variability reflects the combination of substantial industry and regional mobility frictions.

6 Conclusion

Our evaluation of the worker-level incidence of the first five years of the China Shock has generated several new insights about the shock's impact: 1) the well-document manufacturing employment losses from increased competition from Chinese imports were accompanied by substantial, but largely offsetting, employment losses and gains outside manufacturing due primarily to greater competition for exports abroad and expansion of existing importers of Chinese products; 2) most of the firm-level employment losses and gains induced by China's WTO entry were experienced by large, high-paying, multinational firms; 3) despite the concentration of job losses within manufacturing, large shares of earnings and particularly employment losses were experienced by workers outside manufacturing; and 4) despite the concentration of job loss at high-paying firms, equilibrium percentage earnings losses and particularly net employment losses were greater for initially low and medium-paid workers.

Perhaps more importantly, the mechanisms that we highlight that generate these findings are likely to play important roles in shaping the incidence of any future shock to the international trade environment. First, trade shocks that affect either export market competition at key U.S. export destinations or import market access for countries who produce large quantities of cheaper inputs or final goods cause particularly substantial shifts in the distribution and level of employment among trading firms, especially multinationals. The additional channels targeting exporters and importers and their disproportionate impact on multinational firms have received inadequate attention in the literature in part because much of their employment impact takes place outside manufacturing, where data is often less reliable or available, and in part because data on related-party trade activities at the firm level is often not available. Second, imperfect mobility of human capital across firms causes job ladders within and across industries, so that even trade shocks that target high paying firms or industries produce large shares of shock-induced earnings gains or losses that trickle down to lower-paid and initially unemployed workers. Third, even neutral trade shocks that generate job gains and losses of comparable size and composition are likely to cause short-run welfare losses on average, as firm-specific knowledge is eliminated and search, moving, and training costs need to be re-paid. Finally, the degree to which job destruction generates concentrated welfare losses is heavily dependent on how long workers would have stayed or will stay at these jobs. Thus, job retention rates among the kinds of positions likely to be destroyed or created by trade shocks are an underappreciated indicator of the concentration of welfare losses or gains we should expect such shocks to generate.

References

Abowd, John M, Bryce E Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L McKinney, Marc Roemer, and Simon Woodcock, "The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators," in "Producer Dynamics: New Evidence from Micro Data," University of Chicago Press, 2009, pp. 149–230.

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito, "Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence," Technical Report, National Bureau of Economic Research 2019.

Arcidiacono, Peter and Robert A Miller, "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, 2011, *79* (6), 1823–1867.

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

—, —, —, and Jae Song, "Trade Adjustment: Worker-level Evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Bloom, Nicholas, Kyle Handley, André Kurmann, and Philip Luck, "The impact of chinese trade on us employment: The good, the bad, and the apocryphal," in "American economic association annual meetings," Vol. 2019 2019.

Borjas, George J., Jeffrey Grogger, and Gordon H. Hanson, "Comment: On Estimating Elasticities of Substitution," *Journal of the European Economic Association*, 2012, *10* (1), 198–210.

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

Carballo, Jeronimo, Kasandra McLean, and Richard Mansfield, "How Are a Firm's Labor and International Trade Activity Related?," Working Paper 2023.

Chiappori, Pierre-André, Dam Linh Nguyen, and Bernard Salanié, "Matching with random components: simulations," *Work. Pap., Columbia Univ., New York*, 2019.

Choo, Eugene and Aloysius Siow, "Who Marries Whom and Why," *Journal of Political Economy*, 2006, *114* (1), 175–201.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum, "Trade and manufacturing jobs in Germany," *American Economic Review*, 2017, *107* (5), 337–42.

Decker, Colin, Elliott H. Lieb, Robert J. McCann, and Benjamin K. Stephens, "Unique Equilibria and Substitution Effects in a Stochastic Model of the Marriage Market," *Journal of Economic Theory*, 2013, *148* (2), 778–792.

Dix-Carneiro, Rafael, "Trade liberalization and labor market dynamics," *Econometrica*, 2014, *82* (3), 825–885.

Erten, Bilge and Jessica Leight, "Exporting Out of Agriculture: The Impact of WTO Accession on Structural Transformation in China," *The Review of Economics and Statistics*, 05 2021, *103* (2), 364–380.

Feenstra, Robert C, Hong Ma, and Yuan Xu, "US exports and employment," *Journal of International Economics*, 2019, *120*, 46–58.

Galichon, Alfred and Bernard Salanié, "Cupid's Invisible Hand: Social Surplus and Identification in Matching Models," *The Review of Economic Studies*, 12 2021, *89* (5), 2600–2629.

Galle, Simon, Andrés Rodríguez-Clare, and Moises Yi, "Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade," Technical Report, National Bureau of Economic Research 2017.

Handley, Kyle, Fariha Kamal, and Wei Ouyang, "A Long View of Employment Growth and Firm Dynamics in the United States: Importers vs. Exporters vs. Non-Traders," Working Papers 21-38, Center for Economic Studies, U.S. Census Bureau December 2021.

Hillier, Frederick S and Gerald J Lieberman, "Introduction to Operations Research. Ninth," 2010.

Hotz, V Joseph and Robert A Miller, "Conditional Choice Probabilities and the Estimation of Dynamic Models," *The Review of Economic Studies*, 1993, *60* (3), 497–529.

Hummels, David, Jakob R Munch, and Chong Xiang, "Offshoring and labor markets," *Journal of Economic Literature*, 2018, *56* (3), 981–1028.

__ , Rasmus Jorgensen, Jakob Munch, and Chong Xiang, "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, June 2014, *104* (6), 1597–1629.

Jarmin, Ron and Javier Miranda, "The Longitudinal Business Database," Working Papers, U.S. Census Bureau, Center for Economic Studies 2002.

Kamal, Fariha and Wei Ouyang, "Identifying U.S. Merchandise Traders: Integrating Customs Transactions with Business Administrative Data," Working Papers, U.S. Census Bureau, Center for Economic Studies 2020.

Kim, Gueyon and Dohyeon Lee, "Offshoring and Segregation by Skill: Theory and Evidence," Technical Report 2020.

Koopmans, Tjalling C and Martin Beckmann, "Assignment Problems and the Location of Economic Activities," *Econometrica: Journal of the Econometric Society*, 1957, pp. 53–76.

Kovak, Brian K and Peter M Morrow, "The Long-Run Labor Market Effects of the Canada-US Free Trade Agreement," Technical Report, National Bureau of Economic Research 2022.

Lichter, Andreas, Andreas Peichl, and Sebastian Siegloch, "The own-wage elasticity of labor demand: A meta-regression analysis," *European Economic Review*, 2015, *80*, 94–119.

Mansfield, Richard, "How Local Are U.S. Labor Markets?: Using an Assignment Model to Forecast the Geographic and Skill Incidence of Local Labor Demand Shocks," Technical Report, working paper 2019.

Menezes-Filho, Naércio Aquino and Marc-Andreas Muendler, "Labor reallocation in response to trade reform," Technical Report, National Bureau of Economic Research 2011.

Menzel, Konrad, "Large Matching Markets as Two-Sided Demand Systems," *Econometrica*, 2015, *83* (3), 897–941.

Mourifié, Ismael, Aloysius Siow et al., "Cohabitation versus marriage: Marriage matching with peer effects," *Available at SSRN*, 2014.

Pierce, Justin R. and Peter K. Schott, "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, July 2016, *106* (7), 1632–62.

Salanié, Bernard and Alfred Galichon, "Cupid's Invisible Hand: Social Surplus and Identification in Matching Models," 2011.

Shapley, Lloyd and Martin Shubik, *Game Theory in Economics: Chapter 3: the" Rules of the Games"*, Rand, 1972.

Traiberman, Sharon, "Occupations and import competition: Evidence from Denmark," *American Economic Review*, 2019, *109* (12), 4260–4301.

Vilhuber, Lars, "LEHD Infrastructure S2014 files in the FSRDC," Working Papers 18-27, Center for Economic Studies, U.S. Census Bureau 2018.

7 Tables and Figures

Table 1: Employment Growth Effects of Exposure to China's WTO Entry

	Import Competition	Export Competition	Import Access	Export Access
	Constant Treatment Effect			
Exposure	-0.0387***	-0.280***	0.123***	-0.0082
	(0.00388)	(0.0251)	(0.0201)	(0.0072)
	Treatment Effects by Trade Engagement Status			
Exposure	-0.0298***	-0.157***	-0.00174	-0.0120
	(0.00448)	(0.0354)	(0.0370)	(0.0119)
×Non-traded	(Baseline)			
×Importer Only	-0.103***	–	(Baseline)	–
	(0.0207)	–		–
×Exporter Only	0.0308***	(Baseline)	–	(Baseline)
	(0.00970)		–	
×Exporter and Importer	-0.0532***	-0.123*	0.142***	0.00925
	(0.0165)	(0.0642)	(0.0471)	(0.0181)
×RP X|M	-0.0321	-0.0601	0.232***	0.00941
	(0.0201)	(0.0638)	(0.0569)	(0.0186)
×RP X&M	-0.100***	-0.253***	0.138*	-0.0134
	(0.0347)	(0.0875)	(0.0738)	(0.0221)
Exposure Measure				
Mean	0.320	0.0084	0.0123	-0.0103
Standard Deviation	0.123	0.0771	0.0334	0.5902
Additional Controls				
Other Exposure Measures	X	X	X	X
Trade Engagement	X	X	X	X
Number of Establishments	X	X	X	X
Employment Growth	X	X	X	X
Trade Value Growth	X	X	X	X
FE Region, Age, Size×Pay	X	X	X	X
FE NAICS-2		X	X	X
Observations (000s)	994	994	994	994
R-Squared	0.101	0.103	0.103	0.103

Source: LFTTD and LBD databases.

Notes: The first two panels report the coefficient(s) for the exposure measure for each channel-specific regression (see column headings) from restricted versions of specification (16) in Section 4.2. The first panel imposes equal sensitivity to shock exposure among all firms. The second panel allows only firms' trade engagement status to drive treatment effect heterogeneity, and displays separate coefficients by trade status. Standard errors are clustered at the firm level. ***,**, and * denote significance at the 1%, 5%, and 10% levels. The third panel reports the mean and standard deviation of each channel's exposure measure. The last two panels describe each regression's controls and sample.

Table 2: Firm-Level Distribution of Shock-Induced Employment Gains and Losses by Channels

				Shock Size over Time (000s)				
Channel			**2002**	**2003**	**2004**	**2005**	**2006**	**Total**
Import Competition			-183	-119	-104	-115	-123	-646
Export Competition			-122	-94	-40	-40	-33	-330
Import Access			91	89	49	20	-9	240
Total			-211	-122	-95	-135	-165	-729
				Cumulative Shock Size by Industry (000s)				
	Res. Cons. Util.	**Manuf.**	**Wholes. Retail**	**Leis. Admin. Transp.**	**Finance Real Estate Prof. Serv.**	**Information**	**Educ. Health Gov.**	**Total**
Import Competition	0	-646	0	0	0	0	0	-646
Export Competition	-8	-102	-138	0	-68	-14	2	-330
Import Access	1	-10	190	20	21	16	-0	240
Total	-7	-757	53	21	-45	3	1	-729
				Cumulative Shock Size by Trade Engagement (000s)				
		Non-Traded	**Importer Only**	**Exporter Only**	**Exporter & Importer**	**Related Party Importer or Exporter**	**Related Party Importer & Exporter**	**Total**
Import Competition		-19	-33	24	-79	-73	-466	-646
Export Competition		0	0	-9	-12	-21	-287	-330
Import Access		0	0	0	22	69	149	240
Total		-19	-32	14	-69	-24	-597	-729
				Cumulative Shock Size by Firm Average Pay (000s)				
				Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**	**Total**
Import Competition				-22	-94	-248	-281	-646
Export Competition				-14	-24	-81	-209	-329
Import Access				86	97	26	30	240
Total				49	-19	-302	-456	-729
				Cumulative Shock Size by Region (000s)				
	West Coast	**South West**	**Great Plains**	**Deep South**	**Upper South**	**Mid-West**	**North-East**	**Total**
Import Competition	-98	-62	-44	-87	-86	-157	-111	-646
Export Competition	-64	-40	-17	-42	-37	-67	-59	-329
Import Access	48	46	20	25	18	55	26	240
Total	-112	-54	-41	-104	-104	-168	-143	-728

Source: LFTTD and LBD data.

Notes: This table reports estimates of the number of jobs created or removed between 2002 and 2006 by China's WTO entry based on predicted values from the firm-level, channel-specific regressions (16) in Section 4.2. Each panel disaggregates the total employment shock by the combination of channel and a second characteristic: year (1st panel), industry (2nd panel), trade engagement status (3rd panel), firm size quartile (4th panel), firm average pay quartile, and geographic region. See Section A5 for detailed descriptions of the industry, trade engagement, and region categories.

Table 3: The Earnings and Unemployment Impacts of the China Shock by Initial Earnings Category, Industry, and Trade Engagement Status

Initial Deciles	Earnings			Unemployment		Earnings			Unemployment	
	Level	%Change	Share	Rate	Share	Level	%Change	Share	Rate	Share
	Manufacturing - RP M&X					Manufacturing - Non-Traded				
1-2	-2161.66	-8.87	0.34	0.63	0.56	-527.48	-2.74	0.28	0.31	0.92
3-5	-4898.84	-12.81	7.81	0.44	3.99	-813.55	-2.32	1.13	0.19	1.5
6-8	-13023.79	-9.75	19.37	0.28	4.77	-1936.73	-1.48	1.06	0.12	0.74
9-10	-15921.48	-5.46	21.01	0.24	3.63	-2597.79	-0.82	0.55	0.09	0.22
	Wholesale/Retail - RP M&X					Wholesale/Retail - Non-Traded				
1-2	232.74	1.37	-0.29	0.17	1.2	-164.32	-0.98	0.42	0.22	3.15
3-5	97.21	0.29	-0.15	0.13	1.16	-241.93	-0.71	0.77	0.13	2.34
6-8	-2416.05	-1.84	1.32	0.12	0.84	-539.94	-0.41	0.63	0.08	1.08
9-10	-7099.56	-2.27	3.68	0.16	0.89	-917.04	-0.29	0.52	0.06	0.41
	Information					Education/Health/Government				
1-2	-181.21	-1.04	0.05	0.23	0.4	-9.3	-0.05	0.05	0.13	3.51
3-5	-269.49	-0.73	0.18	0.14	0.51	18.3	0.05	-0.17	0.06	2.96
6-8	-811.12	-0.61	0.47	0.1	0.66	125.86	0.09	-0.64	0.03	1.81
9-10	-1733.23	-0.53	1.17	0.11	0.83	-8.92	0	-0.04	0.03	0.85
	Natural Resources/Construction/Utilities					Leisure/Administration/Transportation				
1-2	-238.55	-1.24	0.22	0.29	1.5	-139.82	-0.86	1.17	0.23	10.93
3-5	-286.18	-0.79	0.77	0.18	2.74	-234.65	-0.71	1.87	0.15	6.77
6-8	-680.7	-0.51	1.15	0.12	2.25	-539.52	-0.41	1.45	0.1	2.96
9-10	-1261.72	-0.42	1.41	0.09	1.17	-880.92	-0.28	1	0.08	1.04
	Finance/Real Estate/Professional Services									
1-2	-191.67	-1.04	0.31	0.2	1.82					
3-5	-298.96	-0.82	1.26	0.11	2.61					
6-8	-1058.97	-0.8	2.8	0.08	2.41					
9-10	-2023.32	-0.57	5.73	0.09	2.66					

Source: Simulation results based on LEHD, LFTTD and LBD data.
Notes: This table reports the average simulated impact of China's WTO entry on several outcomes by initial earnings category (rows), industry category (panel) and (for some panels) firm trade engagement category on several outcomes. The outcomes include cumulative 5-year (2002-2006) earnings (in 2020 $), cumulative earnings as a percentage of initial annual earnings, share of national shock-induced earnings losses, increase in per-year unemployment rate, and share of national shock-induced employment losses.

Table 4: **Evaluating the Regional Earnings and Unemployment Incidence of Trade Shocks**

	West Coast	South West	Great Plains	Deep South	Upper South	Mid-West	North-East
	Cumulative 2002-2006 Earnings Changes (2020 $)						
Overall	-563.13	-394.16	-618.37	-683.24	-1039.42	-1043.99	-888.39
Manufacturing	-4244.11	-3366.56	-3375.01	-4115.28	-4305.36	-4245.17	-4579.92
N.Res./Cons./Util.	-86.64	-306.24	-385.02	-288.82	-565.07	-584.71	-503.82
Wholesale/Retail	-166.53	-139.6	-230.63	-483.65	-657.16	-431.7	-701.09
Leis./Admin./Trans.	-15.48	55.47	-221.87	-212.68	-491.78	-348.27	-358.2
Information	-408.47	-436.98	-369.5	-690.31	-713.12	-843.54	-325.04
Fin./RE/Prof. Serv.	-468.34	-286.07	-366.01	-494.64	-773.32	-823.69	-694.43
Educ./Health/Gov.	232.96	243.41	27.49	23.16	-218.81	-23.96	-60.69
Unemployed	-464.75	-343.73	-526.84	-731.71	-970.69	-815.87	-854.52
	Per-Year Changes in the Unemployment Rate						
Overall	0.14	0.11	0.11	0.15	0.13	0.15	0.15
Manufacturing	0.29	0.22	0.19	0.29	0.23	0.24	0.30
N.Res./Cons./Util.	0.14	0.12	0.12	0.15	0.14	0.17	0.17
Wholesale/Retail	0.13	0.10	0.11	0.15	0.13	0.14	0.16
Leis./Admin./Trans.	0.15	0.13	0.14	0.16	0.15	0.18	0.18
Information	0.11	0.10	0.11	0.15	0.11	0.15	0.11
Fin./RE/Prof. Serv.	0.10	0.08	0.08	0.11	0.09	0.12	0.10
Educ./Health/Gov.	0.05	0.05	0.05	0.06	0.05	0.06	0.05
Unemployed	0.22	0.17	0.16	0.25	0.24	0.23	0.24
Stylized Shock Targeting Midwestern Non-Trading Manufacturing Firms							
	Earnings Change (2020 $)						
Manuf. - Non-Traded	-18.56	-63.02	-221.34	-39.30	-162.94	-5458.52	-22.76
Manuf. - Traded	-23.22	-60.36	-196.95	-47.26	-146.68	-605.94	-29.00
Non-manufacturing	-9.95	-49.04	-151.96	-27.93	-95.89	-417.55	-8.90
Unemployment	-61.44	-102.03	-197.69	-73.39	-163.68	-642.58	-61.02

Source: Simulations based on LEHD, LFTTD and LBD data.

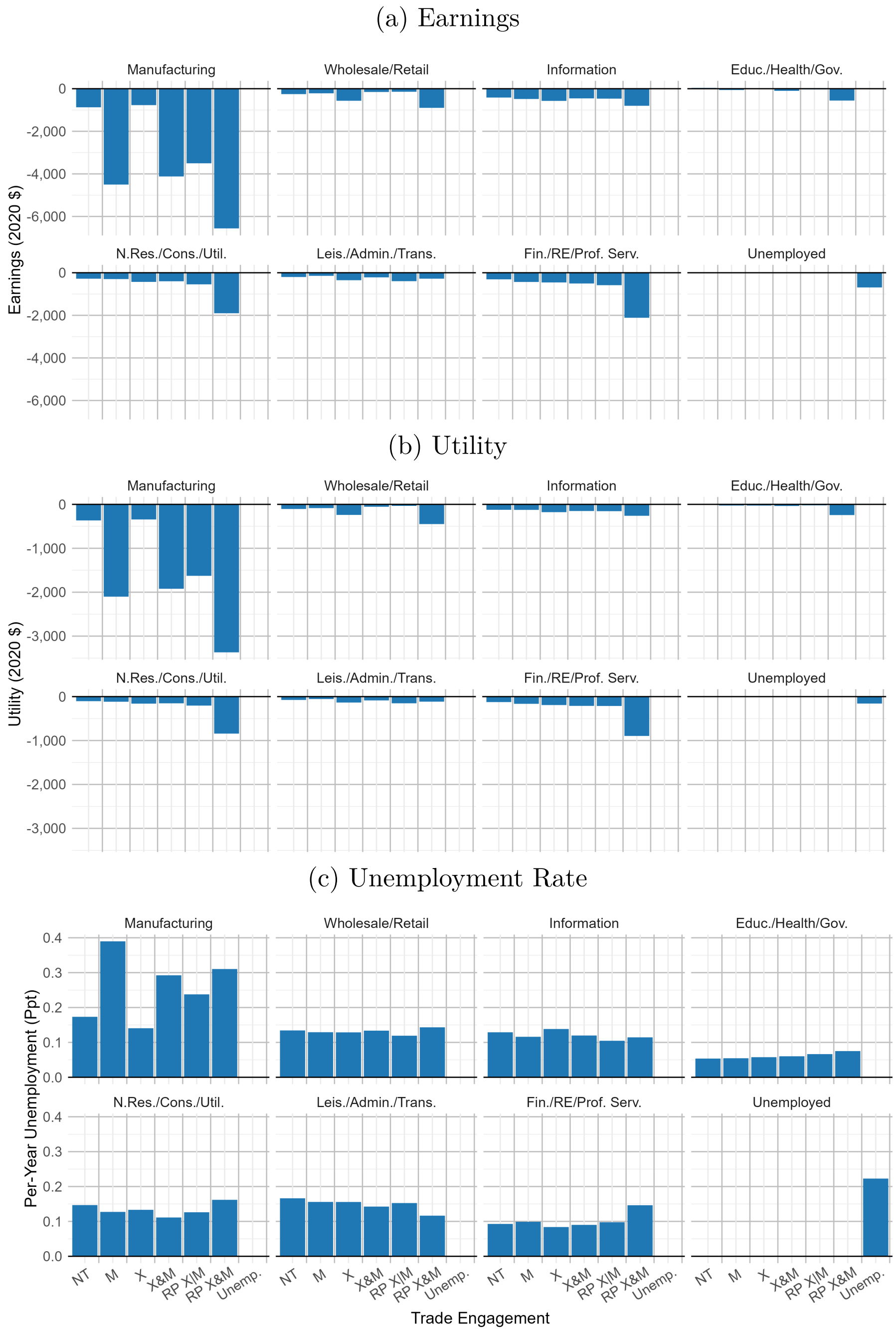
Notes: The first panel of this table reports the mean cumulative 2002-2006 earnings loss (in 2020 $) induced by China's WTO entry by worker's initial (2001) industry (rows) and region (columns). The second panel displays the mean per-year changes in the unemployment rate (in percentage points) induced by China's WTO entry incurred by each industry/region combination. The third panel reports the mean simulated earnings loss after one year from a stylized targeted shock that removes 1% of all U.S. employment (112,000 jobs) exclusively from manufacturing non-trade jobs in the Midwest region. For each region (columns), losses are reported for workers initially in the targeted non-traded manufacturing sector in each region, as well as for workers from trading manufacturing firms, from other non-manufacturing industries, and from initial unemployment.

Figure 1: Mean Earnings, Utility, and Employment Gains and Losses from China's WTO Entry by Industry Category and Channel

Source: Simulation Results based on LEHD, LFTTD and LBD data.

Notes: This figure displays the average simulated impact of China's WTO accession on five-year (2002-2006) cumulative earnings (in 2020 $), money-metric utility (also in 2020 $), and per-year probability of unemployment by channel (colored bars) and workers' 2001 industry category (X-axis).

Figure 2: Cumulative 2002-2006 Earnings, Utility and Employment Losses Induced by the China Shock by Worker's Initial Industry Category and Trade Engagement Status

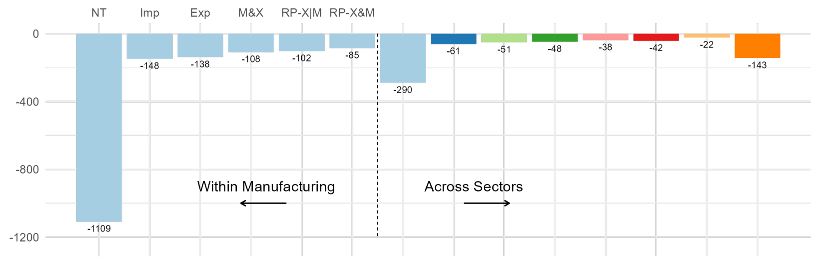


Source: Simulation results based on LEHD, LFTTD and LBD data.

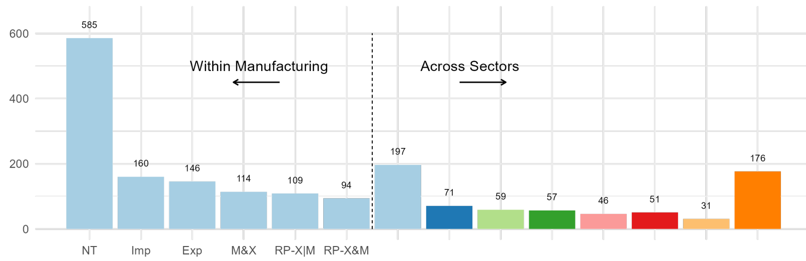
Notes: This figure displays the average simulated impact of China's WTO accession on five-year (2002-2006) cumulative earnings (in 2020 $), money-metric utility (also in 2020 $), and per-year probability of unemployment by the industry category (sub-panels) and trade engagement status (X-axis) of workers' 2001 (pre-shock) employers.

Figure 3: Simulated Earnings Impacts of Artificial Shocks that Remove or Add 1% of U.S. Employment (112,000 Jobs) Exclusively from/to the Non-Traded Manufacturing Sector or the RP X&M Manufacturing Sector

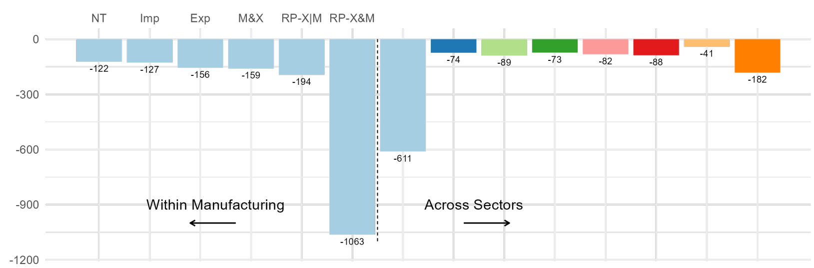
(a) Negative Non-traded Manufacturing Shock - Earnings Losses



(b) Positive Non-traded Manufacturing Shock - Earnings Gains



(c) Negative RP X&M Manufacturing Shock - Earnings Losses

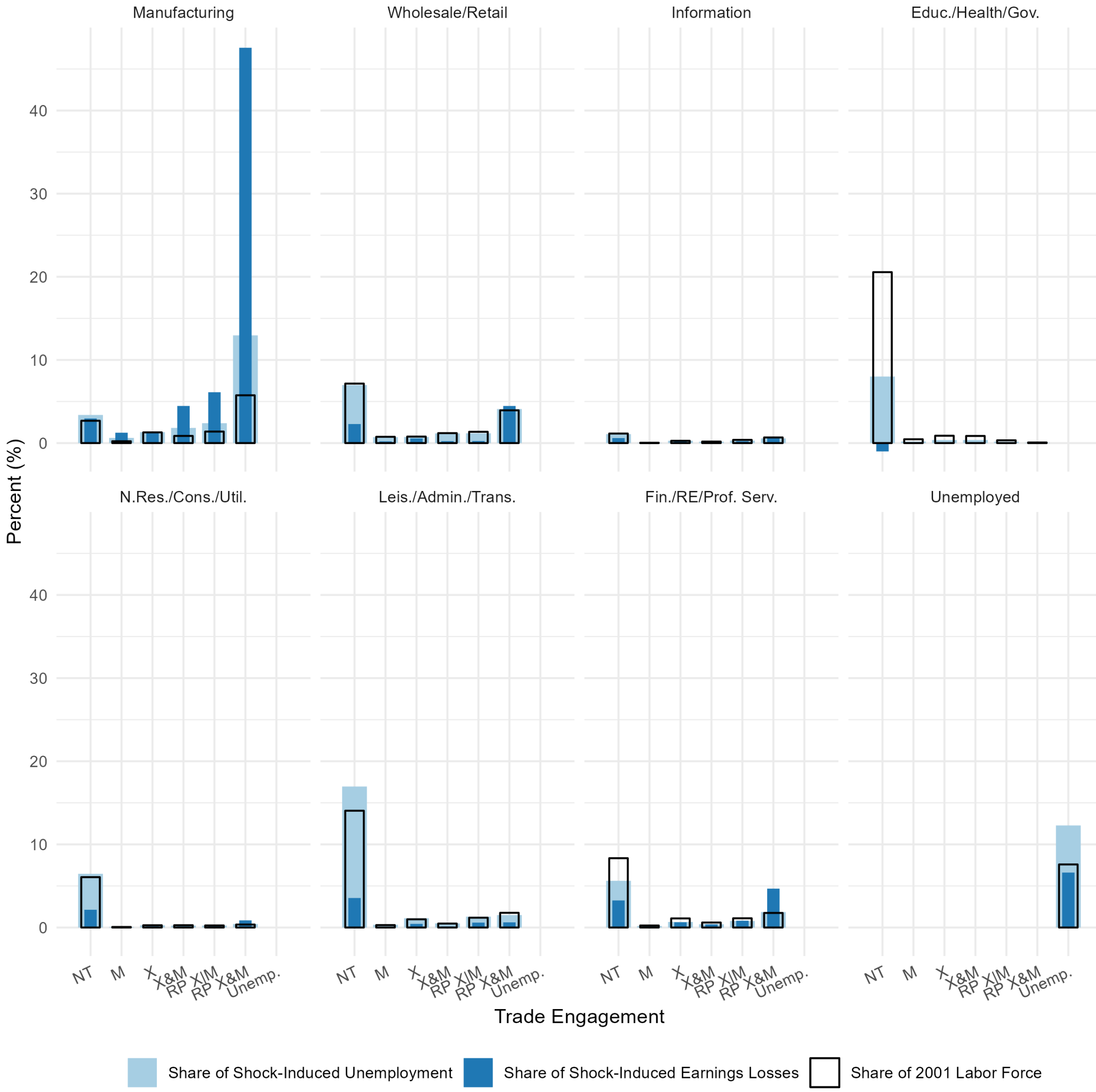


(d) Positive RP X&M Manufacturing Shock - Earnings Gains

Source: Authors' calculations based on data LEHD, LFTTD and LBD.

Notes: This figure reports simulated impacts on the next year's earnings of artificial shocks that remove (panels A and B) or add 112,000 jobs (panels B and D) exclusively from/to the non-traded manufacturing sector (panel A and panel B) or the RP X&M manufacturing sector (panel C and panel D). In each panel, the multi-colored bars right of the vertical dotted line show the earnings gains or losses by the industry category of the worker's firm, while the blue bars to the left display the breakdown of earnings gains and losses by the firm's trade engagement status.

Figure 4: Shares of National Shock-Induced Job Losses and Earnings Losses Accounted for By Initial Industry and Trade Engagement Status Combinations

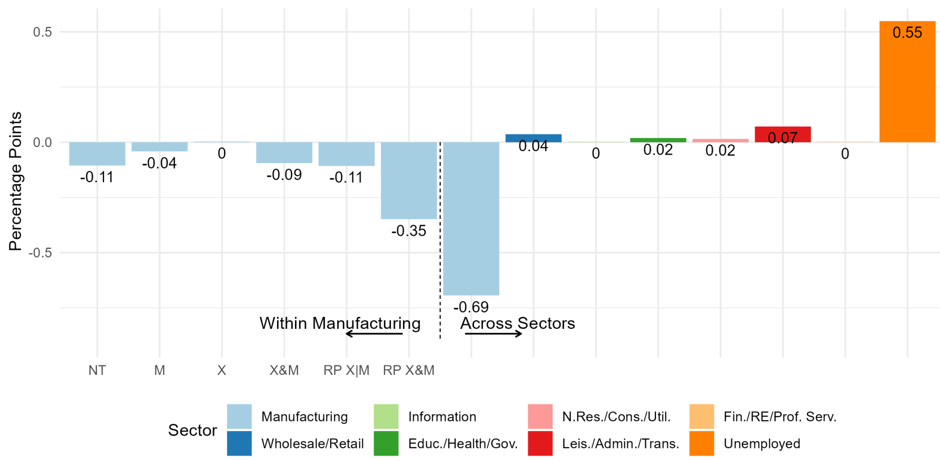


Source: Simulation results based on LEHD, LFTTD and LBD data.

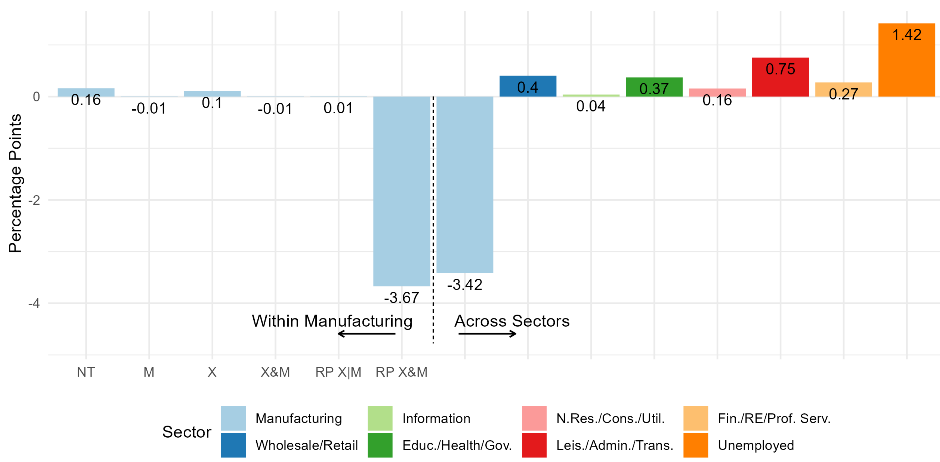
Notes: This figure displays the estimated shares of national earnings losses (narrow, dark blue bars) and employment losses (wide, light blue bars) induced by China's WTO entry accounted for by workers from combinations of initial industry (different panels) and initial firm's trade status (X-axis categories in each panel). Each combination's initial (2001) share of the U.S. labor force is also displayed in hollow, medium-width bars as a natural point of comparison.

Figure 5: Shock-Induced Changes in the Conditional Distribution of Firm Type Destinations among Workers Initially at Non-Trading and RP X&M Manufacturing Firms

(a) Non-trading Manufacturing Workers - Changes in Transition Percentages



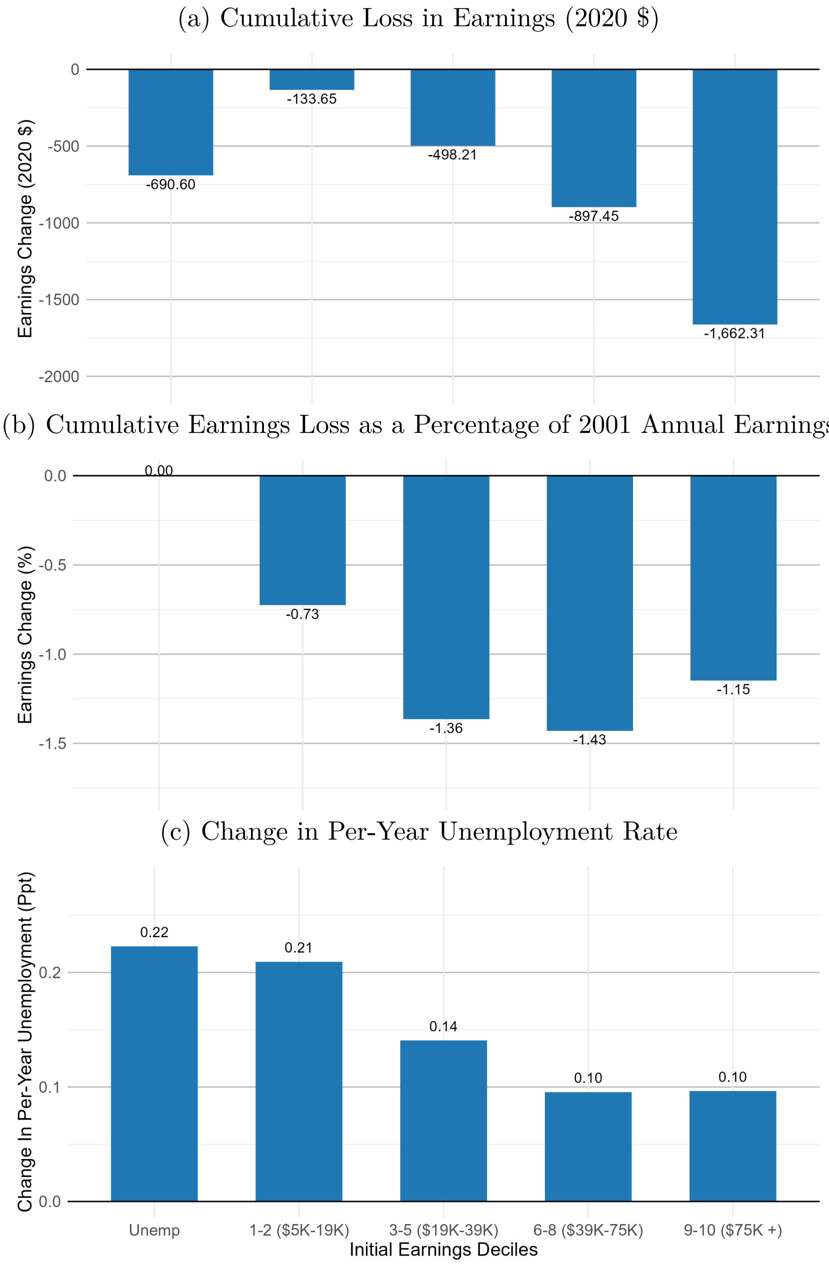
(b) RP X&M Manufacturing Workers - Changes in Transition Percentages



Source: Simulation results based on LEHD, LFTTD and LBD data.

Notes: This figure reports the average simulated change induced by China's WTO accession in the percentage of workers transitioning to jobs other sectors (multi-colored bars right of the vertical dotted line) and to jobs in other trade engagement statuses within manufacturing among non-traded manufacturing workers (panel A) and RP X&M manufacturing workers (panel B).

Figure 6: Mean Changes in Cumulative 2002-2006 Earnings and Per-Year Unemployment Rate Induced by China's WTO Entry by Initial Earnings Category



Source: Simulation results based on LEHD, LFTTD and LBD data.

Notes: Panel A displays the estimated mean change in cumulative 2002-2006 earnings (in 2020 $) induced by China's Entry among workers in each initial earnings/unemployment category. Panel B expresses this cumulative change as a percentage of each category's pre-shock (2001) annual earnings level. Panel C displays the mean per-year increase in unemployment rate induced by China's WTO entry by initial earnings/unemployment category.

Appendix

A1 Nesting the Human Resources Problem within a Standard Profit Maximization Problem

A1.1 A Partial Equilibrium Model of the Trade Engagement Decision

Our theoretical model nests a complex firm-level profit maximization problem featuring interrelated importing, exporting, and worker staffing decisions within a broader labor market equilibrium. The profit maximization problem allows us to describe sources of firm heterogeneity that lead firms to make different choices about whether and how to engage in international trade. The combined model shows how shocks to the trade environment differentially affect the magnitude and composition of employment among firms engaged in alternative trade channels.

We solve the firm's profit maximization problem in three stages:

1. Firms choose how many units to produce and whether to export their products (either via arms-length or related-party transactions).

2. Firms choose the number of worker positions to fill and the amount of non-labor inputs to purchase, including whether to buy these inputs domestically or import them at arms-length or via related-party transactions. The chosen inputs must be sufficient to produce the number of units determined in stage 1.

3. Firms choose which workers will fill the number of positions determined in stage 2.

We first present an overview of the production function in Section A1.2. Then, since the problem can best be solved via backward induction, we present the final stage human resources problem in Section 2.1 and Section A1.3. We use the solution to the human resources problem to solve the second stage cost minimization problem in Section A1.4. We use the resulting total cost function to solve the first stage profit maximization problem in Section A1.5. Finally, Section 2.3 of the main text shows how firms' staffing choices are combined with workers' labor supply choices to yield the equilibrium allocation and compensation of labor.

A1.2 Production Side

The output Y_j of firm j with total factor productivity Φ_j is given by:

$$Y_j = \Phi_j K_j^{\varkappa} L_j^{\varpi} M_j^{\varrho} \tag{22}$$

K_j is producer j's capital stock, assumed to be previously determined and fixed in the short run.[25] L_j is a labor aggregate that combines the productive contributions of the workers hired into N_j positions, while M_j is an aggregate of non-labor inputs from both domestic and international sources. ϱ, $\varkappa$ and ϖ are parameters of the Cobb-Douglas production technology.

[25] We treat K as a fixed input purely to simplify notation. It is straightforward to allow K to be flexibly chosen in the same manner as M.

A1.3 Revisiting the Human Resources Problem

The labor aggregate L_j is composed of the sum of the productivities of the workers hired for the N_j positions the firm has chosen to fill:

$$L_j = \sum_{k=1}^{N_j} \alpha_{l(k)}^{f(j)} + \tilde{\sigma}_f \mu_{l(k)k} \tag{23}$$

where $l(k)$ denote the type of the worker that is chosen to fill position k, defined below as a combination of categories of observed worker characteristics. Similarly, $f(j)$ denotes the type of firm j, defined below by combinations of firm characteristics. From this point forward, we suppress the dependence of l on k, and f on j except where necessary for clarity.

We assume that the firm must choose the number of positions to fill, N_j, and the amount of inputs to purchase, M_j, before the idiosyncratic job-specific productivity components $\{\mu_{lk}\}$ have been realized. Thus, to solve the second stage problem the firm must determine the expected value of the maximized profit contribution from equation (2).

Suppose that the idiosyncratic component μ_{lk} is independently and identically distributed across positions k within an (l, f) pair and follows a type 1 extreme value distribution. Suppose further that $\Psi_j \approx \Psi_f \ \forall j \in f$, and define $\sigma_f \equiv \Psi_f \tilde{\sigma}_f$. Then, using results from McFadden (1974), we derive the following expression for the expected value of the labor aggregate L when its components are chosen to maximize their profit contribution:

$$E[L(N_j, M_j)] = \Psi_f^{-1} N_j \Gamma + \Psi_f^{-1} N_j \ln\left(\sum_{l \in \mathcal{L}} e^{(\Psi_f \alpha_l^f - W_l^m)/\sigma_f}\right) + \Psi_f^{-1} N_j \sum_{l \in \mathcal{L}} \frac{e^{(\Psi_f \alpha_l^f - W_l^m)/\sigma_f}}{\sum_{l' \in \mathcal{L}} e^{(\Psi_f \alpha_{l'}^f - W_{l'}^f)/\sigma_f}} W_l^m \tag{24}$$

where Γ is the Euler-Mascheroni constant. The function $E[L(N^*, M^*)]$ is an input to the firm's second-stage cost minimization problem, which we consider next.

A1.4 Cost Minimization Problem

Let M_j be an index that combines domestic and imported inputs:

$$M_j = \left[\left(M_j^d\right)^\zeta + \left(M_j^{m,al}\right)^\zeta + \left(b^{rp} M_j^{m,rp}\right)^\zeta\right]^{1/\zeta} \tag{25}$$

where M_j^d captures domestic inputs, $M_j^{m,al}$ captures inputs imported at arms length, and $M_j^{m,rp}$ captures inputs imported from related parties. $b^{rp} > 1$ captures the degree of increased productivity of imported inputs from related parties. Note that M_j^d, $M_j^{m,al}$ and $M_j^{m,rp}$ can be assumed to implicitly represent indices of product- or industry-specific inputs.

The firm minimizes its total production cost (which excludes fixed costs of exporting, described below) for a given quantity $\bar{Y}$:

$$
\begin{aligned}
TPC(Y, W(\cdot,\cdot), P_M) = \min_{M_j, N_j} \; & W(M_j, N_j)N_j + P_M^d M_j^d \\
& + P_M^{m,al} M_j^{m,al} + P_M^{m,rp} M_j^{m,rp} + P^K \overline{K} \\
& + f_j^{m,al} \mathbb{1}(M^{m,al} > 0) + f_j^{m,rp} \mathbb{1}(M^{m,rp} > 0) \\
\text{subject to } & Y = \Phi_j M_j^{\varrho} K_j^{\varkappa} L_j(M_j, N_j)^{\varpi} \\
& M_j = \left[\left(M_j^d\right)^{\zeta} + \left(M_j^{m,al}\right)^{\zeta} + \left(b^{rp} M_j^{m,rp}\right)^{\zeta} \right]^{1/\zeta}
\end{aligned} \tag{26}
$$

where $L_j(M_j, N_j)$ is the solution to a sub-problem solved above that maximizes the profit contribution of a staff of N_j workers given M_j units of materials, and $W(M_j, N_j)$ is the expected per-position compensation for this staff.[26] $P_M = [P_M^d, P_M^{m,al}, P_M^{m,rp}]$ is a vector containing the per-unit prices of domestic inputs, arms-length imported inputs, and inputs imported from related parties, respectively.

Note that the fixed costs of both arms-length and related-party importing, $f_j^{m,al}$ and $f_j^{m,rp}$ respectively, are assumed to be heterogeneous across firms. Furthermore, the fixed cost of arms-length importing is assumed to be less than the fixed cost of related-party importing ($f_j^{m,al} < f_j^{m,rp} \; \forall \; j$), but related-party imported materials are assumed to be more productive than their arms-length counterparts. Thus, firms will vary in how they source their materials, but they will always source all materials using the form of trade engagement.

A1.5 Profit Maximization Problem

Given its total production cost function $TPC(\bar{Y}, W(*,*), P_M)$, the firm solves the following profit maximization problem:

$$
\begin{aligned}
\max_{Y^d, X^{al}, X^{rp}} \; & P^d(Y^d)Y^d + P^{x,al}(X^{al})X^{al} + P^{x,rp}(X^{rp})X^{rp} \\
& - TPC(Y, W(\cdot,\cdot), P^m) - f_j^{x,al} \mathbb{1}(X^{al} > 0) - f_j^{x,rp} \mathbb{1}(X^{rp} > 0)
\end{aligned} \tag{27}
$$

where $Y = Y^d + X^{al} + X^{rp}$. The demand functions $P^{x,rp}(X)$ and $P^{x,al}(X)$ implicitly incorporate trade costs. In order to accommodate the observed variation in approaches to serving foreign markets, we assume that the demand curve for related-party exports strictly dominates that for arms-length exports ($P^{x,rp}(X) > P^{x,al}(X) \; \forall \; X$), but that this greater revenue potential requires a higher fixed cost to set up a foreign affiliate ($f_j^{x,rp} > f_j^{x,al}$).[27] Finally, we assume that the fixed cost of exporting either through arms-length or related-party transactions are heterogeneous across firms.

[26] Note that the expected per-position compensation $W(M_j, N_j)$ depends on the choices of materials and positions because these choices alter the expected optimal composition of worker types, and these worker types differ in their required salaries.

[27] To justify assuming $P^{x,rp}(X) > P^{x,al}(X)$, one could assume that firms selling through related-party affiliates avoid a middle man who adds an additional markup that firm j does not receive. Another possibility is that products sold through related-party affiliates have a higher appeal for foreign consumer due to the fact that they perceived the firm as local.

A2 Assignment Model Implementation and Extensions

A2.1 Constructing Counterfactual Allocations and Utilities

This appendix derives the alternative equilibrium conditions used to solve for counterfactual allocations and utility changes in the absence of information on vacancies by firm type.

Recall that the necessary stability conditions for a solution to the social planner's problem (equivalent to decentralized equilibrium) can be written as:

$$\delta_{ik} = 1 \text{ iff } k \in \arg\max_{k \in \mathcal{K} \cup 0} \pi_{ik} - V_k^* \text{ and } i \in \arg\max_{i \in \mathcal{I} \cup 0} \pi_{ik} - U_i^* \tag{28}$$

where δ_{ik} is an indicator for whether worker i and position k form a job match, U_i^* and V_k^* represent the shadow prices of worker i and position k, and π_{ik} captures the joint surplus from the match. Koopmans and Beckmann (1957) show that when unmatched agents only exist on one side of the market, the dual problem payoffs need only be recovered on one side of the market in order to construct the stable assignment.

Thus, we can focus attention initially on the worker's problem. Recall from (7) that the joint surplus combines the worker and firm's match payoffs, $\pi_{ik} = U_{ik} + V_{ik}$, and that the systematic component of joint surplus common to all matches of types $(l(i), f(k))$ can be written as $\theta_l^f \equiv \Psi_f \alpha_l^f + \gamma_l^f$. Then we can rewrite the joint surplus as:

$$\pi_{ik} = \theta_l^f + \sigma_f \mu_{lk} + \sigma_l \epsilon_i^f. \tag{29}$$

Substituting (29) into (28) we obtain:

$$\max_{\{\mathcal{K} \cup 0\}} \theta_l^f + \sigma_f \mu_{lk} + \sigma_l \epsilon_i^f - V_k^* \tag{30}$$

Following Galichon and Salanié (2021), we can then rewrite this optimization problem as a two-stage problem:

$$\max_{\{\mathcal{F}\}} \left[\theta_l^f + \sigma_l \epsilon_i^f + \max_{k: f(k) = f} \sigma_f \mu_{lk} - V_k^* \right] \tag{31}$$

Switching signs, we can rewrite the second half as:

$$\max_{\{\mathcal{F}\}} \left[\theta_l^f + \sigma_l \epsilon_i^f - \min_{k: f(k) = f} V_k^* - \sigma_f \mu_{lk} \right] \tag{32}$$

Define $\tilde{V}_{lf} = \min_{k: f(k) = f} V_k^* - \sigma_f \mu_{lk}$, and let $\tilde{U}_{lf} = \theta_l^f - \tilde{V}_{lf}$. Then we can rewrite the workers problem as:

$$\max_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} + \sigma_l \epsilon_i^f \right] \tag{33}$$

Using tools from convex analysis, Salanié and Galichon (2011) show that $\tilde{U}_{lf}$ is identified from observed matching patterns for a more general class of assignment models, and that for the particular heteroskedastic logit specification of payoffs we adopt:

$$\tilde{U}_{lf} = \sigma_l (\ln P(f|l) - \ln P(\tilde{f}|l)) \tag{34}$$

Comparing (9) and (34), we see that $\tilde{U}_{lf} = \gamma_l^f + W_l^f - (\gamma_l^{\tilde{f}} + W_l^{\tilde{f}})$, where $\tilde{f}$ is the normalized firm type. Note that

$$\arg\max_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} + \sigma_l \epsilon_i^f\right] = \arg\max_{\{\mathcal{F}\}} \left[\gamma_l^f + W_l^f - (\gamma_l^{\tilde{f}} + W_l^{\tilde{f}}) + \sigma_l \epsilon_i^f\right] = \arg\max_{\{\mathcal{F}\}} \left[\gamma_l^f + W_l^f + \sigma_l \epsilon_i^f\right] \quad (35)$$

where the last equality uses the fact that the normalization term $\gamma_l^{\tilde{f}} + W_l^{\tilde{f}}$ is common to all types f and thus does not affect worker type l's optimal firm type. Thus, there is no inconsistency between the two versions of the worker's problem (5) and (33).

However, the alternative formulation of the worker's problem based on the stability condition and positions' shadow values suggests a more computationally efficient approach to computing counterfactual allocations: find the changes in mean shadow values, denoted V_f^{CF}, that set the supply of counterfactual positions h_f^{CF} equal to worker demand.

Specifically, the worker's problem in the counterfactual labor market is:

$$\arg\max_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} - V_f^{CF} + \sigma_l \epsilon_i^f\right] \quad (36)$$

Recalling the assumption that ϵ_i^f follows an i.i.d Type 1 extreme value distribution, we recover an alternative logit expression for a type l worker's conditional choice probability:

$$P(f|l) = \frac{e^{(\tilde{U}_{lf} - V_f^{CF})/\sigma_l}}{\sum_{f' \cup 0} e^{(\tilde{U}_{lf'} - V_{f'}^{CF})/\sigma_l}} \quad (37)$$

Inserting equation (37) in place of (6) into the market clearing conditions (8), imposing that all vacancies get filled by removing the firm's outside option (effectively setting $\alpha_0^f = -\infty$), and summing both sides over worker types l yields a set of F feasibility conditions requiring that aggregate demand for each position type equal supply of each position type:

$$\sum_l m_l^{CF} \frac{e^{(\tilde{U}_{lf} - V_f^{CF})/\sigma_l}}{\sum_{f' \cup 0} e^{(\tilde{U}_{lf'} - V_{f'}^{CF})/\sigma_l}} = h_f^{CF} \; \forall \, f \in \{\mathcal{F} \cup 0\} \quad (38)$$

If we normalize the shadow value or "profit" for nonemployment, V_0^{CF}, to 0, these F equations depend on F endogenous equilibrium mean shadow (i.e. profit) values $\{V_f^{CF}\}$. Solving this system of equations for any set of counterfactual supply and demand compositions m_l^{CF} and h_f^{CF} not only yields predicted mean profit changes by firm type, but also yields the unique aggregate counterfactual allocation (including transitions to unemployment), since (37) can be evaluated at $\{V_f^{CF}\}$ and combined with m_l^{CF} to deliver the count of (l, f) job matches, $P^{CF}(l, f)$. Note that constructing (38) only requires estimates of $\tilde{U}_{lf} = \sigma_l(\ln P(f|l) - \ln P(\tilde{f}|l))$, which can be constructed using calibrated values of σ_l and empirical log conditional probabilities $\ln \hat{P}(f|l)$ and $\ln \hat{P}(\tilde{f}|l))$.

Furthermore, this same approach can be used on the other side of the market to generate L equations that can be solved for the equilibrium changes in mean utility values $\{U_l^{CF}\}$ (and the identical equilibrium allocation):

$$\sum_{f \cup 0} h_f^{CF} \frac{e^{(\tilde{V}_{lf} - U_l^{CF})/\sigma_f}}{\sum_{l'} e^{(\tilde{V}_{l'f} - U_{l'}^{CF})/\sigma_f}} = m_l^{CF} \ \forall \ l \tag{39}$$

where $\tilde{V}_{lf} = \sigma_f(\ln P(l|f) - \ln P(\tilde{l}|f))$ (analogous to the worker side). This requires treating unemployment as a dummy "position" type, whose position count h_0^{CF} can be inferred once the assumption that all vacancies are filled is imposed (assuming $I > K$).[28] This assumption also implies that the optimal allocation is fully determined by relative utility changes: one type's utility change can be normalized to 0, and one of the L equations can be removed.

The normalized type we select for both utility and mean earnings changes is the one we estimate to be most insulated from the China Shock. To make this determination, we first identify worker types that were not directly affected by the China Shock, in the sense that their initial industry-trade status-region combinations receive zero estimated firm-level employment shock in the chosen year. Then, we assess whether each worker type's prospects for alternative employment have improved or declined (i.e. they are indirectly exposed to the shock) by using each type's baseline conditional distribution of firm type destinations to construct a probability-weighted average of the share of positions gained or lost at each position type. We then normalize the type whose average is closest to zero, since this suggests that the kinds of jobs they generally transition to have neither become more nor less plentiful.

Note that the market clearing conditions (39) can be trivially altered to accommodate separate surplus values for job stayers vs. movers within type-pair, discussed in Section 2.6:

$$h_0^{CF} \frac{e^{(\tilde{V}_{l,0}^0 - U_l^{CF})/\sigma_0}}{\sum_{l'} e^{(\tilde{V}_{l',0}^0 - U_{l'}^{CF})/\sigma_0}} + \sum_f h_f^{CF} \sum_{z \in \{0,1\}} \frac{e^{(\tilde{V}_{l,z}^f - U_l^{CF})/\sigma_f}}{\sum_{l',z' \cup 0} e^{(\tilde{V}_{l',z'}^f - U_{l'}^{CF})/\sigma_f}} = m_l^{CF} \, \forall \, l \tag{40}$$

Furthermore, our approach to accommodate the lack of detailed vacancy data has yielded substantial computational savings as well. Choo and Siow (2006) show that when singles are included on both sides of the market, the $L \times F$ equilibrium conditions can be collapsed to $L+F$ equations. By imposing $P(0|f) = 0$, we can compute counterfactual equilibria by solving a system of only $\min\{L, F\}$ equations.

Thus, whenever singles can be observed on one side of the market and assumed away on the other, one can use a very large type space on a chosen side of the market. This result could be useful in other contexts, such as student-to-school allocations, where singles are unlikely to exist on one side of the match (e.g. due to truancy laws). For example, in our case we end up considering ~5,000 worker types but ~12,000 firm types, which allows us to model the impact of multifaceted trade shocks extremely flexibly. In particular, theoretical trade models predict that the magnitude and direction of exposure in a trade war and firms' labor market responses likely depend heavily on initial trade status, industry, firm size, and average firm pay, but most alternative empirical models are unable to accommodate such heterogeneity.

[28] These dummy unemployment positions represent a computational mechanism for incorporating workers' payoffs from unemployment, $\{U_{i0}\}$, akin to "balancing" an unbalanced assignment problem (Hillier and Lieberman (2010)). We have confirmed that the two systems of equations yield identical equilibrium allocations.

A2.2 Deriving Counterfactual Earnings Changes

It remains to show that the changes in earnings transfers $\{W_l^{f,CF}\}$ can also be recovered using this alternative computational approach. Consider rearranging equation (9) to solve for W_l^f - $W_l^{\tilde{f}}$. If we replace the original data-provided counterparts $P(\cdot|\cdot)$ with the newly-computed counterfactual conditional choice probabilities $P^{CF}(\cdot|\cdot)$ and duplicate this equation with a second difference equation for worker type l' rather than l, we obtain:

$$W_l^{f,CF} - W_l^{\tilde{f},CF} = \sigma_l[\ln P^{CF}(f|l) - \ln P^{CF}(\tilde{f}|l)] - \gamma_l^f + \gamma_l^{\tilde{f}} \tag{41}$$

$$W_{\tilde{l}}^{f,CF} - W_{\tilde{l}}^{\tilde{f},CF} = \sigma_{\tilde{l}}[\ln P^{CF}(f|\tilde{l}) - \ln P^{CF}(\tilde{f}|\tilde{l})] - \gamma_{\tilde{l}}^f + \gamma_{\tilde{l}}^{\tilde{f}} \tag{42}$$

Performing the analogous operation using the position-side CCPs from (10), we obtain:

$$W_l^{f,CF} - W_{\tilde{l}}^{f,CF} = \sigma_f[\ln P^{CF}(\tilde{l}|f) - \ln P^{CF}(l|f)] + \Psi_f(\alpha_l^f - \alpha_{\tilde{l}}^f) \tag{43}$$

$$W_l^{\tilde{f},CF} - W_{\tilde{l}}^{\tilde{f},CF} = \sigma_{\tilde{f}}[\ln P^{CF}(\tilde{l}|\tilde{f}) - \ln P^{CF}(l|\tilde{f})] + \Psi_{\tilde{f}}(\alpha_l^{\tilde{f}} - \alpha_{\tilde{l}}^{\tilde{f}}) \tag{44}$$

Combining (41) and (44) yields:

$$\begin{aligned} W_l^{f,CF} - W_{\tilde{l}}^{\tilde{f},CF} &= \sigma_l \ln P^{CF}(l,f) - (\sigma_l + \sigma_{\tilde{f}}) \ln P^{CF}(l,\tilde{f}) \\ &\quad + \sigma_{\tilde{f}} \ln P^{CF}(\tilde{l},\tilde{f}) - \gamma_l^f + \gamma_l^{\tilde{f}} + \Psi_{\tilde{f}}\alpha_l^{\tilde{f}} - \Psi_{\tilde{f}}\alpha_{\tilde{l}}^{\tilde{f}} \end{aligned} \tag{45}$$

(45) reveals that even though identification of $\{\Psi_f\alpha_l^f\}$ and $\{\gamma_l^f\}$ requires F and L normalizations respectively, counterfactual earnings transfers are identified up to a single scale normalization (the value for $W_{\tilde{l}}^{\tilde{f},CF}$ must be normalized for a particular choice of $(\tilde{l},\tilde{f})$).[29]

A bit more algebra reveals further intuition about the relationship between earnings gains and utility gains. First, recall the identification of $\tilde{V}_{lf}$:

$$\tilde{V}_{lf} = \sigma_f(\ln P^{smooth}(l|f) - \ln P^{smooth}(l'|f))$$

Next, note that the following optimization problems all yield the same maximizing worker i for any given set of $\{\epsilon_{if}\}$ draws:

$$\begin{aligned} &\arg\max_i \tilde{V}_{lf} - \overline{U}_l^{CF} + \sigma_f\epsilon_{if} = \arg\max_i \tilde{V}_{lf} - (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) + \sigma_f\epsilon_{if} \\ &= \arg\max_i \alpha_{lf} - W_{lf}^{CF} + \sigma_f\epsilon_{if} = \arg\max_i \alpha_{lf} - \alpha_{l'f} - (W_{lf}^{CF} - W_{l'f}^{CF}) + \sigma_f\epsilon_{if} \end{aligned} \tag{46}$$

This equation suggests the the first and third objectives must be equal for each firm type up to a firm type-specific constant:

$$(W_{lf}^{CF} - W_{l'f}^{CF}) = (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) - \tilde{V}_{lf} + (\alpha_{lf} - \alpha_{l'f}) \tag{47}$$

[29] Note that one can generate an alternative formula for $W_l^f - W_{\tilde{l}}^{\tilde{f}}$ by combining equations (42) and (41). These two expressions are equivalent as long as the set of surplus difference-in-differences Θ identified from the data is held fixed in the counterfactual simulation.

This relates differences in counterfactual earnings changes among worker types within a firm type to utility changes. Performing an analogous comparison of the two different versions of the worker's objectives yields a relationship between earnings differences among firm types for a given worker type and firm counterfactual profit adjustments.

$$(W_{l'f}^{CF} - W_{l'f'}^{CF}) = \tilde{U}_{l'f} - (\overline{V}_{f}^{CF} - \overline{V}_{f'}^{CF}) - (\gamma_{l'f} - \gamma_{l'f'}) \tag{48}$$

Adding (47) and (48) yields:

$$(W_{lf}^{CF} - W_{l'f'}^{CF}) = \tilde{U}_{l'f} - \tilde{V}_{lf} + (\overline{U}_{l}^{CF} - \overline{U}_{l'}^{CF}) - (\overline{V}_{f}^{CF} - \overline{V}_{f'}^{CF}) + (\alpha_{lf} - \alpha_{l'f}) - (\gamma_{l'f} - \gamma_{l'f'}) \tag{49}$$

Next, we use the fact that our estimate of $\alpha_{lf} - \alpha_{l'f}$ is $\hat{\alpha}_{lf} - \hat{\alpha}_{l'f} = \tilde{V}_{lf} + W_{lf}^{data} - W_{l'f}^{data}$. Similarly, $\hat{\gamma}_{l'f} - \hat{\gamma}_{l'f'} = \tilde{U}_{l'f} - (W_{l'f}^{data} - W_{l'f'}^{data})$. Plugging these into (49) yields:

$$(W_{lf}^{CF} - W_{l'f'}^{CF}) = (\overline{U}_{l}^{CF} - \overline{U}_{l'}^{CF}) - (\overline{V}_{f}^{CF} - \overline{V}_{f'}^{CF}) + W_{lf}^{data} - W_{l'f'}^{data} \tag{50}$$

So counterfactual earnings differences reflect counterfactual utility differences, profit differences, and baseline earnings differences. In particular, this equation shows that counterfactual utility changes are reflected one-for-one in counterfactual earnings changes.

A2.3 Identification and Estimation of $\{\sigma_l\}$ and $\{\sigma_f\}$

In this appendix, we discuss our procedure for calibrating $\{\sigma_f\}$ and $\{\sigma_l\}$. We calibrate these parameters by combining multiple years of job matching and earnings data from the LEHD with the assumption that none of σ_f, σ_l, nor the systematic worker and firm components of surplus vary meaningfully over the small interval of years we consider:

$$\Psi_f^t \alpha_l^{f,t} = \Psi_f \alpha_l^f \qquad \gamma_l^{f,t} = \gamma_l^f \qquad \sigma_f^t = \sigma_f \qquad \sigma_l^t = \sigma_l \qquad \forall\, t \tag{51}$$

We first define Δ_x as a difference operator over the subscript x and x', and rewrite equation (9) to be year-specific:

$$\Delta_l W_l^{f,t} / \sigma_f^t = \Delta_l \ln P^t(l,f) - \Delta_l \psi_f^t \alpha_l^{f,t} / \sigma_f^t \tag{52}$$

Then, taking a difference among two versions of (52) for years t and $t-s$ and imposing the assumptions (51), we obtain:

$$\Delta_l W_l^{f,t} - \Delta_l W_l^{f,t-s} = \sigma_f \left[\Delta_l \ln P^t(l,f) - \Delta_l \ln P^{t-s}(l,f) \right] \tag{53}$$

In principle, (53) represents a set of quasi-demand equations, and one could estimate the semi-elasticities $\{\sigma_f\}$ by running F different panel regressions of earnings changes on changes in (l,f) match counts. However, in order for such an estimator to deliver consistent estimates $\{\sigma_f\}$, one would need a set of valid supply-side instruments for $\Delta_l \ln P^t(l,f) - \Delta_l \ln P^{t-s}(l,f)$ for each type f. We experimented with using changes in m_l over time as a model-based instrument to isolate supply shocks in $\Delta_l \ln P^t(l,f) - \Delta_l \ln P^{t-s}(l,f)$, but found the results to be very sensitive to small differences in specification, in line with others in the literature (Borjas et al. (2012)). Instead, we exploit the fact that, conditional on $\{\Psi_f \alpha_l^f\}$, $\{\sigma_f\}$ pins down the firm type's elasticity of substitution among alternative worker types, and we calibrate $\{\sigma_f\}$ by selecting an elasticity of substitution from the literature. Specifically, let η_f denote the elasticity of substitution across all pairs of worker types for each position type f:

$$\ln P^t(l,f) - \ln P^t(l',f) = \eta_f \left[\ln W_l^{f,t} - \ln W_{l'}^{f,t}\right] \tag{54}$$

Taking a difference of (54) across t and $t-s$, substituting (53) for $\ln P^t(l,f) - \ln P^t(l',f)$, and rearranging allows one to express σ_f in terms of η_f and observed difference-in-differences in earnings and log earnings:

$$\sigma_f = -\frac{\Delta_t \Delta_l W_l^{f,t}}{\eta_f \Delta_t \Delta_l ln W_l^{f,t}} \tag{55}$$

We choose the implied elasticity of 7.4 from Borjas et al. (2012)'s estimate of the elasticity of substitution between high school graduates and high school dropouts, and impose $\eta_f = 7.4 \,\forall\, f$. Note that imposing a common elasticity still yields a distribution of σ_f semi-elasticities.

We take an analogous approach on the worker side of the market to calibrate σ_l. Since the literature is largely silent on workers' elasticity of substitution among earnings offers from different types of positions, we again impose $\eta_l = 7.4 \,\forall\, l$.

Reassuringly, this approach generates σ_l values that increase with initial worker earnings and σ_f values that increase with average worker pay, so that a dollar of additional wages causes less substitution for high paid workers and for high paying firms. Note also that counterfactual allocations do not depend on $\{\sigma_l\}$ and $\{\sigma_f\}$. These parameters are only necessary for properly scaling earnings and welfare changes.

A2.4 Endogenizing Vacancies

In this appendix we discuss how we relax the exogeneity of the number of positions to be filled by firm type by treating it as endogenously responding to the earnings cost per efficiency unit of labor required by the current labor market. We then show how to solve jointly for the number of positions by type h_f and the earnings per type pair W_l^f via a fixed point algorithm. The resulting pair $(\{h_f\}, \{W_l^f\})$, when combined with the worker counts $\{m_l\}$, yields a stable allocation among existing workers and positions and satisfies each firm's optimality conditions with respect to the number of positions.[30]

Note that endogenizing the set of positions to be filled has advantages relative to incorporating detailed vacancy data even if such data existed, since many firms that never post vacancies would nonetheless hire additional workers if earnings levels decreased, or would remove vacancies or positions if earnings levels increased. This is particularly relevant when evaluating counterfactuals featuring shocks that change prevailing earnings levels. Also, the duration of most posted vacancies is quite short, while we are considering reallocation over the period of a year.

In the first step of the fixed point procedure, the firm chooses the number of positions N_j^0 (and thus the index of labor inputs L_j^0 from the model in Appendix A1) to maximize profits given the initial earnings vector $\{W_l^{0,f}\}$, which implicitly also determines the marginal product

[30] In principle, one could extend this approach to the worker side as well in order to account for endogenous mobility into or out of the labor force, perhaps through immigration.

of labor Ψ_j^0.[31] In the second step, the new values of N_j and Ψ_j can then be aggregated to the firm type level for each type f and supplied to the assignment model as h_f and Ψ_f. Finally, in the third step the set of market clearing conditions (38) can be re-solved to compute a new set of interim earnings values $W_l^{f,1}$. As long as the costs of adjusting the number of positions is not too small, iterating between these three steps will cause convergence to a fixed point featuring equilibrium values for $\{h_f\}$ and $\{W_l^f\}$.

In the absence of data on capital and materials, rather than implement the full disaggregated structural approach just outlined, we instead replace the first two steps with an existing estimate of elasticity of employment with respect to the cost of an efficiency unit of labor from the minimum wage literature (Lichter et al. (2015)).

A2.5 Mapping China's Accession into a Sequence of Assignment Model Shocks

We attempt to isolate the labor market impact of China's WTO accession by estimating a sequence of five single-year counterfactual demand shocks between 2001-2002 and 2005-2006, each of which mimics the form of the static shocks summarized in Section 4.3. Our goal is to approximate the evolution that the labor market would have experienced had China not joined the WTO during this period.

To construct the counterfactual labor market matching for the initial 2001-2002 shock, we estimate surplus values $\{\theta_g^{0102}\}$ and their worker and firm components $\{\gamma_g^{0101}\}$ and $\{\Psi_f^{0102}\alpha_g^{0102}\}$ using realized 2001-2002 job flows/retentions and earnings, following equations (11), (9), and (10), and hold these values fixed when constructing the 2001-2002 counterfactual allocation. This approach implicitly assumes that any evolution in surpluses and surplus components between the 2000-2001 and 2001-2002 transitions is due to other secular trends in the labor market unrelated to China's WTO entry. Similarly, we hold fixed the observed 2001 composition of worker types, presumed to be predetermined prior to the shock: $m_l^{0102,CF} = m_l^{0102}$. We then construct the counterfactual number of positions of type f, $h_f^{0102,CF}$, by restoring or removing from the observed employment level the part of type f's 2001-2002 employment growth estimated to be eliminated or generated by China's WTO entry in equation (18) in Section 4:

$$h_f^{0102,CF} = h_f^{0102} - Shock_{f,0102}^{Total} \tag{56}$$

When isolating the role of a single channel, we replace $Shock_{f,0102}^{Total}$ with $Shock_{f,0102}^{IC}$, $Shock_{f,0102}^{EC}$, or $Shock_{f,0102}^{IA}$. Finally, we assume that the parameters $\{\sigma_l\}$ and $\{\sigma_f\}$ governing elasticities of substitution remain fixed at values estimated using the 1999-2000 and 2000-2001 labor markets.

We then solve the system of equations (40) described in appendix A2.2 to generate the 2001-2002 utility changes and allocation of workers that would have transpired in the absence of China's WTO accession, and use (45) to solve for the corresponding equilibrium earnings changes. To recover the change in worker mobility induced by the first year of the China Shock, we simply subtract the counterfactual allocation from the observed 2001-2002 allocation.

Next, to capture the cumulative nature of the multi-year China Shock, we use our 2001-2002 counterfactual allocation and earnings change distribution to generate the counterfactual

[31] In order to evaluate the profit level associated with any choice of N_j, one needs to assume a value of the marginal revenue product of labor Ψ_j^0 in order to compute $E[L_j|N_j, Psi_j]$ from equation (24) in Appendix A1.3. Since knowledge of L_j (along with M_j and $\overline{K}_j$ implies an updated marginal revenue product of labor Ψ_j^1, one can iterate between updating Ψ_j^k and updating $N_j^{*,k}$ until both stabilize and N_j^* and Ψ_j^* are determined.

worker type distribution for the 2002-2003 simulation, m_l^{0203}. This requires calculating the number of workers ending 2002 in each (region, industry, trade engagement) combination who are predicted to have received earnings in the appropriate decile. We assume that the initial distribution of earnings is uniform between the cutoffs defining each earnings category, and use the counterfactual earnings change W_g^{CF} to determine the shares of workers in each transition group who remain in/switch earnings deciles relative to the previous year. Specifically, let $e(l)$, $i(l)$, $r(l)$, $te(l)$ denote the earnings decile, industry, region, and trade engagement category associated with worker type l, respectively, and let t denote the origin year in the origin-destination year pair. We update the worker type distribution via:

$$m_l^{t+1} = \sum_{g'} 1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \ \& \ e(l(g')) = e(l)\right] \#(g') \times (1 - \frac{|\Delta W_{g'}^{CF}|}{interval\ size_e}) + \\ 1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \ \& \ e(l(g')) = e(l) - 1 \ \& \ \Delta W_{g'}^{CF} > 0\right] \frac{\#(g') \times |\Delta W_{g'}^{CF}|}{interval\ size_e} + \\ 1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \ \& \ e(l(g')) = e(l) + 1 \ \& \ \Delta W_{g'}^{CF} < 0\right] \frac{\#(g') \times |\Delta W_{g'}^{CF}|}{interval\ size_e} \tag{57}$$

For $t = 2002$ and each subsequent year, we continue to assume that year-to-year changes in surplus values and components were induced by other macroeconomic shocks unrelated to China's WTO accession, and set $\theta_g^{t,CF} = \theta_g^t$, $\gamma_g^{t,CF} = \gamma_g^t$, and $\alpha_g^{t,CF} = \alpha_g^t$, where θ_g^t, γ_g^t, and α_g^t are estimated (11), (9), and (10) with observed worker allocations between t and $t+1$. Next, note that after the first year of the simulation, the economy is inheriting different distributions of worker types and position types than those observed in the data. Thus, the observed allocation in year pair t no longer serves as a useful comparison for isolating the impact of the China Shock during year t. So we must generate two counterfactual allocations for year t. The first adds the observed change in the distribution of position counts between t and $t-1$, $(h_f^t - h_f^{t-1})$, to the previous year's counterfactual position counts. This creates a composite shock that combines the year t China Shock with any other concurrent shocks to labor demand:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) \tag{58}$$

The second counterfactual then restores jobs by subtracting the (usually negative) estimated China Shock component (e.g. $Shock_{f,0203}^{Total}$) from (18) in Section 4:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) - Shock_{f,t}^{Total} \tag{59}$$

For each counterfactual demand shock, we solve for the allocation and utility changes using (40) and the earnings changes using (45). We then subtracting the second counterfactual allocation, utility changes, and earnings changes from their analogues from the first counterfactual. This isolates the impact of year t of the China Shock relative to a baseline in which China had not joined the WTO in any previous year but other concurrent shocks had occurred and continued to occur. We then use the allocation from the second counterfactual to update the worker type and position type distributions for the next year via (57), (20), and (21), and continue in this vein through the 2005-2006 allocation.

Evaluating the cumulative five-year impact among worker types requires extending the methods for assessing incidence used for our single-period shocks. Note that each period's simulated allocation yields utility and employment changes by worker type ($\Delta_t U_l^{t+1,CF}$ and $\Delta_t P^{t+1,CF}(f=0|l)$) and earnings changes by transition group $\Delta_t W_g^{t+1,CF}$. In order to track the accumulation of impacts for workers classified by their pre-shock (2001) types, we generate a transition matrix among worker types in adjacent years with elements $P(l^{t+1}|l^t)$ using (57) but conditioning on the time t worker type:

$$
\begin{aligned}
P(l^{t+1}|l^t) = \sum_{g'|l(g')=l^t} & 1\left[(ind,r,te)(f(g')) = (ind,r,te)(l)\,\&\, e(l(g')) = e(l)\right] \frac{\#(g') * (1-\Delta W_{g'})}{interval\ size_e} + \\
& 1\left[(ind,r,te)(f(g')) = (ind,r,te)(l)\,\&\, e(l(g')) = e(l) - 1\ \&\ \Delta W_{g'} > 0\right] \frac{\#(g') * \Delta W_{g'}}{interval\ size_e} + \\
& 1\left[(ind,r,te)(f(g')) = (ind,r,te)(l)\,\&\, e(l(g')) = e(l) + 1\ \&\ \Delta W_{g'} < 0\right] \frac{\#(g') * \Delta W_{g'}}{interval\ size_e}
\end{aligned} \tag{60}
$$

We then use backward induction to accumulate expected outcomes over multiple years for workers of type l at time t by using the mean 2006 outcomes (e.g. welfare) by 2006 worker type $E[U_g^{2006}|l^{2006}]$ as the base case and using the transition probabilities $P(l^{t+1}|l^t)$ to form the induction step. Specifically, we compute expected cumulative utility changes as follows:

$$
\begin{aligned}
E[TotU^{t+1}|l^t] &= U_l^t + \sum{}_{l'} U_{l'}^{t+1} P(l'|l^t) \\
E[TotU^{t+1}|l^{t-1}] &= U_{l^{t-1}}^{t-1} + \sum{}_{l'} E[TotU^{t+1}|l^t = l'] P(l'|l^{t-1}) \\
&\vdots \\
E[TotU^{t+1}|l^{t_0}] &= U_l^{t_0} + \sum{}_{l'} E[TotU^{t+1}|l^{t_0+1} = l'] P(l'|l^{t_0})
\end{aligned} \tag{61}
$$

One can compute expected cumulative earnings or unemployment probability changes using a similar approach by replacing U_l^t where appropriate.

A3 Imputation

A3.1 Overview

Because estimation and simulation of the assignment model requires a complete set of counts at the job match type level (l, f, z), this appendix describes the imputation procedures we implement to fill remaining gaps in (l, f, z)-level counts. There are two principal sources of incomplete data. The first stems from the fact that we only obtained LEHD job-level records for the subset of 25 U.S. states that approved our project. Furthermore, a handful of these states only begin to provide data to the Census Bureau in the middle of our sample period. Thus, employment matches are missing for a subsample of states and years. We generally address missing data on job matches by 1) using LBD employment counts by firm type observed for all 50 states, 2) multiplying by an industry-specific scaling factor designed to handle differences in industry coverage between the LEHD and LBD, and 3) distributing these employment counts by type f across (l, f, z) combos using the conditional distribution $P(l, z|f)$ observed in the in-sample LEHD state with the most similar distribution of firm types to the chosen state. We aggregate from states to regions only after completing imputation.

The second source of incomplete data stems from the fact that the LEHD contains indicators that report whether a worker was not employed in a covered position anywhere in the United States, but do not assign nonemployed workers to a state or region, and do not classify nonemployed workers among unemployment, self-employment, exit from the labor force, and employment in an uncovered sector (e.g. armed forces or the federal government). [32] We address missing information for nonemployed workers by using the empirical distribution of locations and labor force status among nonemployment workers observed in the American Community Survey over several years. The following subsections provide the exact imputation formulas we use separately by type of labor market transition: Employment-to-Employment (E-E), Employment-to-Nonemployment (E-NE), Nonemployment-to-Employment (NE-E), and Nonemployment-to-Nonemployment (NE-NE).

A3.2 Employment-to-Employment (E-E) Transitions

Let $s_{l(i)}$, $ind_{l(i)}$, and $te_{l(i)}$ capture the U.S. state, industry and trade engagement status associated with worker i's prior year establishment and firm, which are common among workers of the same type l, and let $e_{l(i)}$ capture the worker's prior year earnings category. Similarly, let $s_{f(i)}$, $ind_{f(i)}$, $te_{f(i)}$, $fs_{f(i)}$, and $fe_{f(i)}$ represent the state, industry, trade engagement, firm size category, and firm average pay category of the position and associated firm with which the worker matches in the current period. Finally, let $z_{l(i),f(i)}$ be an indicator that equals one if the worker is retained by the same firm as the previous year, and zero otherwise. The count of job matches by (l, f, z) combination can then be denoted $\#(s_l, ind_l, te_l, e_l, s_f, ind_f, te_f, fs_f, fe_f, z_{lf})$.

Our imputation procedure exploits the following decomposition of the full (l, f, z) count:

$$\begin{aligned}\#(s_l, ind_l, te_l, e_l; s_f, ind_f, te_f, fs_f, fe_f, z_{lf}) =& \#(s_f, ind_f, te_f, fs_f, fe_f) \times P(s_l|s_f, ind_f, te_f, fs_f, fe_f) \\ & \times P(ind_l, te_l, e_l, z_{lf}|s_l, s_f, ind_f, te_f, fs_f, fe_f)\end{aligned} \tag{62}$$

When both the worker's initial U.S. state s_l and the position's state s_f are in the observed subsample, each component in (62) is directly observed in our database, so no imputation is necessary. When s_f is in the observed subsample but s_l is not, we assume that the distribution of worker prior year states conditional on the firm type with which they match is independent of the firm type's trade status, firm size, and average pay conditional on state and industry. This permits us to approximate the second component in (62) with the empirical conditional distribution of worker prior year states conditional on current state and industry observed over a moving window of five years of the American Community Survey: $P(s_l|s_f, ind_f, te_f, fs_f, fe_f) \approx P(s_l|s_f, ind_f) = \hat{P}^{ACS}(s_l|s_f, ind_f)$. Then, we construct the third component of (62) by substituting the worker type's actual U.S. state with the observed state featuring the most similar distribution of firm types, denoted $\hat{s}_l$, and using the analogous observed conditional distribution:

$$P(ind_l, te_l, e_l, z_{lf}|s_l, s_f, ind_f, te_f, fs_f, fe_f) \approx P^{LEHD}(ind_l, te_l, e_l, z_{lf}, |\hat{s}_l, s_f, ind_f, te_f, fs_f, fe_f) \tag{63}$$

When instead s_f is not observed, we use the same ACS approach to construct the second component, but we condition on the most similar state, $\hat{s}_f$, in place of s_f in the third component

[32] A few states do not report data for the first several years (see Abowd et al. (2009) and Vilhuber (2018)). For these years, the indicator for out-of-sample employment only reports employment among states who provide data to the Census Bureau.

of (62). In addition, we replace the firm type count $\#(s_f, ind_f, te_f, fs_f, fe_f)$ with its observed analogue in the LBD. In order to preserve the national scale of LEHD employment, we also re-scale the LBD firm type count by an adjustment factor computed using the most similar state that captures differences in the industry coverage between the LEHD and LBD:[33]

$$\#(s_f, ind_f, te_f, fs_f, fe_f) \approx \#^{LBD}(s_f, ind_f, te_f, fs_f, fe_f) \times \frac{\#^{LEHD}(\hat{s}_f, ind_f, te_f)}{\#^{LBD}(\hat{s}_f, ind_f, te_f)} \quad (64)$$

When neither the worker's state nor the position's state is observed, we continue to use the ACS to construct the second component in (62), and we approximate the third component by replace both s_l and s_f with $\hat{s}_l$ and $\hat{s}_f$.

A3.3 Employment-to-Nonemployment (E-NE) Transitions

Now consider the case in which a worker transitions from employment in a sample state into either nonemployment or employment not covered by the LEHD sampling frame. Our goal is to isolate transitions to unemployment (E-U) from other E-NE transitions. We do this by rescaling the count of observed E-NE transitions for the chosen worker type by an estimate of the share of transitions that would classified as E-NE in the LEHD that are true E-U transitions. We estimate this share by assuming that trade engagement status does not predict whether an E-NE transition is spurious conditional on the other worker type characteristics, and exploiting the fact that the ACS distinguishes E-U transitions from transitions out of the labor force, transitions into self-employment, and transitions into uncovered employment (i.e. armed services or federal government):

$$\#(s_l, ind_l, te_l, e_l; U) \approx \#^{LEHD}(s_l, ind_l, te_l, e_l; NE) \times \hat{P}^{ACS}(E-U|E-NE, s_l, ind_l, e_l) \quad (65)$$

When the worker's state is not in our sample, we replace the LEHD count of E-NE transitions by worker type with an estimate that combines the LBD count of prior year employment in the worker type's state, industry, and trade engagement with an estimate of the share of transitions out of the same industry-trade engagement combination from the most similar observed state that are E-NE transitions from the chosen earnings category. As before, the LBD count is re-scaled to account for discrepancies in industry coverage between the LBD and LEHD:

$$\begin{aligned}\#(s_l, ind_l, te_l, e_l; U) \approx & \#^{LBD}(s_l, ind_l, te_l) \frac{\#^{LEHD}(\hat{s}_l, ind_l, te_l)}{\#^{LBD}(\hat{s}_l, ind_l, te_l)} \\ & \times P^{LEHD}(e_l, E-NE|\hat{s}_l, ind_l, te_l) \times \hat{P}^{ACS}(E-U|E-NE, s_l, ind_l, e_l)\end{aligned} \quad (66)$$

A3.4 Nonemployment-to-Employment (NE-E) Transitions

Next, consider the case of workers who transition into employment from nonemployment. When the firm's state is observed, the LEHD provides a count of NE-E transitions ending in employment with the chosen firm type. However, the LEHD does not indicate the worker's initial state, and it does not distinguish new entrants to the labor market from workers returning from unemployment. We treat young workers less than 25 years old in the LEHD as new entrants, and treat workers over 25 years old as returnees from unemployment. We then use

[33] When a state reports to our sample in later years, we construct the scaling factor for that state using its own ratio from its first year of appearance in the sample.

the distribution of state-to-state transitions observed in the ACS to impute the distribution of worker initial states conditional on joining a firm in the chosen state and industry, separately for young and older workers (denoted a_l).

$$\#(s_l, a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \approx \#^{LEHD}(a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \times \hat{P}^{ACS}(s_l|a_l, s_f, ind_f) \quad (67)$$

When the firm's state is unobserved, we replace the LEHD count of NE-E transitions with an LBD count of firm type employment combined with an estimate from the most similar state in the LEHD of the share of current year employment in the analogous firm type for that state that was hired from nonemployment in the chosen worker state. As before, the LBD count is re-scaled to account for discrepancies in industry coverage between the LBD and LEHD:

$$\begin{aligned}\#(s_l, a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \approx \#^{LBD}&(s_f, ind_f, te_f, fs_f, fe_f)\frac{\#^{LEHD}(\hat{s}_f, ind_f, te_f)}{\#^{LBD}(\hat{s}_f, ind_f, te_f)} \\ &\times P^{ACS}(s_l|a_l, s_f, ind_f) \\ &\times P^{LEHD}(a_l, NE-E|s_l, \hat{s}_f, ind_f, te_f, fs_f, fe_f) \end{aligned} \quad (68)$$

If the origin state is also unobserved, we replace s_l with its most similar state $\hat{s}_l$ in (68).

A3.5 Nonemployment-to-Nonemployment (NE-NE) Transitions

Finally, consider workers who transition from nonemployment back into nonemployment. Because we only wish to include those in the labor force in the destination year, we need to count new entrants who fail to find employment as well as the long-term unemployed. Since the LEHD struggles to distinguish long-term unemployed workers from workers who leave the country, die, or retire, we rely on the American Community Survey to provide counts of NE-U and U-U transitions. We treat workers as long-term unemployed if they report that they are older than 25, currently unemployed, and worked fewer than 26 weeks in the past year. We treat workers as new entrants if they are at most 25 years old, are currently unemployed, and worked fewer than 26 weeks in the past year. Since unemployed workers do not have firm characteristics, and we do not track the worker's state if they are unemployed in the current (destination) year (as opposed to the previous (origin) year), new entrant and long-term unemployed counts only need to be constructed separately by the worker's origin state.

$$\#(s_l, a_l, NE; U) = \hat{\#}^{ACS}(s_l, a_l, NE; U) \quad (69)$$

A4 Smoothing Procedure

In this appendix we describe how we smooth the empirical distribution of job matches across groups, $\hat{P}(g)$, prior to estimation in order to generate accurate estimates of the sets of identified difference-in-differences of joint surplus values $\{\theta_g\}$ and their accompanying worker and firm subcomponents $\{\gamma_g\}$ and $\{(\Psi\alpha)_g\}$. We smooth for two reasons. First, such smoothing serves as a "noise infusion" technique that removes the risk that individual or establishment identities could be revealed by estimates presented in the paper, as required of all research results based on confidential microdata in Federal Statistical Research Data Centers (FSRDCs). Second, smoothing is necessary because there are sufficiently few observations per match group such that many match groups are rarely or never observed in a given allocation simply due to sampling error, despite substantial underlying match surpluses. Essentially, $\hat{P}(g)$ only consistently estimates $P(g)$ as the number of observed job matches per group I/G approaches infinity.

We overcome this sampling error problem by assuming that the underlying frequency $P(g)$ with which a job match belongs to a particular match group is a smooth function of the observed characteristics that define group g (following Hotz and Miller (1993) and Arcidiacono and Miller (2011)). This permits the use of a kernel density estimator that computes a weighted average of the empirical probabilities $\hat{P}(g')$ of "nearby" groups g' that feature "similar" vectors of characteristics to generate a well-behaved approximation of $P(g)$ from the noisy empirical distribution $\hat{P}(g)$.

Such smoothing introduces two additional challenges. First, excessive smoothing across other match groups erodes the signal contained in the data about the degree of heterogeneity in the relative surplus from job matches featuring different combinations of worker and firm characteristics. Since a primary goal of the paper is to highlight the role of such heterogeneity in forecasting the labor market incidence of trade shocks, decisions about the appropriate bandwidth must be made with considerable thought. The second, related challenge consists of identifying which of the worker and position characteristics that define other groups make them "similar", in the sense that the surplus $\{\theta_{g'}\}$ is likely to closely approximate the surplus θ_g whose estimate we wish to make more precise.

Recall that each group $g \equiv g(l, f, z)$ is a combination of 1) the industry category (which we denote $i(l)$, trade engagement status (denoted $t(l)$, region $(r(l))$, and earnings decile $(e(l))$ associated with workers' initial jobs; 2) the hiring/retaining firms' industry $(i(f))$, trade engagement status $(t(f))$, region $(r(f))$, firm size $(fs(f))$ and firm average of worker earnings $(fe(f))$; and 3) the indicator $z(g) \equiv z(i, k)$ for whether the firms $j(i)$ and $j(k)$ are the same, so that worker i is a job stayer $(z(g) = 1)$ rather than a mover $(z(g) = 0)$.

Our goal is to preserve as accurately as possible any signal in the data about the strongest sources of skill complementarity and portability, tastes for amenities, and search/recruiting training costs. To this end, we posit that a position's industry most affects how productive workers from different industries and trade engagement statuses will be at the job (as opposed to, say, the position's region). Similarly, we expect non-trivial training and switching costs associated with changing industry, particularly if the worker is also switching trade engagement status. To capture this intuition, when predicting the industry and trade engagement category of workers hired by a given position, wherever possible the kernel estimator should place non-zero weight only on alternative groups g' that share the same worker and firm industries and trade engagement categories $(ind(l(g)) = ind(l(g')), te(l(g)) = te(l(g')),$ $ind(f(g)) = ind(f(g'))$, and $te(f(g)) = te(f(g')))$. Along the same lines, given the prevalence of assortative matching on skill and skill requirements even within industries, we expect that an establishment's size and average pay will be strong predictors of the skill of the workers they hire (proxied by past earnings decile). And a position's region should be the strongest predictor of the regional distribution of workers they hire, given large anticipated regional mobility costs.

To develop a smoothing approach that embodies these principles, we first classify worker characteristics into two subvectors: $\mathbf{L}_l^1 = [Industry_l, Trade\,Engagement_l]$, $\mathbf{L}_l^2 = [Earnings\,Decile_l,$ $Region_l]$. We do the same for firm characteristics: $\mathbf{F}_f^1 = [Industry_f, Trade\,Engagement_f]$, $\mathbf{F}_l^2 = [Avg.\,Pay\,Quartile_f, Firm\,Size\,Quartile_f, Region_f]$. Next, we exploit the fact that $P(g)$

can be decomposed via:

$$
\begin{aligned}
P(g) =& P(g|f(g))h(f(g)) = P([l(g), f(g), z(g)]|f)h(f(g)) = P([\mathbf{L}^1_{l(g)}, \mathbf{L}^2_{l(g)}, z(g)]|f)h(f(g)) \\
=& P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g), f)P([\mathbf{L}^2_{l(g)}, z(g)]|f)h(f(g)) \\
=& \sum_{z' \in \{0,1\}} 1(z(g) = z')P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = z', f)P([\mathbf{L}^2_{l(g)}, z(g) = 0]|f)h(f(g)) \Rightarrow \\
P(g) =& 1(z(g) = 1)1(\mathbf{L}^1_{l(g)} = \mathbf{F}^1_{f(g)})P([\mathbf{L}^2_{l(g)}, z(g) = 1]|f)h(f(g)) \\
& + 1(z(g) = 0)P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = 0, f(g))P([\mathbf{L}^2_{l(g)}, z(g) = 0]|f)h(f(g))
\end{aligned} \tag{70}
$$

where the first two lines use the law of total probability and the set of characteristics that define $l(g)$ and $z(g)$, and the third line uses the fact that $z(g)$ only takes on two values (0 for job movers and 1 for stayers). The last line uses the fact that $P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, 1(z(g) = 1), f(g)) = 1(\mathbf{L}^1_{l(g)} = \mathbf{F}^1_{f(g)}) = 1(ind(l(g)) = ind(f(g))\&te(l(g)) = te(f(g)))$, since a potential stayer associated with a particular firm type must have already been working at the same industry and trade engagement category in the previous period (for computational reasons, we use an establishment's destination year category for both origin and destination years if it switches industry or location between the two periods). We use separate kernel density estimator procedures to estimate each of $P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = 0, f(g))$, $P(\mathbf{L}^2_{l(g)}, z(g) = 0|f(g))$, and $P(\mathbf{L}^2_{l(g)}, z(g) = 1|f(g))$.

Consider first the estimation of $P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = 0, f(g))$, the conditional probability that a particular new hire would be originally working at an establishment with industry $ind(l)$ and trade engagement category $te(l)$, given the hired worker's initial earnings category and region $\mathbf{L}^2_{l(g)}$ and the destination firm's type f. Let $D(g, g')$ denote the metric capturing how similar an alternative group g' is to g for the purpose of estimating the propensity for firms of type f to hire workers from a particular industry/trade engagement category (conditional on skill level and region). As discussed above, wherever possible we only assign non-infinite distance $D(g, g') < \infty$ (i.e. non-zero weight) to empirical conditional probabilities $P(\mathbf{L}^1_{l(g')}|\mathbf{L}^2_{l(g')}, z(g') = 0, f(g'))$ of alternative groups g' that feature the same worker industry and trade engagement ($ind(l(g')) = ind(l(g))$ and $te(l(g')) = te(l(g))$) *and* the same firm industry and trade engagement ($ind(f(g')) = ind(f(g))$ and $te(f(g')) = te(f(g))$).[34]

$D(g, g')$ assigns the smallest distance to alternative groups g' that also feature the same firm type ($f(g') = f(g)$), so that g and g' only differ in the initial earnings decile and region of hired workers. In particular, the closer $earn(l(g))$ is to $earn(l(g'))$, the smaller is the assigned distance $D(g, g')$, but the profile flattens so that all groups g' that differ from g only due to $earn(l(g'))$ contribute to the weighted average (analogously for regions). $D(g, g')$ assigns larger (but still noninfinite) distance to groups g' featuring firm types that also differ on firm size, average pay, or region dimensions. The more different the firm composition of the group, the smaller is its weight, with the profile again flattening so that all groups g' featuring the same worker and firm industries and trade engagement categories receive non-zero weight. Thus, groups with less similar worker and firm characteristics receive non-negligible weight only when there are too few observations from groups featuring more similar worker and firm characteristics to form reliable estimates. The weight assigned to a particular alternative

[34]There are a very small number of worker and firm types that are never observed in any job match. By necessity, we put positive weight on groups featuring nearby origin or destination locations in such cases.

group g' also depends on the number of observed new hires made by $f(g')$ among workers at a particular skill level $earn(l(g'))$ and from a particular region $reg(l(g'))$ (i.e. featuring characteristics $\mathbf{L}^2_{l(g')}$). This object, denoted $N(g')$ below, determines the signal strength of the empirical CCP $\hat{P}(\mathbf{L}^1_{l(g')}|\mathbf{L}^2_{l(g')}, z(g') = 0, f(g'))$. Thus,

$$P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = 0, f(g)) \approx \sum_{g'} \left(\frac{\phi(D(g',g)N(g'))}{\sum_{g''} \phi(D(g'',g)N(g''))} \times \hat{P}(\mathbf{L}^1_{l(g')}|\mathbf{L}^2_{l(g')}, z(g') = 0, f(g')\right) \quad (71)$$

where $\phi(\cdot)$ is the normal density function (used as the kernel density), and $\frac{\phi(D(g',g)N(g'))}{\sum_{g''} \phi(D(g'',g)N(g''))}$ represents the weight given to a particular nearby match group g'.[35]

Next, consider the estimation of $P(\mathbf{L}^2_{l(g)}, z(g) = 1|f(g))$ and $P(\mathbf{L}^2_{l(g)}, z(g) = 0|f(g))$, the conditional probabilities that either a job stayer or mover with characteristics $\mathbf{L}^2_{l(g)}$ (i.e. originally paid at a particular earnings quartile (or possibly unemployed for movers) and originally from a particular region) will be hired to fill a position of position type f. Let $D^{move}(g, g')$ and $D^{stay}(g, g')$ represent the metrics capturing how similar alternative groups g' are to g for the purpose of estimating the propensity for firms of type f to hire (or retain) workers with particular characteristics $\mathbf{L}^2_{l(g)}$.

$D^{move}(g, g')$ and $D^{stay}(g, g')$ each assign infinite distance (i.e. zero weight) to groups g' featuring different combos of firm size, average pay, and industry than the target group g. $D^{move}(g, g')$ ($D^{stay}(g, g')$) assigns small distances to the conditional probabilities for groups g' associated with hiring new (retaining) workers with the same $\mathbf{L}^2$ characteristics among firms from the same firm type $f(g) = f(g')$ but who are hiring from adjacent earnings deciles. The distance metric increases in the dissimilarity of earnings deciles between g and g', but flattens beyond a threshold distance, so that groups featuring all worker earnings categories (but shared values of other characteristics) contribute to the estimate.

Larger (but finite) distance values for $D^{move}(g, g')$ and $D^{stay}(g, g')$) are assigned to conditional probabilities from groups g' that feature different (but similar) firm industry and trade status categories from $\mathbf{F}^1_{f(g)}$ (so $\mathbf{F}^1_{f(g)} \neq \mathbf{F}^1_{f(g')}$ and thus $f(g) \neq f(g')$) but the same combination of $\mathbf{F}^2$ characteristics (avg. pay, size, and region). Again, the distance metric increases in the dissimilarity between $te(f(g))$ and $te(f(g'))$, but eventually flattens at a large but non-infinite value. As before, the weight given to a group g' also depends on the number of total hires made by firms of type $f(g')$, which is proportional to $h(f(g'))$.

Again, the motivation here is that the targeted skill level and region and the retention/new hire decision (conditional on the utility bids required by workers in different industries/trade engagement categories) is likely to be driven more by a firm's skill requirements (proxied by size and mean pay) and region than by its industry or trade engagement category. Since there still may be correlated unobserved heterogeneity in production processes among firms with greater reliance on international trade conditional on the other firm observables, we place greater weight on the skill/retention decisions of firms with similar patterns of trade. Firms from different supersectors and with dissimilar trade patterns receive non-negligible weight only when too few local observations exist to form reliable estimates. Estimators for

[35] A standard deviation of 3 was used as the bandwidth for both this and the kernel densities presented below. The results were insensitive to moderate changes in bandwidth, though choosing a very small bandwidth resulted in very volatile estimates across very similar worker types, highlighting the need for smoothing.

$P(\mathbf{L}^2_{l(g)}, z(g) = 1|f(g))$ and $P(\mathbf{L}^2_{l(g)}, z(g) = 0|f(g))$ can be written as:

$$P(\mathbf{L}^2_{l(g)}, z(g) = 0|f(g)) \approx \textstyle\sum_{g'}\left(\frac{\phi(D^{move}(g',g)h(f(g')))}{\sum_{g''}\phi(D^{move}(g'',g)h(f(g'')))} \times \hat{P}(\mathbf{L}^2_{l(g')}z(g') = 0|f(g')\right) \quad (72)$$

$$P(\mathbf{L}^2_{l(g)}, z(g) = 1|f(g)) \approx \textstyle\sum_{g'}\left(\frac{\phi(D^{stay}(g',g)h(f(g')))}{\sum_{g''}\phi(D^{stay}(g'',g)h(f(g'')))} \times \hat{P}(\mathbf{L}^2_{l(g')}, z(g') = 1|f(g')\right) \quad (73)$$

Bringing the pieces together, this customized smoothing procedure has a number of desirable properties. First, by requiring the same industry-trade status combos for workers and positions as a necessary condition for non-zero weight when estimating the propensity for particular firm types to hire workers from each industry and trade engagement status, one can generate considerable precision in estimated CCPs without imposing assumptions about complementarities in skills offered and required or costs of searching/recruiting among different industries or trade engagement statuses. Second, at the same time, one can still use information contained in the hiring and retention choices of firms from different industries and with different patterns of trade to learn about the propensity for firms of different sizes, pay levels, and regions to retain and hire workers from particular regions and from particular skill levels/unemployment. Third, the procedure places non-trivial weight on match groups featuring less similar worker and firm characteristics only when there are too few observed hires/retentions made by firms associated with groups featuring very similar characteristics to yield reliable estimates. Fourth, overall the estimated probabilities $P(g|f)$ place weight on many groups, so that no element of the resulting smoothed distribution contains identifying worker or firm information, eliminating disclosure risk.

A5 Data Appendix

This appendix provides detail about how we define trade engagement, regions and industries.

A5.1 Trade Engagement Definitions

We classify firms' pattern of trade engagement into six categories: non-traded (NT), arms' length importer only (M), arms' length exporter only (X), arms' length exporter and importer (X&M), related parties exporter or importer, but not both (RP X|M), and related parties exporter and importer (RP X&M). To quality for a given active trade status, a firm must have an annual trade flow of at least $50,000 dollars in the respective year in the relevant categories of trade. Thus, given that we distinguish arms-length and related-party transactions for both exports and imports, we categorize firms' trade engagement separately in each year t as follows:

- NT - Non-traded firms: less than $50,000 each of arms-length imports, related-party imports, arms-length exports, and related-party exports.
- M - Arms-length importer only: at least $50,000 of arms-length imports, less than $50,000 of arms-length exports, related-party exports and related-party imports.
- X - Arms-length exporter only: at least $50,000 of arms-length exports, less than $50,000 of arms-length imports, related-party exports and related-party imports.
- X&M - Arms-length exporter and arms-length importer: at least $50,000 of both arms length imports, and arms length exports, less than $50,000 of related-party exports and

related-party imports.

- RP X|M - Related-party exporter or importer: at least $50,000 of related-party imports or exports but not both. There is no restriction or requirement in either their arms-length imports or arms-length export activities.
- RP X&M - Related-party exporter and importer: at least $50,000 of related-party imports and $50,000 of related-party exports. There is no requirement or restriction in either their arms-length imports or arms-length export activities.

A5.2 Region Definitions

We divide the continental U.S. into seven regions: Northeast, Mid-Atlantic & Appalachia (denoted Upper South for brevity), Midwest, Great Plains, Southwest, West Coast, and Deep South. Each region is defined as follows:

- Northeast: New York, Pennsylvania, Delaware, Maine, Massachusetts, Connecticut, Vermont, New Hampshire, Rhode Island, and New Jersey.
- Mid-Atlantic and Appalachia (Upper South): Maryland, District of Columbia, Virginia, Tennessee, Kentucky, West Virginia, and North Carolina.
- Midwest: Indiana, Iowa, Illinois, Wisconsin, Michigan, Ohio, and Minnesota.
- Great Plains: Oklahoma, Arkansas, Montana, North Dakota, Kansas, Missouri, Nebraska, South Dakota, Wyoming, and Idaho.
- Southwest: Colorado, Arizona, New Mexico, Texas and Utah.
- West Coast: California, Nevada, Oregon, and Washington.
- Deep South: Florida, Georgia, Alabama, Mississippi, Louisiana, and South Carolina.

A5.3 Industry Categories

We first classify firms' industries according to their two-digit NAICS 2002 classifications, and then combine different two-digit sectors based on similarity in distributions of pay and trade engagement to define the following industry groups:

- Natural Resources, Construction, and Utilities: All establishments classified in sectors 11, 21, 22 or 23.
- Manufacturing: All establishments classified in sectors 31, 32, or 33.
- Wholesale and Retail Trade: All establishments classified in sectors 42, 44, or 45.
- Leisure, Transportation, Administration, and Other Services: All establishments classified in sectors 48, 49, 71, 72, or 81.
- Information: All establishments classified in sector 51.
- Finance, Real Estate and Professional & Business Services: All establishments in sectors 52, 53, 54, 55 or 56.
- Education, Health and Government: All establishments in sectors 61, 62, or 92.

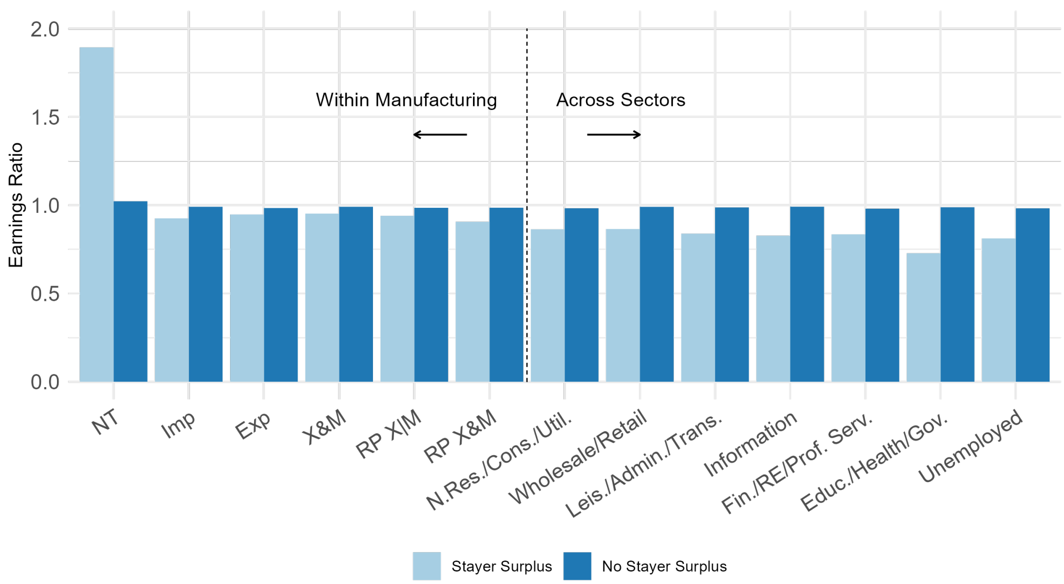
A6 Additional Results

Table A1: Evaluating Sensitivity to Regression Specification: Correlations in Predicted Firm-Level Employment Growth Among Specifications Featuring Varying Sources of Heterogeneity in Exposure Sensitivity

	Import Competition	**Export Competition**	**Import Access**
No Interactions	0.9826	0.9424	0.9812
Trade Engagement	0.9996	0.9444	0.9915
Trade Engagement + Firm Size	–	0.9444	0.9922
Trade Engagement + Firm Size + Sector	0.9804	–	–

Source: Authors' calculations based on LEHD, LFTTD and LBD data.
Notes: This table reports the correlation in predicted employment changes among firm types across different specifications (rows) for the three channels listed in the column headings. The specifications vary the degree of heterogeneity permitted in treatment effects of greater values of the chosen channel's exposure measure, with the row labels indicating which firm characteristics are allowed to drive heterogeneity in treatment effects. See (16) in Section 4.2 for the generic estimating equation.

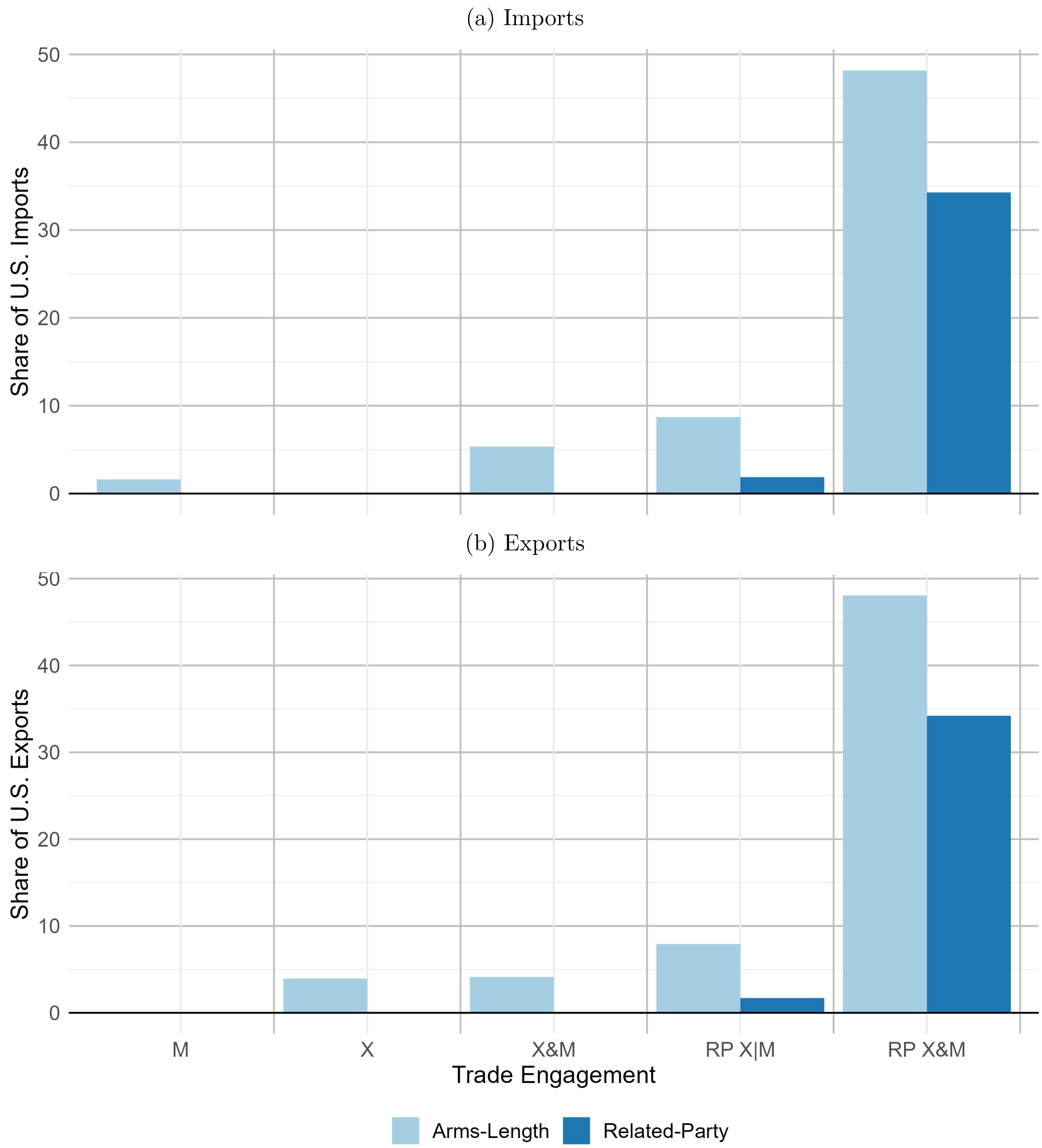
Figure A1: Illustrating the Role of Extra Joint Surplus from Job Retention as a Source of Asymmetric Earnings Impacts of Equivalently Sized Positive and Negative Employment Shocks



Source: Simulation results based on LEHD, LFTTD and LBD data

Notes: This figure displays ratio of simulated earnings losses to earnings gains from pairs of simulations featuring negative and positive employment shocks to the non-traded manufacturing sector of equivalent size and composition. The light (dark) blue bars display the earnings ratio among workers when joint surplus values for job retentions are allowed (not allowed) to differ from surplus values for job transitions within firm type.

Figure A2: Shares of Total U.S. Goods Imports and Exports by Trade Engagement



Source: Authors' calculations based on LFTTD and LBD data.

Notes: This figure displays the shares of U.S. total imports (top panel) and total exports (bottom panel) accounted for by firms in each trade engagement category.