Firm Trade Exposure, Labor Market Competition, and the Worker Incidence of Trade Shocks*

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Abstract

This paper examines how the composition of firm exposure and competition among imperfectly substitutable workers mediate the earnings, welfare, and unemployment incidence of changes in the international trade environment.

We merge LEHD job match records with firm-level import and export records from the LFTTD and use them to estimate a 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 firm composition of shock exposure does matter for medium-run worker-level earnings incidence, with workers at the highly exposed multinational manufacturing firms bearing the largest shock-induced earnings losses. However, considerable exposure exists outside of manufacturing, especially among multi-industry and multinational firms and within the wholesale/retail industry, which experienced substantial shock-induced job creation and destruction relative to unexposed firms. Moreover, 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 large share of earnings losses and particularly unemployment increases.

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1 Introduction

The last twenty years have spawned an appreciation for 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 should be blamed for increased income inequality, rural and regional poverty, and political polarization.

Yet understanding the labor market incidence of multifaceted trade shocks, such as trade agreements and tariff changes, is a complex endeavor. 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 and firms compete elsewhere with and for the directly affected workers. This paper seeks to unpack the mechanisms that drive the labor market incidence of trade shocks by addressing each of these factors in the context of a major change in the trade environment, China's World Trade Organization (WTO) accession (the "China Shock").

We start by using employer-employee data from the Longitudinal Employer-Household Dynamics database (LEHD) to estimate a rich equilibrium assignment model of the U.S. labor market. The model places very few functional form restrictions on the forces that 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 allows flexible matching among a large set of worker and firm types defined by combinations of several characteristics, including region, sector, past earnings and trade engagement status. We motivate our types using summary statistics illustrating the heterogeneity in hiring and retention patterns among firms in different industries with different levels of trade activity, and show how these empirical patterns are captured by the large set of parameters governing the model's job matching process.

To evaluate the distributional effects of the China Shock, we construct and feed to our estimated assignment model a set of firm type-specific counterfactual employment growth paths that approximate the evolution of employment in the shock's absence based on predicted values from regressions relating firm-by-industry level employment growth to relative shock exposure.

To assess firms' shock exposure, we use customs data from the Longitudinal Foreign Trade Transactions Database (LFTTD) merged with firm-level revenue data from the Longitudinal Business Database (LBD) to construct plausibly exogenous shift-share measures of firms' exposure to four different channels: import competition in domestic markets and export access in China, as well as two less-studied channels - export competition from Chinese products in other foreign export markets, and import access for existing goods importers. Our exposure measures exploit the particular mix of products firms were selling or buying, and consist of either revenue or cost-weighted averages of product-level changes in Chinese tariffs or tariff gaps capturing the size of potential U.S. tariff increases whose threat was eliminated by China's

WTO entry (Pierce and Schott (2016)).

We use establishment-level LBD data to construct employment growth at the firm-by-industry level. The data's granularity allows us to explore heterogeneity in exposure sensitivity to each channel by industry and form of trade engagement (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 generally and China Shock exposure specifically occurs outside manufacturing and is concentrated among multinational firms.

We aggregate fitted regression values to generate counterfactual employment growth paths for each of the model's firm types that serve as the model's inputs. Because the regressions only capture relative changes in growth due to differences in direct shock exposure, scaling our calibrated labor demand shock requires imposing that unexposed firms' employment was unaffected by the China shock, which omits the component of shock-induced growth driven by indirect shock exposure (e.g. due to spillovers operating through consumer demand).[1] The model then produces simulations in which earnings adjustments and labor market reallocation translate these channels' relative labor demand shifts from 2002 to 2006 into equilibrium worker earnings, utility, and unemployment incidence.

While the need to normalize the shock's scale prevents a definitive accounting of the China Shock's worker impact, our calibrated shock captures large relative shifts in labor demand across many types of firms created by four channels of China Shock exposure, so that our simulations can produce a reasonable characterization of the China Shock's relative if not absolute incidence across many worker types. More importantly, the simulations reveal how competition among imperfectly substitutable workers and positions can distribute the incidence of multifaceted trade shocks in ways that would be difficult to predict based on the distribution of firm exposure, employment sensitivity, and associated worker composition.

Our analysis reveals five key insights. First, while we confirm that concentrated shock exposure within manufacturing can generate concentrated losses for manufacturing workers, the ability to differentiate exposure by channel and by trade status within manufacturing reveals that losses were particularly large for workers at the subset of manufacturing firms who import and export with related parties (denoted $RPXM$ firms). This is partly because such firms engage most heavily with trade at baseline, making them particularly exposed to each of our channels, but also because these multinationals are best equipped to respond to increased access to Chinese imports by outsourcing key tasks, exacerbating the already substantial employment losses from the import and export competition channels.

Second, we show that considerable exposure and associated employment impacts extend beyond the manufacturing sector. This is partly driven by multi-industry firms in which employment at non-manufacturing establishments is sensitive to import competition exposure

[1] We do augment our regression model with input-output-based exposure as a robustness check.

for goods produced by their firms' manufacturing establishments. However, the ability to observe product-level exports for all firms also reveals substantial export competition exposure for non-manufacturing firms (particularly multinational firms). We find that export exposure caused 388,000 in relative employment losses between 2002 and 2006 at exposed vs. non-exposed firms, with 49.7% percent from non-manufacturing establishments. Similarly, high exposure to our import access channel generated large relative employment gains of 478,000 jobs over five years in exposed wholesale-retail firms relative to non-exposed counterparts, since such access generates a strong scale effect that is not offset by a substitution effect. The contrasting responses of wholesale/retail and manufacturing to import access exposure highlights the value of allowing exposure sensitivity to vary by industry.

Third, we show that labor market competition can reverse the sign of relative incidence across worker types from that predicted based on shocks' firm composition, so that even industries and trade categories whose firms enjoy net job growth can feature earnings and employment losses for their workers. For example, our calibrated firm-level shock adds 73,450 jobs at wholesale/retail RPXM firms over five years (0.4% of their pre-shock total per year), but our simulations suggest that their 2001 workers suffer 577 in shock-induced cumulative 5-year earnings losses and 0.38% greater per-year unemployment risk relative to the most insulated worker type. This is because a) displacement via other channels leads other sectors' workers to compete for the newly created jobs and limits wholesale/retail workers' job opportunities elsewhere; b) most wholesale/retail job creation was at low-paying firms with high job turnover rates; and c) job creation leads to smaller welfare and earnings gains from job creation than the corresponding losses from job destruction. Essentially, job destruction eliminates previously valuable firm-specific experience and forces costly job search for workers, while filling new positions also requires search/recruiting costs, limiting its surplus creation in the short run. More generally, we see that job retention rates among the kinds of positions likely to be destroyed or created by labor demand shocks are an underappreciated indicator of the concentration of welfare losses/gains they will generate. These results highlight the value of incorporating job switching frictions at the firm-level rather than merely the occupation or industry level.

Fourth, increased labor market competition from a tighter labor market causes substantial shares of earnings and particularly employment losses from initially concentrated shocks to ripple outward to seemingly unexposed types. For example, we find that workers initially in the leisure/administration/transportation sector account for 10.7% of earnings losses and 22.2% of increased unemployment from our calibrated shock even though their firms are generally not directly targeted by any of the channels. Similarly, initially unemployed workers (including new entrants) who had no job to target nonetheless account for 13.4% of shock-induced full year unemployment spells, since many are on the margin of employability and would have found jobs in the absence of the shock. That said, allowing for heterogeneity in the degree of substitutability is important: we find that workers in the education/health/government sectors are much better insulated, accounting for only 5% of earnings losses and 9.7% of increased unemployment despite featuring the largest baseline labor force share (22%).

Finally, labor market competition also transmits shock incidence down the job ladder. We find that mean reductions in earnings growth and increases in full-year unemployment were larger for initially low-paid and unemployed workers, despite greater employment losses at firms with mostly high-paid workers. In particular, workers with below-median 2001 pay accounted for 48% of earnings losses and 67% of unemployment increases, even though our shock assigns net creation of 92,000 job to firms in the lowest-paying worker-weighted quartile. Thus, the China Shock is likely to have exacerbated earnings inequality in the medium run.

This paper contributes most directly to the literature on the labor market incidence of shocks to the international trade environment. One strand 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 assess greater competition in foreign export markets and expanded opportunities for exporting (see Dauth et al. (2017) and Feenstra et al. (2019)). We adopt Pierce and Schott (2016)'s product-level tariff gap measure, but extend their approach by measuring import competition exposure at the firm rather than industry level, by using firms' import and export product mixes to generate analogous measures for the export competition, import access and export access channels, and by allowing the employment impact of exposure to vary by firms' trade engagement and size. 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 Bloom et al. (2024) emphasize that shock-induced job reallocation from manufacturing to non-manufacturing establishments can change a firm's industry classification.

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 short- and long-run impacts on workers initially in the most exposed firms, industries, or locations (e.g. Menezes-Filho and Muendler (2011), Autor et al. (2014), Hummels et al. (2014), Kovak and Morrow (2022), Autor et al. (2025)). These papers generally compare average labor market outcomes for worker subpopulations in "treated" manufacturing industries or locations with concentrations of such industries to those not directly affected by the relevant trade shock.

The most similar such paper is contemporaneous work by Pierce et al. (2024), who also use the LEHD, LBD, and LFFTD to study the China Shock's worker-level incidence. Like us, they find that more exposed manufacturing workers suffered substantial earnings losses, non-manufacturing workers benefited from greater exposure to cheaper inputs within their sectors, and shock exposure was more likely to cause unemployment for low-paid workers. While they directly relate measures of worker exposure to worker outcomes, our approach uncovers important equilibrium impacts on workers whose firms were neither directly nor indirectly exposed, but who directly or indirectly compete with those initially displaced, such as leisure/hospitality workers and the initially unemployed, rather than treating them as control groups. We also provide insight into the mechanisms generating these findings by assessing how worker impacts are mediated through both the composition of firm exposure via several channels and the competition among substitutable workers. For example, we show that much of the wholesale-retail employment gain was concentrated among firms that already imported the particular goods whose tariff risk had been removed. We also find that higher-paid manufacturing workers lose a smaller share of their earnings than their lower-paid counterparts despite disproportionately working at the RPXM firms who are most exposed to greater import and export competition.

Another part of the literature relies more heavily on theoretical models of trade to broadly characterize the spatial and sectoral redistribution of welfare generated by trade shocks (e.g. Caliendo et al. (2019), Adao et al. (2019), and Galle et al. (2017)). These papers emphasize the importance for worker incidence of spatial mobility frictions and equilibrium price adjustments in the product and labor markets, as well as offsetting increases in labor demand from importers, exporters, multinationals, and downstream buyers of imported inputs. These papers solve jointly for equilibrium in multiple markets, and in some cases consider dynamic adjustments (e.g. Caliendo et al. (2019)), but they generally feature simple labor markets with very limited worker heterogeneity, and they primarily focus on employment and earnings at the industry-location level. They do not explore the degree to which trade-engaged and multinational firms 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.

A few recent papers combine matched employer-employee data and customs records with a theoretical model that permits the simulation of a distribution of welfare impacts from trade shocks (e.g. Kim and Lee (2020), Artuc et al. (2021), Adão et al. (2022)). The most similar to ours, Adão et al. (2022), also examines how trade shocks contribute to worker-level earnings inequality via import and export channels, utilizes a model with arbitrary firm heterogeneity in the composition of their demand among many types of workers, and illustrates equilibrium spillover effects of shocks across worker types. They also provide an explicit theoretical integration of the product and labor markets. However, they focus on changes in long-run earnings inequality from a counterfactual autarkic environment in a small country, Ecuador, and abstract from the frictions associated with changing firm, industry, and region that shape the short- and medium-run incidence of trade shocks that we address in the U.S. context, where a major domestic market exists. While we rely on reduced-form regressions to translate the product market shock to changes in firm-level employment growth, our approach provides a richer description of the kinds of firms who are most exposed to and responsive to trade shocks. Our assignment model also features a richer labor supply side with unrestricted worker tastes for firm amenities and heterogeneity in job-switching frictions within and across firm types.

This allows our simulations to demonstrate the nature of worker reallocation necessary to re-equilibrate the market over several years, including transitions to and from unemployment.

Several other papers (e.g. Dix-Carneiro (2014), Traiberman (2019), Kim and Lee (2020), Yi et al. (2024)) use matched employer-employee data to explicitly assess the frictions that limit labor market adjustment to trade shocks. These papers document how costs of switching industries, occupations, and regions, along with heterogeneity in comparative advantages, affect which kinds of workers experience the largest losses from increased import competition.[2] We build on these papers by allowing surplus from job transitions to depend on whether workers are switching not just industries or regions but particular firms, which Artuc et al. (2021) shows is of first-order importance. We also incorporate heterogeneity in relative job match surpluses across firms of different size, average pay, and form 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.

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 (2024), we demonstrate how to accommodate missing data on unmatched partners on one side of the market.

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 5.2 presents and interprets our worker-level incidence estimates of the China Shock. Finally, Section 7 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.

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

[2] See McLaren (2017) for a summary of earlier research on dynamic labor market responses to globalization.

below as combinations of categories of observed characteristics. We assume for tractability that each worker type's productivity in a given position does not depend on which types fill the other positions (at least among those seriously considered). This implies that the HR staff can maximize workforce's profit contribution by separately maximizing the profit contributions of each position and adding together these maximized profit contributions:

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

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 (see Appendix, A1), and is treated as exogenous by the human resources staff. $W_{l(k)}^{f(k)}$ 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 so that the required pay $\{W_l^f\}$ is taken by the firm as given. Thus, $V_{lk}\equiv\Psi_j(\alpha_{l(k)}^{f(j)}+\tilde{\sigma}_f\mu_{l(k)k})-W_{l(k)}^{f(k)}$ captures a type l worker's profit contribution in position k when k acts as the marginal position (as is appropriate for evaluating staffing adjustments).

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:

$$P(l|f)=e^{(\Psi_f\alpha_l^f-W_l^f)/\sigma_f}\Big/\sum\nolimits_{l'\cup 0}e^{(\Psi_f\alpha_{l'}^f-W_{l'}^f)/\sigma_f} \tag{2}$$

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).

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 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.

2.2 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 (1):

$$U_{if(k)} = \gamma_{l(i)}^{f(k)} + \sigma_{l(i)}\, \epsilon_i^{f(k)} + W_{l(i)}^{f(k)} \tag{3}$$

$\gamma_{l(i)}^{f(k)}$ 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 worker i. Non-pecuniary components might include the worker's tastes for position k's amenities or establishment j's location, 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 Midwest region workers prefer positions in the Midwest, while $\epsilon_i^{f(k)}$ might capture worker i's particular taste for Midwest positions beyond the mean among other Midwest workers of the same type. $\sigma_{l(i)}$ captures the relative importance of the systematic vs. idiosyncratic components in determining the non-pecuniary payoff, which may vary by worker type. $W_{l(i)}^{f(k)}$ captures the annual earnings a type l worker 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:

$$\max_{f \in \mathcal{F}} \gamma_{l(i)}^{f(k)} + \sigma_{l(i)}\, \epsilon_i^{f(k)} + W_{l(i)}^{f(k)} \tag{4}$$

As with the production side, the systematic components $\{\gamma_{l(i)}^{f(k)}\}$ are objects of interest to be identified and estimated, while $\{\sigma_l\}$ are calibrated (Section A2.3). $\{\epsilon_i^{f(k)}\}$ are assumed to follow an i.i.d Gumbel distribution across all (i, f) pairs, so that the conditional probability that a type l worker accepts (or continues) a type f position adheres to the usual logit formula:[3]

$$P(f|l) = e^{(\gamma_l^f + W_l^f)/\sigma_l} \Big/ \sum_{f' \cup 0} e^{(\gamma_l^{f'} + W_l^{f'})/\sigma_l}. \tag{5}$$

2.3 Labor Market Equilibrium

Define the joint surplus from a job match (i, k) as the sum of the worker and firm payoffs:

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

$$\pi_{ik} = U_{if(k)} + V_{l(i)k} \tag{6}$$

Since the annual earnings W_l^f cancel out in the joint surplus, the model is a transferable utility assignment game as defined by Koopmans and Beckmann (1957). Shapley and Shubik (1972) show that 1) this game has a unique and efficient stable allocation that 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 2) this 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).

Specifically, equations (2) and (5) 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 and h_f denote the counts of type l workers and 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:

$$m_l \frac{e^{(\gamma_l^f + W_l^f)/\sigma_l}}{\sum_{f' \cup 0} e^{(\gamma_l^{f'} + W_l^{f'})/\sigma_l}} = h_f \frac{e^{(\Psi_f \alpha_l^f - W_l^f)/\sigma_f}}{\sum_{l' \cup 0} e^{(\Psi_f \alpha_{l'}^f - W_{l'}^f)/\sigma_f}} \ \forall (l, f) \in \mathcal{L} \times \mathcal{F} \tag{7}$$

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 (7) is determined by $L \times F$ earnings values $\{W_l^f\}$. Decker et al. (2013) prove that these equilibrium conditions yield a unique aggregate allocation that is consistent with the disaggregate stable matching. Choo and Siow (2006) show that when single counts are available on both sides of the market, the equations (7) can be collapsed to $L + F$ equations governing the equilibrium singles counts by worker and firm type.

2.4 Identification

Consider first the taste parameters $\{\gamma_l^f\}$ and the composite revenue parameters $\{\Psi_f \alpha_l^f\}$. Assume that mean earnings $\{W_l^f\}$ and population match frequencies $P(l, f)$ are observed for each (l, f). Taking log differences of (5) and (2), respectively, between a chosen firm (worker) type f (l) and a reference type $\tilde{f}$ $(\tilde{l})$ and rearranging yields:

$$\gamma_l^f - \gamma_l^{\tilde{f}} = \sigma_l (\ln P(f, l) - \ln P(\tilde{f}, l)) - W_l^f + W_l^{\tilde{f}} \tag{8}$$

$$\Psi_f (\alpha_l^f - \alpha_{\tilde{l}}^f) = \sigma_f (\ln P(l, f) - \ln P(\tilde{l}, f)) + W_l^f - W_{\tilde{l}}^f \tag{9}$$

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

Let $\theta_l^f \equiv \Psi_f \alpha_l^f + \gamma_l^f$ capture the mean joint surplus among (l, f) matches. Adding (8) and (9) 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:

$$(\theta_l^f - \theta_{\tilde{l}}^f) - (\theta_l^{\tilde{f}} - \theta_{\tilde{l}}^{\tilde{f}}) = (\sigma_f + \sigma_l) \ln P(l,f) - (\sigma_f + \sigma_{\tilde{l}}) \ln P(l',f) - (\sigma_{\tilde{f}} + \sigma_l) \ln P(l,f') + (\sigma_{\tilde{f}} + \sigma_{\tilde{l}}) \ln P(l',f') \quad (10)$$

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 (8) and (9). Disproportionately high earnings in these matches compared to l and f's alternative matches suggests that particularly high worker productivity at these firms drives the comparative advantage, while relatively low earnings despite high match rates suggests that l-type workers' strong taste for f's drives the comparative advantage.

2.5 Counterfactual Equilibria

We generally simulate 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 (7) yields unique counterfactual allocations $P^{CF}(l, f)$ and earnings transfers $W_l^{CF,f}$ for any such scenario.[4]

However, 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.[5] 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.[6]

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 $\{V_f^*\}$. Moreover, Koopmans

[4]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 (7) reveals that the normalization cancels out in each equilibrium condition. The same is true for $\Psi_f \alpha_{\tilde{l}}^f$ in (2). Thus, identification of *relative* preferences and productivities suffices to generate unique counterfactual allocations $P^{CF}(l, f)$ and transfers $W_l^{CF,f}$.

[5]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.

[6]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.

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 these insights to rewrite worker and firm choice probabilities in terms of identifiable joint surplus components and the equilibrium shadow prices. We use these alternative formulations, combined with the (temporary) assumption that all vacancies are filled, to construct a system of $L-1$ equations that yield counterfactual mean utility changes by worker type $\{U_l^{*,CF}\}$ relative to a normalized type, along with the equilibrium allocation.[7] 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 (8) and (9) yields the equilibrium earnings vector $\{W_l^{f,CF}\}$.

To develop intuition for this approach to market clearing, conceptualize the entire U.S. labor market as a massive first price ascending auction. Each position can bid on any worker, and the position bidding the highest utility wins the worker. Positions' utility bids are anchored by the worker's valuation of the firm's amenities $(\gamma_l^f + \epsilon_i^f)$, but can be adjusted using changes in salary. Workers 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 transfers W_l^f do not vary across job matches within (l, f) type pairs.

This analogy reveals that even though workers' tastes affect the baseline utility associated with any firm's bid, changes in bids due to shock-induced changes in demand for a worker type must take the form of salary adjustments. Thus, the shock-induced utility changes we estimate are naturally scaled as easily interpretable earnings equivalents. Estimated mean earnings and utility losses differ because shock-induced reallocations across firm types cause changes in mean amenity quality that are offset by earnings compensating differentials and do not affect utility.

Importantly, our approach to address lack of data on vacancies yields substantial computational savings as well. By imposing $P(0|f) = 0$, computing 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.[8] 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.

[7] The assumption that all vacancies fill 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.

[8] 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).

2.6 Allowing for Additional Heterogeneity: Movers and Stayers

To this point, our model has not distinguished retained workers from new hires of the same type l. However, the joint surplus from maintaining existing job matches is generally considerably larger than among new job matches with observationally similar workers: moving, search, and training costs need not be re-paid, firm-specific experience may make the incumbent more productive, and incumbents may have selected the particular firm due to high idiosyncratic tastes ϵ_i^f. We show below that ignoring surplus differences between incumbents and new hires can obscure important asymmetries in shock incidence between positive and negative shocks.

Thus, in our empirical work we distinguish job stayers from movers with an indicator $z_{i,k}$ that equals 1 when i is an incumbent at establishment k and 0 otherwise.[9] Define the transition group $g \equiv g(i,k) = [l(i), f(k), z(i,k)]$. We represent the mean nonpecuniary worker, firm, and joint surplus payoffs among (l, f) matches with incumbent indicator z as γ_g, $\Psi_f \alpha_g$, and θ_g, where we suppress dependence of g on l, f, z, i and k. The surplus premium to job retention is identified via the log difference in the rates of job retentions versus 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.[10] 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. $\{\sigma_f\}$ and $\{\sigma_l\}$ are not identified from a single cross-sectional allocation, but instead require observing multiple matching markets and imposing restrictions on the relationships among the surplus parameters that govern them. After experimenting unsuccessfully with IV approaches, we chose to calibrate $\{\sigma_f\}$ and $\{\sigma_l\}$ by selecting worker and firm elasticities of substitution from the literature (6.9 from Berger et al. (2021) and 7.4

[9] 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.

[10] 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.

from Borjas et al. (2012)) and using the fact that, conditional on $\{\Psi_f \alpha_g\}$ and $\{\gamma_g\}$, $\{\sigma_f\}$ and $\{\sigma_l\}$ pin down the respective elasticities of substitution.

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 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.

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

We 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 a full description in Appendix A2.5.

We first estimate the worker and firm surplus components $\{\gamma_g^t\}$ and $\{\Psi_f^t \alpha_g^t\}$ for each period $t \in \{2001-02, ..., 2005-2006\}$ using realized year t job flows/retentions and earnings, and hold these values fixed when constructing each year t's counterfactual allocation. This approach implicitly assumes that any evolution in surplus components between the period $t-1$ and t transitions is due to other secular labor market trends unrelated to China's WTO entry. 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.

To construct the counterfactual allocation for the initial 2001-2002 shock, we hold fixed the observed 2001 composition of worker types $\{m_l^{0102}\}$ (presumed to be determined pre-shock), and form 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 that we estimate was eliminated or generated by China's WTO entry using equation (17) in Section 4.2 below. We then solve the system of equations (30) derived in Appendix A2.2 to generate the 2001-2002 changes in worker utility and allocation that would have transpired in the shock's, and use (35) to solve for the corresponding earnings changes. Subtracting each worker type's mobility and earnings outcomes from their observed 2001-2002 counterparts isolates the changes attributable to the first year of the China Shock.

Estimating shock impacts in subsequent years requires two adjustments to this approach. First, we use year $t-1$'s counterfactual allocation and earnings to create a worker type transition matrix that implies an updated year t counterfactual worker type distribution, $m_l^{t,CF}$. Second, because the counterfactual economy is now inheriting different worker and position type distributions than in the data, we must generate two counterfactual allocations for each year t. The first adds the observed change in the distribution of position counts between year t and year $t-1$, $(h_f^t - h_f^{t-1})$, to the previous year's counterfactual position counts. This creates a composite shock that combines the year t China Shock with other concurrent shocks to labor demand. The second counterfactual then restores jobs by subtracting the (usually negative) estimated China Shock component. After solving for each shock's allocation, utility, and earnings changes using (30) and (35), we subtract the second set of changes from the first. This isolates the impact of year t of the China Shock relative to a baseline in which China never joined the WTO but other concurrent shocks had occurred and continued to occur.

We generally report expected cumulative or average per-year outcomes over the full five years by workers' 2001 type. This requires combining each period's simulated outcome changes with a transition matrix among worker types in adjacent years and using backward induction.

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. We first merge 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)) with 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)). For manufacturing establishments, we merge in product-level sales from the Census of Manufacturers. Our nationwide LBD-LFTTD sample, used to construct our labor demand shock, contains on average 4.7M firms, 6.1M establishments, and 105M 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.

Our worker-level analysis combines the LFTTD with the Longitudinal Employer-Household Dynamics (LEHD) database, which follows the near universe of workers as they transition between jobs in 25 states that account for 60% of U.S. employment (see Vilhuber (2018)).[11] The database reports workers' earnings by job-quarter along with their establishments' industry codes and locations. It also indicates whether workers were employed (earnings > 0) 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 70M workers per year. Together, these data allow us to estimate a very flexibly parameterized assignment model of the U.S. labor market.

[11] 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.

3.1 Assigning Job Matches to Types

Our assignment model requires classifying workers and jobs into types and groups. For firms, we sought characteristics to define types that capture heterogeneity in both the nature of firms' exposure to trade shocks and 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 $\Psi_f \alpha_g$.

Central to our analysis is our categorization of the firm's trade engagement. Among trading firms, we distinguish those engaging in importing only, exporting only, and importing and exporting, since they experience different shock exposure, and Handley et al. (2021) show that each accounts for large shares of U.S. employment (2.0%, 12.4%, and 38.3% respectively in 2001) that vary meaningfully by industry and by region. We also separate firms engaged in "related-party" importing and/or exporting with their own foreign affiliates, since we show in (Carballo et al., 2024) that multinationals who both import and export within-firm are particularly large, high-paying, and intensive in their trading. 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.[12] 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 (see Appendix A5 for details):

Trade Engagement (6) - the trade engagement of the position's firm: non-trading (NT), arms-length importer only (M), arms-length exporter only (X), arms-length importer and exporter (X&M), related party exporter and importer (RPXM), and related party exporter or related party importer but not both (RP X|M).

Industry (7) - the industry of the position's establishment. We group together NAICS sectors that feature similar trade engagement and average worker pay distributions 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 services, leisure/transportation/administration, and education/health/government.

Region (7) - the region of the position's establishment: Northeast, Midwest, Great Plains, West Coast, Southwest, Deep South, Mid-Atlantic/Appalachia (we exclude Alaska and Hawaii).

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.

Firm Average Pay (4) - the quartile of the position's firm in the firm average worker earnings

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

distribution, with cutoffs defined so that 25% of employment is in each pay bin.

While our baseline model allows firms to be reassigned to types each year in order to capture subsequent exposure following initial firm adjustments, in Section 5.2 we assess robustness to fixing firms' types based on year 2001 characteristics.

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

Earnings decile cutoffs are based on 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 better capture 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 initially unemployed if they earn less than $5,000 at their dominant job, and their 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. Below we show that firms disproportionately hire workers from the same industry and trade engagement status, 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 $g \equiv g(l(i), f(k), z(i, k))$. Each $P(g)$ element captures the share of all year-to-year worker transitions between dominant (highest earnings) jobs consisting of workers from a given earnings category, industry, state, and 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.[14]

Our rich type space 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 simulation of the model requires a complete set of counts at the group g level, we implement an imputation procedure (detailed in Appendix A3) to fill gaps in our group counts. Broadly speaking, we address missing LEHD data on job matches from 25 states by 1) multiplying LBD employment counts by firm type from all 50 states by an industry-specific scaling factor to handle LBD-LEHD differences in industry coverage, and 2) 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.

[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.

[14] Only (l, f) combinations in which l and f share a region and industry have job stayer groups ($z(i, k) = 1$).

We then assign locations to unemployed workers and distinguish them from workers who are self-employed, federally employed, or out of 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 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 $\hat{P}(g)$ and $\hat{W}_l^F$ prior to estimation by replacing each group's values with kernel-density weighted averages among groups featuring "similar" worker and position characteristics. Essentially, this allows the data to reveal surplus heterogeneity where its signal is strong but prevents overfitting by limiting surplus variation across similar groups when the data's signal is weak because few matches are at risk of being made.[15] Because results based on unsmoothed group counts and earnings are strikingly similar to the smoothed results (nearly always within 1%), we relegate the description of our customized smoothing procedure to Appendix A4.

3.3 Describing the Matching Process: Job Flows and Surplus Determinants

While our model has the feature that it places few a priori restrictions on how workers match to firms, such flexibility and complexity can obscure the economic forces that determine how the model translates firm-level shocks into worker-level labor market outcomes. Thus, this section highlights several patterns of labor market mobility and sorting observed in the data that drive the variation in estimated joint surplus parameters and ultimately shape model simulations.

To this end, the first row of Table 1 reports the frequency of various kinds of transitions between workers' 2001 and 2002 primary employers (or unemployment) in our data, while the remaining rows provide corresponding breakdowns among particular worker and firm subpopulations based on categories of the characteristics that define our worker and firm types.

Row 1 reveals that 79.1% of initially employed workers stayed with their primary employers the next year, with 17.1% finding a new employer and 3.8% becoming unemployed. Through the lens of the model, this implies that job retention usually generates a large combined surplus for workers and firms, so that shocks that eliminate positions may impose substantial welfare losses on the workers who held them. Among those switching employers, 91.6% remain in the same region (col. 6), 53.2% remain in the same industry (col. 7), and 59.5% choose firms with the same trade status (col. 8). This is consistent with large geographic mobility/search

[15] The smoothing procedure is based on the intuition that 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.

frictions and high value to workers, firms or both from staying within the same industry.

Rows 2-5 show that job turnover is far larger for workers initially below median earnings: only 65% and 77% of workers in deciles 1-2 and 3-5 stay with their original employer, compared to 85% and 87% of those in deciles 6-8 and 9-10. This suggests that lower paid workers are generating less surplus, making them more vulnerable to increased competition from displaced workers, but also more willing to move to alternative opportunities, as reflected in their higher E-E rates. The lowest paid workers are also far more likely to become unemployed for the bulk of the following year. They are also much more likely to switch industries when they do find an alternative job (54.1% and 51.8% for deciles 1-2 and 3-5 vs. 43.3% and 37.5% for deciles 6-8 and 9-10), but slightly less likely to switch regions than the highest paid workers.

Rows 8-14 provide separate hiring and retention profiles by industry category. Manufacturing has the highest retention rates (82.1%), suggesting that preserving job matches is particularly valuable to either workers or firms in this industry, while the generally low-paying wholesale/retail (72.9%) and transportation/hospitality/other services industries (67.1%) have particularly low rates. These two industry categories are also far more likely to hire workers directly from unemployment (9.9% and 13.1% vs. 6.7% among other industries' hires).

Interestingly, row 14 reveals that the education/health/government sectors are fairly segregated from the rest of the labor market. They retain a high share of their workers (80.8%), rarely hire from unemployment (6.2%), and disproportionately hire from other educ./health/gov. firms (59%, compared to 49% of E-E hires by other industries). Given that firms in these sectors also import and particularly export less than other sectors, their workers are likely to be quite insulated from most trade shocks, consistent with our simulation results below.

Rows 15-20 show that RPXM firms retain more workers (80.0%) and hire less from unemployment (5.6%) than firms of any other trade status. Their E-E hires also disproportionately stem from other RPXM firms (42.1% vs. RPXM's 15.5% U.S. employment share). This is consistent (Carballo et al., 2024), who find that the most trade-engaged firms compete heavily with each other for the highest-skilled workers, offering pay premia to attract and keep them.

Table 2 illustrates how these hiring and mobility patterns are captured by the estimated joint surplus parameters $\{\hat{\theta}_{lf}\}$ that govern the model's predictions about shock-induced worker reallocation. Column 1 reports coefficients from a regression of standardized $\hat{\theta}_{lf}$ values on various combinations of worker, firm, and job characteristics among those that define match groups g, while columns 2 and 3 provide separate coefficients for the firm and worker non-pecuniary components of the surplus, $\hat{\alpha}_{lf}$ and $\hat{\gamma}_{lf}$. Recall that joint surplus values are identified by odds ratios of match frequencies, while the two components are identified by earnings premia relative to match frequencies, so that inordinately high pay implies a large firm share of the non-pecuniary surplus, making it willing to pay a premium to facilitate such matches.[16]

[16]Since difference-in-differences of θ values fully determine counterfactual objects (Mansfield, 2024), the relevant variation in θ stems from combinations of worker and firm characteristics rather than one side's alone.

Consistent with the transition rates, the estimated joint surplus is 1.53 s.d. higher when a transitioning worker's initial and hiring establishment share a region, with elevated firm and worker components (.98 and .70 s.d.s), suggesting that both sides highly value forming within-region matches. Even transitions to adjacent regions create .3 s.d. higher surplus than more distant transitions, with a roughly even component split. By contrast, the .48 s.d. surplus premium from within-industry job transitions is fully driven by the firm component, suggesting they strongly value industry experience (or incur lower recruiting costs from within-industry hires), while workers do not mind switching industry when changing jobs. The firm component also mostly accounts for the .31 s.d. extra surplus when high-paid workers move to high-paying firms, consistent with production complementarities between worker skill and firm productivity.

Matches in which both the original and hiring firm share $RPXM$ status generate a moderate .26 s.d. higher surplus, while sharing any other trade status generate a smaller but nontrivial .15 s.d. higher surplus than status-switching job transitions, although the worker/firm surplus split varies across the two. Finally, preserving an existing match yields a 1.14 sd boost beyond the within-region and within-industry premia, with about 75% of the pre-transfer value accruing to the firm, consistent with a large value of avoiding recruiting/training costs and a smaller but meaningful value of avoiding search/moving costs for the worker.

Overall, these estimates suggest that the model accurately captures the sources of heterogeneity in mobility frictions and complementarities in the data. Next, we discuss how we form the firm-level employment shock caused by China's WTO entry that we feed to the model.

4 Measuring the China Shock at the Firm Level

Our assignment model requires as inputs separate vectors of firm type-specific employment changes attributed to China's WTO entry for each of five post-shock years (2002-2006) we consider. We begin by using national firm- and establishment-level LBD data to form separate estimates of shock-induced firm×industry-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 Pierce and Schott (2016): 1) construct shift-share measures to isolate exogenous variation in firm-level exposure to each channel; 2) regress employment growth at the firm×industry×year level on the four exposure measures along with controls that remove the influence of other correlated labor demand shocks; 3) collect fitted values and aggregate to the firm type level to form the estimated labor demand shock $h_{t,f}^{CF}$.

Our measures are generally conservative in assigning exposure to avoid 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, since baseline fitted values will not capture shock-induced responses and product market spillovers at seemingly unexposed firms (though we consider up/downstream exposure as a robustness check). Rather than produce a definitive accounting of the shock's labor demand impact, our goals are to 1) demonstrate the importance of overlooked channels, 2) illustrate heterogeneity among firm types in exposure and sensitivity to exposure, and 3) provide a reasonable quantification of the overall employment demand shock to feed into the assignment model to assess worker-level equilibrium incidence.

4.1 Exposure Measures

Consider first the import competition channel, which isolates employment changes from greater competition for U.S. manufacturers from imported Chinese products in the U.S. market.

Pierce and Schott (2016) construct exposure by 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, $\overline{TG}_n$. Instead of using an industry-level average, we construct a firm-level measure by 1) weighting the tariff gap for each NAICS6 product code by the product code's share of the firm's total sales reported in the Census of Manufacturers[17], and 2) multiplying the resulting weighted average tariff rate by the domestic share of the firm's total revenue based on LBD revenue and LFTTD total exports. Step 2) seeks to isolate only the domestic component of increased competition from Chinese goods. This yields:

$$IC_{jt} = (\sum\nolimits_p \frac{Sales^{CM}_{jpt-1}}{Tot.Sales_{jt-1}} \overline{TG}_p) \frac{(Rev^{LBD}_{jt} - Tot.Exports^{LFTTD}_{jt})}{Rev^{LBD}_{jt}} \tag{11}$$

This measure of exposure assumes that the threat of tariff increases had previously deterred investment in Chinese production and exporting capacity in certain sectors, and that its removal caused relatively larger increases in Chinese investment, production, and exports to the U.S. for products with higher potential tariffs relative to the WTO tariff.[18] By isolating the tariff gap variation, it seeks to remove other causes of increased Chinese imports that also directly affect employment, such as labor supply shifts, automation opportunities, and contemporaneous product demand shocks.

The export competition channel considers employment changes at U.S. exporting firms in foreign markets due to increased competition from China's post-WTO production expansion. We measure firm-level exposure in year t via a weighted average of the tariff gaps associated of the firm's exported products p, with each product's export value as a share of the firm's total LBD revenue as weights:

$$EC_{jt} = \sum\nolimits_p (X_{pjt-1}/Rev^{LBD}_{jt-1})TG_p \tag{12}$$

where X_{pjt-1} is the value of firm j's exports of product class p in year $t-1$ and Rev^{LBD}_{jt-1} is

[17] See Appendix A5.4 more details on the product-level sales data.

[18] We tried isolating the domestic component of competition at the product rather than firm level by subtracting product-level LFTTD exports from product-level sales from the Census of Manufacturers. However, the two measures' scales were often mismatched, perhaps because the Census of Manufacturers' measures the "total value of shipments", and intra-firm shipments may lead this to overstate total sales.

firm j's revenue in $t-1$. Since Chinese competition in foreign markets affects U.S. exporters in many industries, we construct EC_{jt} for all exporting firms.

The product-level tariff gaps in our exposure measure use U.S. tariffs rather than those of the relevant export markets. We do this because the EU, the world's non-US largest import market, had already granted permanent MFN status to China well before its WTO entry (Feng et al., 2017), but also because Liu and Ma (2020) show that sectors experiencing greater reductions in U.S. tariff uncertainty not only innovated faster, but also increased Chinese exports to other non-US countries by more as well. Furthermore, Cui and Li (2023) show that such sectors exhibited more firm entry as well.[19]

The import access channel considers U.S. firms' response to expanded opportunities to import from China. Firm j's year t exposure to this channel is measured as a weighted average of tariff gaps of the products it imported in $t-1$, with products' shares of estimated total costs as weights:

$$IA_{jt} = \sum\nolimits_p (M_{pjt-1}/\widehat{TC}_{jt-1})TG_{pt} \tag{13}$$

where M_{pjt-1} 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 a firm's 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 its 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 already importing the particular products whose potential tariff fell. These firms have already paid any fixed costs of coordinating imports of these products, so they are well positioned to quickly expand imports.[20]

Lastly, our export access channel considers possible employment gains at exporting firms whose products face falling Chinese tariffs. We measure firm j's export access exposure as the

[19]Breinlich et al. (2022)'s model suggests that increased opportunities to export to the U.S. might create economies of scale in China that then lower the cost of exporting to other countries, further supporting a causal link between U.S. tariff gaps and increased export competition from China abroad. The same line of argument also implies that import and export competition exposure might compound each other by reducing scale economies among U.S. manufacturers, complicating efforts to perfectly distinguish the two channels. Nonetheless, it implies that exporters are more exposed to the shock, and that including both measures increases our ability to fully capture firms' overall tariff gap exposure.

[20]In Section 6 we consider an alternative exposure measure that restricts exposure to firms that were already importing the relevant products *from China* and discuss its advantages and disadvantages.

average tariff reduction in the products exported to China weighted by their revenue shares:

$$EA_{jt} = \sum\nolimits_p (X^{China}_{pjt-1}/Rev^{LBD}_{jt-1})\Delta\tau_{pt} \tag{14}$$

where X^{China}_{pjt-1} 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.[21]

Table 3 provides the mean and standard deviation of each exposure measure among our full regression sample of firm-industry-years at risk of exposure to at least one channel in row 1. The remaining rows report these values separately by industry category and by trade engagement status within our two most exposed industries, manufacturing and wholesale/retail. The reported means are firm-weighted to match the variation used in our regressions.

Column 1 shows that import competition channel generates substantial exposure among manufacturing firms. For the average firm, the revenue-weighted average tariff gap for domestic sales is 28.6%, suggesting that considerable tariff uncertainty was removed for their Chinese competitors. By contrast, for the export competition channel, the corresponding revenue-weighted average tariff gap for exports is only 0.5% (col. 2), since most manufacturing firms do not export, and exports generally account for a small share of sales for those that do export. However, the largest firms tend to be the most reliant on exports, so the difference in firm-weighted average exposure between the two channels vastly overstates the difference in employment-weighted exposure. Indeed, the mean exposure among $RPXM$ firms within manufacturing is nearly seven times the average among all manufacturing firms; such firms account for 2% of firms but 47% of employment.

Interestingly, mean import competition exposure among $RPXM$ wholesale/retail firms is a substantial 13.9%, even though we limit import competition exposure only to firms with at least one manufacturing establishment. This is consistent with our evidence below that large firms that are primarily wholesale/retail frequently operate manufacturing establishments.

Turning to import access (col. 3), the cost-weighted mean tariff gap for Chinese imports for the average at-risk firm is 4.1%, suggesting that importing firms also experienced a meaningful reduction in tariff uncertainty. While non-trivial exposure exists in every sector, manufacturing importers and particularly wholesale-retail firms account for the bulk of import access exposure, since they are most likely to be directly engaged in importing. Finally, the average at-risk firm experienced only a 1.1% China-export-weighted mean Chinese tariff reduction (col. 4), with low exposure even for the large $RPXM$ manufacturers, which reflects Chinese exports' small shares of export revenue even for the few firms that exported to China in the early 2000s.

While the differential industry and trade status composition of exposure across our four channels will be important for understanding the China Shock's worker-level winners and losers, our regressions below rely exclusively on within-industry and within-trade status variation to

[21] 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.

identify firm employment responses per unit of each exposure measure so as to mitigate bias from unobserved industry and trade shocks and trends. Essentially, identifying variation for each channel's exposure measure stems from varying exposure intensity among exposed firms as well as comparisons to control groups of firms in the same trade and industry categories whose input or product mix happened to yield a zero tariff gap. Table 4 shows that 53% and 36% of import competition exposure variance exists within 4-digit and 6-digit NAICS industries, respectively. The within-industry variance shares are even larger for the other exposure measures: 97% and 96% for export competition, 86% and 84% for import access, and over 99% for both for export access. Thus, little statistical power is sacrificed by exploiting idiosyncratic firm variation. Note that import competition's high between-sector share suggests that it produces a more concentrated shock than the other channels, a theme we revisit below.

4.2 Regression Specification

Our estimating equation is given by:

$$\begin{aligned}\Delta_t ln(N_{jnt}) = &\sum\nolimits_c Exposure^c_{jt} \times \Big[\sum\nolimits_{s=1}^{4} \sum\nolimits_{rp=0}^{1} \nu^c_{s,rp} 1(fs_{jt} = s) 1(ts_{jt} = rp) \\ &+ \sum\nolimits_{ind=1}^{7} \sum\nolimits_{rp=0}^{1} \delta^c_{ind,rp} 1(n = ind) 1(ts_{jt} = rp)\Big] \\ &+ \boldsymbol{\vartheta} \mathbf{X}_{jnt-1} + \mathbf{D}^{te}_{jnt-1} \boldsymbol{\omega}^{te} + \mathbf{D}^{i}_{jnt-1} \boldsymbol{\omega}^{i} + \mathbf{D}^{fs \cdot fe}_{jt-1} \boldsymbol{\omega}^{fs \cdot fe} + \epsilon_{jnt}\end{aligned} \tag{15}$$

where $\Delta_t ln(N_{jnt})$ captures log employment growth among firm j's establishments in industry n between year $t-1$ and t, and $Exposure^c_{jt}$ is channel c's exposure measure. $1(ts_{jt} = rp)$ is an indicator for whether firm j exports and imports with related parties, $1(fs_{jt} = s)$ are indicators for firm j's firm size quartile in year t, and $1(n = ind)$ are indicators for the industry categories defined above. $\{\nu^c_{s,rp}\}$ and $\{\delta^c_{ind,rp}\}$ capture the degree of differential growth sensitivity to channel c exposure for firms in chosen firm size and industry categories, with separate sensitivity allowed within each category for $RPXM$ and non-$RPXM$ firms. Theory provides strong reasons to expect heterogeneity in exposure sensitivity in these dimensions.[22]

Note that for multi-industry firms, we create separate observations for groups of establishments in different industry categories. This allows, for example, the retail arm of a manufacturing firm to potentially be affected by shock exposure, but does not impose that it is affected symmetrically. Indeed, in the case of an import access shock, the firm may outsource tasks that their manufacturing workers used to do so as to lower unit costs, which then causes them to sell more goods and hire more retail staff or reallocate existing workers (Bloom et al., 2024). This flexibility permits us to accurately capture the industry composition of the aggregate employment shock we input to the assignment model, improving its predictions about which kinds of unexposed workers will face stiffer labor market competition.

[22] For example, large firms tend to have higher productivity, and thus may better retain market share when exposed to greater international competition, but also may tend to produce generic versions of goods that more closely compete with China. Similarly, multinationals may more easily create new exporting establishments in China, while wholesale/retail firms usually cannot produce the inputs they import, unlike manufacturing firms.

Table 5 shows why careful treatment of multi-industry firms is necessary: 72.7% of LBD employment is concentrated at multi-industry firms, with 49.7% at firms operating establishments in three or more industries, even with only seven highly aggregated industry categories. In fact, multi-industry firms account for at least two-thirds of employment in all sectors. The second panel reports the frequency of establishments in each secondary industry for firms that are primarily manufacturing or wholesale/retail, the two most exposed industry categories. Almost 46% of employment in manufacturing firms occurs at those that also operate a wholesale/retail establishment, with 31% and 41% at firms that operate a trans/hosp./admin., and/or prof./bus. services establishment. Similarly, among wholesale/retail firms, 40%, 50%, and 60% of employment is concentrated among those that operate an establishments in these three industry categories, respectively. Thus, intrafirm spillovers to seemingly untargeted sectors are likely to be quantitatively important.

Because the same firm may be exposed to the China Shock via multiple channels, we include all exposure measures and associated interactions in the same regression. The regression sample consists of all firm-years with $t \in [2002, 2006]$ that are at risk of exposure to at least one channel. This includes any firm that either operated a manufacturing establishment or imported or exported goods internationally in year $t-1$. Non-trading firms without manufacturing activity 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.

We also include other firm characteristics $\mathbf{X}_{jt-1}$ that control for broader trends in firm growth and trade activity that may be correlated with exposure: lagged values of employment growth, total imports, and total exports. $\mathbf{D}^{te}_{jt-1}$, $\mathbf{D}^{i}_{jt-1}$, and $\mathbf{D}^{fs \cdot fe}_{jt-1}$ are design matrices for each trade engagement category, 4-digit NAICS industry, and combination of average pay decile and size category (using 10 BLS categories), with corresponding fixed effects $\boldsymbol{\omega}^{te}$, $\boldsymbol{\omega}^{i}$, and $\boldsymbol{\omega}^{fs \cdot fe}$.

We drop observations with fewer than 5 workers in $t-1$ due to exceptionally volatile employment growth, but otherwise weight all observations equally, since weighting by employment may lead idiosyncratic shocks to a few extremely large firms to unduly influence the estimates, dramatically reducing the effective sample size. However, since we expect large firms to operate differently than small firms on many dimensions, we interact not only our exposure variables but also our continuous control variables by firm size categories.

4.3 Regression Results

Table 6 reports our estimates of the effects of firm-level exposure to China's WTO entry on firm-industry employment growth. Because our full specification is flexibly parametrized, we focus on coefficients from simplified specifications that capture several key patterns. Column 1 reports exposure coefficients for each channel from a model that imposes homogeneous sensitivity across all types of firms. All four exposure coefficients are statistically significantly at a 99% confidence level. Relative to a non-exposed firm, mean import and export competition exposure predict 0.19% and 0.11% employment losses, respectively, while mean import access exposure increases annual growth by 0.13%. In contrast to these sizable impacts, mean export access exposure predicts a negligible 0.0004% loss. Given its unimportance, we focus on the other three channels, but we include export access in our estimate of the China Shock's impact.

Column 2 allows exposure sensitivity to differ by whether the firm had more vs. less than 250 $t-1$ employees. We find that large firms are considerably more sensitive to import competition exposure, suffering 0.59% employment losses at mean exposure compared to 0.16% for small firms. This is consistent with the idea that Chinese imports may compete more directly with products of large firms.

Columns 3 and 4 allow the coefficients from the first two columns' specifications to vary by whether the firm is a related-party importer and exporter. Both columns show that $RPXM$ firms are about twice as sensitive per unit of export competition exposure as non-$RPXM$ firms, regardless of whether we restrict comparisons to similarly-sized firms. This may reflect their ability to respond by shifting production to low-wage countries, including China itself.

Interestingly, while columns 2 and 3 do not show evidence of heterogeneity in sensitivity to import access exposure by size or $RPXM$ status when these characteristics are interacted separately, column 4 shows that the one-way interactions are hiding two-way heterogeneity: among small firms, $RPXM$ firms generate more employment growth per unit of import access exposure, while among large firms, $RPXM$ status predicts small *losses* from greater exposure. In Section 6, we show that introducing industry-specific heterogeneity resolves this puzzle: greater import access increases employment growth among most industries (particularly wholesale/retail), but it reduces employment growth among manufacturing firms, which tend to be both large and multinational. This is consistent with manufacturers responding by outsourcing workers' tasks, as emphasized in the literature (e.g. Hummels et al. (2018)).[23]

Importantly, F-statistics reported in the bottom panel show that the model featuring size×RPXM interactions significantly outperforms those with only size or only $RPXM$ interactions, and that our full model that also adds industry×$RPXM$ interactions generates further statistically significant gains in model fit. These findings indicate the existence of substantial multi-dimensional heterogeneity in sensitivity to exposure that varies by channel. Our assignment model is designed to accommodate and evaluate such a multi-faceted shock.

One possible concern is that these regressions only capture responses to direct exposure to our four channels. However, some firms may be indirectly exposed, so that the China Shock's treatment effect on the control groups is not zero. One mechanism, emphasized by Pierce et al. (2024), operates through input-output links: firms that rely heavily on selling to directly

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

exposed firms ("downstream exposure") suffer reduced product demand that lowers labor demand, while firms that buy from exposed firms ("upstream exposure") either enjoy cheaper inputs due to Chinese competition or lose key suppliers entirely, creating ambiguous but possibly important labor demand effects. Thus, columns 5 and 6 augment 1 and 4, respectively, by adding measures of both upstream and downstream exposure. These consist of industry-level weighted averages of the sum of import and export competition exposure (since both capture greater product market competition and are scaled by firm revenue), with the downstream and upstream measures using industry output and input shares, respectively, as weights.

We find statistically significant negative employment effects of downstream exposure and positive but statistically insignificant effects of upstream exposure, which is broadly consistent with Pierce et al. (2024)'s worker-level estimates. However, these measures only vary at the six-digit NAICS level for which input-output tables are available, so the estimates are much noisier, much more sensitive to specification, and much less robust to correlations with other unrelated industry shocks than our direct exposure coefficients. Furthermore, because our direct exposure estimates primarily rely on firm-level variation within 6-digit industries, they are virtually unaffected by the inclusion of our upstream and downstream exposure measures. Thus, we rely on the baseline specification (15) to produce the predicted employment shock counts for the assignment model, but present worker-level incidence estimates from shocks that include upstream and downstream exposure effects as a robustness check in Section 6.

A second source of indirect effects stems from decreased consumer demand for local non-traded services after layoffs at directly exposed firms. Autor et al. (2013), Autor et al. (2024), and Pierce et al. (2024) show that local spillovers can be large. While our estimates capture spillovers to seemingly unrelated establishments within the same firm, they do not capture local spillovers to unrelated service firms. As discussed, this will likely cause understatement of shock-induced employment gains and particularly losses.[24] Despite this "missing intercept" problem, we believe the quality of our microdata and the flexibility of our regression modeling should yield accurate estimates of the relative employment impact of the China shock across various firm subpopulations and channels if not the exact aggregate magnitude.

[24] Our approach also does not capture shock-induced firm death or entry (in the first year). However, Bloom et al. (2024) find that most shock-induced employment losses, at least in manufacturing, are due to downsizing and intrafirm reallocation to non-manufacturing establishments rather than firm death, which is captured by our approach. In principle, our estimates of U.S. employment losses could be overstated if equilibrium wage reductions due to shock-induced layoffs induce enough additional hiring at otherwise non-exposed firms (a third source of indirect effects). Our assignment model is designed to capture compositional shifts in hiring via this exact mechanism, but it does not capture wage-induced changes in employment levels by firm type. However, Appendix A2.4 uses existing estimates of employment elasticities with respect to the cost per efficiency unit of labor to show that such employment expansions at non-exposed firms are likely to be quite small.

5 Results: The China Shock's Firm and Worker Incidence

This section presents the paper's principal findings. We first aggregate our regression results to assess how the China Shock affected nationwide employment at firms with direct exposure relative to those without. This exercise also serves to characterize the firm-level composition of the calibrated shock we send to our assignment model, which imposes the additional assumption that employment at firms without any direct exposure was unaffected by the China Shock in order to set the shock's absolute scale. Then we discuss the calibrated shock's worker incidence and assess the degree to which it is mediated by the shock's firm composition.

5.1 Firm-Level Employment Incidence

We form each firm-industry's employment shock for each channel and year by subtracting a counterfactual scenario featuring zero exposure from (15)'s fitted value:

$$Shock^c_{jt} = \exp\left(\widehat{\Delta \ln N}_{jnt}(Exposure^c_{jt} = Exposure^c_{j,2000}) - \widehat{\Delta \ln N}_{jnt}(Exposure^c_{jt} = 0)\right) \times N_{jnt} \quad (16)$$

We then aggregate each channel's shock to the firm-type level: $Shock^c_{ft} = \sum_{j \times n \in f} Shock^c_{jt}$.[25] These channel-specific shocks serve as inputs to our assignment model simulations, which translate these firm type-level shocks into worker type-level earnings, utility, and unemployment incidence. When evaluating the full worker-level impact of China's WTO entry, we combine the employment impacts from all four channels into a single shock:

$$Shock^{Total}_{jt} = Shock^{IC}_{jt} + Shock^{EC}_{jt} + Shock^{IA}_{jt} + Shock^{EA}_{jt} \quad (17)$$

Aggregating across all four channels, we find that firm exposure generated a substantial net loss of 628,000 jobs relative to non-exposed firms.

Table 7 summarizes the calibrated 2002-2006 shock that we feed to our assignment model. We organize our discussion around key findings displayed in bold text.

The export competition and import access channels substantially exacerbate and offset the relative employment losses from import competition. Aggregating across all four channels, we find that exposed firms suffered a substantial net loss of 628,000 jobs relative to non-exposed firms. Though import competition accounts for 99.2% of this relative net employment loss, we find that net job destruction from export competition exposure (388,000 jobs) and net job creation from import access exposure (407,000 jobs) are 62.2% and 65.3% as large but almost fully offsetting. Expanded opportunities to export to China account for only 3.8% (24,000) of the relative net job loss.

Non-manufacturing establishments account for large shares of gross employment changes. On one hand, Table 7's first panel shows that net job destruction among

[25] 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.

manufacturing establishments fully accounts for the estimated relative U.S. net job destruction induced by the China Shock, with the import competition (45.6%), export competition (30.8%), and import access channels (23.5%) each contributing substantially. On the other hand, 51.8% of the relative job destruction via import and export competition and all the job creation via expanded import access occurred among non-manufacturing establishments.

Specifically, 53.5% of the relative import competition job losses accrue to non-manufacturing establishments whose firms also operate a manufacturing establishment, with the largest contributions coming from wholesale/retail (21.3%), professional & business services (12.2%), and administration/transportation (10.1%). Non-manufacturing firms accounted for 51% of job losses from the export competition channel, with the same industry groups experiencing the largest non-manufacturing losses (24.5%, 12.1%, and 10.6%, respectively).

By contrast, exposed establishment in the wholesale-retail sector had quite large relative net job gains from the import access channel ($\sim$ 478,000 jobs) that dwarfed manufacturing's import access losses ($\sim$ 149,000 jobs). Overall, wholesale-retail enjoyed relative shock-induced net job creation of 248,000 jobs despite high sensitivity to both export and import competition. Expanded import access also created another $\sim$65,000 jobs across several service sectors (leisure & hospitality, administration, transportation, and information). These findings underscore the need to consider non-manufacturing industries when evaluating trade shocks. Interestingly, firms in the education/health/government sectors, with mostly white-collar service jobs, were virtually isolated from the China Shock, with no significant employment changes via any channel despite comprising 22.8% of baseline employment.

Multinational firms engaged in intrafirm international trade account for the vast majority of each channel's shock-induced employment changes. Table 7's second panel decomposes each channel's net employment change by trade engagement status. Multinational firms (RPXM and RP X|M) contribute at least 70% of the aggregate job change from our three primary channels despite representing only 26.6% of U.S. jobs. This reflects the fact that such firms' account for 83.0% of U.S. international goods imports and 81.6% of exports (Figure A1). For the import competition channel, multinational firms dominate relative employment loss primarily because they dominate baseline employment at risk: RPXM and RP X|M firms account for 58.5% of employment at manufacturing and 61.8% of shock-induced job destruction, compared to 22.0% and 13.7% for non-trading firms. RPXM firms' slightly disproportionate concentration of losses relative to employment share reflects their greater mean exposure (Table 3) rather than differential sensitivity to import competition exposure.

Relative job destruction from export competition is even more concentrated among multinationals, with RPXM accounting for 90.7%. In this case, such extreme concentration reflects both RPXM firms' greater exposure as well as greater sensitivity to exposure (as reflected in much larger coefficients). Recall that within manufacturing, RPXM firms' mean exposure is triple that of exclusively arms-length exporters, and RPXM firms in general are over twice as sensitive per unit of export competition exposure as exclusively arms-length exporters. Overall, 64.8% of job destruction at RPXM firms stems from the export competition channel, highlighting the sensitivity of these multinational firms to market conditions abroad.

Similarly, 78.2% of relative job creation caused by greater import access occurs at multinational firms, with RPXM accounting for 37.8% and RP X|M accounting for 40.4%. The large RP X|M share reflects the prevalence in service industries of related-party importing but not exporting, while the $RPXM$ share actually understates its importance, since $RPXM$ job creation via import access in wholesale/retail is offset by job destruction in manufacturing.

Employment losses were substantial in all regions, but disproportionately large in the Midwest. We distribute our firm× industry shock across regions based on regions' employment shares among firms' establishments in the chosen industry. Table 7's third panel reveals that the shock's relative impact on exposed establishments was fairly broadly distributed across U.S. regions, both by channel and overall. However, the share of job losses experienced by the Midwest and Mid-Atlantic/Appalachia ("Upper South") regions were 34% and 14% higher than their respective initial employment shares, while the job loss shares were 77%, 82%, and 83% as large as initial employment shares in the West Coast, Southwest, and Deep South. The Midwest's concentration of net employment losses reflects greater per-capita exposure to losses from import and export competition as well as smaller per-capita gains from greater import access. In contrast, disproportionate shares of import access job gains helped to offset job losses from the other two channels for the coastal regions and the Southwest.

Shock-induced relative employment losses are concentrated at high-paying firms, while gains are concentrated at low-paying firms. Table 7's last panel presents firm employment changes by channel and employment-weighted average pay quartile. Firms in the top two quartiles account for 67% and 81% of jobs destroyed by the import and export competition channels in our calibrated shock despite employing 50% of U.S. workers. By contrast, the two lowest paying quartiles account for 88% of jobs created by expanded import access, with the bottom quartile gaining nearly 100,000 jobs across all three channels. At first blush, this finding suggests that the shock may have primarily targeted high-paid workers while expanding job opportunities for low-paid workers, and thus could have reduced income inequality. However, a major goal of the paper is to explore whether labor market competition causes equilibrium worker incidence to deviate substantially from what one might predict based on the kinds of workers hired by targeted firms. Thus, characterizing the shock's worker incidence requires the counterfactual assignment model simulations presented in the next section.

5.2 Worker-Level Earnings, Welfare, and Unemployment Incidence

Recall that our worker-level incidence results rely on our calibrated shock whose scale is set by imposing zero shock-induced employment change at firms without direct exposure via our four channels. Since our goal is to better understand how the composition of firm exposure and employment responses mediate worker-level incidence for trade shocks more generally, our insights remain valid even if the calibrated shock imperfectly approximates the China Shock.

Workers at multinational manufacturing firms experience the largest earnings, welfare, and employment losses. The rightmost bars in each group of Panel (a) of Figure 1 display our estimates of the cumulative 2002-2006 earnings impact of China's WTO entry among workers classified by their 2001 sector. In keeping with much of the literature, we find that the average manufacturing worker in 2001 experiences large cumulative earnings losses over the next five years worth \$4,158 as a result of the China Shock (in 2023 dollars). Average earnings losses in other sectors are generally far smaller, between \$232 and \$1353.

Panel (a) of Figure 2 displays the five year earnings incidence of the full (all channels) China Shock by industry and trade engagement combination. Workers initially at manufacturing establishments in RPXM firms suffered the largest cumulative earnings loss (\$6,296), far above any other trade category, while losses for manufacturing workers in nontrading firms were only about one-fifth as large (\$1,378). An important driver of the concentrated earnings losses for RPXM manufacturing workers is the destruction of 135,000 RPXM manufacturing jobs via the import access channel, which exacerbated already large import and export competition shocks for such firms. In every other industry, the import access channel is either an important job creator or nearly neutral, and it is only a minor source of job destruction for other trade statuses within manufacturing. As discussed above, bi-directional related-party traders may be ideally situated to begin outsourcing inputs, since they can potentially produce customized inputs embodying the same technology abroad.

More generally, workers at $RPXM$ firms suffer the largest per-capita losses in every sector except wholesale/retail, where their losses are second largest. This reflects large multinationals' high China Shock exposure due to strong reliance on international trade.

Panel (b) of Figures 1 and 2 display analogous results for money-metric utility rather than earnings. In both figures, we see that earnings and utility exhibit extremely similar incidence distributions across sectors, channels, and trade engagement categories. However, earnings impacts are considerably larger in magnitude than utility impacts, even though the money-metric welfare impacts are scaled as earnings equivalents.

This discrepancy occurs primarily because 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, at least in the short run. Given the similarity in the distribution of losses and gains for these two outcomes, henceforth we focus on earnings and employment outcomes rather than welfare so as to facilitate comparison with reduced-form findings from the literature.

Panel (c) of Figure 1 displays the China Shock's impact on annualized unemployment risk between 2002 and 2006, both overall and by channel. While workers initially in manufacturing bear the largest increases in full-year unemployment risk of around 0.25% per year, other sectors' workers still endure increases between one-third and two-thirds as large. These results indicate that most displaced manufacturing workers 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 RPXM firms, with meaningful increases in the unemployment risk for workers from all trade engagement categories and industries. As we show below, RPXM firms generally employ a greater share of high paid workers whose skills are sufficiently portable that they can outcompete workers for either the remaining RPXM jobs or jobs at firms with less trade engagement.

The import access channel generates considerably smaller worker earnings gains than its firm employment impact would suggest. The three leftmost bars of Figure 1 Panel (a) display 5-year earnings impacts of shocks that isolate a single channel.[26] Each panel's first group of bars aggregates over industries. We find that the import and export competition shocks produce per-capita earnings losses of \$873 and \$480, while the import access shock yields earnings gains of only \$140 despite causing more net job growth (406,000 jobs) than the net job destruction caused by the export competition channel (387,000 jobs). We provide two explanations for the import access channel's disproportionately small earnings impact.

First, the import access channel's job creation mostly came from wholesale/retail and leis./admin./trans., which have much higher job turnover rates (27% and 33%) than manufacturing (18%), which bore the majority of the export competition channel's job destruction. Also, the lion's share of job creation from greater import access occurred in low-paying firms. Thus, the jobs created by expanded import access tended to be low surplus jobs with low quality amenities and/or low pay, and that workers that took them did not benefit for long.

Second, the model exhibits asymmetry in the magnitude and concentration of earnings changes between equally-sized positive and negative shocks, which further limits the earnings impact of the mostly positive import access shock. For example, in our simulation isolating the import access shock, per-capita earnings losses in manufacturing (\$809) are larger than the earnings gains in wholesale/retail (\$758), even though per capita job destruction in manufacturing is only 39% as large as per capita job creation in wholesale/retail (Figure 2(a)).

This incidence asymmetry between positive and negative shocks stems from the extra surplus generated by job retention that we demonstrated in Section 3.3. Because moving, search and training costs have already been paid and firm-specific knowledge has been formed, incumbent workers have far higher expected surplus with their existing employers than at equivalent jobs with other employers. Thus, when their jobs are destroyed, they suffer large welfare

[26]This channel "decomposition" need not sum to the China Shock's total impact, since the shocks interact with one another in equilibrium and the total includes small earnings losses from the export access channel.

losses. By contrast, new hiring due to positive shocks requires new moving, search, and training costs, and thus creates smaller surplus gains. Moreover, without firm-specific experience, many worker types are close substitutes, so idiosyncratic surplus components play a larger role in shaping the resulting allocation, so that welfare gains disperse widely across types.

We confirm this interpretation by running two pairs of single-period simulations featuring customized labor demand shocks that add and remove an equivalent number of non-traded manufacturing positions. The first pair, which uses baseline surplus values, features earnings losses among non-traded manufacturing workers from the negative shock that are nearly twice the gains from the positive shock (Figures A2 (a) and (b)). The second pair uses the same stylized shocks but restricts 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 (Figure A2 (c)).

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.

Labor market competition substantially disperses firm-level shocks outward to less-exposed industries and trade statuses, particularly for unemployment incidence. While our first findings highlight which worker types were most affected by the China Shock, per-worker losses can mislead us about the shock's aggregate burden if the most affected types make up small shares of the U.S. labor force. Thus, Figure 3 displays, for each industry and trade category, its 2001 labor force share (black-outlined bars) and its 2001 workers' estimated shares of U.S. earnings losses (narrow dark blue bars) and increased unemployment (wide light blue bars). The labor force shares remind us that the vast majority of U.S. employment occurs outside manufacturing and in nontrading firms.

Even though manufacturing establishments account for all the lost national net employment (Table 7), their 2001 workers only experience 48.8% of aggregate earnings losses and a paltry 20.8% of additional years of unemployment. These gaps reflect the role of equilibrium adjustments in spreading the initial shock. Specifically, displacement of manufacturing workers, combined with redirection of non-manufacturing workers discouraged from seeking manufacturing jobs, expands labor supply to other industries, lowering their pay levels. In addition, if firms' number of positions is inelastic in the short run, skilled manufacturing workers may outcompete less productive workers in these industries for positions, limiting their promotion opportunities and pushing them to unemployment or less desirable positions elsewhere. An analogous pattern occurs for trade engagement: the initial RPXM workers bear 47.7% of national earnings losses even though RPXM firms account for 86.3% of employment loss.

These equilibrium forces imply that even industries and trade categories whose firms enjoy net job growth due to the China Shock generally feature earnings and employment losses for their workers. For example, we estimate that the shock added 73,450 jobs at wholesale/retail

RPXM firms over five years (0.4% of their pre-shock total per year), but their 2001 workers suffer $577 in shock-induced cumulative earnings *losses* and 0.38% *greater* per-year unemployment risk relative to the most insulated worker type. This partly reflects increased competition for jobs like theirs and reduced opportunities elsewhere. However, many workers initially at unexposed firms also experience direct exposure by moving to firms or sectors that were or became exposed, 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 examining how the China Shock altered natural worker reallocation. Figure 4(a) shows the shock-induced change in destination composition among workers leaving RPXM manufacturing firms, who shed ∼86,000 jobs per year due to the shock. The shock causes 0.39% more of these workers (>9,000 extra workers) to move to the leisure/admin./trans. sector per year, 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 sizable 0.7% increase in the share of leaving workers who become unemployed. Nonetheless, the ability of most RPXM manufacturing workers to find alternative jobs, albeit at lower pay, explains the much greater dispersion of unemployment incidence than earnings incidence. Since nontrading manufacturing firms were far less exposed, fewer of their workers are induced to leave (panel (b)), but they very disproportionately move to unemployment (0.36% increase) compared to jobs elsewhere in manufacturing or in other industries. Thus, these workers, who generally have lower initial pay, face a harder time finding alternative employment.

The increased competition for jobs in the low-paid leisure/ administration/ transportation industries is also reflected in Figure 3, which shows that their 2001 workers bear 10.7% of earnings losses and 22.2% of increased unemployment even though their firms are generally not directly targeted by any of the channels. Workers in the natural resources/utilities sector also bear a much larger share of earnings and unemployment losses than their tiny share of firm-level job losses would suggest. By contrast, workers in the education/health/government sector are much better insulated, accounting for only 5% of earnings losses and 9.7% of increased unemployment despite their larger baseline labor force share (22% vs. 18%). This indicates that other industries' workers do not generate enough surplus with education/health/government employers to effectively compete with these workers. This finding corroborates the intuition that manufacturing workers and professionals are very poor substitutes, and reflects the high rates of both job retention and intra-industry mobility within education/health/government.

Unlike industries, regional shares of earnings losses and unemployment increases mostly mirror the regional shares of firm-level employment losses, suggesting that the large regional mobility frictions documented in Section 3.3 dampen the dispersion of incidence. Specifically, row 1 of Table 8 shows that regional differences in firm-level job losses translate to differences in per-worker earnings losses: the Midwest region suffered the largest per-worker earnings losses ($1,507), while the Deep South region was most insulated ($524). The larger losses in the

Midwest reflect greater percentage employment loss in most industries as well as high baseline manufacturing employment. The Deep South's small losses reflect its low baseline share of workers with high pay at stake, since it has similar per-capita exposure to other regions.

Table 8's second panel shows the corresponding impacts of the shock on per-year unemployment. The regional pattern is fairly similar, except that the Deep South's substantial shock exposure is more reflected in unemployment rate increases than earnings.

Labor market competition also substantially disperses firm-level shocks downward to less-exposed low-paid and unemployed workers. Thus, despite net job creation at low-paying firms, lower-paid workers experience disproportionate welfare and particularly employment losses.

The substantial unemployment increases for workers from the low-paying leis./ admin./ trans. sectors suggest that an implicit job ladder mediated the China Shock's incidence. To this end, Figure 5 displays earnings and unemployment outcomes by initial earnings category. Economywide, earnings losses increase with higher initial earnings, but percentage losses decrease. In general, low and lower-middle paid workers' share of national earnings losses from the China Shock exceeds their initial share of national earnings, while the opposite holds for the highest paid workers. Thus, the shock contributed to greater earnings inequality despite causing substantial net job creation among the lowest-paying employment-weighted quartile of firms and major job destruction among the highest-paying quartiles. This counterintuitive result underscores the importance of assessing equilibrium incidence at the worker level rather than relying on the distribution of firm- or sector-level payroll changes. Interestingly, the opposite holds for unemployment: increases are larger for lower and middle-paid workers, but they have much higher baseline rates of transition to unemployment, so the shock made the composition of unemployment risk among initial earnings categories less regressive.

Table 9 investigates which industry/trade combinations drive these aggregate findings. Rows 1-4 of column 1 display earnings incidence by initial earnings category among workers initially in the hardest hit RPXM manufacturing sector. The national patterns mostly recur, with earnings losses strictly increase with initial pay. Those in the top two national deciles lose an estimated $7,640 on average over 5 years relative to the economy's most insulated workers. In fact, due to RPXM manufacturing's high share of highly paid workers, their decile 9-10 workers bore 15.5% of national earnings losses, far more than the bottom *five* deciles (5.8%). In this sense, the disproportionate job losses among high-paying firms in general and RPXM firms in particular translate to a greater burden among high-paid workers, at least in the most targeted sector. Percentage losses relative to baseline pay peak for decile 3-5 workers (1.9% of earnings per year), however, before declining to 0.8% for deciles 9-10.

Column 4 shows that increases in unemployment risk fall monotonically with RPXM manufacturing workers' initial pay, with deciles 1-2 workers experiencing a 0.53% higher unemployment rate per year compared to 0.19% for deciles 9-10. These patterns imply that high paid workers either outcompete less skilled/experienced workers for remaining manufacturing jobs or generate more surplus with firms in other industries. Notably, even though non-traded manufacturing's firm-level per capita job losses were only one-fifth as large as $RPXM$ manufacturing, its lowest paid workers' earnings losses and increased unemployment risk are half as large (col. 6-10). This suggests that increased competition for jobs from displaced RPXM workers particularly affects non-traded manufacturing's low-paid workers.

Table 9's second panel displays the earnings and employment losses for workers initially within the wholesale/retail sectors at RPXM and arms-length importing (M) firms. Even though the China Shock generated 240,000 net jobs at wholesale/retail firms, we see only tiny earnings gains and small earnings losses, respectively, for initially low paid workers at RPXM and M firms in this sector compared to the most insulated workers. These patterns are partly explained by the asymmetrically small impact of job creation discussed above. 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, a more subtle mechanism suppressing earnings gains stems from the very low job retention rates among wholesale/retail's low-paid workers: only 62% of decile 1-2 workers at RPXM wholesale/retail firms retained their dominant job between 2001 and 2002, compared with 81% from deciles 9-10 and 92% among educ./health/gov. workers from deciles 9-10. This implies that many wholesale/retail workers who kept a job they would have lost or gained a promotion would have soon moved to other jobs anyway, limiting their earnings gains relative to a counterfactual without the China Shock. Put simply, greater job security in or expanded access to a low quality job minimally improves earnings or utility prospects.

Though firms in leis./admin./trans. sectors were only mildly exposed to the China Shock, Table 9 also shows that percentage earnings losses and increased unemployment risk both decrease monotonically with initial earnings deciles, with their lower-paid workers bearing a non-trivial increased unemployment risk of 0.14-0.21% per year. This is consistent with their being near the bottom of the economy-wide job ladder. By contrast, firms in the educ./health/gov. sectors also experienced very little direct shock exposure, but earnings losses are 25-65% as large as in leis./admin./trans. across earnings categories, and unemployment increases are 30-60% as large and truly tiny for higher paid workers (0.03%). The high-paying jobs in these sectors often require very high levels of specialized education and training, so workers displaced by the China Shock are particularly poor substitutes for these workers, insulating the latter from trade shocks more generally.

Finally, a key advantage of our data and assignment model is the ability to track what happens to initially unemployed workers. Figure 3 shows that such workers (including new entrants), many of whom would have found jobs faster in the absence of the China Shock, account for 13.4% of all shock-induced full year unemployment spells despite making up 9.05% of the 2001 labor force. Both new entrants and older (over age 25) unemployed workers experience larger increases in per-person unemployment rate (0.15% and 0.20% per year, respectively) than the mean in any non-manufacturing sector, despite lacking an initial job for the trade shock to target, and despite the substantial job creation in the wholesale/retail sector, which frequently hires workers from unemployment. Interestingly, we find that only 5.8% of initially unemployed workers would have taken manufacturing positions in the absence of the shock. Instead, the shock pushes initially employed workers to positions in other sectors that frequently hire workers from unemployment, such as non-trading service firms. Thus, existing long-term unemployed workers act as last resort hires for firms, making their employment status vulnerable even to shocks harming firms with workers who are seemingly poor substitutes.

Most workers are quite sensitive to aggregate shocks, even when their own type of job is untargeted. In well-integrated labor markets, intense but localized shocks become quite diffuse in their incidence, while large aggregate shocks that affect most workers will strongly impact labor market outcomes even for workers in the seemingly untargeted job types. By contrast, intense but localized shocks generate highly concentrated incidence in segmented labor markets, while workers not directly exposed to even a large aggregate shock may be virtually unaffected. Because the China Shock was both large and quite varied in its targeting, with both heavily exposed and highly insulated firm types, it provides an ideal opportunity to assess more broadly the degree of U.S. labor market integration.

To this end, we regress worker types' average shock-induced changes in earnings and unemployment rates in our baseline simulation on measures of worker types' "local" and "aggregate" exposure to firm-level job loss. We approximate local exposure using the shock-induced percentage change in firm-level employment within each worker type's initial region-industry-trade status in the chosen year, while aggregate exposure is captured by the worker-weighted average of this measure among all worker types besides the worker's own. Column 1 of Table 10 shows that a 1% decrease in aggregate exposure produces 2.5 times the predicted earnings loss (∼\$100,000) as a 1% decrease local exposure, holding other firm types' employment fixed (∼\$40,000). In one sense, more sensitivity to indirect exposure to a 1% aggregate shock than direct exposure to a 1% local shock suggests that U.S. labor markets are quite integrated, at least among region-industry-trade status combinations. However, with 3,528 worker types in the model, an average worker type makes up ∼.03% of all employment, so a 1% aggregate shock to all other types often produces thousands of times more national job loss than a 1% shock targeting only one worker type's jobs. So in another sense, workers are still highly sensitive to labor demand shocks within their own firm types compared to shocks to any other firm type.

The unemployment rate results are more extreme, with a 1% increase in a worker's indirect aggregate exposure yielding 10 times the rise in unemployment rate of a 1% increase in strictly local exposure (col. 2). This mirrors our findings above that many workers displaced by a localized shock can outcompete other workers for job opportunities in their firm types, so that most workers are far from the unemployable margin unless there is a large aggregate shock.

Columns 3 and 4 augment these regressions by interacting both local and aggregate exposure with the worker type's earnings category. The ratio of coefficients across exposure measures stays between two and four throughout the earnings distribution, but earnings sensitivity to both kinds of exposure rises with initial earnings, since high paid workers have more to lose from a shock that threatens their job. In contrast, low paid workers' unemployment rates are much more sensitive to both local and aggregate exposure than higher paid workers, consistent with their job matches generally producing, making them more likely to be the economy's marginal employees. Finally, while local exposure is undefined for initially unemployed workers (since they have no associated firm type), we find that those over 25 years old have extremely high earnings and unemployment rate sensitivity to aggregate labor market conditions compared to those initially employed and twice the sensitivity of "new entrants" 25 and under, consistent with the latter being more productive (if less experienced) than the older unemployed.

6 Robustness Checks

Table 11 assess the robustness of our earnings impacts by industry, trade status, and initial earnings category to a variety of methodological choices. To ease comparisons, col. 1 and 2 re-report our baseline results for the full China Shock and for the import access channel only.

Column 3 examines sensitivity to controlling for 6-digit rather than 4-digit NAICS fixed effects when creating our firm-level shocks. An advantage of using firm-level data to form exposure measures is the ability to fully control for arbitrary unobserved industry shocks at such a low level of disaggregation. Earnings losses are around 20% smaller than in our baseline, but feature a very similar distribution, reflecting the fact that most of the variation driving our initial regression results already came from firm comparisons within 6-digit industries.

Column 4 reports results that incorporate employment creation and destruction due to upstream and downstream exposure. Because our regression estimates suggest that downstream exposure generates substantial additional firm-level employment losses that are not offset by the small gains from upstream exposure, the augmented shock imposes 30-50% larger earnings losses than our baseline. Thus, accounting for indirect I-O effects is potentially important for the shock's estimated magnitude, consistent with Pierce et al. (2024), though these results are sensitive to specification. However, the distribution of earnings gains and losses across industries, trade statuses, and initial earnings categories is generally quite stable, so that none of our main results about relative incidence are sensitive to including these additional channels.

Column 5 holds industry and trade status fixed at 2001 values for firms already operating in 2001, rather than letting them evolve as they do in the data. On one hand, changes in industry and trade status could be endogenous responses to the shock itself, so that later net employment losses in formerly manufacturing firms might still reflect the kinds of jobs that manufacturing workers held or could have held. On the other hand, a firm that has transformed from primarily manufacturing to primarily wholesale/retail might respond to subsequent waves of shocks more like other wholesale/retail firms.[27] We find that fixing industry and trade status reduces manufacturing losses and slightly increases losses for some trade statuses within wholesale/retail. This reflects Bloom et al. (2024)'s finding that the period's wholesale/retail job growth stemmed partly from firms converting establishments from manufacturing to wholesale/retail, since here we allow existing workers to be potential job stayers at such positions, restoring some of the earnings losses from removing the possibility of retaining one's job.

Column 6 examines whether our earnings inequality results are sensitive to the assumption that joint surplus comparative advantages are exogenous to the China Shock. In particular, here we allow the China Shock to possibly change the relative productivity of workers within the most exposed firms, perhaps because imported inputs act as complements to high paid skilled workers/managers and substitutes for low paid production staff (Hummels et al., 2018; Keller and Utar, 2023). Specifically, we 1) compute the observed mean change in estimated relative surpluses from matching with high vs. low paid workers among manufacturing and wholesale jobs for each shock year, and 2) treat this change as fully induced by the shock (an extreme assumption) and impose it along with the baseline firm-level employment demand shock. Allowing for endogenous surplus changes causes slightly larger earnings losses for initially low paid workers and slightly smaller earnings losses for moderately high paid workers, but with minimal overall impact on the shock's implications for earnings inequality.

Column 7 presents earnings impacts of a simulated China Shock that excludes the export access channel, since it generated employment changes that were inconsistent in sign and statistical significance across specifications, and theory predicts that expanded export access should cause labor demand increases rather than decreases. The earnings incidence is negligibly affected, consistent with the tiny size of the export access shock ($\sim$ 20,000 jobs lost).

The shock evaluated in columns 8 and 9 restricts import access exposure to firms that already imported *from China* the goods whose tariff threat was removed, and treats as unexposed those who initially imported such goods from other countries. This measure is quite conservative, as it isolates the intensive margin response of those with an existing Chinese importer of the targeted goods, and controls for endogeneous selection into becoming an importer of such goods, but could understate the impact of expanded import access by treating as control firms those that can easily find a Chinese supplier once incentivized. Since we only alter import access exposure, we focus on comparing simulations that isolate the import access shock (cols. 2 and 9). As expected, the conservative measure shrinks the earnings gains for wholesale/retail (by $\sim$30%) and the earnings losses in manufacturing, with the largest reductions for $RPXM$ manufacturing firms that can easily source their inputs from Chinese suppliers.

The last two columns demonstrate the importance of allowing exposure sensitivity to vary

[27] Endogenous industry and trade status changes are less consequential for our identification strategy, which exploits firms' product composition, than one where firm exposure depends on industry and trade classifications.

by industry/$RPXM$ status. It reports results from a simulation based on simplified regressions that omit such interactions combinations, so that exposure sensitivity only varies by firm size/$RPXM$ combinations. While the overall results are generally fairly similar, requiring common sensitivity to import access exposure removes the negative outsourcing effect among manufacturing workers and weakens the gains from import access outside manufacturing to fit the overall slope of employment with respect to greater import access exposure.

7 Conclusion

Our evaluation of the worker-level incidence of the first five years of the China Shock has generated several new insights: 1) the well-documented 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; 2) most of the firm-level employment losses and gains induced by China's WTO entry occurred at large, high-paying, multinationals; 3) despite the concentration of job losses within manufacturing, large shares of earnings and particularly employment losses were borne by non-manufacturing workers; and 4) despite the concentration of job loss at high-paying firms, equilibrium losses of earnings growth and particularly net employment were greater for initially low and medium-paid workers.

Perhaps more importantly, we highlight several mechanisms generating these findings that are likely to shape the incidence of any future shock to international trade. First, trade shocks that affect either competition at key U.S. export destinations or access to imports from major producers of cheaper inputs or final goods can cause large shifts in the distribution and level of employment among trading firms, especially multinationals. These channels and their particular impact on multinational firms have received inadequate attention in part because much of their employment impact occurs outside manufacturing, where data is often less reliable or available, and because data on firm-level related-party trade is often unavailable. Second, imperfect mobility of human capital across firms causes job ladders within and across industries, so that large shares of earnings gains or losses trickle down to lower-paid and initially unemployed workers even for trade shocks targeting high-paying firms or industries. Third, even neutral trade shocks that generate job gains and losses of similar size and composition are likely to cause short-run average welfare losses, as firm-specific knowledge is lost and search, moving, and training costs must be re-paid. Finally, how concentrated welfare loss from job destruction will be depends strongly on how long workers would otherwise have stayed. Thus, job retention rates among the kinds of positions likely to be destroyed by labor demand shocks are an underappreciated indicator of the concentration of welfare losses they will generate.

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8 Tables and Figures

Table 1: Decompositions of Job Flows by Categories of Worker and Firm Characteristics

	Stayers	**E-E**	**E-N**	**N-E**	**N-N**	**Same Region**	**Same Sector**	**Same Trade Eng.**
Overall Employed	0.791	0.171	0.038			0.916	0.532	0.595
	Unemployed							
Young Unemployed				0.920	0.080			
Old Unemployed				0.761	0.239			
	Initial Earnings							
Deciles 1-2	0.650	0.266	0.084			0.928	0.459	0.603
Deciles 3-5	0.770	0.192	0.039			0.921	0.482	0.593
Deciles 6-8	0.848	0.131	0.021			0.915	0.567	0.599
Deciles 9-10	0.869	0.113	0.018			0.897	0.625	0.584
	Industry							
Res./Cons./Util.	0.729	0.173		0.098		0.921	0.517	0.731
Manufacturing	0.821	0.127		0.052		0.906	0.441	0.440
Wholesale/Retail	0.729	0.172		0.099		0.924	0.473	0.445
Trans./Hosp./Admin.	0.671	0.196		0.133		0.921	0.530	0.630
Information	0.770	0.162		0.068		0.912	0.375	0.450
Fin./RE/Prof. Serv.	0.741	0.184		0.075		0.906	0.492	0.561
Educ./Health/Gov.	0.808	0.130		0.062		0.926	0.594	0.739
	Trade Engagement							
NT	0.740	0.165		0.096		0.921	0.522	0.761
M	0.748	0.161		0.091		0.929	0.492	0.100
XM	0.751	0.175		0.074		0.920	0.504	0.150
XM	0.774	0.153		0.073		0.920	0.503	0.128
RP X|M.	0.748	0.172		0.080		0.919	0.482	0.176
RP X&M.	0.800	0.144		0.056		0.900	0.503	0.421
	Firm Average Pay							
Q1	0.655	0.191		0.154		0.927	0.512	0.644
Q2	0.760	0.158		0.082		0.919	0.496	0.603
Q3	0.796	0.146		0.058		0.915	0.511	0.581
Q4	0.796	0.154		0.050		0.909	0.538	0.542
	Firm Size							
$<$ 250 employees	0.727	0.174		0.099		0.921	0.506	0.670
$>$ 250 employees	0.778	0.150		0.073		0.916	0.525	0.499

Source: LEHD, LFTTD and LBD databases.

Notes: Columns 1-5 of the first row of 1 reports the composition of year-to-year transitions between dominant jobs (or unemployment) among all initially employed worker-year observations in our simulation sample (spanning 2001-2002 to 2005-2006). "Stayers" reports the share of job retentions among all transitions, while "E-E", "E-N" report the shares that transitioned to another employer and unemployment, respectively. For initially unemployed workers, "N-E" and "N-N" report the share who did and did find qualifying employment in chosen year. Among workers that made E-E transitions, "Same Region/Sector/Trade Eng." report the share whose new employer's region/industry category/trade engagement category matched that of their previous employer. The remaining rows display these shares by either worker initial earnings category or the hiring firm's industry, trade engagement, average, pay, or size category.

Table 2: What Drives the Variation in Joint Surplus Values? - Regressions of Joint Surpluses on Job Transition Characteristics

	θ_{lf}	α_{lf}	γ_{lf}
1(Same Region)	1.526***	0.977***	0.702***
	(0.0007)	(0.0008)	(0.0009)
1(Adjacent Region)	0.302***	0.178***	0.158***
	(0.0006)	(0.0007)	(0.0008)
1(Same Sector)	0.481***	0.539***	-0.0628***
	(0.0006)	(0.0007)	(0.0008)
1(Same Earnings)	0.308***	0.244***	0.0835***
	(0.0007)	(0.0009)	(0.0010)
1(Same RP X&M)	0.264***	0.00211	0.327***
	(0.0014)	(0.0017)	(0.0019)
1(Same Trade Status)	0.151***	0.192***	-0.0478***
	(0.0008)	(0.0009)	(0.0010)
1(Stayer)	1.114***	0.894***	0.290***
	(0.00301)	(0.00358)	(0.00391)
Observations	7,019,000	7,019,000	7,019,000
R-squared	0.472	0.251	0.108

Source: LEHD, LFTTD and LBD databases.

Notes: ***,**, and * denote significance at the 1%, 5%, and 10% levels. Column 1 of Table 2 presents coefficients from regressions of estimated joint surplus values θ_g at the worker-type×firm-type× stayer/mover indicator level on combinations of the characteristic categories that define the group. Columns 2 and 3 consider the firm (α_{lf}) and worker (γ_{lf}) non-pecuniary components of the joint surplus, respectively. "1(Same Region)" and "1(Adjacent Region)" are indicators indicator for whether the worker type $l(g)$ and firm-type $f(g)$ are associated with the same region and adjacent region, respectively. "1(Same Sector")" captures whether $l(g)$ and $f(g)$ are associated with the same industry category, so that all job transitions in such groups are within-sector. "1(Same Earnings)" capture whether the worker type $l(g)$ has median baseline earnings *and* the firm type $f(g)$ has above median average worker pay (intended to capture skill/productivity complementarities). "1(Same Trade Status)" indicates whether the worker type and firm type belong to the same trade engagement status, while "1(Same RP X&M)" indicates whether the transitions in the chosen group g involve workers already at RPXM firms staying or moving to other RPXM firms. "1(Stayer)" indicates whether group g is associated with workers who remain at the same firm as the previous year.

Table 3: Means and Standard Deviations of the Four Channel-Specific Exposure Measures by Industry and Trade Engagement Status Among Firm-Industry-Years in the Regression Sample.

	Import Competition	Export Competition	Import Access	Export Access
Overall	0.148	0.010	0.041	-0.011
	(0.084)	(0.013)	(0.042)	(0.003)
		Industry		
N.Res./Cons./Util.	0.062	0.011	0.019	-0.008
	(0.130)	(0.029)	(0.052)	(0.142)
Manufacturing	0.286	0.005	0.011	-0.002
	(0.182)	(0.020)	(0.044)	(0.017)
Wholesale/Retail	0.034	0.011	0.097	-0.01281
	(0.107)	(0.029)	(0.126)	(1.787)
Leis./Admin./Trans.	0.051	0.017	0.027	-0.042
	(0.124)	(0.038)	(0.069)	(3.746)
Information	0.045	0.010	0.018	-0.004
	(0.116)	(0.028)	(0.052)	(0.019)
Fin./RE/Prof. Serv.	0.093	0.015	0.036	-0.010
	(0.159)	(0.034)	(0.078)	(0.221)
Educ./Health/Gov.	0.026	0.015	0.010	-0.010
	(0.092)	(0.038)	(0.042)	(0.086)
		Manufacturing		
NT	0.286			
	(0.184)			
M	0.322		0.085	
	(0.191)		(0.095)	
X	0.284	0.019		-0.005
	(0.175)	(0.033)		(0.029)
XM	0.296	0.019	0.063	-0.005
	(0.177)	(0.034)	(0.086)	(0.014)
RP X|M.	0.274	0.026	0.060	-0.008
	(0.172)	(0.040)	(0.093)	(0.064)
RP X&M.	0.264	0.034	0.113	-0.011
	(0.15)	(0.042)	(0.102)	(0.029)
		Wholesale/Retail		
M	0.009		0.146	
	(0.059)		(0.127)	
X	0.018	0.015		-0.017
	(0.080)	(0.033)		(2.235)
XM	0.029	0.014	0.136	-0.006
	(0.104)	(0.030)	(0.128)	(0.040)
RP X|M.	0.040	0.015	0.144	-0.045
	(0.116)	(0.034)	(0.137)	(3.712)
RP X&M.	0.139	0.026	0.158	-0.010
	(0.166)	(0.038)	(0.120)	(0.143)

Source: LFTTD and LBD databases.

Notes: The top panel of Table 3 displays the mean and standard deviation (in parentheses) among firm-industry-year observations in our regression sample assigned to each industry category of the exposure measures listed in the column labels. See section 4.1 for definitions of the various exposure measures. The regression sample consists of all firm-years that were at risk of exposure via at least one channel (see section 4.2), which captures all internationally trading firms as well as purely domestic firms that operated at least one manufacturing establishment in the chosen year. The second and third panels report separate means and standard deviations of each exposure measure for each firm trade engagement status among firm-year observations whose firm's predominant employment is in manufacturing or wholesale/retail, respectively.

Table 4: Decomposing the Variance in Exposure to Each Channel into Within- and Between-Industry Components

	Variance Share	
	NAICS 4	**NAICS 6**
Import Competition	0.4713	0.644
Export Competition	0.0281	0.04154
Import Access	0.1452	0.164
Export Access	0.0017	0.0020

Source: LEHD, LFTTD and LBD databases.
Notes: Column 1 presents the share of the variance among all firm-year observations that exists between means at that NAICS 4-digit industry level for each of the four channel's exposure measure (rows). Column 2 presents the corresponding variance share that exists between NAICS 6-digit industry means.

Table 5: The Share of Employment at Single vs. Multi-Sector Firms by Primary Industry

	Employment Share		
	Single Sector	**2 Sectors**	**3 or < Sectors**
Overall	0.2729	0.2301	0.4969
N.Res./Cons./Util.	0.2222	0.2376	0.5402
Manufacturing	0.4296	0.1566	0.4138
Wholesale/Retail	0.2363	0.2119	0.5517
Leis./Admin./Trans.	0.2351	0.3131	0.4518
Information	0.1509	0.2125	0.6367
Fin./RE/Prof. Serv.	0.2947	0.2122	0.4930
Educ./Health/Gov.	0.263	0.2234	0.5136

	Employment Share						
	N. Res. Cons. Util.	**Manuf.**	**Whole. Retail**	**Leis. Adm. Trans.**	**Inform.**	**Fin. Real Est. Prof. Srv.**	**Educ. Health Gov.**
Manufacturing	0.1456		0.4589	0.3109	0.0839	0.4066	0.0359
Wholesale/Retail	0.06059	0.4023		0.5009	0.1777	0.6000	0.0238

Source: LEHD, LFTTD and LBD databases.
Notes: The first panel of Table 5 provides the share of employment is in firms operating establishments in a single industry category, two industry categories, or three or more industry categories, among firms whose employment plurality is in the industry category provided in the row label. The second panel provides the share of firms whose employment plurality is in either manufacturing or wholesale/retail that also operate establishments in each of the other industry categories given by the column labels. The table shows that large shares of national employment are concentrated in multi-industry firms, and that large manufacturing and wholesale/retail firms often operate establishments in each other's industry. They also often operate establishments in the transportation and professional services sectors.

Table 6: Employment Growth Effects of Exposure to China's WTO Entry

	(1)	(2)	(3)		(4)		(5)	(6)	
			No RPXM	RPXM	No RPXM	RPXM		No RPXM	RPXM
Import Competition	-0.0135***		-0.0134***	-0.0177			-0.0146***		
	(0.0032)		(0.0032)	(0.0123)			(0.0032)		
× **1(< 250 Employees)**		-0.0114***			-0.0115***	-0.0086		-0.0126***	-0.0089
		(0.0033)			(0.0033)	(0.0159)		(0.0033)	(0.0159)
× **1(> 250 Employees)**		-0.0401***			-0.0429***	-0.0333*		-0.0434***	-0.0336*
		(0.0118)			(0.0128)	(0.0189)		(0.0128)	(0.0189)
Export Competition	-0.116***		-0.0986***	-0.228***			-0.117***		
	(0.0172)		(0.0181)	(0.0518)			(0.0172)		
× **1(< 250 Employees)**		-0.111***			-0.0989***	-0.231***		-0.0991***	-0.231***
		(0.0178)			(0.0184)	(0.0647)		(0.0184)	(0.0647)
× **1(> 250 Employees)**		-0.185***			-0.0856	-0.189**		-0.0858	-0.190**
		(0.0639)			(0.0839)	(0.0871)		(0.0840)	(0.0871)
Import Access	0.0328***		0.0337***	0.0330*			0.0328***		
	(0.00680)		(0.00716)	(0.0189)			(0.00681)		
× **1(< 250 Employees)**		0.0333***			0.0305***	0.0630***		0.0304***	0.0631***
		(0.0070)			(0.0073)	(0.0229)		(0.00726)	(0.0229)
× **1(> 250 Employees)**		0.0333			0.113***	-0.0156		0.113***	-0.0154
		(0.0244)			(0.0365)	(0.0308)		(0.0365)	(0.0308)
Export Access	-0.0004***		-0.0004***	0.0058			-0.0004***		
	(4.77e-05)		(4.54e-05)	(0.0373)			(4.78e-05)		
× **1(< 250 Employees)**		-0.0004***			-0.0004***	-0.0005		-0.0004***	-0.0005
		(4.60e-05)			(4.52e-05)	(0.0351)		(4.52e-05)	(0.0351)
× **1(> 250 Employees)**		0.0137			0.002	0.120		0.002	0.121
		(0.0155)			(0.009)	(0.077)		(0.009)	(0.077)
Upstream Exposure							0.0196	0.0192	
							(0.0305)	(0.0305)	
Downstream Exposure							-0.0966***	-0.0960***	
							(0.0175)	(0.0175)	
Additional Controls	X	X	X		X		X	X	
Fixed Effects	X	X	X		X		X	X	
Observations	903,000	903,000	903,000		903,000		903,000	903,000	
R-Squared	0.112	0.112	0.112		0.112		0.112	0.112	
				Specification Tests					
Model Test						**(4) vs (1)**	**(4) vs (2)**	**(4) vs (3)**	**(Full) vs (4)**
F-statistic						2.250	2.217	2.023	2.909
						[0.0213]	[0.0233]	[0.0186]	[0.00006]

Source: LEHD, LFTTD and LBD databases.

Notes: Table 6 reports the coefficients on firm-level measures to each of four channels through which China's WTO entry affected firm employment growth, in some cases interacted with other firm characteristics, from restricted versions of specification (15) in Section 4.2. Specification (1) imposes equal sensitivity among all firms to each channel of shock exposure. Spec. (2) allows sensitivity to each channel's exposure measure to vary by the firm's $RPXM$ status, i.e. whether the firm imported and exported with related-parties in the chosen year. Spec. (3) allows sensitivity to each exposure meaure to vary by the combination of $RPXM$ status and firm size (> vs. < 250 employees). Spec. (4) augments spec. (1) with measures of the firm's upstream and downstream exposure based on NAICS6-level input-output tables (see Section 4.2). Spec. 5 augments spec. (3) with measures of upstream and downstream exposure. 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. All baseline continuous controls and fixed effects described in Section 4.2 are included in each specification.

Table 7: **Firm-Level Distribution of Shock-Induced Relative Employment Gains and Losses by Channels**

		Cumulative Shock Size by Industry (000s)						
	Total	**Res. Cons. Util.**	**Manuf.**	**Wholes. Retail**	**Leis. Admin. Transp.**	**Finance Real Estate Prof. Serv.**	**Information**	**Educ. Health Gov.**
Import Competition	-623	-17	-289	-133	-63	-76	-31	-14
Export Competition	-388	-5	-195	-96	-41	-47	-12	7
Import Access	407	21	-149	478	46	-7	19	-1
Export Access	-24	-3	0	-1	-7	-9	0	-3
Total	-628	-4	-633	248	-65	-139	-24	-11
		Cumulative Shock Size by Trade Engagement (000s)						
	Total		**Non-Traded**	**Importer Only**	**Exporter Only**	**Exporter & Importer**	**Related Party Importer or Exporter**	**Related Party Importer & Exporter**
Import Competition	-623		-50	-12	-59	-68	-111	-324
Export Competition	-388		0	0	-8	-9	-19	-352
Import Access	407		0	30	0	59	164	154
Export Access	-24		0	0	-2	0	-1	-21
Total	-628		-50	18	-69	-18	33	-543
		Cumulative Shock Size by Region (000s)						
	Total	**West Coast**	**South West**	**Great Plains**	**Deep South**	**Upper South**	**Mid-West**	**North-East**
Import Competition	-623	-84	-74	-45	-84	-81	-145	-109
Export Competition	-388	-65	-45	-25	-45	-45	-85	-77
Import Access	407	72	59	25	61	45	62	82
Export Access	-24	-4	-4	-2	-3	-2	-6	-5
Total	-628	-81	-64	-47	-71	-83	-174	-109
		Cumulative Shock Size by Firm Average Pay (000s)						
	Total				**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
Import Competition	-623				-60	-139	-186	-237
Export Competition	-388				-42	-30	-91	-225
Import Access	407				198	162	42	5
Export Access	-24				-4	-3	-5	-13
Total	-628				92	-10	-240	-470

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 among firms exposed to at least one of our four channels relative to unexposed firms. The estimates are based on predicted values from the firm-level, channel-specific regressions (15) 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 8: 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						
Overall	-896.9	-883.7	-1084.3	-524.4	-1065.6	-1507.5	-976.2
Manufacturing	-3927.1	-3469.9	-4099.0	-3453.7	-4090.3	-4678.4	-4464.1
N.Res./Cons./Util.	-510.8	-690.2	-720.1	-236.7	-625.4	-1049.1	-539.5
Wholesale/Retail	-282.8	-413.6	-502.1	22.4	-451.0	-690.2	-195.6
Leis./Admin./Trans.	-551.9	-632.9	-685.2	-209.3	-625.4	-898.3	-563.1
Information	-1163.7	-1324.4	-1297.0	-940.7	-1051.5	-1938.6	-1515.0
Fin./RE/Prof. Serv.	-1005.4	-1066.5	-1064.0	-634.2	-1036.6	-1562.4	-1280.8
Educ./Health/Gov.	-244.2	-284.1	-360.1	83.5	-296.5	-423.6	-114.6
Unemployed	-696.5	-731.3	-867.2	-474.7	-929.4	-1145.0	-898.3
	Per-Year Changes in the Unemployment Rate						
Overall	0.09	0.10	0.11	0.13	0.12	0.15	0.12
Manufacturing	0.17	0.17	0.18	0.24	0.19	0.23	0.25
N.Res./Cons./Util.	0.10	0.10	0.13	0.14	0.12	0.18	0.14
Wholesale/Retail	0.08	0.09	0.10	0.11	0.10	0.14	0.10
Leis./Admin./Trans.	0.11	0.12	0.15	0.15	0.14	0.19	0.15
Information	0.09	0.11	0.13	0.16	0.12	0.18	0.13
Fin./RE/Prof. Serv.	0.07	0.08	0.10	0.11	0.09	0.13	0.09
Educ./Health/Gov.	0.04	0.04	0.05	0.06	0.05	0.07	0.05
Unemployed	0.13	0.15	0.17	0.21	0.19	0.23	0.19

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 2023 $) 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.

Table 9: 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 X&M					Manufacturing - Non-Traded				
1-2	-2142.79	-7.06	-0.26	0.53	0.52	-836.75	-3.48	-0.34	0.28	0.94
3-5	-4577.06	-9.60	-5.58	0.35	3.56	-1231.57	-2.82	-1.31	0.18	1.60
6-8	-6239.04	-7.76	-14.32	0.22	4.18	-1555.03	-2.05	-1.33	0.12	0.84
9-10	-7639.69	-4.24	-15.46	0.19	3.23	-2058.69	-1.08	-0.67	0.09	0.25
	Wholesale/Retail - RP X&M					Wholesale/Retail - M				
1-2	-544.42	-2.57	-0.52	0.14	1.10	-224.21	-1.08	-0.04	0.14	0.21
3-5	-364.89	-0.87	-0.44	0.09	0.93	83.28	0.20	3.72	0.09	0.20
6-8	-468.36	-0.61	-0.45	0.08	0.63	361.26	0.48	10.83	0.07	0.10
9-10	-1092.76	-0.52	-0.83	0.08	0.53	834.10	0.40	11.78	0.06	0.04
	Information					Education/Health/Government				
1-2	-639.23	-2.94	-0.15	0.23	0.44	-277.23	-1.30	-1.05	0.12	3.73
3-5	-600.81	-1.30	-0.30	0.14	0.60	-237.35	-0.54	-1.69	0.05	3.14
6-8	-859.05	-1.06	-0.78	0.11	0.85	-195.76	-0.25	-1.56	0.03	1.96
9-10	-1307.85	-0.62	-1.32	0.12	1.02	-233.89	-0.13	-0.92	0.03	0.94
	Natural Resources/Construction/Utilities					Leisure/Administration/Transportation				
1-2	-536.67	-2.24	-0.37	0.26	1.51	-449.17	-2.21	-2.88	0.21	11.12
3-5	-545.43	-1.20	-1.13	0.16	2.73	-544.21	-1.32	-3.32	0.14	6.98
6-8	-571.51	-0.72	-1.50	0.10	2.24	-610.25	-0.80	-2.53	0.09	3.03
9-10	-844.91	-0.48	-1.50	0.08	1.20	-925.70	-0.50	-1.66	0.07	1.10
	Finance/Real Estate/Professional Services									
1-2	-510.31	-2.22	-0.62	0.18	1.87					
3-5	-684.49	-1.51	-2.20	0.10	2.79					
6-8	-989.76	-1.25	-4.21	0.08	2.69					
9-10	-1659.49	-0.68	-7.04	0.08	2.99					

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 2023 $), 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 10: How Integrated Are U.S. Labor Markets? The Sensitivity of Earnings and Employment Outcomes to the Idiosyncratic vs. National Component of the China Shock

	Earnings ($)		**Unemployment Rate**	
	(1)	**(2)**	**(3)**	**(4)**
Aggregate shock share	102,800**		0.9155**	
	(1507)		(0.010)	
× Deciles 1-2		75,400**		2.039**
		(4,491)		(0.019)
× Deciles 3-5		111,600**		1.027**
		(4,494)		(0.019)
× Deciles 6-8		131,867**		0.6576**
		(4,498)		(0.019)
× Deciles 9-10		192,700**		0.6522**
		(4,499)		(0.019)
× New Entrants		124,900**		1.244**
		(28,630)		(0.118)
× Unemployed		262,700**		3.833**
		(28,620)		(0.118)
Type shock share	40,740**		0.0931**	
	(317)		(0.002)	
× Deciles 1-2		21,150**		0.1952**
		(596.6)		(0.002)
× Deciles 3-5		32,430**		0.09602**
		(596.9)		(0.002)
× Deciles 6-8		37,523**		0.0565**
		(595)		(0.002)
× Deciles 9-10		46,600**		0.05298**
		(595)		(0.002)
Observations	8,900	8,900	8,900	8,900
R-squared	0.760	0.760	0.760	0.760

Source: Simulations based on LEHD, LFTTD and LBD data.
Notes: "Type shock share" measures the China Shock-induced change in employment as a share of baseline employment among the firm types that employ the worker type associated with the observation. "Aggregate shock share" measures the worker-weighted leave-one-out mean of "Type shock share" among all worker types except the one associated with the observation. Thus, the reported coefficients on "Type shock share" in columns (1) and (3) capture the sensitivity of workers' earnings and unemployment rate outcomes, respectively, to labor demand shocks at its current type of firm, holding fixed the common or nationwide component of the China Shock. The coefficients on "Aggregate shock share" in columns (1) and (3) capture the sensitivity of workers' earnings and unemployment rates to the common or nationwide component of labor demand shocks, holding its own associated firm type's employment shock fixed. Columns (2) and (4) report separate coefficients for these outcomes and shock measures by workers' initial earnings category. The regression is run at the worker type level, uses simulated shock-induced earnings and unemployment rate as outcomes, and pools all five years of simulated shocks between 2002 and 2006.

Table 11: Assessing Robustness of Worker-Level Earnings Incidence Results to Alternative Regression and Simulation Specifications

Type	**Baseline**		**NAICS6**	**IO**	**Fixed**	**Endog.**	**No Export**	**Import Access China**		**No Industry Interac.**	
	Comp.	**Imp. Acc.**			**TC-Ind.**	**Surplus**	**Access**	**Comp.**	**Imp. Access**	**Comp.**	**Imp. Access**
Manufacturing	-4158.1	-809.2	-3772.6	-5424.7	-3601.9	-4277.2	-4307.1	-3834.9	-156.4	-3623.1	340.0
NT	-1378.0	10.2	-1366.8	-2220.2	-1136.5	-1566.1	-1374.2	-1263.3	54.2	-1466.4	218.8
M	-2108.1	-426.6	-2209.0	-2876.8	-1693.2	-2104.3	-2099.4	-1810.3	-239.1	-1602.2	345.0
X	-2435.7	-71.5	-2657.5	-3669.2	-1994.7	-2591.5	-2437.0	-2308.7	11.6	-2428.3	224.1
XM	-2969.0	-352.1	-3180.8	-4069.1	-2459.4	-3079.9	-2979.0	-2846.9	-218.8	-2456.9	473.9
RP X|M	-3345.3	-210.8	-3342.8	-4619.8	-3119.8	-3467.4	-3356.5	-3386.4	-97.7	-2885.5	612.6
RP X&M	-6295.6	-1584.8	-5399.8	-7808.1	-5464.5	-6379.0	-6608.3	-5712.5	-293.9	-5328.7	336.8
Wholesale/Retail	-361.1	757.9	-107.1	-801.1	-276.0	-479.1	-344.1	-388.5	685.6	-944.6	432.2
NT	-431.7	241.0	-324.8	-740.9	-392.0	-639.8	-437.7	-416.8	221.3	-713.0	264.5
M	163.3	885.7	375.0	-296.8	98.6	85.7	174.4	-96.6	565.3	-323.8	672.2
X	-678.3	298.4	-525.9	-1308.2	-574.9	-637.7	-654.0	-657.1	237.0	-925.2	282.6
XM	9.7	1027.1	329.9	-477.4	-140.4	6.0	43.5	-295.2	671.2	-457.6	809.2
RP X|M	201.6	1339.4	628.4	-298.8	-20.3	243.7	258.9	-207.3	875.5	-310.7	1066.7
RP X&M	-577.1	1481.4	-109.0	-1178.1	-189.4	-661.6	-538.6	-431.3	1577.3	-1853.9	386.5
N.Res./Cons./Util.	-446.5	136.3	-365.3	-717.3	-393.2	-483.2	-445.0	-417.1	113.9	-676.2	204.2
Leis./Adm./Trans.	-392.3	379.0	-259.3	-854.6	-336.3	-420.1	-383.5	-456.5	263.4	-650.5	404.4
Information	-1132.5	127.5	-1052.7	-1851.4	-912.9	-1159.3	-1117.8	-1098.6	116.0	-1319.4	229.2
Fin./RE/Prof. Serv.	-987.8	330.5	-826.4	-1664.5	-853.7	-1010.7	-976.4	-1088.1	223.6	-1159.7	454.3
Educ./Health/Gov.	-1329.6	437.9	-1063.1	-2212.7	-1275.8	-1349.3	-1305.7	-1513.8	297.4	-1523.7	554.7
NT	-3458.6	-93.9	-2780.9	-4636.0	-2623.9	-3529.7	-3540.9	-3274.2	381.4	-3620.6	339.8
M	-628.3	197.9	-505.8	-998.3	-665.8	-609.5	-583.7	-655.5	85.0	-908.6	193.0
X	-592.2	211.9	-457.0	-985.9	-478.7	-609.5	-588.7	-596.9	174.9	-909.3	243.9
XM	-1352.6	521.9	-830.0	-2101.8	-909.3	-1355.5	-1324.4	-1628.4	282.3	-1835.2	280.1
RP X|M	-1136.0	156.1	-888.3	-1865.1	-852.2	-1137.5	-1107.9	-1169.0	121.2	-1339.4	256.5
RP X&M	-232.4	82.2	-191.1	-346.0	-209.9	-241.3	-237.0	-197.4	65.0	-463.2	162.7
Young Unemployed	-609.9		-474.3	-962.2	-520.9	-643.6	-607.0	-587.9		-863.3	
Old Unemployed	-973.2		-752.4	-1470.2	-801.1	-976.9	-950.0	-941.0		-1200.4	
Deciles 1-2	-445.0		-320.7	-707.6	-366.4	-493.0	-426.3	-397.8		-703.9	
Deciles 3-5	-737.6		-615.2	-1132.3	-634.5	-807.8	-750.5	-702.1		-967.9	
Deciles 6-8	-1117.1		-951.5	-1645.5	-956.5	-1141.3	-1152.6	-1090.8		-1303.6	
Deciles 9-10	-1804.7		-1530.0	-2780.2	-1555.5	-1938.0	-1913.7	-1910.6		-2110.6	

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

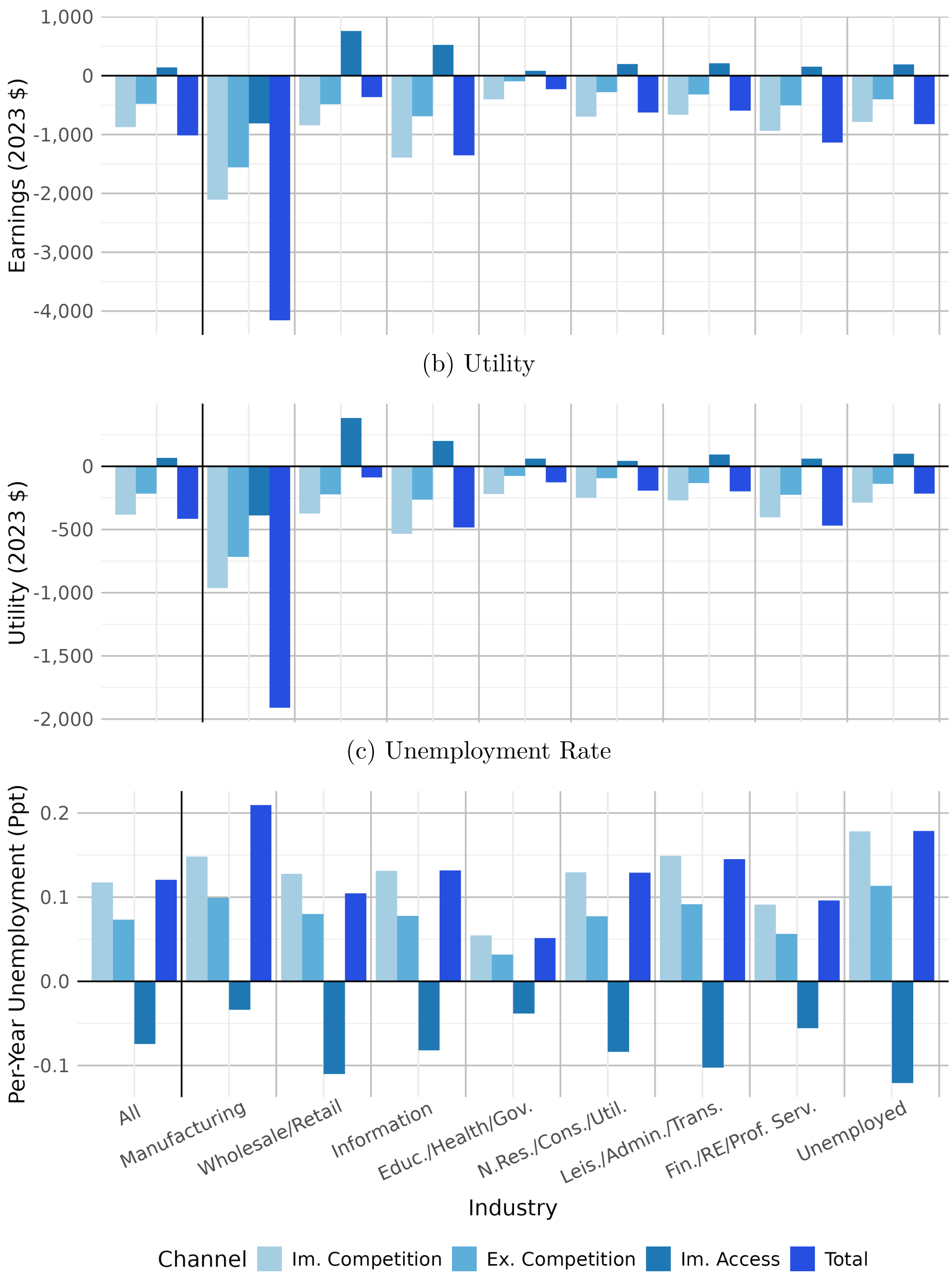
Notes: This table assesses the robustness of our primary worker incidence findings by reporting the average simulated impact of China's WTO entry on cumulative 2002-2006 earnings for various worker and firm subpopulations across a variety of alternative regression and simulation specifications: "Baseline Comp." and "Baseline Imp. Access" reproduce the results from our primary specification for the composite (all channels) shock and for the import access shock in isolation. "IO" uses a firm-level employment shock that includes job gains and losses due to input-output-based upstream and downstream exposure. "Fixed TS-Ind" assigns establishments to types based on their 2001 industry and their firm's 2001 trade status when constructing the firm-level employment shock. "Endog. Surplus" allows the relative joint surplus from manufacturing positions matching with high-paid vs. low-paid workers to also be affected by China's WTO entry. "NAICS6" controls for fixed effects for NAICS 6-digit industries rather than 4-digit industries when estimating the relationship between firm-level employment growth and firm-level exposure to each channel. "No Export Access" excludes job loss generated by the export access channel when simulating the China Shock's overall impact to demonstrate the channel's practical insignificance. "Import Access China" restricts import access exposure to firms that were previously importing specifically from China the products whose tariff risk was removed. "No Industry Interac." imposes that firms from all industries are equally sensitive to each channel's exposure measure conditional on size and trade status. Earnings losses for both the composite shock and the import access shock are reported for both the "Import Access China" and "No Industry Interac. specifications.

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

(a) Earnings

(b) Utility

(c) Unemployment Rate

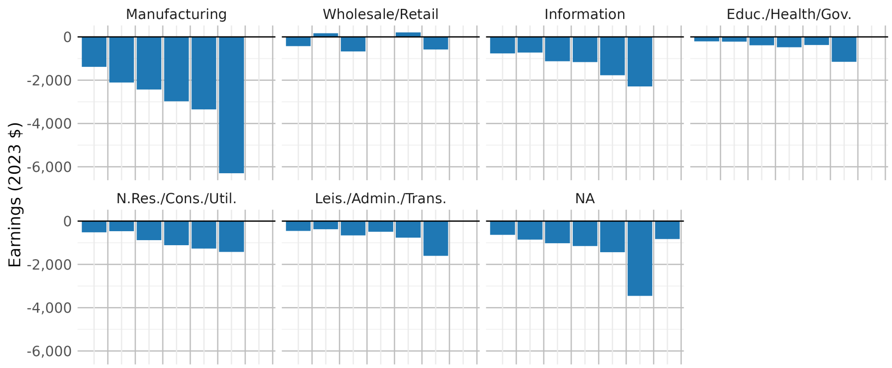


Source: Simulation Results based on LEHD, LFTTD and LBD data.

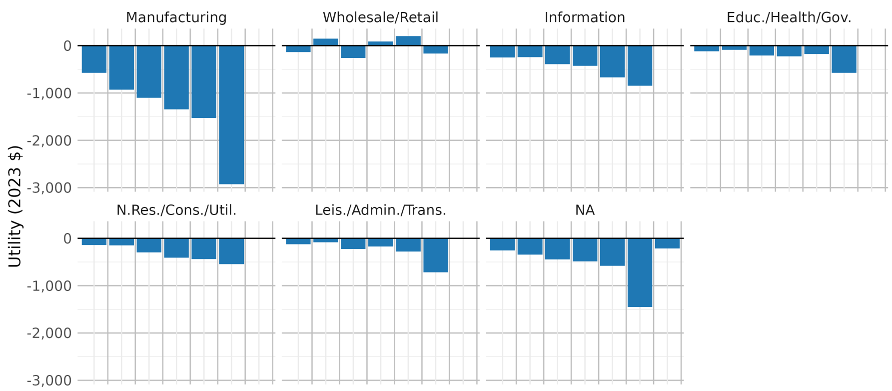
Notes: This figure displays the average simulated impact of China's WTO accession on five-year (2002-2006) cumulative earnings (in 2023 $), money-metric utility (also in 2023 $), and per-year probability of unemployment by channel (colored bars) and workers' 2001 industry category (X-axis).

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

(a) Earnings



(b) Utility

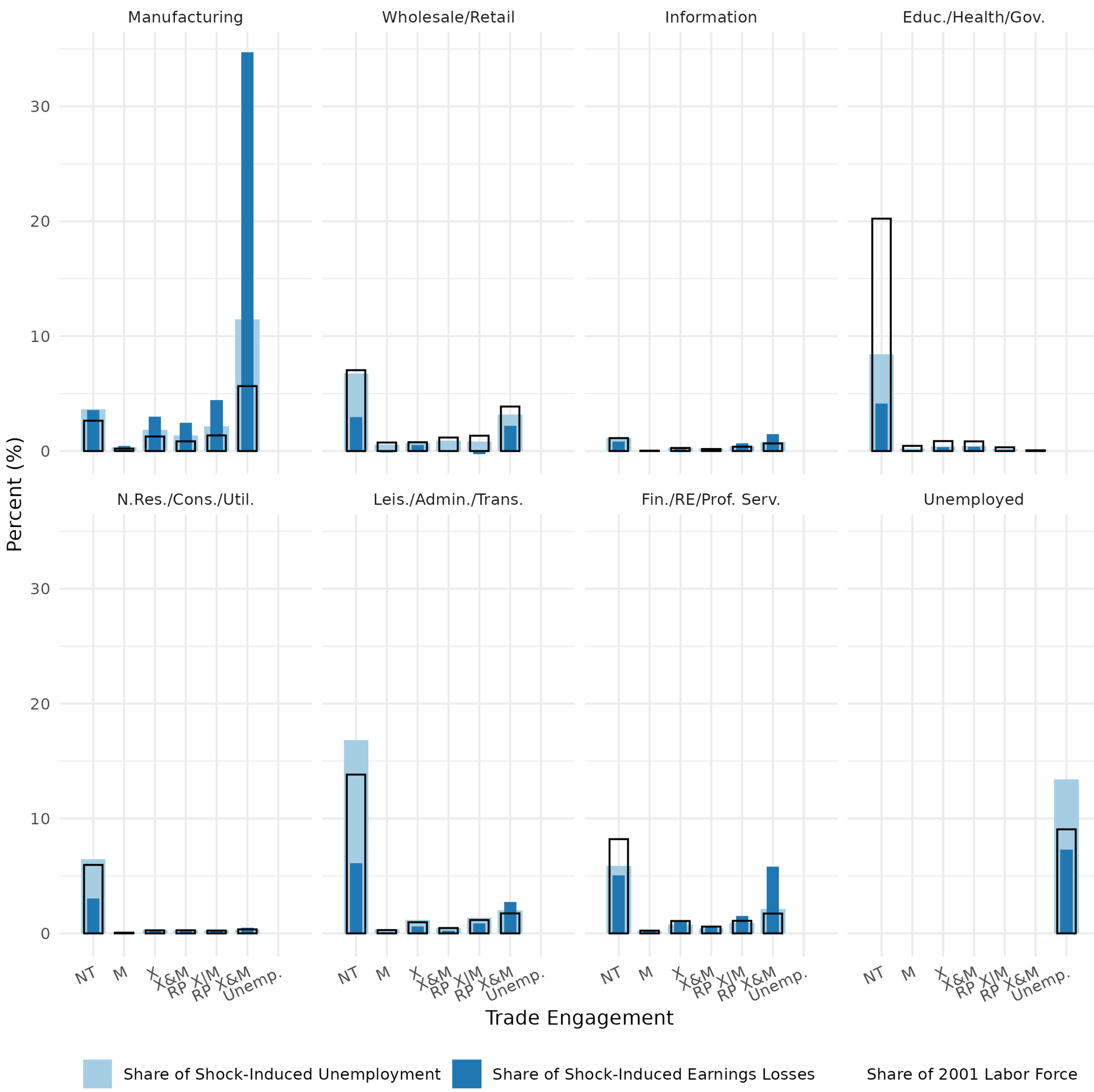


(c) Unemployment Rate

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 2023 \$), money-metric utility (also in 2023 \$), 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: 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 4: Shock-Induced Changes in the Conditional Distribution of Firm Type Destinations among Workers Initially at Non-Trading and RPXM Manufacturing Firms

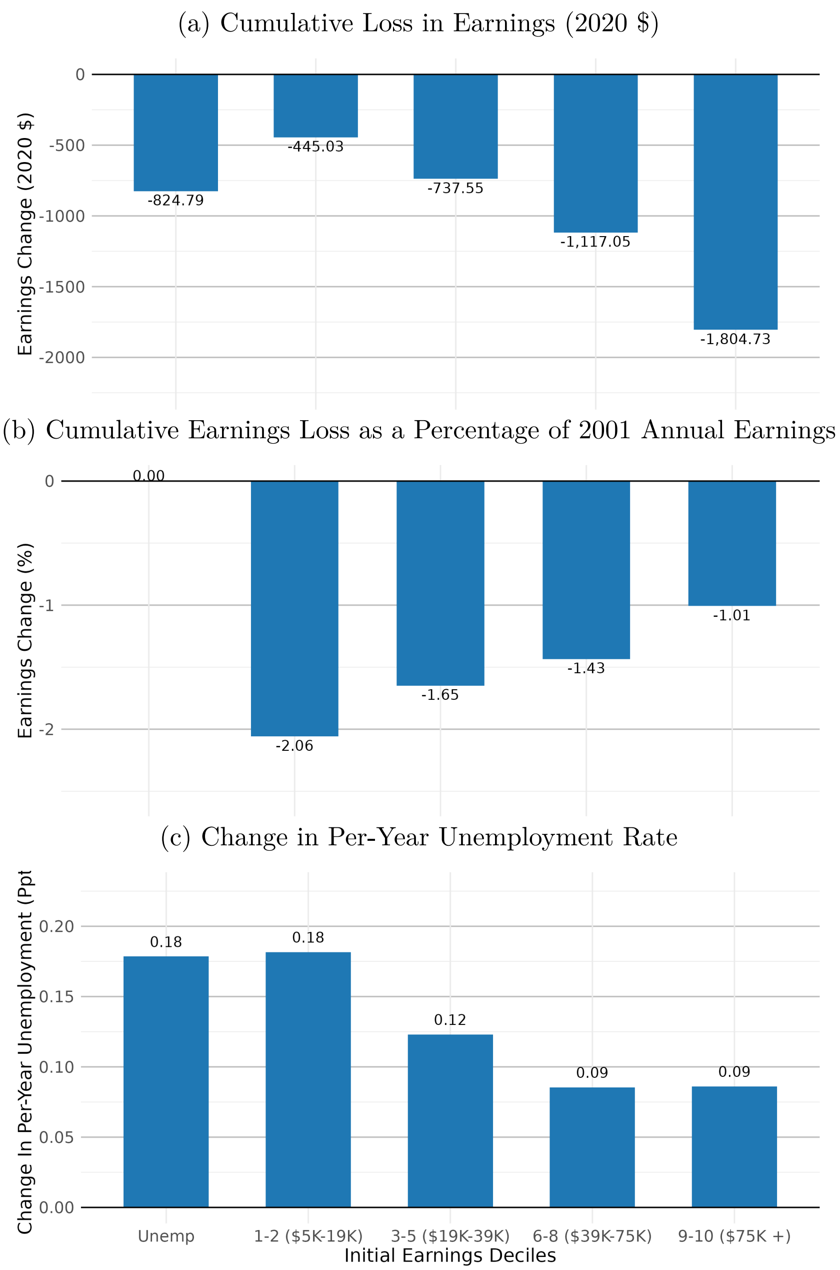
(a) RPXM Manufacturing Workers - Changes in Transition Percentages

(b) Non-trading 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 RPXM manufacturing workers (panel B).

Figure 5: 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 2023 $) 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

See Online Appendix for more details.

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:

$$\delta_{ik} = 1 \text{ iff } k \in \arg\max\nolimits_{k \in \mathcal{K} \cup 0} \pi_{ik} - V_k^* \text{ and } i \in \arg\max\nolimits_{i \in \mathcal{I} \cup 0} \pi_{ik} - U_i^* \tag{18}$$

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 (6) 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:

$$\pi_{ik} = \theta_l^f + \sigma_f \mu_{lk} + \sigma_l \epsilon_i^f. \tag{19}$$

Substituting (19) into (18) we obtain:

$$\max\nolimits_{\{\mathcal{K} \cup 0\}} \theta_l^f + \sigma_f \mu_{lk} + \sigma_l \epsilon_i^f - V_k^* \tag{20}$$

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

$$\max\nolimits_{\{\mathcal{F}\}} \left[\theta_l^f + \sigma_l \epsilon_i^f + \max\nolimits_{k: f(k)=f} \sigma_f \mu_{lk} - V_k^*\right] \tag{21}$$

Switching signs, we can rewrite the second half as:

$$\max\nolimits_{\{\mathcal{F}\}} \left[\theta_l^f + \sigma_l \epsilon_i^f - \min\nolimits_{k: f(k)=f} V_k^* - \sigma_f \mu_{lk}\right] \tag{22}$$

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:

$$\max\nolimits_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} + \sigma_l \epsilon_i^f\right] \tag{23}$$

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:

$$\tilde{U}_{lf} = \sigma_l(\ln P(f|l) - \ln P(\tilde{f}|l)) \tag{24}$$

Comparing (8) and (24), 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

$$\arg\max_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} + \sigma_l \epsilon_i^f\right] = \arg\max_{\{\mathcal{F}\}} \left[\gamma_l^f + W_l^f - (\gamma_l^{\tilde{f}} + W_l^{\tilde{f}}) + \sigma_l \epsilon_i^f\right] = \arg\max_{\{\mathcal{F}\}} \left[\gamma_l^f + W_l^f + \sigma_l \epsilon_i^f\right] \tag{25}$$

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 (4) and (23).

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:

$$\arg\max_{\{\mathcal{F}\}} \left[\tilde{U}_{lf} - V_f^{CF} + \sigma_l \epsilon_i^f\right] \tag{26}$$

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:

$$P(f|l) = e^{(\tilde{U}_{lf} - V_f^{CF})/\sigma_l} \Big/ \sum_{f' \cup 0} e^{(\tilde{U}_{lf'} - V_{f'}^{CF})/\sigma_l} \tag{27}$$

Inserting equation (27) in place of (5) into the market clearing conditions (7), 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:

$$\sum_l m_l^{CF} \left(e^{(\tilde{U}_{lf} - V_f^{CF})/\sigma_l} \Big/ \sum_{f' \cup 0} e^{(\tilde{U}_{lf'} - V_{f'}^{CF})/\sigma_l} \right) = h_f^{CF} \; \forall f \in \{\mathcal{F} \cup 0\} \tag{28}$$

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 (27) 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 (28) 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):

$$\sum\nolimits_{f \cup 0} h_f^{CF} \left(e^{(\tilde{V}_{lf} - U_l^{CF})/\sigma_f} \Big/ \sum\nolimits_{l'} e^{(\tilde{V}_{l'f} - U_{l'}^{CF})/\sigma_f} \right) = m_l^{CF} \; \forall \; l \tag{29}$$

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 (29) can be trivially altered to accommodate separate surplus values for job stayers vs. movers within type-pair, discussed in Section 2.6:

$$h_0^{CF} \frac{e^{(\tilde{V}_{l,0}^{0} - U_l^{CF})/\sigma_0}}{\sum_{l'} e^{(\tilde{V}_{l',0}^{0} - U_{l'}^{CF})/\sigma_0}} + \sum_f h_f^{CF} \sum_{z \in \{0,1\}} \frac{e^{(\tilde{V}_{l,z}^{f} - U_l^{CF})/\sigma_f}}{\sum_{l',z' \cup 0} e^{(\tilde{V}_{l',z'}^{f} - U_{l'}^{CF})/\sigma_f}} = m_l^{CF} \, \forall \, l \tag{30}$$

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 (8) 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:

$$W_l^{f,CF} - W_l^{\tilde{f},CF} = \sigma_l[\ln P^{CF}(f|l) - \ln P^{CF}(\tilde{f}|l)] - \gamma_l^f + \gamma_l^{\tilde{f}} \tag{31}$$
$$W_{\tilde{l}}^{f,CF} - W_{\tilde{l}}^{\tilde{f},CF} = \sigma_{\tilde{l}}[\ln P^{CF}(f|\tilde{l}) - \ln P^{CF}(\tilde{f}|\tilde{l})] - \gamma_{\tilde{l}}^f + \gamma_{\tilde{l}}^{\tilde{f}} \tag{32}$$

Performing the analogous operation using the position-side CCPs from (9), we obtain:

$$W_l^{f,CF} - W_{\tilde{l}}^{f,CF} = \sigma_f[\ln P^{CF}(\tilde{l}|f) - \ln P^{CF}(l|f)] + \Psi_f(\alpha_l^f - \alpha_{\tilde{l}}^f) \tag{33}$$
$$W_l^{\tilde{f},CF} - W_{\tilde{l}}^{\tilde{f},CF} = \sigma_{\tilde{f}}[\ln P^{CF}(\tilde{l}|\tilde{f}) - \ln P^{CF}(l|\tilde{f})] + \Psi_{\tilde{f}}(\alpha_l^{\tilde{f}} - \alpha_{\tilde{l}}^{\tilde{f}}) \tag{34}$$

Combining (31) and (34) yields:

$$\begin{aligned} W_l^{f,CF} - W_{\tilde{l}}^{\tilde{f},CF} = {} & \sigma_l \ln P^{CF}(l,f) - (\sigma_l + \sigma_{\tilde{f}}) \ln P^{CF}(l,\tilde{f}) \\ & + \sigma_{\tilde{f}} \ln P^{CF}(\tilde{l},\tilde{f}) - \gamma_l^f + \gamma_l^{\tilde{f}} + \Psi_{\tilde{f}}\alpha_l^{\tilde{f}} - \Psi_{\tilde{f}}\alpha_{\tilde{l}}^{\tilde{f}} \end{aligned} \tag{35}$$

(35) 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:

$$\begin{aligned} & \arg\max_i \tilde{V}_{lf} - \overline{U}_l^{CF} + \sigma_f\epsilon_{if} = \arg\max_i \tilde{V}_{lf} - (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) + \sigma_f\epsilon_{if} \\ & = \arg\max_i \alpha_{lf} - W_{lf}^{CF} + \sigma_f\epsilon_{if} = \arg\max_i \alpha_{lf} - \alpha_{l'f} - (W_{lf}^{CF} - W_{l'f}^{CF}) + \sigma_f\epsilon_{if} \end{aligned} \tag{36}$$

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

$$(W_{lf}^{CF} - W_{l'f}^{CF}) = (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) - \tilde{V}_{lf} + (\alpha_{lf} - \alpha_{l'f}) \tag{37}$$

This relates differences in counterfactual earnings changes among worker types within a firm

[29] Note that one can generate an alternative formula for $W_l^f - W_{\tilde{l}}^{\tilde{f}}$ by combining equations (32) and (31). 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.

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.

$$(W_{l'f}^{CF} - W_{l'f'}^{CF}) = \tilde{U}_{l'f} - (\overline{V}_f^{CF} - \overline{V}_{f'}^{CF}) - (\gamma_{l'f} - \gamma_{l'f'}) \tag{38}$$

Adding (37) and (38) yields:

$$(W_{lf}^{CF} - W_{l'f'}^{CF}) = \tilde{U}_{l'f} - \tilde{V}_{lf} + (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) - (\overline{V}_f^{CF} - \overline{V}_{f'}^{CF}) + (\alpha_{lf} - \alpha_{l'f}) - (\gamma_{l'f} - \gamma_{l'f'}) \tag{39}$$

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 (39) yields:

$$(W_{lf}^{CF} - W_{l'f'}^{CF}) = (\overline{U}_l^{CF} - \overline{U}_{l'}^{CF}) - (\overline{V}_f^{CF} - \overline{V}_{f'}^{CF}) + W_{lf}^{data} - W_{l'f'}^{data} \tag{40}$$

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:

$$\Psi_f^t \alpha_l^{f,t} = \Psi_f \alpha_l^f \qquad \gamma_l^{f,t} = \gamma_l^f \qquad \sigma_f^t = \sigma_f \qquad \sigma_l^t = \sigma_l \qquad \forall\, t \tag{41}$$

We first define Δ_x as a difference operator over the subscript x and x', and rewrite equation (8) to be year-specific:

$$\Delta_l W_l^{f,t} / \sigma_f^t = \Delta_l \ln P^t(l,f) - \Delta_l \psi_f^t \alpha_l^{f,t} / \sigma_f^t \tag{42}$$

Then, taking a difference among two versions of (42) for years t and $t-s$ and imposing the assumptions (41), we obtain:

$$\Delta_l W_l^{f,t} - \Delta_l W_l^{f,t-s} = \sigma_f \left[\Delta_l \ln P^t(l,f) - \Delta_l \ln P^{t-s}(l,f)\right] \tag{43}$$

In principle, (43) 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:

$$\ln P^t(l, f) - \ln P^t(l', f) = \eta_f \left[\ln W_l^{f,t} - \ln W_{l'}^{f,t}\right] \tag{44}$$

Taking a difference of (44) across t and $t - s$, substituting (43) 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:

$$\sigma_f = -\Delta_t \Delta_l W_l^{f,t} / \eta_f \Delta_t \Delta_l ln W_l^{f,t} \tag{45}$$

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 $\eta_l = 7.4 \, \forall \, l$.

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 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

[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.

[31] In order to evaluate the profit level associated with any choice of N_j, one needs to assume a value of 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 (28) 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 Shock 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 5.1. 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 (10), (8), and (9), 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 (17) in Section 4:

$$h_f^{0102,CF} = h_f^{0102} - Shock_{f,0102}^{Total} \tag{46}$$

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 (30) 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 (35) 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}. 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

marginal revenue product of labor Ψ_j^0 in order to compute $E[L_j|N_j, Psi_j]$ from equation (3) in Appendix A1. 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.

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:

$$m_l^{t+1} = \sum\nolimits_{g'} 1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \;\&\; e(l(g')) = e(l)\right] \#(g') \times (1 - \frac{|\Delta W_{g'}^{CF}|}{interval\ size_e})+$$
$$1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \;\&\; e(l(g')) = e(l) - 1 \;\&\; \Delta W_{g'}^{CF} > 0\right] \frac{\#(g') \times |\Delta W_{g'}^{CF}|}{interval\ size_e}+$$
$$1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \;\&\; e(l(g')) = e(l) + 1 \;\&\; \Delta W_{g'}^{CF} < 0\right] \frac{\#(g') \times |\Delta W_{g'}^{CF}|}{interval\ size_e} \quad (47)$$

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 (10), (8), and (9) 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:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) \quad (48)$$

The second counterfactual then restores jobs by subtracting the (usually negative) estimated China Shock component (e.g. $Shock_{f,0203}^{Total}$) from (17) in Section 4:

$$h_f^{t,CF} = h_f^{t-1,CF} + (h_f^t - h_f^{t-1}) - Shock_{f,t}^{Total} \quad (49)$$

For each counterfactual demand shock, we solve for the allocation and utility changes using (30) and the earnings changes using (35). 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 (47), (48), and (49), 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 (47) but conditioning on the time t worker type:

$$P(l^{t+1}|l^t) = \sum\nolimits_{g'|l(g')=l^t} 1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \,\&\, e(l(g')) = e(l)\right] \frac{\#(g') * (1 - \Delta W_{g'})}{interval\ size_e}+$$
$$1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \,\&\, e(l(g')) = e(l) - 1 \;\&\; \Delta W_{g'} > 0\right] \frac{\#(g') * \Delta W_{g'}}{interval\ size_e}+$$
$$1\left[(ind, r, te)(f(g')) = (ind, r, te)(l) \,\&\, e(l(g')) = e(l) + 1 \;\&\; \Delta W_{g'} < 0\right] \frac{\#(g') * \Delta W_{g'}}{interval\ size_e} \quad (50)$$

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:

$$\begin{aligned}
E[TotU^{t+1}|l^t] &= U_l^t + \sum{}_{l'} U_{l'}^{t+1} P(l'|l^t) \\
E[TotU^{t+1}|l^{t-1}] &= U_{l^{t-1}}^{t-1} + \sum{}_{l'} E[TotU^{t+1}|l^t = l'] P(l'|l^{t-1}) \\
&\vdots \\
E[TotU^{t+1}|l^{t_0}] &= U_l^{t_0} + \sum{}_{l'} E[TotU^{t+1}|l^{t_0+1} = l'] P(l'|l^{t_0})
\end{aligned} \tag{51}$$

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

A3 Imputation

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).

A3.1 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

[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.

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:

$$\begin{aligned}\#(s_l, ind_l, te_l, e_l; s_f, ind_f, te_f, fs_f, fe_f, z_{lf}) =& \#(s_f, ind_f, te_f, fs_f, fe_f) \times P(s_l|s_f, ind_f, te_f, fs_f, fe_f) \\ & \times P(ind_l, te_l, e_l, z_{lf}|s_l, s_f, ind_f, te_f, fs_f, fe_f) \end{aligned} \tag{52}$$

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 (52) 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 (52) 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 (52) 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:

$$P(ind_l, te_l, e_l, z_{lf}|s_l, s_f, ind_f, te_f, fs_f, fe_f) \approx P^{LEHD}(ind_l, te_l, e_l, z_{lf}, |\hat{s}_l, s_f, ind_f, te_f, fs_f, fe_f) \tag{53}$$

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 of (52). 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]

$$\#(s_f, ind_f, te_f, fs_f, fe_f) \approx \#^{LBD}(s_f, ind_f, te_f, fs_f, fe_f) \times (\#^{LEHD}(\hat{s}_f, ind_f, te_f)/\#^{LBD}(\hat{s}_f, ind_f, te_f)) \tag{54}$$

When neither the worker's state nor the position's state is observed, we use the ACS to construct the second component in (52), and we approximate the third component by replace both s_l and s_f with $\hat{s}_l$ and $\hat{s}_f$.

A3.2 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):

$$\#(s_l, ind_l, te_l, e_l; U) \approx \#^{LEHD}(s_l, ind_l, te_l, e_l; NE) \times \hat{P}^{ACS}(E-U|E-NE, s_l, ind_l, e_l) \tag{55}$$

When the worker's state is out of 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. The LBD count is also re-scaled to account for discrepancies in industry coverage between the LBD and LEHD:

$$\begin{aligned}\#(s_l, ind_l, te_l, e_l; U) \approx& \#^{LBD}(s_l, ind_l, te_l) \times \left(\#^{LEHD}(\hat{s}_l, ind_l, te_l)/\#^{LBD}(\hat{s}_l, ind_l, te_l)\right) \\ & \times P^{LEHD}(e_l, E-NE|\hat{s}_l, ind_l, te_l) \times \hat{P}^{ACS}(E-U|E-NE, s_l, ind_l, e_l)\end{aligned} \tag{56}$$

[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.

A3.3 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 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).

$$\#(s_l, a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \approx \#^{LEHD}(a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \times \hat{P}^{ACS}(s_l | a_l, s_f, ind_f) \quad (57)$$

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:

$$\begin{aligned} \#(s_l, a_l, NE; s_f, ind_f, te_f, fs_f, fe_f) \approx\ & \#^{LBD}(s_f, ind_f, te_f, fs_f, fe_f) \frac{\#^{LEHD}(\hat{s}_f, ind_f, te_f)}{\#^{LBD}(\hat{s}_f, ind_f, te_f)} \quad (58) \\ & \times P^{ACS}(s_l | a_l, s_f, ind_f) \times P^{LEHD}(a_l, NE - E | s_l, \hat{s}_f, ind_f, te_f, fs_f, fe_f) \end{aligned}$$

If the origin state is also unobserved, we replace s_l with its most similar state $\hat{s}_l$ in (58).

A3.4 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.

$$\#(s_l, a_l, NE; U) = \hat{\#}^{ACS}(s_l, a_l, NE; U) \quad (59)$$

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. 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: $\mathbf{L}^1_l = [Industry_l, Trade\,Engagement_l]$, $\mathbf{L}^2_l = [Earnings\,Decile_l,\,Region_l]$. We do the same for firm characteristics: $\mathbf{F}^1_f = [Industry_f, Trade\,Engagement_f]$, $\mathbf{F}^2_l = [Avg.\,Pay\,Quartile_f, Firm\,Size\,Quartile_f$ Next, we exploit the fact that $P(g)$ can be decomposed via:

$$
\begin{aligned}
P(g) =& P(g|f(g))h(f(g)) = P([l(g), f(g), z(g)]|f)h(f(g)) = P([\mathbf{L}^1_{l(g)}, \mathbf{L}^2_{l(g)}, z(g)]|f)h(f(g)) \\
=& P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g), f)P([\mathbf{L}^2_{l(g)}, z(g)]|f)h(f(g)) \\
=& \sum\nolimits_{z'\in\{0,1\}} 1(z(g) = z')P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = z', f)P([\mathbf{L}^2_{l(g)}, z(g) = 0]|f)h(f(g)) \Rightarrow \\
P(g) =& 1(z(g) = 1)1(\mathbf{L}^1_{l(g)} = \mathbf{F}^1_{f(g)})P([\mathbf{L}^2_{l(g)}, z(g) = 1]|f)h(f(g)) \\
&+ 1(z(g) = 0)P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g) = 0, f(g))P([\mathbf{L}^2_{l(g)}, z(g) = 0]|f)h(f(g))
\end{aligned} \tag{60}
$$

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 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,

$$P(\mathbf{L}^1_{l(g)}|\mathbf{L}^2_{l(g)}, z(g)=0, f(g)) \approx \sum_{g'} \left(\frac{\phi(D(g',g)N(g'))}{\sum_{g''}\phi(D(g'',g)N(g''))} \times \hat{P}(\mathbf{L}^1_{l(g')}|\mathbf{L}^2_{l(g')}, z(g')=0, f(g')\right) \quad (61)$$

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

[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.

[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.

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

$$P(\mathbf{L}^2_{l(g)}, z(g)=0|f(g)) \approx \sum_{g'} \left(\frac{\phi(D^{move}(g',g)h(f(g')))}{\sum_{g''}\phi(D^{move}(g'',g)h(f(g'')))} \times \hat{P}(\mathbf{L}^2_{l(g')} z(g')=0|f(g')\right) \quad (62)$$

$$P(\mathbf{L}^2_{l(g)}, z(g)=1|f(g)) \approx \sum_{g'} \left(\frac{\phi(D^{stay}(g',g)h(f(g')))}{\sum_{g''}\phi(D^{stay}(g'',g)h(f(g'')))} \times \hat{P}(\mathbf{L}^2_{l(g')}, z(g')=1|f(g')\right) \quad (63)$$

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 different data choices implemented in the paper.

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 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 in either their arms-length imports or 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:

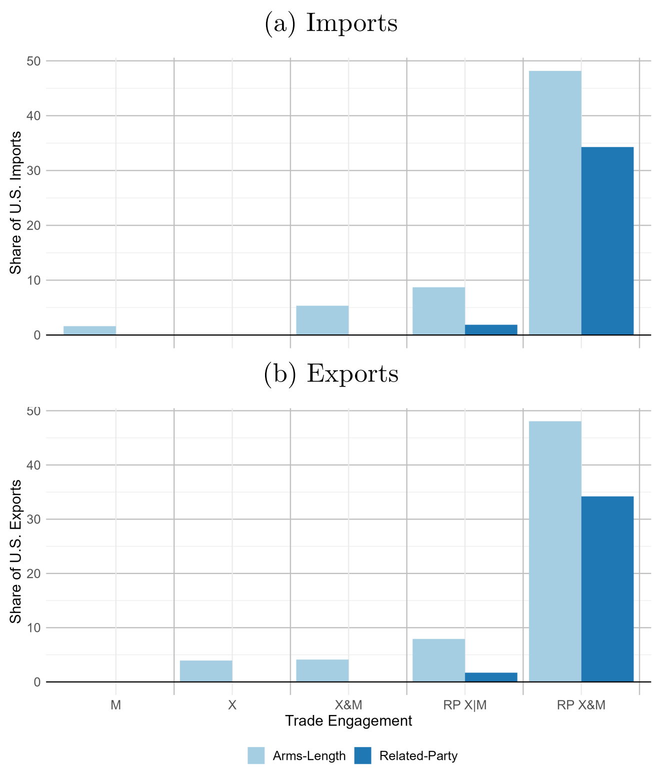
- Natural Resources, Construction, and Utilities: establishments in sectors 11, 21, 22 or 23.
- Manufacturing: establishments classified in sectors 31, 32, or 33.
- Wholesale and Retail Trade: establishments classified in sectors 42, 44, or 45.
- Leisure, Transportation, Administration, and Other Services: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

A5.4 Product-level Domestic Revenue

To measure the import competition channel, we use product level sales from the Census and Annual Survey of Manufacturing. Product class-level and firmwide revenue is reported every five years for each firm in the Economic Census (1997, 2002, and 2007) and yearly for a sample of firms in the Annual Surveys. For unreported years, we interpolate these values using data from surrounding years. For firms with observed data in some year t, we estimate revenue in other years t' by multiplying t' payroll by the revenue-to-payroll ratio in t and assuming that this ratio and the product-level revenue shares remain constant. For firms without any revenue data, we multiply their payroll by the revenue-to-payroll ratio among firms in their trade engagement/industry/firm size/firm avg. pay combination, and assign them the average product composition of those in their industry.

A6 Additional Results

Figure A1: Shares of Total U.S. Goods Imports and Exports by Trade Engagement

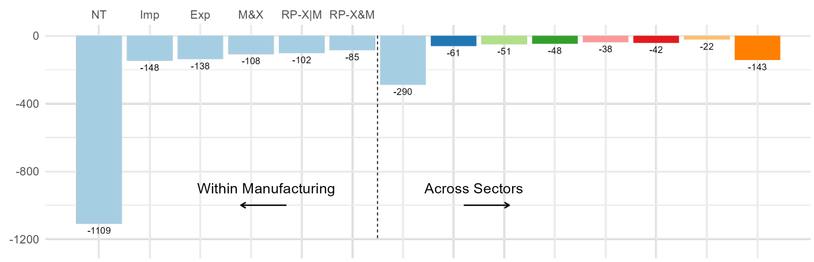


Source: Authors' calculations based on LFTTD and LBD data.

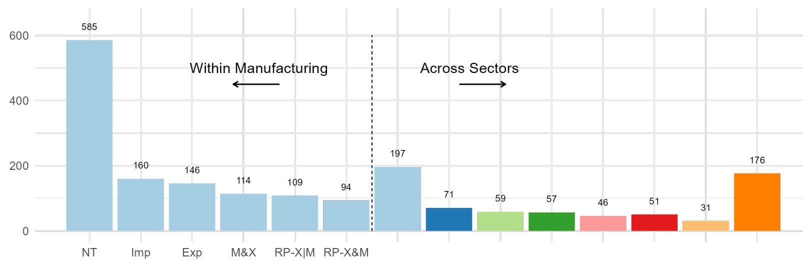
Notes: This figure displays the shares of U.S. total imports (top panel) and total exports (bottom panel) accounted for by firms in each trade engagement category.

Figure A2: Simulated Earnings Impacts Asymmetry of Shocks that of Artificial Shocks that Remove or Add 1% of U.S. Employment (112,000 Jobs)

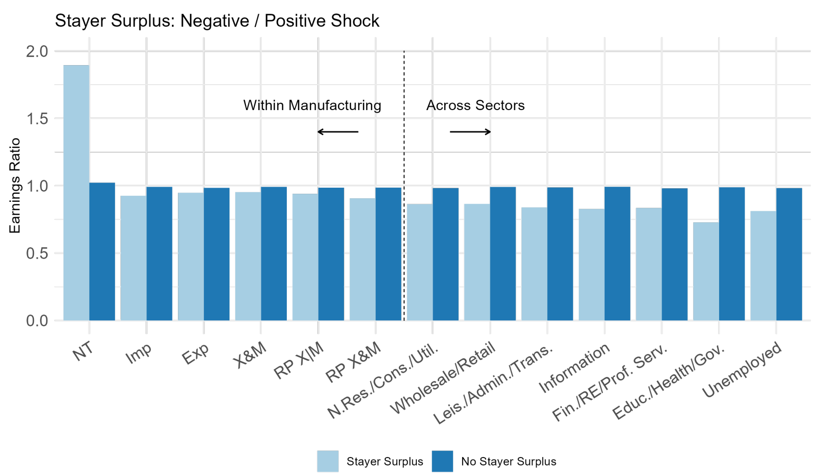
(a) Negative Non-traded Manufacturing Shock - Earnings Losses



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



(c) The Role of Extra Joint Surplus from Job Retention



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 (panel A) or add 112,000 jobs (panel B) exclusively from/to the non-traded manufacturing sector. 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. Panel C displays earnings ratios by industry; for manufacturing, we break out industry by trade-engagement status. Earnings ratios are calculated as the simulated earnings from a negative shock (destruction of jobs) divided by the simulated earnings from a positive shock (creation of jobs). The light blue bars display the earnings ratio among workers when we allow for stayer surplus while the dark blue bars display the earnings ratio among workers when we do not allow for stayer surplus.