To Find Relative Earnings Gains After the China Shock, Look Upstream and Outside Manufacturing*

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Abstract

We find that US workers *outside manufacturing* exhibit relative earnings *increases* after US trade liberalization with China. These relative gains cumulate over time as the beneficial effect of a worker's upstream exposure—increased competition from China in input markets—more than offsets the detrimental impact of her own and downstream (customer) exposures. These relative gains are smaller for non-manufacturing workers with less *ex ante* firm tenure and lower initial earnings, and are absent among manufacturing workers due to a lack of upstream gains and stronger downstream losses.

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1 Introduction

Large literatures in labor economics and international trade investigate the impact of labor demand shocks on worker outcomes across a wide range of economies, including the United States (Jacobson et al., 1993), India (Topalova, 2007), Brazil (Kovak, 2013; Dix-Carneiro and Kovak, 2017), and Canada (Kovak and Morrow, 2022). A major area of recent inquiry is the negative reaction of US manufacturing workers to the "China Shock," driven by US trade liberalization with China in 2000 (Autor et al., 2013; Pierce and Schott, 2016). In this paper, we study how US workers *outside* manufacturing respond to this change in policy via the exposure of the counties in which they work and the position of their industries in the supply chain. We show that a substantial share of non-manufacturing workers exhibit relative earnings *gains* as the beneficial effect of upstream exposure (i.e. competition in input markets) more than offsets the detrimental impact of direct and downstream (i.e., customer) exposure. We thus find long-suspected but previously missing empirical evidence of relative labor market benefits of this US trade liberalization.[1]

Our approach to studying this shock requires detailed information on workers' industry *and* county of employment tracked over a prolonged period of time, which is not typically available, even in other confidential datasets. Toward that end, we make use of the matched employer-employee data from the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. The LEHD is well-suited to our inquiry for two reasons. First, it tracks the earnings of nearly all workers – manufacturing and non-manufacturing – among US states participating in the program, permitting investigation of outcomes across sectors and counties. Second, workers in the LEHD can be matched to a rich set of personal and professional characteristics via links to other Census datasets, e.g., worker traits in the Decennial Census (DC), plant and firm attributes in the Longitudinal Business Database (LBD), and direct exposure to international trade via the Longitudinal Foreign Trade Transactions Database (LFTTD). Controlling for these attributes allows for cleaner comparisons of worker outcomes than can be achieved at higher levels of aggregation, such as across industries or regions, or with other individual-level datasets.

US trade liberalization with China can affect non-manufacturing workers through both industry and spatial channels of exposure and via input-output linkages, and our empirical work is the first to examine these potential channels simultaneously, a contribution that matters crucially to estimated results. While non-manufacturing workers' industries typically don't face tariffs on their output, they may benefit if the liberalization leads to a reduction in input prices or productivity growth among their suppliers (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011), or lose if it induces difficult-to-replace customers to shrink or exit. Non-manufacturing workers may also lose if displaced manufacturing workers reduce demand for local services, or increase competition for service jobs. Regarding the latter, we find via simple decompositions of worker movement between 2000 and 2007 that about half of US non-manufacturing sectors (representing 41 percent of 2000 US private employment) receive net inflows of former manufacturing workers that account for more than 2 percent of their *ex ante* employment.

[1] Jaravel and Sager (2019) highlight benefits to consumers arising from lower prices.

We evaluate the overall impact of a major US trade liberalization *vis-a-vis* China – the granting of Permanent Normal Trade Relations (PNTR) – on non-manufacturing (NM) and manufacturing (M) worker outcomes using a series of worker-level difference-in-differences (DID) regressions. As mentioned, a key innovation of this analysis is that it is the first to focus on workers' industry and county supply chain exposure to the China Shock. "Own-industry" exposure is derived directly from the US tariff schedule and therefore defined only for workers in goods-producing industries. "Own-county" exposure is a Bartik-style average of the exposures of the industries produced in the worker's county, using employment shares as weights. For NM workers, own-county exposure captures the spillover effects of being located near directly affected manufacturing workers. To assess workers' exposure via their supply chain, we use total requirements data from the US input-output table to compute industry and county up- and downstream exposures. *Industry* up- and downstream exposures measure workers' sensitivity to their industries' suppliers and customers. *County* up- and downstream county exposure, by contrast, measure workers' more general susceptibility to the exposure of all suppliers and customers of the industries in their counties, again weighted by employment shares.

Our analysis yields several novel insights. First, consistent with binding geographic frictions to labor mobility assumed in many spatial general equilibrium trade models (e.g., Caliendo et al., 2019; Adão et al., 2019), we find that county exposure is more influential than industry exposure in determining *worker* outcomes for both NM and M workers. Second, we find that exposure along the supply chain has a substantial impact on worker earnings and employment, and that it is asymmetric across NM and M workers. For NM workers, we find large and precisely estimated DID coefficients for county upstream exposure – indicating relative increases in earnings as competition in input markets increases – but that these coefficients are small and not statistically significant for M workers. On the other hand, while estimates for downstream county exposure are negative for workers in both sectors, they are larger in magnitude for M workers. Taking all forms of exposure into account, these estimates indicate that NM workers in the vast majority of county-industry pairs exhibit relative earnings gains of 3 to 29 log points depending on worker tenure at their employing firm. By contrast, M workers experience substantial relative earnings losses. These results suggest that the potential negative spillovers to NM workers from the shock to manufacturing are offset by the positive impact of greater import competition in supplier industries.

Our findings provide comprehensive reduced-form empirical evidence of relative earnings benefits arising from increased Chinese import competition in input markets, and reveal that adopting a broader input-output perspective is critical for understanding worker outcomes outside manufacturing. While Pierce and Schott (2016) and Acemoglu, Autor, Dorn, Hanson, and Price (2016) include up- and downstream exposure in their *industry*-level studies of the impact of Chinese import competition on US manufacturing employment, neither finds evidence of any positive effect.[2] Here, we find that a failure to account for input-output linkages both spatially and by industry leads to the under-estimation of NM workers' relative *gains* as well as under-estimation of M workers' relative *losses*. In this way, our findings are more consistent with recent research examining the 2018-19 US-China

[2] Feenstra and Sasahara (2018) use world input-output tables to calculate the amount of domestic employment supported by US export growth.

tariffs, which find that *increases* in protection negatively affect downstream producers (Flaaen and Pierce, 2019; Bown et al., 2020; Handley et al., 2020; Javorcik et al., 2025).[3] Relative to these papers that focused on short-term responses to recently imposed US-China tariffs, our results characterize the implications of supply-chain exposure to trade shocks over a much longer time horizon. They also provide reduced-form support for the input-output linkages highlighted in the theory and calibrated model counterfactuals of Caliendo et al. (2019); Adão et al. (2019). And lastly, they highlight potential harms to workers in NM sectors that could arise from reviving trade restrictions on goods inputs.

One potential explanation for why NM workers receive more help from upstream exposure and are less harmed by downstream exposure than M workers is an asymmetry in these sectors' sensitivity to supply-chain disruption. If multiple links of a manufacturing supply chain tend to move offshore together due to correlated shocks or the benefits of remaining co-located, as posited in the theoretical literature (Baldwin and Venables, 2013; Antràs and Chor, 2013), downstream links may not be able to benefit from greater upstream exposure, and upstream links may be particularly susceptible to higher competition downstream. For NM sectors, such co-offshoring may not be possible, e.g., a hospital must stay near its patients, and a hotel near its guests.

Consideration of an "annual" (event-study) version of our baseline specification circumstantially supports this interpretation while providing novel estimates of the dynamic effects of exposure to trade shocks via the supply chain. For workers outside manufacturing, we find that the impact of own-county exposure is negative and significant immediately after PNTR, suggesting a rapid and negative impact of the shock. On the other hand, this own-county coefficient is relatively small in magnitude and becomes insignificant, while the up- and downstream coefficients become significant several years later. This timing is consistent with NM industries benefiting from lower costs as they find new, potentially foreign sources of inputs in the years after PNTR, as well as their being harmed by the loss of customers, with the former dominating. The estimated coefficients for M workers exhibit a different pattern. There, the immediate negative and significant impact of own-county exposure gives way to negative, statistically significant and large-in-magnitude downstream coefficients around the time of the Great Recession. This pattern suggests that M industries that initially hang on during their own negative exposure may not survive the loss of their customers, and that this survival became more difficult with the subsequent downturn in manufacturing sparked by the 2007 financial crisis.

We also examine how the impact of PNTR varies according to several forms of worker heterogeneity. First, following the mass-layoff literature described below, we investigate the potential effect of firm-specific human capital on worker outcomes by reporting all regression results for two sets of workers: those who are employed for the entirety of 1993 to 1999 pre-PNTR period but not necessarily by the same firm, and those those employed by the same firm during the entire pre-period. We refer to these groups as "mixed-tenure" and "high-tenure" respectively. We find that relative income gains following PNTR are generally higher for high-tenure NM workers along both the extensive and intensive margins: they are relatively more likely to remain employed, and they exhibit relatively higher

[3] Waugh (2019) finds that Chinese retaliatory tariffs had negative effects on US motor vehicle sales. Greenland, Ion, Lopresti, and Schott (2020) show that firms' reactions to PNTR vary widely within narrow industries, in part due to their access to cheaper inputs from China. Aghion et al. (2021) find similar heterogeneity among French firms' reactions to the China shock.

earnings growth conditional on being employed. Such relative gains are smaller for NM workers with lower tenure.

Second, we investigate how responses to PNTR vary by workers' initial characteristics or their firms' attributes using triple interactions of these traits with the county and industry exposure terms. We find that relative earnings gains are higher among both NM and M workers with *ex ante* higher earnings. For NM workers, this relationship suggests they possess human capital that boosts their competitiveness in a more crowded labor market *vis à vis ex ante* lower-paid workers. For M workers, it may indicate these workers possess skills that are more easily transferable to other industries, areas, or firms. An alternative explanation worth exploring in future research is that such workers may have savings allowing them to be more selective in accepting a new position after the shock.

Two other results also stand out. First, we find that manufacturing workers at smaller and non-diversified firms – i.e. those engaged solely in M or NM activities but not both – have relatively better earnings outcomes than workers at firms that are larger or diversified. The former result provides worker-level evidence consistent with Holmes and Stevens (2014)'s hypothesis that small firms may be more likely to produce customized output less substitutable with Chinese imports, while the latter suggests that a focus on manufacturing may contribute to this ability.[4] Second, outside M, we find that relative earnings gains are higher among women, whites and younger workers.[5]

This paper is most closely related to Autor et al. (2014), who use US Social Security Administration earnings data to examine the outcomes of M workers before and after the growth of US imports from China. Here, we use the LEHD to perform a conceptually similar analysis, but one that is focused on workers outside manufacturing. Our analysis differs in two other important respects. First, we consider workers' exposure along the supply chain, which we find to be a key determinant of both NM and M worker outcomes. Second, we find geographic exposure to be a more important determinant of subsequent earnings than industry exposure, a result that may arise, in part, because our data contain more complete information on a worker's location of employment.

Another paper related to ours is Carballo and Mansfield (2023), who also exploit data from the LEHD to examine how workers are affected by firms' exposure to PNTR via their direct firm-level import and export participation. However, while Carballo and Mansfield (2023) find that the negative effects of import competition in manufacturing spill over to other sectors, here we show that workers outside manufacturing generally experience relative earnings *gains* via the supply chain linkages noted above. We note that our approach – which uses input-output tables to identify greater access to cheaper imported inputs – allows for this channel to affect firms that source inputs from

[4]This result is consistent with evidence for Canadian firms following the Canadian-US Free Trade Agreement (Head and Ries, 1999; Kovak and Morrow, 2022) and US firms facing increased import penetration from China Autor, Dorn, and Hanson (2013).

[5]Kahn, Oldenski, and Park (2022) examine the heterogeneous effects of Chinese import competition and find that Hispanic workers exhibit greater manufacturing employment loss during the China shock, while Autor et al. (2019) focus on differing effects by gender. Conlisk et al. (2022) use data from the Current Population Survey and find differences across gender in terms of labor market outcomes, the college-attendance income premium, and educational attainment decisions. Kamal, Sundaran, and Tello-Trillo (2020) illustrate how import competition results in a decline in the proportion of female employees, promotions, and earnings at firms subject to the Family and Medical Leave Act, compared to firms not subject to this policy. A more general discussion of labor-market adjustment to trade shocks is surveyed in McLaren (2017), McLaren (2022), and Caliendo and Parro (2022).

domestic suppliers and wholesalers in addition to direct importing (i.e. being the importer of record themselves). Furthermore, we allow these input-output linkages to have an impact on firms via both industry and geographic dimensions. Our ability to control for worker, firm, and geographic controls, along with both industry- and geographic-level exposure to import competition also sets our work apart from Wang, Wei, Yu, and Zhu (2018)'s commuting-zone-level analysis of supply chain effects of the China Shock, which uses an augmented version of the approach in Autor, Dorn, and Hanson (2013). And while they also find beneficial effects of increased competition in input markets for services industries, our use of annual worker-level data allows us to consider individual-level earnings, track effects over time, and examine the relevance of worker heterogeneity.

Our focus on US workers outside manufacturing also relates to the commuting-zone level study of the China Shock in Autor, Dorn, and Hanson (2013) and the worker-level analysis of NAFTA in Hakobyan and McLaren (2016). The former finds that greater own-region exposure to imports from China has no impact on non-manufacturing employment but exerts a negative impact on wages. Hakobyan and McLaren (2016) document a decline in wages of 8 percentage points among less-educated NM and M workers in US industries and regions with greater exposure to NAFTA. Here, considering both spatial and industry exposure, as well as supply chain linkages, we find relative earnings gains among NM workers after PNTR, but that these relative gains are less robust for workers with less firm tenure and who have lower *ex ante* earnings.[6]

Our characterization of worker earnings and employment before and after PNTR relates to the broader literature investigating the short- and long-run consequences of "mass layoffs," typically defined as separation by workers with three to six years tenure from an establishment shedding 30 percent or more of its labor force within a year. Papers in this line of research – e.g., Podgursky and Swaim (1987); Jacobson, LaLonde, and Sullivan (1993); Stevens (1997); Sullivan and Wachter (2009) – have documented earnings drops of 30 to 40 percent upon displacement before staging a modest but often incomplete recovery in the subsequent decade. Here, we provide context for such large declines in earnings among displaced manufacturing workers using a plausibly exogenous shock to US trade policy as an alternative approach to identifying "mass layoffs."

Finally, our results offer insight into recent research suggesting regional responses to import competition vary according to relative endowments (Bloom et al., 2019; Eriksson et al., 2019). Bloom et al. (2019) find that higher import competition boosts services and total employment in high-human-capital commuting zones, with no gains to overall employment in manufacturing-intensive low-human-capital regions. While we also find that workers – particularly NM workers – in some geographic areas benefit from increased import competition, we identify a mechanism for this observation that operates through input-output linkages. We also find that for the workers that are

[6]Several papers examine the effect of trade liberalization on manufacturing workers *outside* the United States, e.g., in Brazil (Dix-Carneiro, 2014; Krishna et al., 2014), Denmark (Utar, 2018) and Canada (Kovak and Morrow, 2022). Keller and Utar (2023) and Keller and Utar (2022) investigate the impact of import competition in Denmark on worker polarization and gender inequality, and Deng, Krishna, Senses, and Stegmaier (2021) study differences in how industry versus occupational exposure to import competition affect German workers' income risk. Focusing on a major trade *de-liberalization* – the collapse of the Finnish-Soviet bilateral trade agreement – Costinot, Sarvimäki, and Vogel (2022) find scarring effects on both employment and wages, while also considering industry- and geography-level exposure to the trade shock.

(relatively) harmed by PNTR, the negative effects on earnings are long-lived, persisting through the end of our sample period in 2014, consistent with findings in Autor, Dorn, and Hanson (2021).

The remainder of the paper proceeds as follows. Section 2 summarizes the matched employer-employee data we use, and Section 3 describes the trade liberalization we study. Section 4 describes our empirical strategy and presents our main results. Section 5 describes heterogeneous outcomes by worker attributes, and Section 6 concludes.

2 US Employer-Employee Data

We examine the relationship between US worker outcomes and exposure to PNTR using longitudinally linked employer-employee data from the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program, created as part of the Local Employment Dynamics federal-state partnership. The earnings and employment data are derived from state unemployment insurance (UI) records and the Quarterly Census of Employment and Wages (QCEW). In each quarter in each state, firms subject to state UI laws submit the earnings of their employees to their UI program, where earnings are defined as the sum of gross wages, salaries, bonuses and tips.[7]

States match the firm identifiers in these records to the QCEW, which contains information about where the firms are located and their industries of activity, and pass these data to the US Census Bureau. Census adds information about workers' age, gender, race, birth country and educational attainment derived from several sources, including the Decennial Census. This information is collected in the LEHD's Individual Characteristics File (ICF).[8] Birth country is either US or foreign. Racial categories are White, Black, Asian and Other. Education attainment levels are less than high school, high school or the equivalent, some college, and bachelors degree or higher.[9]

Census uses several levels of firm and establishment identifiers across various datasets. Firms in the LEHD are identified by state employer identification numbers (SEINs). Concordances between SEINs and Census' other identifiers allow us to match workers in the LEHD to a firm in the Longitudinal Business Database (LBD), which tracks employment and other attributes of virtually all privately owned businesses in the United States. Via the LBD, we are able to measure the size, age, and multi-unit status of a worker's firm.

In any given year a worker may be employed by more than one firm. We adopt the convention among LEHD researchers of assigning each worker in each year to the firm at which the worker's earnings are highest. Firms can have multiple establishments, and these establishments can have different six-digit NAICS industry codes and be located in different counties within the state.[10] We

[7]As discussed in greater detail in Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock (2009) and Vilhuber and McKinney (2014), state UI records cover approximately 96 percent of all private sector employees as well as the employees of state and local governments. Prime exceptions are agriculture, self-employed individuals and some parts of the public sector, in particular federal, military, and postal workers.

[8]Workers in the LEHD are identified via anonymous longitudinal person identifiers (PIKs) which have a one-to-one correspondence with their social security numbers and which are used to identify workers in a range of Census datasets. Except for Minnesota, UI records do not contain any information about firms except their identifier.

[9]Note that educational attainment is imputed for the vast majority (92 percent) of PIKs in the LEHD. See Vilhuber and McKinney (2014) for more details.

[10]We use the updated "FK" NAICS industry identifiers provided by Fort and Klimek (2016).

assign workers to establishments within the firm (and, thereby industries and counties) using the firm-establishment imputation in the LEHD's Unit-to-Worker (U2W) file.

As illustrated in Appendix Figure A.1, the number of states for which data are available in the LEHD varies over time. For the descriptive results on workers' industry switching, in Section 4.3 (Table 3, Figure 5 and 6), we use information from the 46 states whose data are in the LEHD starting in 2000.[11] In all of our regression analysis, we rely on data from the 19 states for which information is available over our full pre- and post-PNTR sample period (1993–2014).[12] To track workers across state lines, we also use information from the 46 states that become available after 2000. This allows us to keep in the regression sample individuals who were observed in one of the 19 states during the pre-period but subsequently moved to one of the other 46 states after 2000.

Table 1: 19-State Sample Worker Attributes in 1999

	Non-Manufacturing		Manufacturing	
	Mixed Tenure	High Tenure	Mixed Tenure	High Tenure
Female	0.48	0.46	0.30	0.28
	(0.50)	(0.50)	(0.46)	(0.45)
White	0.84	0.87	0.85	0.87
	(0.37)	(0.34)	(0.36)	(0.34)
Black	0.10	0.08	0.08	0.07
	(0.30)	(0.26)	(0.27)	(0.26)
American Born	0.89	0.89	0.85	0.85
	(0.32)	(0.32)	(0.36)	(0.36)
Less than HS	0.11	0.09	0.14	0.13
	(0.31)	(0.28)	(0.35)	(0.33)
HS	0.28	0.27	0.34	0.34
	(0.45)	(0.44)	(0.47)	(0.47)
Some College	0.34	0.34	0.33	0.32
	(0.47)	(0.47)	(0.47)	(0.47)
College or More	0.28	0.31	0.20	0.21
	(0.45)	(0.46)	(0.40)	(0.41)
Age	34	37	35	38
	(7.8)	(6.5)	(7.4)	(6.2)
Earnings ($000)	34	47	39	47
	(113)	(210)	(89)	(230)

Source: LEHD, LBD, and authors' calculations. Table reports the mean and standard deviation of noted groups of workers in 1999. Samples are 5 percent stratified draws from the 19 states whose information is available in the LEHD during the pre-PNTR period, 1993 to 1999. Workers above the age of 50 in 2000 are omitted. Age and earnings are in years and dollars; all other attributes are the share of observations for which the noted attribute is true. The number of workers in thousands in each 5 percent sample is 789 (Mixed-Tenure NM), 209 (High-Tenure NM), 194 (Mixed-Tenure M), and 69 (High-Tenure M).

Our regression analysis compares outcomes across workers with "mixed" and "high" firm tenure. High-tenure workers are employed by the same firm during the entire 1993 to 1999 pre-PNTR period. The mixed-tenure sample includes workers that are employed for the entirety of the pre-period, but

[11] The 46-state sample represents 96 percent of US overall and manufacturing employment in 2000. Missing from the 46-state sample are Alabama, Arkansas, New Hampshire, Mississippi, and the District of Columbia.

[12] The 19 states are Alaska, Arizona, California, Colorado, Florida, Idaho, Illinois, Indiana, Kansas, Louisiana, Maryland, Missouri, Montana, North Carolina, Oregon, Pennsylvania, Washington, Wisconsin, and Wyoming. Together, they represent 47 percent of total US employment and manufacturing employment in 2000.

not necessarily by the same firm.[13] For computational convenience, we draw representative 5 percent samples from the population of both groups of workers for our regressions. These draws include all workers from "small" counties (i.e., those in the first size decile, with population at or below 5,327 according to the 2000 census), plus a 5 percent random sample of workers from all other, i.e. "large," counties, stratified according to worker attributes (age, gender, race, ethnicity and educational attainment). All regressions are weighted by the inverse probability of selection into the sample. Finally, we exclude workers who would be older than 64 in 2014 to abstract from normal-age retirement.

Within each sample, workers are classified as initially in manufacturing (M) if they are employed in an establishment whose major activity in 1999 is in NAICS industries beginning with "3." All other workers are classified as initially non-manufacturing (NM). Workers not present in the sample during some or all of the post period are classified as not employed (NE) in those years. The predominant reason for NE status is lack of employment – unemployment or labor force exit – but it may also be the result of death, movement to a state (or country) outside the sample of states, for which we don't have data, or movement to a job that is out of scope of the UI system. We note, however, that workers in our regression sample that move to one of the 46 states available in the LEHD after 2000 remain in the sample and are not classified as NE as a result of such moves.

Table 1 summarizes the attributes of the NM and M workers in our high- and mixed-tenure samples as of 1999. Across both groups, high-tenure workers are less likely to be female, more likely to be white, and are more likely to be college educated. They are also older and have higher average earnings. *Vis à vis* their M counterparts, NM workers are more likely to be female and college educated. This disproportionate presence of women in NM employment will be relevant when we examine the heterogeneous effects of exposure to import competition by gender.

3 Defining Industry and County Exposure to PNTR

The US granting of PNTR to China in October 2000 was unique in that it left assessed tariff rates unchanged, but altered the way US imports from China were considered under the two sets of tariffs that comprise the US Tariff Schedule. The first set of US tariffs, known as NTR tariffs, are applied to goods imported from fellow members of the World Trade Organization (WTO) and are generally, but not uniformly, low due to repeated rounds of trade negotiations during the post-war period. The second set of tariffs, known as non-NTR tariffs, were set by the Smoot-Hawley Tariff Act of 1930 and are often substantially higher than the corresponding NTR rates. Imports from non-market economies such as China are by default subject to the higher non-NTR rates, but US law allows the President to grant such countries access to NTR rates on a year-by-year basis subject to annual approval by Congress.

US Presidents granted China such a waiver every year starting in 1980, but, as documented in Pierce and Schott (2016), Congressional votes over annual renewal became politically contentious and less certain of passage following various flash points in US -China relations, in particular the

[13] Because the high-tenure and mixed-tenure samples are drawn independently, in principle, some of the workers in the high-tenure sample could be in the mixed-tenure sample as well.

Chinese government's crackdown on Tiananmen Square protests in 1989. As a result, firms considering engaging in US-China trade prior to PNTR faced the possibility of substantial tariff increases, raising the option value of waiting for a more permanent change in policy (Pierce and Schott, 2016; Handley and Limao, 2017). This uncertainty ended with passage of PNTR, which "locked in" China's access to NTR tariff rates, eliminating the disincentive to US-China trade caused by the annual renewal process, and effectively liberalizing trade between the two countries.

Following Pierce and Schott (2016), we measure industry i's exposure to PNTR as the rise in US tariffs on Chinese goods that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR's extension,

$$Gap_i = Non\,NTR_i - NTR_i. \tag{1}$$

We compute NTR_i and $NonNTR_i$ for 6-digit NAICS industries using simple averages of the respective Harmonized System (HS) level *ad valorem equivalent* tariff rates provided by Feenstra, Romalis, and Schott (2002), mapping HS to NAICS using the concordance developed by Pierce and Schott (2012). We compute this gap using tariffs as of 1999, the year before PNTR. As discussed in Pierce and Schott (2016), an attractive feature of this measure is its plausible exogeneity to employment outcomes after 2000, as 79 percent of the variation in the NTR gap across industries arises from variation in non-NTR rates, set 70 years before. This feature of non-NTR rates rules out reverse causality that would arise if NTR rates were set to protect industries experiencing surging imports: To the extent such activity occurred, the higher NTR *rates* would result in a lower Gap_i, biasing results away from finding an effect of the change in policy.

We follow Topalova (2007) and Pierce and Schott (2020) in computing a Bartik-style county exposure to PNTR as the employment-weighted average Gap_i of the industries it produces. Measures such as these are useful for gauging effects on workers that arise from local labor market shocks. For each US county c,

$$Gap_c = \sum_i \frac{L_{ic}^{1990}}{L_c^{1990}} Gap_i, \tag{2}$$

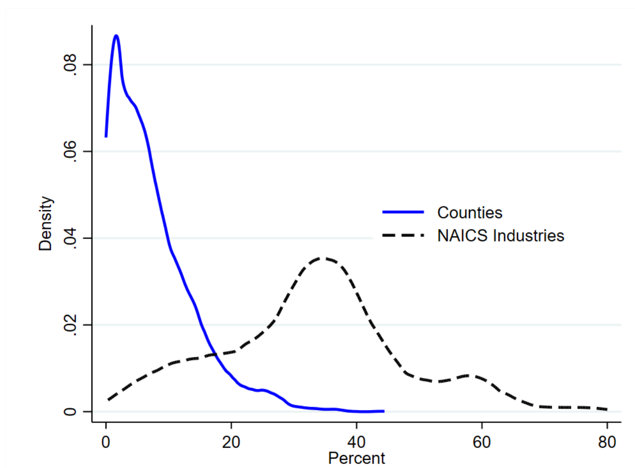
where the employment shares for 1990 are based on county-industry employment recorded in the US Census Bureau's Longitudinal Business Database (LBD), which tracks the employment of virtually all US firms and establishments from 1977 to the present.[14] In this computation, Gap_i is positive only for industries whose outputs are subject to US import tariffs, primarily in the manufacturing sector. For industries whose output is not subject to tariffs, such as service industries, the industry gap is set to zero. The measure of geographic exposure to trade liberalization could also be calculated at a higher level of aggregation. Pierce and Schott (2020) show that measures based on Public Use Microdata Areas—which contain a minimum population of 100,000 and are larger even than

[14] An advantage of the LBD versus the more commonly used and publicly available County Business Patterns (CBP) for computing county-industry labor shares, e.g., as in Autor, Dorn, and Hanson (2013) and Pierce and Schott (2020), is that it contains employment counts for all industries and counties, thereby avoiding issues of suppression to maintain confidentiality in the public version of the CBP (Eckert et al., 2020). Bloom, Handley, Kurmann, and Luck (2019) make use of the LBD for the same reason.

Commuting Zones—yield similar effects to those based on counties.

Figure 1 displays the kernel densities of Gap_i and Gap_c where, for ease of exposition, the former is restricted to industries that appear in the US tariff schedule. As a result, the industry-level distribution omits a large mass at zero representing non-goods industries that are not subject to tariffs. Gap_i has a mean and standard deviation of 33 and 14 percent, while Gap_c has a mean and standard deviation of 7 and 6 percent. Intuitively, the distribution of Gap_c lies to the left of the distribution of Gap_i, reflecting the presence of service industries with NTR gaps of zero. The correlation between Gap_i and Gap_c across workers in our 19-state regression sample is 0.26.[15] Interquartile shifts in exposure are 20.5 and 7.7 percent for industry and county, respectively.

Figure 1: Distribution of Gap_i and Gap_c



Source: LBD, Feenstra et al. (2002), and authors' calculations. Figure displays the distributions of the 1999 NTR gap across 6-digit NAICS industries (Gap_i) and US counties (Gap_c). The former is restricted to the 473 industries that appear in the US tariff schedule.

Trade liberalization episodes such as PNTR may also affect US workers' earnings via their supply chains, i.e., the upstream industries from which their firms purchase inputs or the downstream industries to which they sell their outputs. Measuring supply-chain exposure to PNTR is especially important for determining effects on NM workers who can face effects of import competition via supply chains, even if their industries are not directly affected by tariffs.[16] We compute up- and downstream NTR gaps using total requirements information from the 1997 BEA input-output tables. Gap_i^{up} is the weighted average of all 6-digit NAICS industries k used by industry i and not sharing the same 3-digit root as i, using total requirements input-output coefficients (ω_{ik}^{up}) as weights,

$$Gap_i^{up} = \sum_k \omega_{ik}^{up}\, Gap_k. \tag{3}$$

[15] Autor et al. (2014) report a correlation of 0.12 across workers' industry (four-digit SIC) and region (commuting zone) exposure to Chinese import penetration.

[16] A number of recent papers emphasize the importance of examining input-output linkages when estimating the impact of import competition, e.g., Amiti and Konings (2007); Goldberg, Khandelwal, Pavcnik, and Topalova (2010); Pierce and Schott (2016); Acemoglu, Autor, Dorn, Hanson, and Price (2016); Flaaen and Pierce (2019).

Gap_i^{down} is the analogous weighted average for all the downstream industries outside i's 3-digit root that use industry i.[17]

We compute Gap_c^{up} and Gap_c^{down} by taking employment-weighted averages of Gap_i^{up} and Gap_i^{down}, e.g.,

$$Gap_c^{up} = \sum_i \frac{L_{ic}^{1990}}{L_c^{1990}} Gap_i^{up}. \tag{4}$$

Upstream exposure is therefore higher when the county has more employment in industries whose upstream industries have higher exposure to PNTR.[18]

Industries vary intuitively in terms of their up- and downstream gaps.[19] Hospitals (NAICS 622), for example, has above-median upstream exposure (0.08) as a result of sourcing from Chemicals (NAICS 325), which includes pharmaceuticals, Plastics and Rubber (NAICS 326), and Miscellaneous Manufactures (NAICS 339), which includes medical devices and scientific equipment. As its sales are mostly to final consumers, it has negligible downstream exposure. General Warehousing and Storage (493110), by contrast, has below-median upstream exposure (0.04) but above-median downstream exposure (0.11), as Chemicals (NAICS 325), Electronics (NAICS 334), and Transport Equipment (NAICS 336) are among its most important customers. Software Publishing (NAICS 511210) is an interesting case in that its up- and downstream exposure are both high (0.08 and 0.26) because it has substantial purchases *and* sales to Computer and Electronics (NAICS 334). We provide examples of counties with relatively high and low up- and downstream exposure in Appendix Figure A.2.

4 DID Analysis of Workers' Earnings Response to PNTR

We examine the link between PNTR and worker earnings using a generalized OLS difference-in-differences (DID) specification. This approach compares the impact of county versus industry exposure to the change in policy while controlling for initial worker (j), firm (f), industry (i), and county (c) characteristics—a much richer set of controls than possible with more aggregate data—along with worker and time (t) fixed effects, α_j and α_t. Our baseline specification interacts our six measures of exposure with a dummy variable, *Post*, which takes a value of one in the years following PNTR,

$$\begin{aligned}\{E > 0_{jfcit}, LN_{jfcit}, CR_{jfcit}\} \quad = \quad & \sum_{z \in own,up,down} \varphi_i^z Post \times Gap_i^z + \sum_{z \in own,up,down} \varphi_c^z Post \times Gap_c^z + \\ & Post \times \mathbf{X_{j,1999}} \beta_\mathbf{1} + Post \times \mathbf{X_{f,1999}} \beta_\mathbf{2} + Post \times \mathbf{X_i} \beta_\mathbf{3} + \mathbf{X_{it}} \beta_\mathbf{4} + \\ & \delta_3 Post \times MSH_{c,1999} + \alpha_j + \alpha_t + \epsilon_{jfcit}. \end{aligned} \tag{5}$$

As worker earnings may be zero in some years, we consider for our dependent variable three transformations of earnings recommended by Chen and Roth (2023). The primary transformation used

[17] We omit up- and downstream industries within the same 3-digit root given their high correlation with own exposure.

[18] The means of *Industry* Gap_i^{up}, and *Industry* Gap_i^{down}, *County* Gap_c^{up}, and *County* Gap_c^{down} are 11.3, 11.0, 7.5 and 6.5 percent. Their standard deviations are are 4.3, 8.3, 0.8 and 1.5 percent. Their interquartile ranges are 5.1, 6.6, 1.7 and 1.9 percent.

[19] Appendix Figure A.2 plots up- versus downstream gaps by industry and county, revealing their positive correlation.

throughout the paper is referred to as "CR" (for Chen-Roth), which captures the combined impact of the extensive and intensive margins of employment. As described in Chen and Roth (2023), this approach first replaces any zero earnings with the minimum observed earnings in the sample, then divides earnings by the minimum, and, finally, takes logs. As a result, CR will be zero for observations whose true value is zero and for those whose true observation is the minimum.[20] The second transformation is a dummy for earnings greater than zero, "E>0," which captures the extensive margin of employment. The third transformation is log earnings, or "LN," which measures the intensive margin of earnings conditional on employment by dropping zeros. These latter two transformations are used in certain portions of the analysis as a complement to CR and to highlight the role of particular margins of adjustment.

As discussed in Section 2, the sample period is 1993 to 2014, and our regression sample is a 5 percent stratified random draw of workers aged 64 or younger from the 19 states for which employer-employee data are available in the 1993 to 1999 pre-period. Also as noted in Section 2, we are able to follow these workers across the 46 states available in the LEHD throughout the post-policy-change period. As is standard in LEHD research, regression observations are weighted by the inverse of the probability of being in the sample. Worker, firm, industry, and county attributes are as of 1999.

The first two terms on the right-hand side of the equation are the county and industry DID terms of interest. Industry exposures catch the impact of the policy on the industry in which the worker is employed, which is based on their establishment of employment. County exposures capture the spillover effect of exposure by nearby workers through factors such as labor market competition or changes in aggregate demand. We expect own exposure to have a negative relationship with worker-level earnings as it captures the direct effect of increased import competition in the output of a worker's industry or county. We expect upstream exposure to have a positive impact on worker earnings to the extent that greater openness with China results in lower input prices or greater productivity among input suppliers (Amiti et al., 2014). Downstream exposure, by contrast, is expected to dampen earnings to the extent that it disrupts sales to customers. Our regression specification thus represents a reduced-form approach to assess the kinds of spatial and industry mobility frictions assumed in a range of spatial general equilibrium trade models, e.g., Caliendo et al. (2019); Adão et al. (2019). Similar specifications are employed in a number of empirical analyses, e.g., Hakobyan and McLaren (2016) and Autor et al. (2014).

The next four terms on the right-hand-side of equation 5 are controls for 1999 worker, firm, and industry characteristics interacted with *Post* as well as controls for time-varying industry characteristics. We multiply the 1999 worker, firm, and industry characteristics – which do not change over time and would be completely absorbed by the worker fixed effects – by the *Post* dummy to allow for the relationships between these attributes and earnings to change at the same time as PNTR was granted, assisting us in isolating the impact of the policy change.[21]

[20] We find results similar to CR(Earnings) using two alternate approaches: the arcsin of earnings and the log of earnings plus 1.

[21] Initial worker attributes are age, gender, race, foreign-born status and education. Initial firm characteristics are firm-size categories, trading status, and diversification. Trading status is import only, export only, both or neither. Diversification is an indicator for whether or not the firm operates both manufacturing and non-manufacturing establishments. Initial industry characteristics include exposure to reductions in Chinese import tariffs and production

The remaining terms on the right-hand side of equation 5 represent the worker and year fixed effects needed to identify the DID terms, as well as an interaction of *Post* with county c's 1999 manufacturing share ($MSH_{c,1999}$). This term, recommended by Borusyak et al. (2021), addresses the issue of "incomplete shares" that arises when industry weights for calculating county-level exposure are based on total employment, rather than only manufacturing industries, as in equation 2. In addition, it controls for the extent to which a county is manufacturing-intensive, allowing us to separate the implications of variation in exposure to the policy change.

4.1 Baseline Estimates of Workers' Overall Earnings Response to PNTR

We start by analyzing the impact of PNTR on workers' overall earnings using the CR transformation described in the previous section. Results are reported in Table 2, where the first 4 columns report the DID coefficients of interest for NM workers and the subsequent 4 columns focus on M workers.[22] Even columns report results for the full specification described in equation 5. To highlight the relevance of controlling for exposure via the supply chain, odd columns display estimates for a simpler specification that excludes up- and downstream exposures. Hereafter, we refer to the full equation 5 specification as "$Own + IO$" and the simpler specification as "Own." The former is our preferred specification, while the latter serves as a comparator to highlight the importance of controlling for input-output linkages. For the $Own + IO$ specifications, we include a bottom panel that reports two F-tests: one testing the joint significance of the own, upstream, and downstream industry exposure terms, and the other testing the joint significance of the corresponding county exposure terms.

Table 2 contains several novel results. First, we find that PNTR affects both NM and M workers primarily through spatial rather than industry exposure. That is, industry exposure terms are jointly statistically insignificant in the even columns for both groups of workers, while the county exposure terms are jointly significant across the board. While this primacy of county over industry exposure among manufacturing workers might seem surprising given the strong negative impact of PNTR on manufacturing industry employment reported in Pierce and Schott (2016), the two findings are consistent. The critical distinction is that Pierce and Schott (2016) focus on *industry employment*, while our attention here is on *worker earnings*. As we show below, there is a net outflow of workers from manufacturing to services after PNTR, lowering *employment* in highly exposed industries. The estimates in Table 2 demonstrate that what matters for workers' subsequent *earnings* are the conditions in their county: If the county is highly exposed, workers experience relative earnings declines as labor market competition rises and aggregate demand for local goods and services falls, even if they are initially employed in low-exposure industries.[23] By contrast, workers in less-exposed counties – even if initially employed in high-exposure industries – can transition from manufacturing to services with less of an earnings penalty.[24]

subsidies. Time-varying industry characteristics ($\mathbf{X_{it}}$) capture the elimination of US quotas on textile and clothing products as part of the phasing out of the global Multifiber Arrangement (MFA). These variables are taken from Pierce and Schott (2016) and Pierce and Schott (2020); their construction is described in Appendix Section B.

[22] Appendix Section E reports coefficient estimates and standard errors for other earnings transformations that are reported visually in this Section.

[23] This relationship is also present in raw data as shown in Figure 6, below.

[24] We note that it continues to be the case that higher exposure to PNTR is associated with relative declines in

Table 2: Response of Overall Earnings (CR Transformation) to PNTR

	Mixed Tenure NM		High Tenure NM		Mixed Tenure M		High Tenure M	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var:	CR	CR	CR	CR	CR	CR	CR	CR
Post x $\text{Gap}^{Own}_{Industry}$	.	.	.	.	-.06	-.05	.11	.12
	.	.	.	.	.11	.12	.19	.19
Post x $\text{Gap}^{Down}_{Industry}$	.	-1.72*	.	-1.04	.	-.31	.	-.4
	.	.96	.	.98	.	.28	.	.38
Post x $\text{Gap}^{Up}_{Industry}$	.	2.24	.	2.47*	.	.09	.	.23
	.	1.39	.	1.4	.	.75	.	1.21
Post x $\text{Gap}^{Own}_{County}$	-4.9***	-5.12***	-3.36***	-3.92***	-3.01***	-1.83	-3.06***	-1.36
	.87	1.17	.88	1.11	.63	1.17	.81	1.41
Post x $\text{Gap}^{Down}_{County}$	.	-3.21**	.	-3.92***	.	-3.92**	.	-6.34***
	.	1.49	.	1.47	.	1.52	.	2.1
Post x Gap^{Up}_{County}	.	6.2*	.	9.41***	.	1.85	.	1.81
	.	3.55	.	3.62	.	4.4	.	4.9
R-sq	.45	.45	.44	.44	.45	.45	.44	.44
Obs (000)	17,360	17,360	4,605	4,605	4,274	4,274	1,520	1,520
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Own	Own+IO	Own	Own+IO	Own	Own+IO	Own	Own+IO
Cluster	N4, Cty	N4, Cty	N4, Cty	N4, Cty	N4, Cty	N4, Cty	N4, Cty	N4, Cty
Industry Gaps F		1.633		1.657		.472		.399
Industry Gaps p		.198		.193		.703		.754
County Gaps F		14.4		8.462		11.7		5.811
County Gaps p		0		0		0		.001

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 for workers initially employed in non-manufacturing (NM) and manufacturing (M). The dependent variable is the Chen and Roth (2023) earnings transformation, which is the log of earnings after replacing any zeros with the minimum observed earnings. The sample period is 1993 to 2014. Mixed-tenure workers are employed throughout the 1993 to 1999 pre-period, but not necessarily by the same firm. High-tenure workers are employed by the same firm during the pre-period. *Post* is a dummy variable for years after 2000. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Final two panels report F-statistics for the joint significance of the industry and county exposure DID terms, respectively. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels.

Observing both industry- and geographic-level exposure to trade or policy changes is rare, as it requires access to detailed worker-level data. Among this small set of research, Autor et al. (2014) and Hakobyan and McLaren (2016) find that both dimensions of exposure are associated with negative US labor market outcomes when studying import competition from China and NAFTA, respectively. Costinot et al. (2022) find that the negative effects of worker-level exposure to a reduction in export demand caused by the breakup of a Finland-Soviet bilateral trade agreement are amplified by being

employment for more-exposed manufacturing industries. Indeed, we find results in line with Pierce and Schott (2016) when we aggregate our M samples to the industry-year-level and implement a regression as in that paper.

located in a more-exposed area. None of these studies, however, considers the type of industry- and geography-level input-output linkages, which we find can contribute to relative earnings gains.

The second key message of Table 2 is that accounting for supply chain linkages is important in evaluating workers' response to a labor market shock. For NM workers, we find positive coefficients for county upstream exposure and negative estimates for county downstream exposure that are large and statistically significant at conventional levels. These estimates indicate that NM workers' earnings rise with higher exposure in input markets and fall with greater exposure among customers. Including these channels of exposure is critically important, as they can flip overall estimates of the relationship between exposure to PNTR and NM workers' earnings from negative to positive. In particular, when only including an NM worker's own county exposure (the first column under the headings for mixed-tenure NM and high-tenure NM), we find a *negative* relationship between NM earnings and exposure to PNTR. Inclusion of input-output terms – specifically accounting for more competition in input markets – uncovers offsetting effects, and as discussed in Section 4.2, the richer specification reveals that PNTR is associated with relative earnings *gains* for most NM workers. Two aspects of the relevance of upstream and downstream exposure found here are novel in the literature. First, they provide detailed empirical evidence supporting the input-output linkages highlighted in the model-based GE effects of the China Shock in Caliendo et al. (2019); Adão et al. (2019). Second, while the benefits of upstream exposure to the China Shock have been long-suspected, previous research (Pierce and Schott, 2016; Acemoglu et al., 2016) has not found such effects because it did not consider the geographic input-output linkages included in our analysis.[25]

For M workers, county upstream (and own) exposure coefficients are smaller in magnitude and imprecisely estimated relative to those for NM workers, while downstream estimates are large and statistically significant at conventional levels, particularly for High-Tenure M workers, indicating that M workers are relatively more susceptible to customer exposure than NM workers.[26] One potential explanation for M workers' anemic responsiveness to upstream exposure relative to NM workers is an asymmetry in their sensitivity to supply chain disruption. In manufacturing, several links of a supply chain with varying levels of exposure might move offshore together if productivity depends heavily on proximity, as posited in Baldwin and Venables (2013), i.e., less-exposed downstream links may co-offshore with highly exposed upstream links, or *vice versa*.[27] In that case, the former's upstream exposure affords no benefit, and the latter's downstream exposure is particularly disruptive.[28] For nontradable consumer-facing services like health care and tourism, such co-migration of stages of the

[25] An exception is Wang et al. (2018) who find benefits of higher import penetration in input markets using the identification strategy from Autor et al. (2013).

[26] As discussed below and illustrated in Figure 7, the impact of each channel of exposure varies over time. For example, the coefficient on own-county exposure is negative and statistically significant in the years immediately after PNTR.

[27] Johnson and Moxnes (2023) provide a model in which trade between upstream and downstream industries becomes more spatially concentrated as trade costs fall.

[28] Support for this explanation can be found in the economic geography and existing China Shock literatures. Ellison, Glaeser, and Kerr (2010) find that IO-linked manufacturing industries tend to co-agglomerate within the United States. Pierce and Schott (2016) and Acemoglu et al. (2016) show that US manufacturing plant and industry employment fall with downstream exposure to China but do not rise with upstream exposure, consistent with up- and downstream industries moving offshore in groups, potentially to China. Finally, Long and Zhang (2012) find that manufacturing industries within China become more spatially concentrated, and its regions increasingly specialized, after the China Shock.

supply chain may not be feasible to the extent that they must remain near their customers.[29] Below, we discuss further evidence consistent with this co-offshoring hypothesis that is revealed by examining the timing of effects of the various exposure measures.

4.2 Economic Significance

Assessing the economic significance of the DID coefficients via the standard approach—-an interquartile shift in exposure—-is not applicable in our setting: workers are simultaneously exposed along six different dimensions, so shifting exposure one coefficient at a time does capture their potential joint distributions. As a result, we illustrate the economic significance of our estimates by computing predicted relative earnings for all county–industry pairs in our samples using our estimated coefficients and actual county and industry exposures. Specifically, for each county–industry pair, we use the DID estimates in Table 2 to compute

$$Predicted\ Relative\ Earnings\ Growth_{ic} \;=\; \sum_{y\in\{i,c\}} \sum_{z\in\{o,u,d\}} \hat{\varphi}_y^z Gap_y^z, \tag{6}$$

where the first summation is over county and industry and the second is over own (o), up- (u) and down- (d) stream exposures.[30]

Figure 2 reports the distribution of predicted relative earnings growth across NM and M county-industry pairs under the Own and $Own+IO$ specifications for the CR dependent variable, by sample. The substantial mass of the solid orange curves to the right of zero in the first two panels reveals that the majority of NM county-industry pairs – 64 percent for mixed-tenure and 95 percent for high-tenure – exhibit relative earnings *gains* when accounting for exposure along the supply chain. The magnitude of these effects is larger for high-tenure sample than the mixed-tenure sample, with their respective averages being 3 and 29 log points (3 and 34 percent). By contrast, the third and fourth panels indicate that M workers in nearly all county-industry pairs experience relative earnings losses.

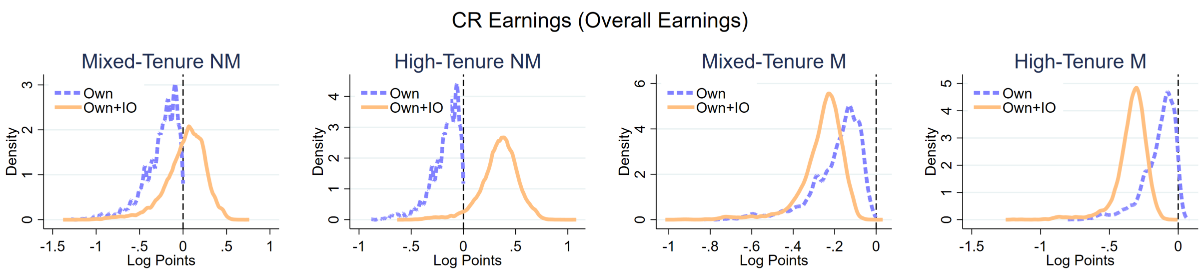
These first two panels also highlight the relevance for NM workers of exposure via input-output links mentioned above. The orientation of the blue curves for the Own specification to the left of zero show that failing to account for input-output relationships – in particular the benefits of exposure via input markets – would erroneously indicate that all NM workers experience relative earnings losses associated with PNTR. For manufacturing workers (the third and fourth panels), by contrast, failing to account for input-output linkages would lead to *underestimation* of the relative earnings losses

[29]PNTR may also benefit NM workers by inducing entry of "factoryless goods producers" like Fitbit and Roku that take advantage of a greater ability to outsource and offshore the physical transformation stages of goods production (Fort, 2023). While difficult to identify using existing BEA input-output tables, this activity may be reflected in M worker flows into Wholesale (NAICS 42) and Professional Services (NAICS 54). We hope to address this channel of job creation more directly in future research.

[30]In principle, one could use the DID coefficients presented in the last section to compute worker-level conditional predicted relative earnings by multiplying each worker's exposure by the estimated coefficients and taking their sum. However, in addition to it not being possible under Census disclosure guidelines, performing this more disaggregated calculation would not add useful information since each worker within an industry-county cell has the same exposure to PNTR.

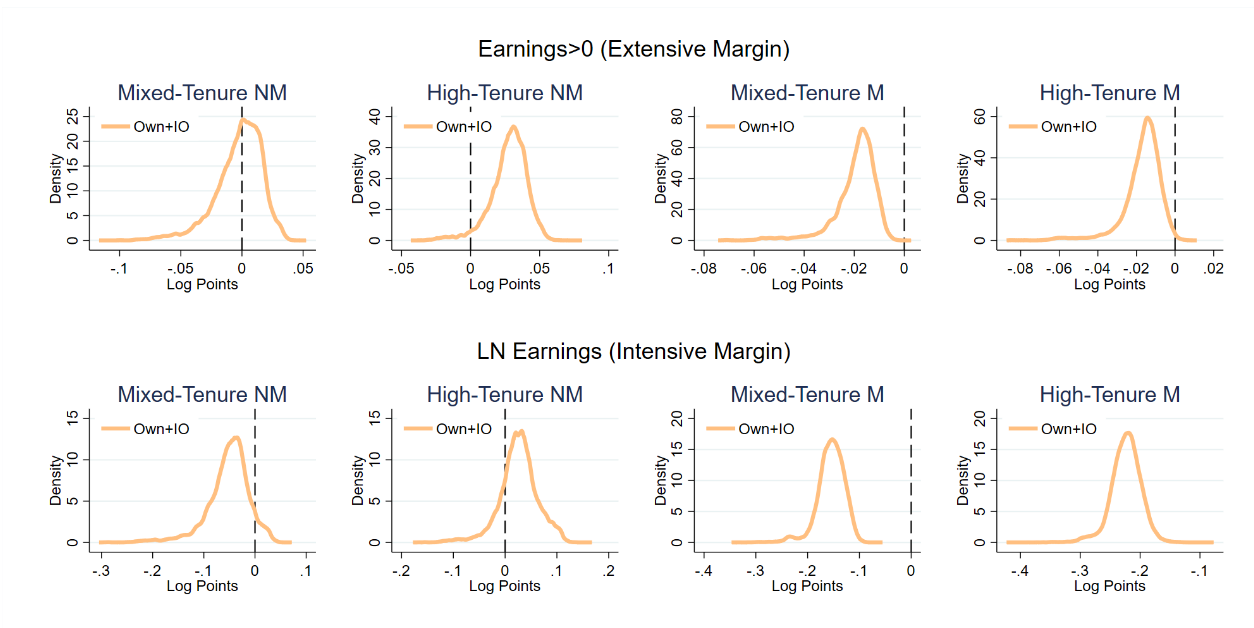
associated with PNTR, as indicated by the orange curves being shifted left relative to the blue. For these workers, accounting for the large negative effects of downstream exposure reveals additional relative earnings losses.

Figure 2: County-Industry Predicted Relative CR Earnings Growth, by Sample



Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure displays predicted relative earnings growth across county-industry pairs for mixed-tenure and high-tenure NM and M workers implied by the estimated Own versus $Own + IO$ DID coefficients. In each case, predictions are for the CR earnings transformation reported in Table 2. Predictions for each county-industry pair are the product of the reported coefficients and actual exposures.

Figure 3: $Own + IO$ County-Industry Predicted Relative CR Earnings Growth, by Sample



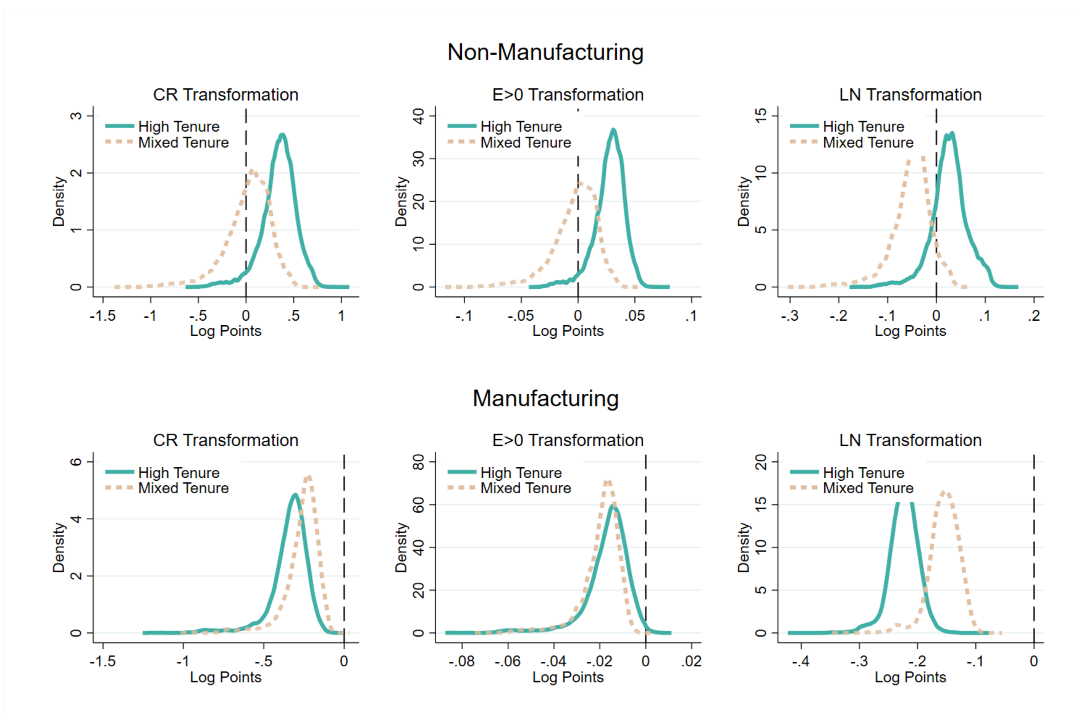
Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure displays predicted relative earnings growth across county-industry pairs for mixed-tenure and high-tenure NM and M workers implied by the estimated $Own+IO$ DID coefficients for the extensive and intensive earnings margins reported in Appendix Tables A.3 and A.4. Predictions for each county-industry pair are the product of the reported coefficients and actual exposures. Note that axes scales differ across plots.

Next, in Figure 3, we examine the margins responsible for the estimated relative effects on earnings. For M workers, the negative relationship between exposure to PNTR and earnings arises both from a lower probability of remaining employed (top row) and lower earnings conditional on employment (bottom row), as indicated by most of the curves' mass appearing to the left of zero. The converse is true for high-tenure NM workers; their relative earnings gains are due to both higher probability of remaining employed and higher earnings. For mixed-tenure NM workers, however, their modest gains are primarily from a higher probability of remaining employed, while most county-industry pairs experience relative earnings losses conditional on employment (left panel of bottom row). We explore differences in reactions for mixed-tenure and high-tenure workers in detail in the next sub-section.[31]

4.3 High-Tenure versus Mixed-Tenure Outcomes and Worker Flows

Figure 4 provides an alternative view of the predicted relative earnings computed in equation 6 with a direct comparison of outcomes for high-tenure and mixed-tenure workers, by earnings transformation. As the top row of this figure makes clear, the relative earnings gains of high-tenure NM workers exceed those of mixed-tenure NM workers, overall (left column, CR), and along both intensive and extensive margins (center and right columns), as indicated by the solid teal curves being shifted to the right of the dashed ochre curves.

Figure 4: $Own + IO$ County-Industry Predicted Relative Earnings Growth, by Sample



Source: LEHD, LBD, and authors' calculations. Figure displays predicted relative earnings growth across county-industry pairs for mixed-tenure and high-tenure NM and M workers implied by the estimated $Own+IO$ DID coefficients. The first panel in each row reports results for overall earnings using the results for the CR earnings transformation reported in Table 2. Subsequent panels in each row present analogous predictions using the coefficient estimates for the extensive and intensive earnings margins reported in Appendix Tables A.3 and A.4. Predictions for each county-industry pair are the product of the reported coefficients and actual exposures.

[31] Given US Census Bureau disclosure constraints, we report the economic significance of our results in Figure 4 using county-industry pairs as a unit of analysis, and treat each county-industry equally. In Figure A.4 of Appendix Section E.1, we show that estimates of economic significance are qualitatively similar when the kernel densities are weighted by the number of workers in each county-industry pair.

One potential explanation for this difference among mixed-tenure versus high-tenure NM workers is the former's greater susceptibility to labor-market competition from displaced manufacturing workers. Indeed, Table 3, which documents US workers' transitions among non-manufacturing (NM), manufacturing (M) and non-employment (NE) between 2000 and 2007, reveals a net flow of 1.9 (=5.8-3.9) million workers from M to NM in the years after the US change in trade policy. This flow represents 1.6 percent (=1.9/118.6) of the number of NM workers in 2000.

Table 3: Gross Flows to and from Manufacturing, 2000-7

	Millions				Percent of Initial Level			
	Sector in 2007				Sector in 2007			
Sector in 2000	NM	M	NE	2000 Total	NM	M	NE	2000 Total
Non-Manufacturing (NM)	85.0	3.9	29.6	118.6	72	3	25	100
Manufacturing (M)	5.8	8.3	4.3	18.3	32	45	23	100
Not Employed (NE)	42.3	3.2	.	45.6	93	7	.	100
2007 Total	133.1	15.4	33.9	182.4	73	8	19	100

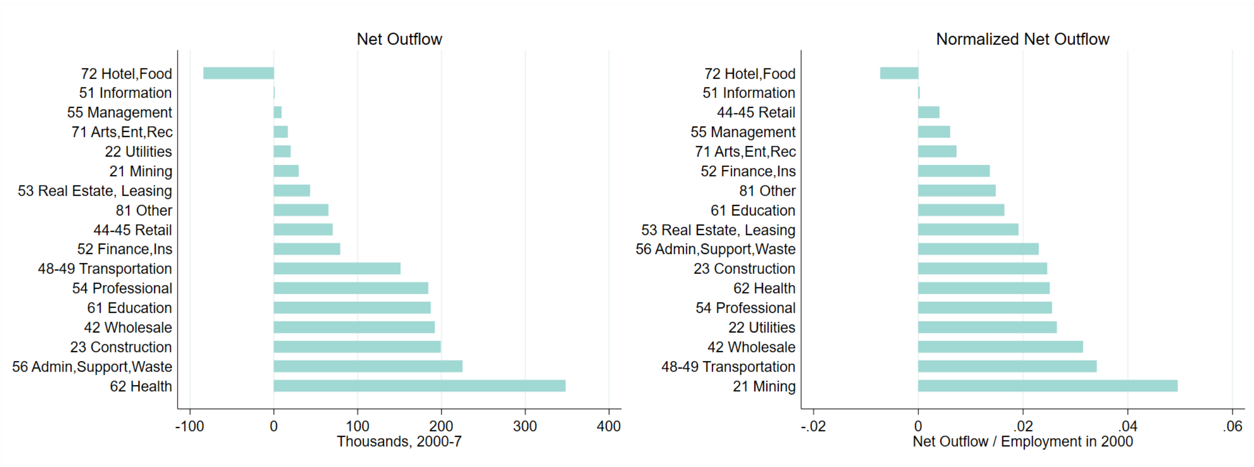
Source: LEHD, LBD and authors' calculations. Table reports the transition paths of employed and not-employed workers from 2000 (row) to 2007 (column) for the 46 states whose information is available in the LEHD starting in 2000. Alabama, Arkansas, New Hampshire and Mississippi as well as the District of Columbia are excluded. Left panel reports levels in millions of workers. Right panel reports shares of initial levels.

Figure 5 provides information about the transitions of former manufacturing workers across sectors that has not been previously reported and can only be computed with longitudinal worker-level data such as the LEHD. It also speaks to potential changes in labor market competition as workers flow at varying rates into different destination sectors. The left panel of this figure decomposes the 1.9 million M worker outflow according to 2-digit NAICS destination sector. As indicated in the panel, the largest net outflow in terms of number of workers is towards healthcare (NAICS 62), with sizable net flows of approximately 200 thousand workers to several other sectors. In the right panel of Figure 5, these net flows are divided by the *ex ante* (year 2000) employment of their destination sector, yielding measures of the extent of net inflows relative to sector size, thus providing a more meaningful measure of the extent of potential labor market competition across non-manufacturing sectors. As indicated in this panel, half of the 2-digit non-manufacturing NAICS sectors exhibit net inflows of manufacturing workers of 2 or more percent of their initial level, including Mining (NAICS 21), Transportation (NAICS 48-9), Wholesale (NAICS 32), Utilities (NAICS 22), Construction (NAICS 23) and Administration, Support, and Waste Management (NAICS 56).[32] Such increased labor-market competition for NM workers in these destination sectors could hold down earnings growth for a given level of labor demand, particularly for low-tenure workers who cycle in and out of employment more frequently and are thus more likely to be engaged in the job search process.

M worker outflows also provide intuition and context for the sharp earnings declines among M workers estimated in Table 2 and displayed in Figures 2 and 3. In Figure 6, we report the "quasi" median change in nominal earnings from 2000 to 2007 exhibited by M workers along all possible 2-digit

[32] Transitions to some of these sectors, e.g., wholesale (NAICS 42) and professional services (NAICS 54), are consistent with workers switching industry but not necessarily occupation (Traiberman, 2019), e.g., an R&D scientist formerly located in a manufacturing plant might move to a research lab.

Figure 5: Net Manufacturing Employment Outflow by Transition Path, 2000-7 (46 States)



Source: LEHD, LBD and authors' calculations. Left panel reports 2000 to 2007 net transitions (outflow less inflow) out of manufacturing by workers' initial 2-digit NAICS sector in the 46 states for which information is available in the LEHD for these years (Alabama, Arkansas, New Hampshire, Mississippi and the District of Columbia are excluded). Right panel reports these net flows divided by destination sectors' initial level of employment.

NAICS transition paths.[33] The left panel of the figure reveals outcomes for all workers, with earnings growth for workers who remain in manufacturing highlighted in red. As indicated in the figure, initial M workers transitioning to relatively low-skill service industries such as staffing agencies (NAICS 56) or accommodation and food services (NAICS 72) exhibit nominal wage *declines* of up to 20 percent. Indeed, considering the five most common destination sectors for former manufacturing workers, shown in the left panel of Figure 5, we see that these transitions tend to disproportionately involve weak or even negative earnings growth. Among the five, transitions to two sectors (construction; wholesale) involve earnings gains just above those for continuing manufacturing workers, one (health) entails lower earnings growth, and two (admin, support, waste; education) involve outright nominal earnings declines. These outcomes are consistent with the generally lower wages paid in these sectors and the popular narrative that well-paid manufacturing workers face large drops in income when they move to service sectors (Scott et al., 2022).[34] Moreover, the bottom row of Figure 4 indicates that the relative earnings losses for M workers associated with PNTR are, if anything, a bit larger for high-tenure workers due to lower earnings conditional on employment.

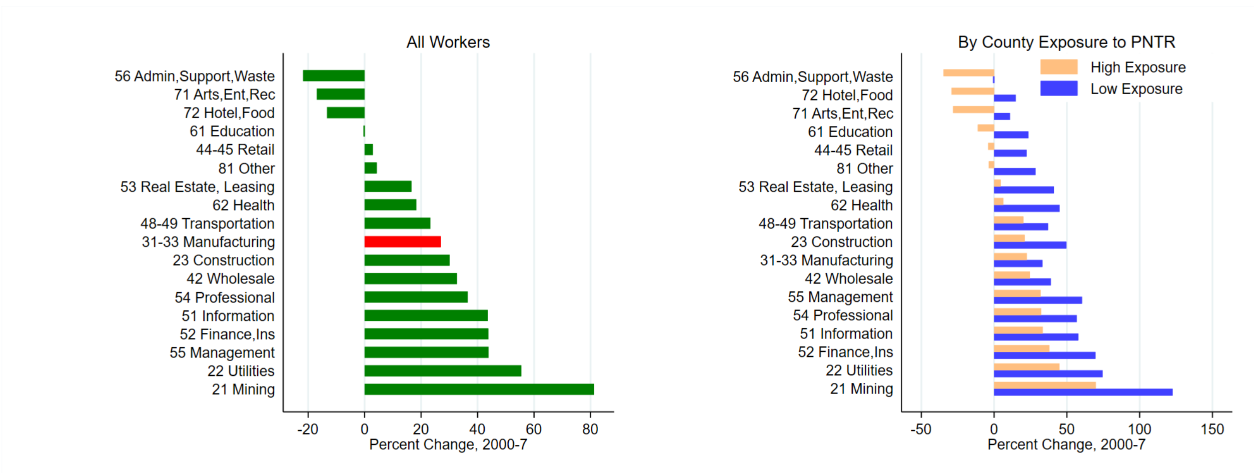
Lastly, the right panel of Figure 6 reports quasi-median earnings growth among workers in counties with the highest versus lowest quartile of Gap^{Own}_{County}. As shown in that panel, earnings growth is lower for workers initially employed in high-exposure counties, across all destination sectors. This finding

[33] Quasi-medians are based on means of groups of workers around the median, as Census Bureau disclosure avoidance procedures do not allow the reporting of true medians, which are necessarily based on one or two individuals. We caution that the estimates in Figure 1 contain a mix of voluntary and involuntary transitions, and that they may involve movement of select groups of workers. We condition on observed worker attributes in our regression analysis.

[34] These apparent wage declines are driven by worker transitions across sectors, rather than differential earnings growth over time within the sectors. According to publicly available data from the BLS, summarized in Appendix Figure A.3, the average hourly earnings for production and non-supervisors in manufacturing (NAICS 3) in 2000 was $13.80, versus $12.00, $11.30, $10.90 and $8.10 for admin, support, waste (NAICS 56), retail (NAICS 44-5), arts, entertainment and recreation (NAICS 71), and accommodation and food services (NAICS 72). Average hourly wage growth from 2000 to 2007 in these data (which, unlike our LEHD data, do not distinguish between comers and goers), was 19 percent in manufacturing, versus 21, 17, 33 and 25 percent in the other sectors just mentioned, respectively.

is consistent with increased labor-market competition from manufacturing workers in high-exposure areas, as well as the scarring effects of job loss documented in Davis and von Wachter (2011) and Huckfeldt (2022).

Figure 6: Median Nominal Earnings Growth Among Initial M Workers, by Transition Path (46 States)



Source: LEHD, LBD, Feenstra et al. (2002) and authors' calculations. Figure displays quasi-median 2000 to 2007 growth in nominal earnings across workers moving from manufacturing to the noted 2-digit NAICS sector between 2000 and 2007 in the 46 states for which information is available in the LEHD for these years (Alabama, Arkansas, New Hampshire Mississippi and the District of Columbia are excluded). Left panel displays growth for all workers. Right panel displays quasi-median growth for workers in the first (low) versus fourth (high) quartile of county exposure to PNTR, defined in Section 3.

4.4 Impact of Exposure to PNTR Across the Post-PNTR Period

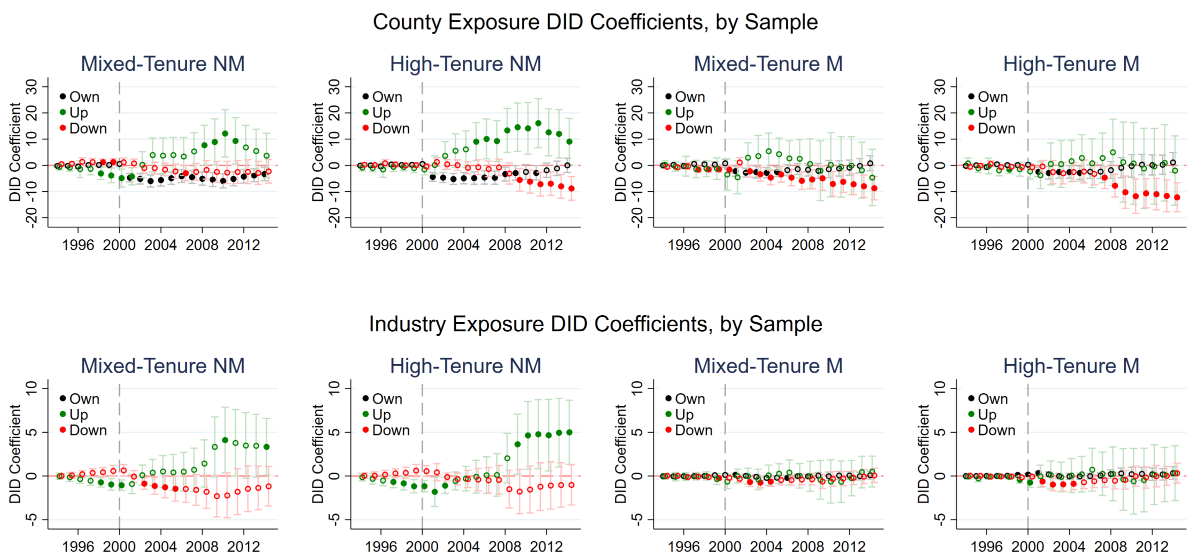
Further insight regarding the effects of exposure to PNTR along the supply chain can be obtained by estimating an "annual" DID specification that replaces the *Post* dummy variables in equation 5 with a full set of year dummies. Results from this regression are reported in Figure 7, with panels for mixed and high-tenure workers for both the NM and M sectors. In this Figure, we plot coefficient estimates for each county (upper panel) and industry (lower panel) exposure term together with their 95 percent confidence intervals. To increase readability, coefficients that are significantly different from zero at the 95 percent level have solid markers, while those that are not statistically significant at that level have hollow markers.

As indicated in the figure, own-county exposure is negative and statistically significant for all four groups of workers in the years immediately after the change in US trade policy, i.e., until at least 2011 for the NM workers and 2005 for M workers. For high-tenure workers, this is the only channel of exposure that is relevant in these immediate post-PNTR years. However, for M workers in particular, county downstream exposure becomes more important in subsequent years, with a notable step down in coefficient estimates toward the end of the sample. This timing for M workers – with an initial negative impact based on their county own exposure, and a later negative impact from (downstream) exposure of their customers – is consistent with the supply chain co-offshoring discussed above. That is, the delayed effect from downstream exposure can eventually lead firms to relocate to be closer to their suppliers.

The Figure also underscores the different effect of upstream exposure for NM versus M workers identified in Table 2. For NM workers—particularly those who are high-tenure—county upstream exposure turns positive almost immediately after 2001 and becomes statistically significant and large in magnitude in subsequent years. *Industry* upstream exposure also turns positive and statistically significant for NM workers in the latter portion of the sample. For M workers, upstream exposure is typically positive in post-PNTR years but is never statistically significant.

These patterns are in line with NM industries benefiting from greater exposure to PNTR among their suppliers relatively soon after the change in policy, with those relative gains somewhat offset by loss of customers toward the end of the sample. M industries, by contrast, experience the latter without the former. The overlap of the negative impact of downstream exposure with the Great Recession for M workers suggests that this channel may become more prominent as the economy weakens.

Figure 7: County and Industry DID Coefficients from Annual Earnings Specification - CR Transformation



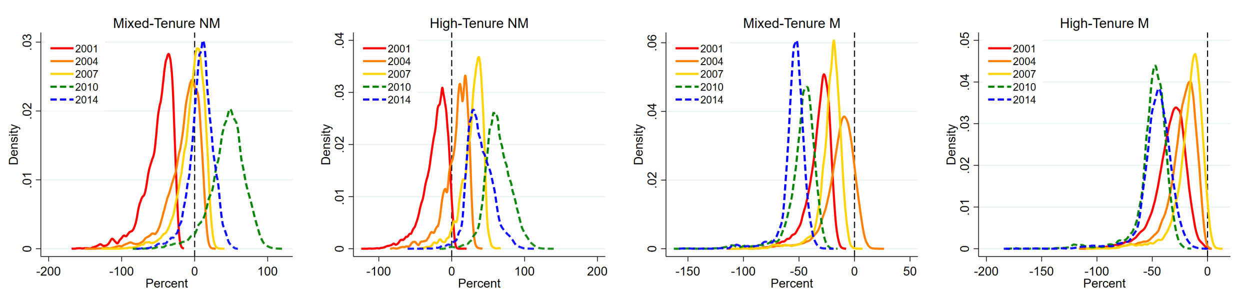
Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Panels display the 95 percent confidence intervals for the county (top row) and industry (bottom row) DID coefficients of interest from an "annual" DID version of equation 5 that replaces the *Post* indicator with a full set of year dummies and uses the CR transformation of earnings as the dependent variable. For each exposure, a solid marker indicates statistical significance.

Next, to illustrate the economic significance of these estimates, we use the estimated coefficients to display predictions of overall relative changes in earnings based on the observed exposure of county-industry pairs, as in Figure 2. Figure 8 displays these predictions at three-to-four year intervals from 2001 to 2014.

The figure highlights important similarities and differences in the relationship between exposure to PNTR and earnings for NM and M workers. Notably, the bulk of the mass of the four red curves for 2001 is to the left of zero, indicating that almost all workers – whether NM or M , mixed-tenure or high-tenure – exhibit relative earnings losses in the short-run after the policy change. This finding is intuitive given the negative relationship with *own* exposure in the early post-PNTR years for all workers.

Over time, the implications of PNTR diverge sharply for NM and M workers. For M workers, higher exposure to the policy change is consistently associated with relative earnings losses, which become larger after the Great Recession as the negative coefficients on *downstream* exposure grow in magnitude and statistical significance. By contrast, NM workers experience relative earnings gains across years, particularly among high-tenure NM workers. Figure 7 shows that these gains are driven by positive effects of *upstream* exposure, which take several years to materialize. The absence of such an *upstream* boost for M workers helps explain their worsening outcomes relative to NM workers. For NM workers, the positive upstream effect peaks around 2010 before gradually fading, suggesting that the gains from cheaper inputs are front-loaded: Once firms have absorbed the initial cost reductions and competitive pressures adjust, the marginal benefits to workers diminish.

Figure 8: Distribution of County-Industry Predicted Relative Earnings Growth, by Year and Sample



Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure displays the distribution of predicted relative earnings growth over time across county-industry pairs for mixed-tenure and high-tenure NM and M workers. Predictions are based on the estimated $Own + IO$ DID coefficients reported in Figure 7. For each county-industry pair, they are the product of the reported coefficients and actual exposures. Curves are solid for years up to the Great Recession, and dashed afterwards.

The existing literature has reached differing conclusions on the long-term implications of trade liberalization and similar shocks for earnings. On the one hand, Dix-Carneiro and Kovak (2017) find that effects of a Brazilian trade liberalization on regional earnings continue to grow 20 years after the liberalization, and Autor, Dorn, and Hanson (2021) find similarly persistent effects on US manufacturing employment arising from Chinese import competition. On the other hand, Bloom et al. (2019), find that the latter effects dissipate after 2007 in high-human-capital areas, and Kovak and Morrow (2022) show that for Canadian workers subject to larger tariff reductions in their industries, rapid transitions to industries less exposed to import competition mean that there was little effect on long-run cumulative earnings. Our results inject new findings into this debate by highlighting the centrality of differences in effects for M and NM workers, which are driven by input-output linkages.

5 Heterogeneous Outcomes By Worker and Firm Attributes

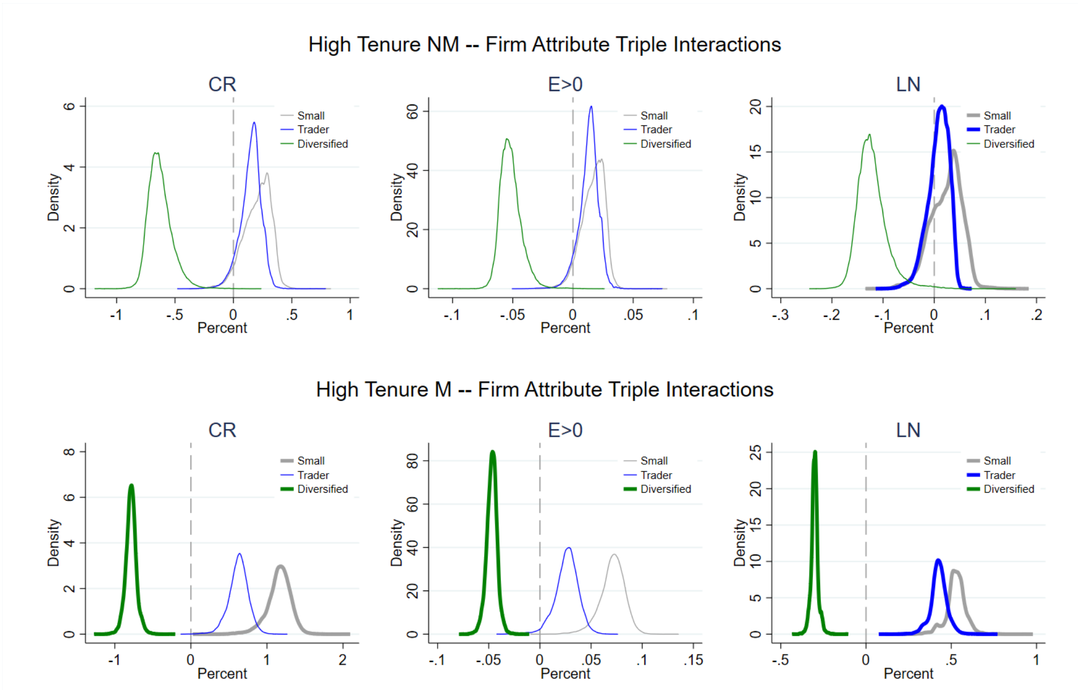
Building on the examination of differences by high-tenure and mixed-tenure workers above, in this section, we examine whether responses to PNTR vary by workers' initial (i.e., 1999) characteristics and those of their employing firm. We use a version of equation 5 that includes triple interactions of these attributes with own, upstream, and downstream county and industry exposure DID terms and run separate regressions for each earnings transformation and initial sector of worker, as well as each characteristic. We consider both worker and firm-level characteristics, binned into binary outcomes: females versus males; non-whites versus whites; workers aged 30 and below ("young") versus those that are older; workers that have at least a bachelors degree ("$\geq$ College") versus those with less educational attainment; workers in the fourth quartile of earnings ("Q4 Earnings") versus those in the lower quartiles; workers at firms with fewer than 50 employees ("small") versus larger firms; workers at trading versus non-trading firms; and workers at firms that have both M and NM establishments ("diversified") versus firms with only M or only NM plants.[35] While several papers mentioned above have examined heterogeneous worker-level outcomes to Chinese import competition (Kamal et al., 2020; Kahn et al., 2022; Conlisk et al., 2022), we are able to consider a wider set of worker characteristics (existing work typically focuses on differences by gender and race), to account for detailed input-output linkages, and to examine the role of firm characteristics.

As above, we assess economic significance using predicted county-industry relative earnings growth, and results are displayed visually in Figures 9 and 10.[36] In this case, however, we report only the *differential* impact of the demographic characteristic, i.e., the product of the triple-interaction DID coefficients and industry-county exposures. These distributions represent the differential predicted relative earnings growth associated with each attribute versus its left-out partner, e.g., females versus males. Distributions are organized by earnings transformation, as in earlier figures, with the upper and lower panels in each figure focused on initial NM and M workers, respectively. The figures also report statistical significance of the estimates, with distributions in bold if the underlying F-statistic of the triple interactions from which it is computed are statistically significant at conventional levels, and thin otherwise.

[35] Workers' initial sector is determined by the industry code of their establishment. Diversification captures the broader activities of their firms. For context, Appendix Figure A.5 reports the distribution of workers in 2000 across two-digit NAICS sectors by gender, race, education level, and age using publicly available data from the LEHD extract tool.

[36] Estimated coefficients are relegated to Appendix Tables A.5 to A.7. Appendix Table A.8 reports the F-statistics for each group of triple interactions. Consistent with the pattern of results reported in the last section, we find that the county exposure triple interactions are more likely to be statistically significant at conventional levels than the industry exposure triple interactions.

Figure 9: Triple-Interaction County-Industry Predictions by Workers' Firms' Attributes



Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure displays differential predicted relative county-industry earnings for noted worker's firm attribute versus those not possessing that attribute using the triple-interaction DID coefficients discussed in the text and reported in Appendix Tables A.5 to A.7. Distributions are in bold if the F-statistic for the county and industry triple-interaction terms, reported in the final two columns of Appendix Table A.8, are jointly significant at the 10 percent level.

The figures convey several novel aspects of heterogeneous worker responses to trade liberalization. In particular, as shown in Figure 9, we find that initial *firm* characteristics are important determinants of subsequent M worker earnings outcomes. First, as shown by the bolded gray curves in the bottom row of the figure, we find that M workers initially employed at small firms have relatively better earnings outcomes than those employed at large firms. This result is consistent with Holmes and Stevens (2014)'s argument that small firms are more likely to produce customized output that is less substitutable with Chinese imports.[37] By contrast, the relative benefits of working at a small firm are more limited for NM workers: The upper row shows that despite modestly higher earnings conditional on remaining employed (upper right panel), the triple interaction terms for the more comprehensive CR transformation (upper left panel) are not statistically significant as a group. Second, M workers employed at diversified firms have relatively worse earnings outcomes than those employed at firms with only manufacturing establishments (bolded green curves, lower panel). This result is somewhat surprising, as transitioning from M to NM might in principle be easier for workers at firms that span both sectors, and allow for retention of firm-specific human capital, even if those activities are in different locations. On the other hand, a strict focus on manufacturing activities may

[37]Empirical evidence in line with this finding for M workers is also present in the appendix of the working paper version of Autor et al. (2014) and Kovak and Morrow (2022).

contribute to firms' ability to produce the kinds of goods Holmes and Stevens (2014) have in mind.[38] Finally, we find that workers at trading firms experience relatively better outcomes than those at firms that do not trade, though this result is only present for earnings conditional on employment (LN).

Figure 10 examines heterogeneous responses by workers' demographic attributes. The Figure shows that demographic characteristics tend to be more relevant for relative earnings for NM workers (top row) than M. First, in terms of gender (gray curves), we find that female NM workers experience relatively better labor market outcomes than males, in terms of all three outcomes.[39] With respect to race (blue curves), NM workers who are not white exhibit relatively worse earnings outcomes in terms of CR, reflecting lower subsequent earnings conditional on employment and a lower but imprecisely estimated probability of being employed.[40] For age, the typical NM worker under 30 ("young," in the Figure) performs modestly better than older workers when considering CR, with a higher probability of employment offsetting relatively lower earnings conditional on employment. While we find some differences in terms of workers with or without bachelors degrees, there is no statistically significant difference in terms of CR, which captures both probability of employment and earnings conditional on employment.[41]

Lastly, perhaps the most widespread heterogeneous response we find among worker attributes relates to initial earnings. As shown by the bold red curves with substantial mass to the right of zero in every panel, we find that those with initially high earnings perform relatively better in terms of subsequent labor market outcomes than those with initially lower earnings. While this finding is consistent with results for M workers in Autor et al. (2014), here we find it holds for both M and NM workers and across all three labor market outcomes. This relatively better performance may indicate that those with initially high earnings possess skills that are more easily transferable to other industries, areas, or firms. It may also reflect a greater ability—perhaps due to savings—to be more selective in accepting a new job, resulting in a better match.

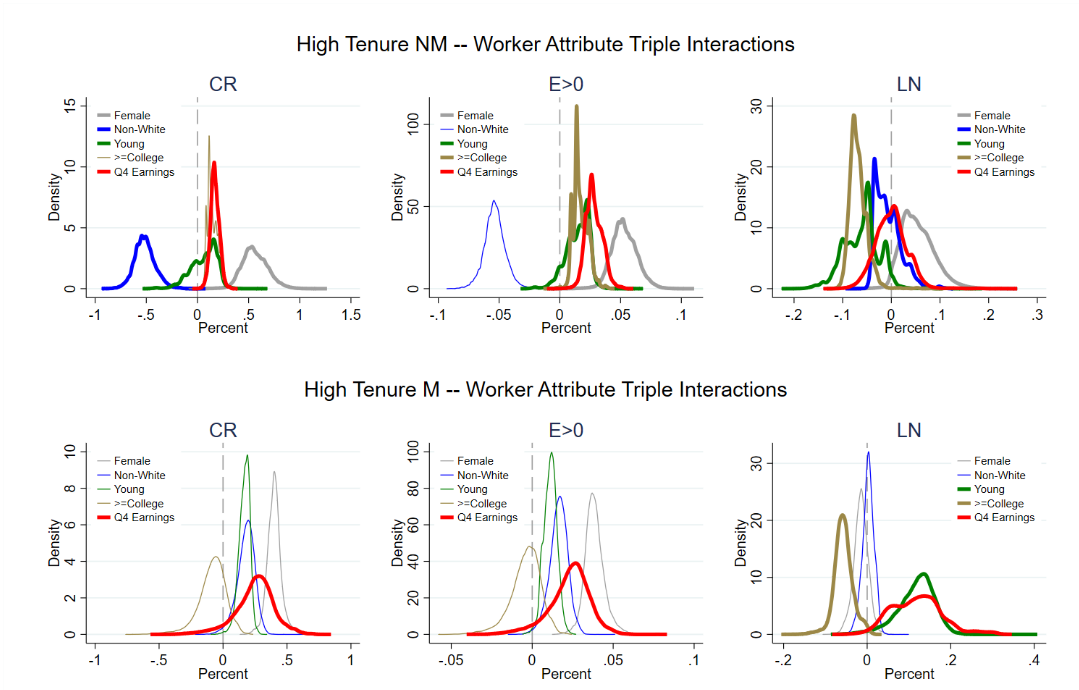
[38] To the extent that multinational firms are more likely to be diversified, this result is also consistent with Boehm, Flaaen, and Pandalai-Nayar (2020)'s finding that multinationals account for a disproportionate share of the decline in US manufacturing employment due to their greater ability to offshore production.

[39] These relatively better outcomes may, however, be the result of women entering the labor market or increasing hours to offset male partners' lost income as in Besedeš, Lee, and Yang (2021).

[40] Kahn, Oldenski, and Park (2022) examine the potential for differential effects of import competition by worker race and ethnicity and find that, for a given level of exposure, trade competition has similar effects for white and minority workers. However, the over-representation of Hispanic workers in highly exposed industries implies that they experience greater manufacturing employment losses than whites, on net. Kamal, Sundaran, and Tello-Trillo (2020) demonstrate how import competition leads to a decrease in the female share of employment, promotions, and earnings at firms covered by the Family and Medical Leave Act in comparison to those not protected by this policy.

[41] Greenland, Lopresti, and McHenry (2016) find that import competition is associated with increases in high school graduation rates. Ferriere, Navarro, and Reyes-Heroles (2022) find that college enrollment exhibits a relative increase in areas with greater exposure to Chinese import competition, driven by young people in the middle and top of the household wealth distribution. Building on this work, Conlisk, Navarro, Penn, and Reyes-Heroles (2022) find that enrollment increases more for women, due to a larger increase in the female college premium that occurs in response to import competition.

Figure 10: Triple-Interaction County-Industry Predictions by Demographic Attributes



Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure displays differential predicted relative county-industry earnings for noted worker demographic attribute versus those not possessing that attribute using the triple-interaction DID coefficients discussed in the text and reported in Appendix Tables A.5 to A.7. Distributions are in bold if the F-statistic for the county and industry triple-interaction terms, reported in the final two columns of Appendix Table A.8, are jointly significant at the 10 percent level.

6 Conclusion

While extensive research examines the implications of increased import competition for regions and industries, many questions about outcomes for individual workers – who may move between industries and regions, as well as in and out of employment – remain unanswered. This paper provides a detailed analysis of US workers' response to a large labor market shock induced by US trade liberalization with China. Our analysis uncovers novel results related to two aspects of the effects of trade liberalization that have received only limited attention: The role of input-output linkages in driving effects on earnings and a dichotomy in impact for non-manufacturing versus manufacturing workers.

Using linked employer-employee data from the US Census Bureau, we introduce novel and comprehensive measures of workers' exposure to trade liberalization with China. These measures account for the direct exposure to increased competition in the worker's own industry, as well as competition in its input and customer markets. Importantly, due to our use of linked data, we are also able to construct measures of geographic exposure based on the workers' counties of residence, which are useful for gauging effects of local labor market shocks.

Our results indicate that geographic exposure is most relevant for driving workers' earnings responses to the trade liberalization, highlighting the salience of spatial versus sectoral frictions and implying that workers' ultimate earnings profiles are more affected by their neighbors' exposure to the shock than the industry in which they're initially employed. We present circumstantial evidence that part of this effect arises from increased competition in local labor markets as displaced manufacturing workers move to – often lower-paid – service sectors. Our comprehensive measures of exposure via supply supply chains also reveal long-suspected but previously missing evidence of beneficial effects for workers of increased import competition in input markets. For non-manufacturing workers, such "upstream" exposure is associated with relative gains in earnings. For manufacturing workers, however, these gains are muted, and exposure via competition in customer markets exacerbates the negative effects of exposure in one's own county.

Due to these differences in effects of trade liberalization via input-output linkages, we show that there are substantial differences in effects for non-manufacturing versus manufacturing workers. Specifically, we show that after accounting for input-output linkages, most non-manufacturing workers experience relative earnings gains in response to PNTR due to the increased competition in input markets. For manufacturing workers, accounting for input-output linkages indicates that relative earnings losses are even larger than in specifications that do not take into account such supply chain effects.

Our analysis also focuses on heterogeneous effects by worker and firm characteristics. The first finding of heterogeneous effects comes from examination of differences in outcomes for a sample of high-tenure workers – those continuously employed by the same firm – versus one that includes workers who switch employers. We show that high-tenure workers in the non-manufacturing sector perform relatively better in response to trade shocks than their lower-tenure peers, while high-tenure manufacturing workers, if anything, fair a bit worse due to lower earnings conditional on employment. Exploring outcomes by dimensions of firm heterogeneity, we show that workers at small and trading firms perform relatively better than their counterparts, while those at diversified firms fare worse. In terms of demographic characteristics, we find that women and those with initially high incomes perform relatively better in response to the trade shock.

Our results provide new information on longstanding questions related to the responses of workers to increases in import competition and help elucidate some of the distributional and long-term effects of import competition examined in Autor et al. (2021), Bloom et al. (2019), and Autor et al. (2025). They are also useful for evaluating the overall impact of current proposals in the United States to raise trade barriers against China and other countries. Future research could delve deeper into the relative importance of declining aggregate demand and labor market competition in explaining the primacy of geographic exposure to the trade shock.

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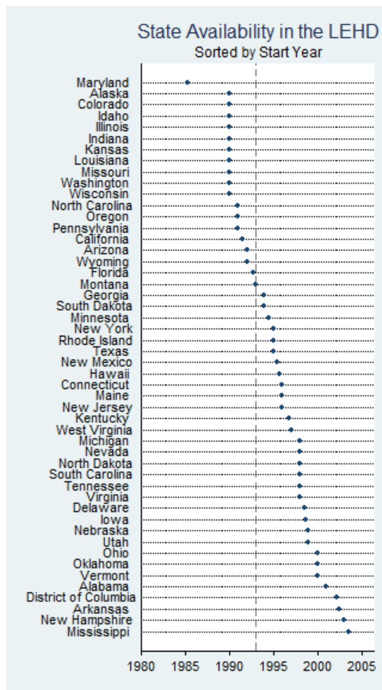
Online Appendix (Not for Publication)

This online appendix contains additional empirical results as well as more detailed explanations of data used in the main text.

A State Coverage in the LEHD

The set of states included in the LEHD varies over time as summarized in Figure A.1. We use the 46 states available as of 2000 in examining worker movement between M and NM sectors in Section 4.3, and the 19 states present from 1993 to 2014 for our regression analysis.

Figure A.1: State Availability in the LEHD



Source: Vilhuber and McKinney (2014). Figure displays the availability of state data in the LEHD. Dashed vertical line shows 1993, the cutoff for inclusion in the regression sample.

Table A.1 reports the 1999 NM, M and total employment, by state for each sample using publicly available information from the Business Dynamics Statistics (BDS) program available at https://www.census.gov/programs-surveys/bds.html.

Table A.1: Number of NM and M Workers in 1999, by State

State	Sample	NM	M	Total	State	Sample	NM	M	Total
Alaska	19 &46	0.18	0.01	0.20	Massachusetts	46	2.54	0.39	2.93
Arizona	19 &46	1.63	0.19	1.82	Michigan	46	3.15	0.81	3.96
California	19 &46	10.43	1.74	12.17	Minnesota	46	1.93	0.37	2.31
Colorado	19 &46	1.66	0.16	1.82	Nebraska	46	0.62	0.11	0.73
Florida	19 &46	5.52	0.42	5.94	Nevada	46	0.82	0.04	0.86
Idaho	19 &46	0.37	0.07	0.44	New Jersey	46	3.06	0.39	3.44
Illinois	19 &46	4.46	0.85	5.31	New Mexico	46	0.50	0.04	0.54
Indiana	19 &46	1.95	0.63	2.58	New York	46	6.31	0.72	7.03
Kansas	19 &46	0.91	0.19	1.10	North Dakota	46	0.23	0.02	0.25
Louisiana	19 &46	1.41	0.16	1.57	Ohio	46	3.85	0.97	4.82
Maryland	19 &46	1.82	0.16	1.97	Oklahoma	46	0.99	0.17	1.15
Missouri	19 &46	1.96	0.37	2.33	Rhode Island	46	0.34	0.07	0.41
Montana	19 &46	0.27	0.02	0.29	South Carolina	46	1.23	0.34	1.57
North Carolina	19 &46	2.57	0.75	3.32	South Dakota	46	0.25	0.05	0.30
Oregon	19 &46	1.11	0.21	1.32	Tennessee	46	1.86	0.47	2.34
Pennsylvania	19 &46	4.16	0.79	4.95	Texas	46	6.76	0.95	7.70
Washington	19 &46	1.86	0.29	2.15	Utah	46	0.76	0.12	0.88
Wisconsin	19 &46	1.79	0.57	2.36	Vermont	46	0.20	0.04	0.24
Wyoming	19 &46	0.16	0.01	0.17	Virginia	46	2.41	0.36	2.78
Connecticut	46	1.28	0.24	1.52	West Virginia	46	0.47	0.07	0.55
Delaware	46	0.32	0.04	0.36	Alabama	Neither	1.28	0.34	1.62
Georgia	46	2.80	0.53	3.33	Arkansas	Neither	0.72	0.23	0.95
Hawaii	46	0.40	0.01	0.42	District of Columbia	Neither	0.39	0.00	0.39
Iowa	46	1.00	0.24	1.24	Mississippi	Neither	0.72	0.22	0.94
Kentucky	46	1.17	0.29	1.46	New Hampshire	Neither	0.43	0.10	0.53
Maine	46	0.39	0.08	0.47					

Source: BDS and authors' calculations. Table reports the non-manufacturing (NM), manufacturing (M) and total employment, in millions, by state in 1999. Second column in each panel indicates whether the states is in our 19 and 46-state samples, where all states in the 19-state sample are also in the latter. Overall M, NM and total employment for the 19-state sample in 1999 is 44.2, 7.6 and 51.8. The analogous totals for the additional states in the 46-state sample are 45.7, 7.9 and 53.6. For states not in either sample they are 3.5, 0.9 and 4.4.

B Industry Variable Construction

In this section we describe how the industry controls referenced in Section 4 are constructed.

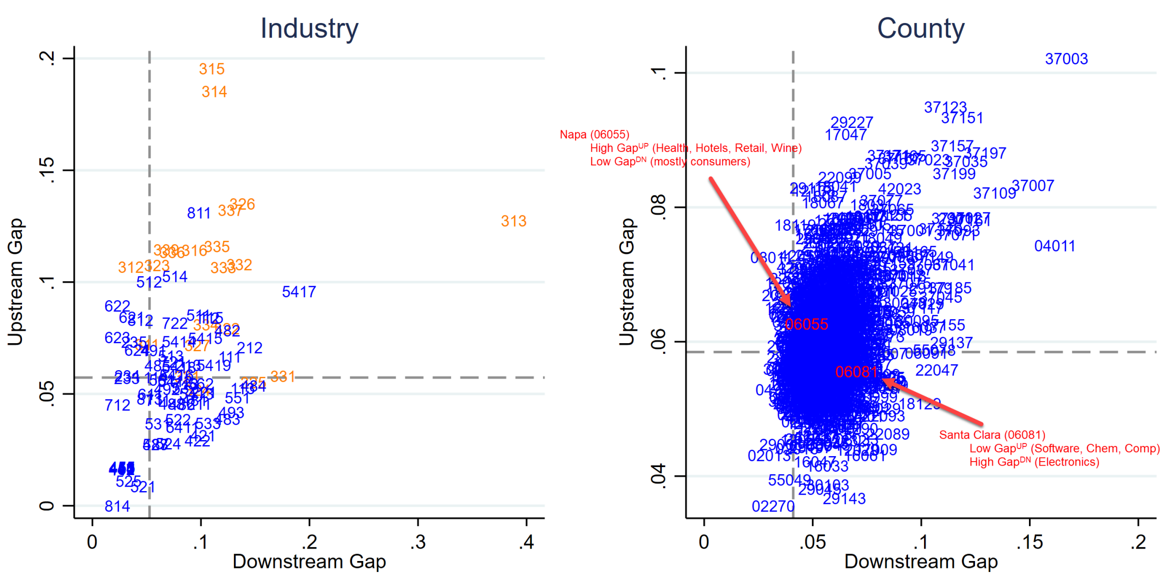
MFA Exposure: We control for expiration of the Multi-Fiber Arrangement, which occurs in stages during our sample period. Khandelwal, Schott, and Wei (2013) provide details on this policy:

> The [MFA] and its successor, the Agreement on Textile and Clothing (ATC), grew out of quotas imposed by the United States on textile and clothing imports from Japan during the 1950s. Over time, it evolved into a broader institution that regulated the exports of clothing and textile products from developing countries to the United States, European Union, Canada and Turkey...Bargaining over these restrictions was kept separate from multilateral trade negotiations until the conclusion of the Uruguay Round in 1995, when an agreement was struck to eliminate the quotas over four phases. On January 1, 1995, 1998, 2002, and 2005, the United States was required to remove textile and clothing quotas representing 16, 17, 18 and the remaining 49 percent of their 1990 import volumes, respectively.

Relaxation of quotas on Chinese imports did not occur until it became a member of the World Trade Organization in 2001; as a result, its quotas on the goods in the first three phases were relaxed in early 2002, and its quotas on the goods in the fourth phase were relaxed as scheduled in 2005. The order in which goods were placed into a particular phase was chosen by the United States.

We calculate counties' exposure to elimination of the MFA in three steps, as in Pierce and Schott (2020). These steps include: 1) measuring the extent to which MFA quotas were binding using the average fill rate of the industry's constituent import products, following Khandelwal, Schott, and Wei (2013); 2) computing counties' labor-share-weighted-average fill rate across industries for each phase; 3) cumulating the calculated fill rates as each phase of expiration takes place, so that the measure of exposure to the MFA rises over time, as additional quotas are removed. See Appendix D of Pierce and Schott (2020) for additional details.

Figure A.2: Average Up- and Downstream Gaps



Source: CBP, BEA, Feenstra et al. (2002), and authors' calculations. Left panel displays mean industry up- and downstream NTR gap, Gap_i^{up} and Gap_i^{down}, across 3-digit NAICS sectors, except for 541, which is broken out by 4-digit sectors. Manufacturing industries are highlighted. Right panel reports up- and downstream gaps for each county in our 19 state regression sample, Gap_c^{up} and Gap_c^{down}, with Napa (06055) and San Mateo (06081), California highlighted. Counties are identified by 5-digit FIPS codes.

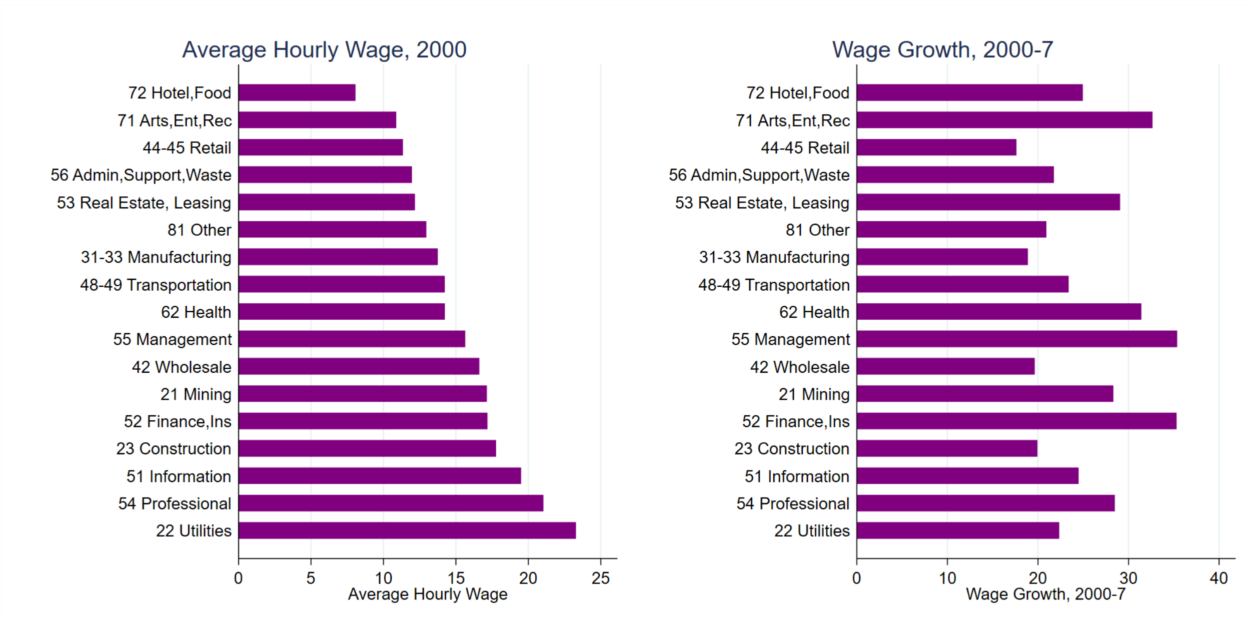
Changes in Chinese Policy: China instituted a number of policy changes as part of its accession to the WTO, and for which we control, including reducing import tariff rates and production subsidies. As in Pierce and Schott (2016), we use product-level data on Chinese import tariffs from 1996 to 2005 from Brandt, Van Biesebroeck, Wang, and Zhang (2017) to compute industry-level changes in Chinese import tariffs. We use data from the Annual Report of Industrial Enterprise Statistics published by China's National Bureau of Statistics (NBS) as a measure of changes in production subsidies. We construct county-level measures of exposure to each of these policy changes using labor share weights and then interact these measures with an indicator for post-PNTR years. See Appendix D of Pierce and Schott (2020) for additional details.

Up- and Downstream NTR Gaps: The left panel of Figure A.2 reports the average up- and downstream NTR gaps by 3-digit NAICS industry, while the right panel of the figure reports the up- and downstream gap for all counties in our 19 state sample. Manufacturing sectors are highlighted in the left panel, while Napa and Santa Clara, California are highlighted in the right panel. These two counties illustrate how counties – even when geographically similar – can have very different up- and downstream NTR gaps due to their differing industrial structures. As indicated in the figure, Napa is more heavily concentrated in non-tradable services such as Retail (NAICS 44-5), Accommodation and Food (NAICS 72), and Health (NAICS 62), while Santa Clara is more heavily dependent on manufacturing, particularly Computers and Electronics (NAICS 334). Within manufacturing, Napa is concentrated in production at Wineries (NAICS 312130).

C Publicly Available Data on Wages and Wage Growth by Sector

As a complement to the worker-level transitions reported in Section 4.3, Figure A.3 reports the average hourly wages as of 2000, of production and non-supervisory workers, as well as wage growth from 2000-2007 by major sector using publicly available data from the US Bureau of Labor Statistics. As indicated in the figure, the average hourly wage for production and non-supervisors in Manufacturing (NAICS 3) in 2000 was 13.8 dollars. The analogous averages for ASW (NAICS 56), Retail (NAICS 44-5), Arts, Entertainment and Recreation (NAICS 71), and Accommodation and Food Services (NAICS 72) were 12.0, 11.3, 10.9 and 8.1, or 13, 18, 21 and 41 percent less than those in manufacturing in that year.

Figure A.3: Wages and Wage Growth, by 2-digit NAICS (Public BLS Data)



Source: BLS and authors' calculations. Left panel displays the average hourly wage of production and non-supervisory workers by 2-digit NAICS sector in 2000. Right panel displays nominal growth in these average hourly wages from 2000 to 2007.

D Flows from M, Alternate Time Periods (46-State Sample)

Table A.2 reports beginning and ending employment at the 1-digit NAICS sector level from 2000 to 2005, a shorter time period than the 2000 to 2007 period examind in the main text. As indicated in the table, the largest net outflows from manufacturing employment are to Not Employed (-.7 million), Business Services (-.6 million), Wholesale, Retail, Transportation and Warehousing (.5 million), Education and Health (-.42 million), and Mining, Utilities, and Construction (-.22 million). Only two 1-digit sectors, Agriculture, Forestry, Fishing and Hunting, and Arts, Entertainment, Accommodation and Food exhibit net inflows into manufacturing, of .04 and .05 million, respectively.

E DID Estimates for $E > 0$ and LN Earnings Transformations

This section contains baseline DID estimates for the $E > 0$ (Table A.3) and LN (Table A.4) earnings transformations discussed in the main text. They are presented in the same format as Table 2, which reports analogous estimates for the CR earnings transformation.

Table A.2: 2000-5 Transitions by 1-digit NAICS Sector (46-State Sample)

Employment (Millions)

	Sector in 2005										Total in
Sector in 2000	1	2	3	4	5	6	7	8	9	NE	2000
Agriculture, Forestry, Fishing and Hunting(1)	0.57	0.09	0.11	0.13	0.11	0.05	0.06	0.02	0.01	0.62	1.79
Mining, Utilities, Construction (2)	0.04	5.43	0.33	0.59	0.83	0.30	0.21	0.11	0.18	2.49	10.49
Manufacturing (3)	0.08	0.55	8.94	1.78	1.55	0.64	0.38	0.19	0.14	3.43	17.68
Wholesale, Retail, Transportation, Warehousing (4)	0.09	0.88	1.29	13.83	3.22	1.78	1.19	0.50	0.34	6.08	29.18
Business Services (5)	0.07	0.93	1.04	2.43	14.79	1.99	0.97	0.41	0.39	6.70	29.73
Education, Healthcare (6)	0.02	0.22	0.22	0.85	1.41	16.00	0.44	0.25	0.38	4.35	24.14
Arts, Entertainment, Accommodation, Recreation (7)	0.04	0.42	0.43	1.61	1.67	1.16	4.73	0.26	0.16	3.36	13.84
Other Services (except Public Administration) (8)	0.01	0.13	0.14	0.43	0.43	0.36	0.18	1.52	0.06	1.27	4.52
Public Administration (9)	0.01	0.12	0.05	0.18	0.28	0.38	0.09	0.04	3.41	0.95	5.51
Not Employed (NE)	0.75	2.80	2.65	8.50	7.25	5.54	7.23	1.50	0.89		37.11
Total in 2005	1.69	11.56	15.20	30.33	31.53	28.20	15.49	4.81	5.94	29.25	174.00

Employment as a Percent of Initial Level

	Sector in 2005										Total in
Sector in 2000	1	2	3	4	5	6	7	8	9	NE	2000
Agriculture, Forestry, Fishing and Hunting(1)	32	5	6	7	6	3	4	1	1	35	100
Mining, Utilities, Construction (2)	0	52	3	6	8	3	2	1	2	24	100
Manufacturing (3)	0	3	51	10	9	4	2	1	1	19	100
Wholesale, Retail, Transportation, Warehousing (4)	0	3	4	47	11	6	4	2	1	21	100
Business Services (5)	0	3	3	8	50	7	3	1	1	23	100
Education, Healthcare (6)	0	1	1	4	6	66	2	1	2	18	100
Arts, Entertainment, Accomodation, Recreation (7)	0	3	3	12	12	8	34	2	1	24	100
Other Services (except Public Administration) (8)	0	3	3	9	9	8	4	34	1	28	100
Public Administration (9)	0	2	1	3	5	7	2	1	62	17	100
Not Employed (NE)	2	8	7	23	20	15	19	4	2		100
Total in 2005	1	7	9	17	18	16	9	3	3	17	100

Source: LEHD, LBD, and authors' calculations. Table reports the transition paths of employed and not-employed workers from 2000 (row) to 2005 (column) by 1-digit NAICS sector (in parentheses) for the 46 states whose information is available in the LEHD starting in 2000. Alabama, Arkansas, New Hampshire and Mississippi as well as the District of Columbia are excluded. Upper panel reports levels in millions of workers. Lower panel reports shares of initial levels.

Table A.3: Response of Employment to PNTR

	Low Tenure NM		High Tenure NM		Low Tenure M		High Tenure M	
Earnings Transformation:	$E > 0$	$E > 0$	$E > 0$	$E > 0$	$E > 0$	$E > 0$	$E > 0$	$E > 0$
Post x $\text{Gap}^{Own}_{Industry}$	.	.	.	.	-.01	-.01	.01	.01
	.	.	.	.	.01	.01	.02	.02
Post x $\text{Gap}^{Down}_{Industry}$	.	-.15	.	-.07	.	-.01	.	-.02
	.	.1	.	.09	.	.02	.	.03
Post x $\text{Gap}^{Up}_{Industry}$	.	.14	.	.14	.	.02	.	.04
	.	.14	.	.12	.	.06	.	.09
Post x $\text{Gap}^{Own}_{County}$	-.39***	-.42***	-.25***	-.31***	-.23***	-.16	-.25***	-.15
	.08	.11	.07	.1	.06	.11	.07	.12
Post x $\text{Gap}^{Down}_{County}$	.	-.19	.	-.25**	.	-.27*	.	-.47***
	.	.14	.	.13	.	.14	.	.17
Post x Gap^{Up}_{County}	.	.44	.	.75**	.	.12	.	.26
	.	.31	.	.3	.	.37	.	.39
R-sq	.41	.41	.41	.41	.41	.41	.41	.41
Obs (000)	17,360	17,360	4,605	4,605	4,274	4,274	1,520	1,520
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gaps F		1.002		0.446		0.468		0.212
Industry Gaps p		0.393		0.721		0.706		0.888
County Gaps F		10.522		6.376		7.521		5.223
County Gaps p		0		0		0		0.002

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 for workers initially employed in non-manufacturing (NM) and manufacturing (M) . The dependent variable is a dummy for whether the worker is employed, $E > 0$. The sample period is 1993 to 2014. Mixed-tenure workers are employed throughout the 1993 to 1999 pre-period, but not necessarily by the same firm. High-tenure workers are employed by the same firm during the pre-period. *Post* is a dummy variable for years after 2000. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Final two panels report F-statistics for the joint significance of the industry and county exposure DID terms, respectively. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels.

Table A.4: Response of $ln(Earn)$ to PNTR

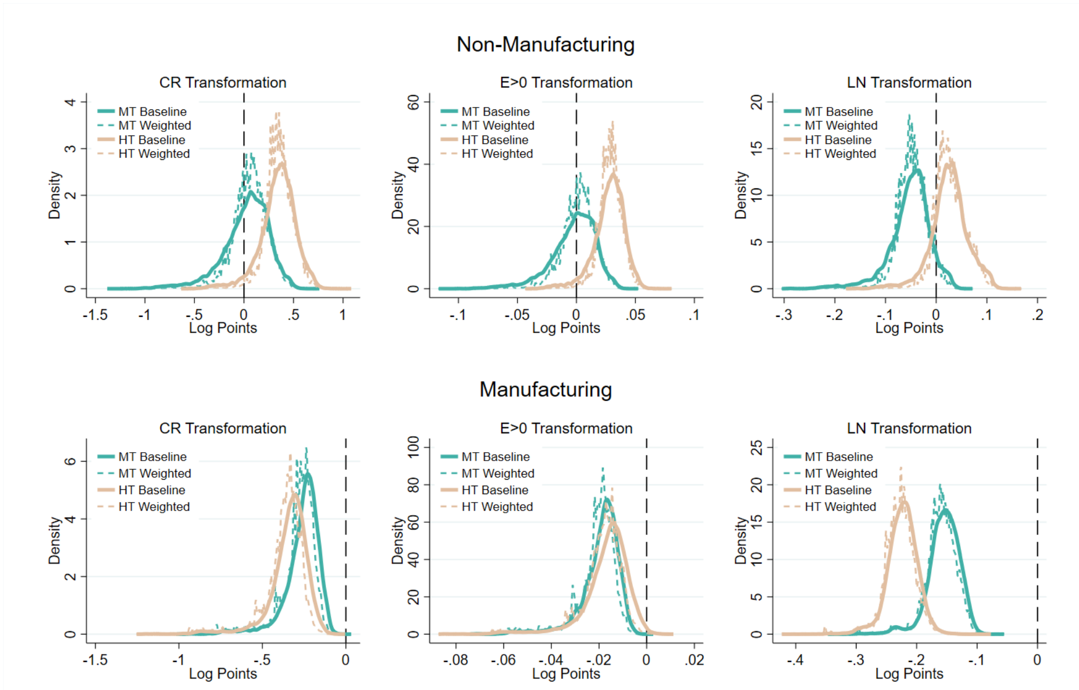
	Low Tenure NM		High Tenure NM		Low Tenure M		High Tenure M	
Dep Var:	LN	LN	LN	LN	LN	LN	LN	LN
Post x $\text{Gap}^{Own}_{Industry}$	.	.	.	.	.05	.09*	.06	.09
	.	.	.	.	.05	.05	.06	.06
Post x $\text{Gap}^{Down}_{Industry}$	.	-.14	.	-.19	.	-.28**	.	-.21*
	.	.17	.	.2	.	.11	.	.11
Post x $\text{Gap}^{Up}_{Industry}$	.	.62**	.	.74**	.	-.27	.	-.34
	.	.25	.	.29	.	.24	.	.31
Post x $\text{Gap}^{Own}_{County}$	-.96***	-.69***	-.69***	-.6***	-.54***	.18	-.34	.5
	.15	.18	.17	.2	.18	.24	.2	.33
Post x $\text{Gap}^{Down}_{County}$	.	-1.02***	.	-.95***	.	-1.11***	.	-1.35**
	.	.27	.	.36	.	.33	.	.53
Post x Gap^{Up}_{County}	.	.24	.	1.09	.	-.82	.	-1.77
	.	.64	.	.71	.	1	.	1.13
R-sq	.61	.61	.63	.63	.57	.57	.56	.56
Obs (000)	15,370	15,370	4,173	4,173	3,830	3,830	1,378	1,378
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gaps F		2.253		2.144		2.964		1.951
Industry Gaps p		0.083		0.096		0.037		0.128
County Gaps F		22.63		9.158		6.289		3.150
County Gaps p		0		0		0.001		0.029

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 for workers initially employed in non-manufacturing (NM) and manufacturing (M) . The dependent variable is log earnings, $ln(Earn)$. The sample period is 1993 to 2014. Mixed-tenure workers are employed throughout the 1993 to 1999 pre-period, but not necessarily by the same firm. High-tenure workers are employed by the same firm during the pre-period. *Post* is a dummy variable for years after 2000. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Final two panels report F-statistics for the joint significance of the industry and county exposure DID terms, respectively. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels.

E.1 Weighting

Given US Census Bureau disclosure constraints, we report the economic significance of our results in Figure 4 using county-industry pairs as a unit of analysis, and treat each county-industry equally. An alternate approach is to weight county-industry pairs in the predicted relative earnings distributions by their number of workers in the pre-period. In Figure A.4, we compare the unweighted distributions from Figure 4 (solid lines) to their weighted counterparts (dashed lines), by specification and sample. As shown in the Figure, the estimates of economic significance are qualitatively highly similar under the two weighting approaches. The primary difference is the larger mass around the center of the weighted distributions, indicating that highly-populated county-industry pairs tend to fall near the middle of the distribution of exposure to PNTR.

Figure A.4: Predicted Relative Earnings, Baseline versus Employment-Weighted



Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Figure compares our baseline county-industry predicted relative earnings distributions to versions of these distributions where each county-industry in the distribution is weighted by its employment in the pre-period. Distributions are plotted for for mixed-tenure (MT) and high-tenure (HT) NM and M workers. Coefficient estimates for the baseline predictions are reported in Tables 2, A.3 and A.4.

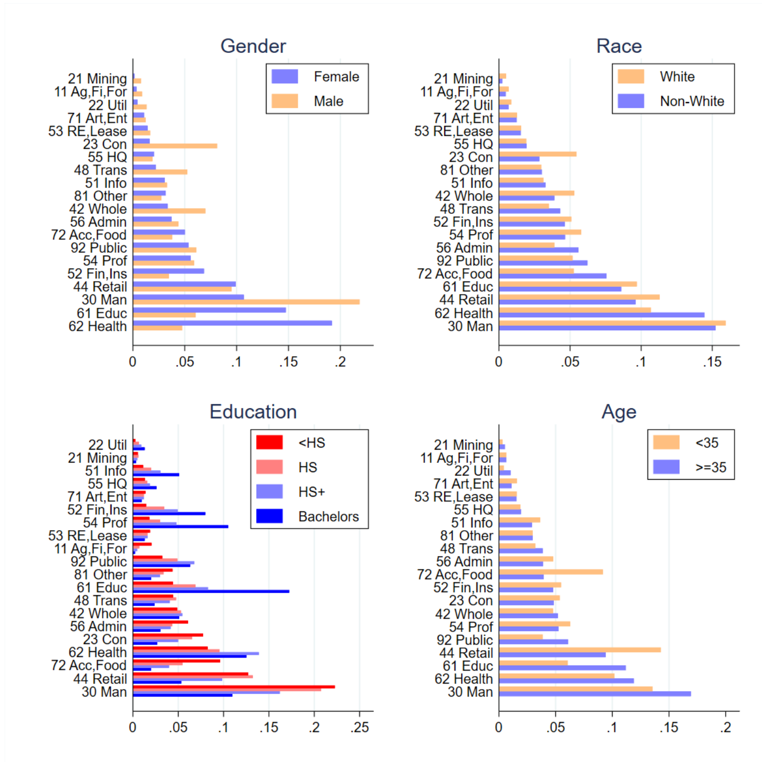
F Demographic Characteristics of Workers, by Sector

Figure A.5 plots the distribution of workers across sectors by gender, race, age, and education in 2000 using data publicly available from the LEHD extract tool. As indicated in the first panel, females are relatively more concentrated in Education (NAICS 61) and Healthcare (NAICS 62), while males are employed disproportionately in Construction (NAICS 23), Transportation (NAICS 48), Wholesale (NAICS 48), and Manufacturing (NAICS 3). Non-white workers (panel 2) are concentrated in Administrative Services (NAICS 56), Accommodation and Food (NAICS 72), and Healthcare (NAICS 62), while white workers work disproportionately in Construction (NAICS 23), Wholesale (NAICS 42), Education (NAICS 61), and Retail (NAICS 44). Less highly educated workers are concentrated in Administrative Services (NAICS 56), Construction (NAICS 23), Accommodation and Food (NAICS 72), Retail (NAICS 44) and Manufacturing (NAICS 3). Finally, younger workers are especially concentrated in Accommodation and Food (NAICS 72) and Retail (NAICS 44), while Education (NAICS 61) and Manufacturing (NAICS 3) skew older.

G Results for Triple-Interaction Demographic Specifications

This section reports estimated coefficients (in Tables A.5 to A.7) for the triple-interaction specifications discussed in Section 5. F-statistics for the significance of the county and industry triple

Figure A.5: Worker Demographics in 2000 (Public LEHD Data)



Source: LEHD and authors' calculations. Figure displays distribution of workers across two-digit NAICS sectors by gender, race, educational attainment, and age in 2000 from publicly available LEHD data downloadable at https://ledextract.ces.census.gov/j2j/emp.

interactions are reported in Table A.8.

Table A.5: Triple-Interaction Demographic Regressions (CR,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Attribute x Ind Gap	CR	NM	0	0	0	0	0	0	0	0
	CR	NM	0	0	0	0	0	0	0	0
Post x Attribute x Ind Up Gap	CR	NM	2.636**	2.183**	–3.577***	1.436*	1.006	–3.041	–1.405	-.396
	CR	NM	1.274	0.914	1.296	0.804	1.109	2.025	1.378	2.793
Post x Attribute x Ind Down Gap	CR	NM	–1.825**	.09	1.409	-.688	-.445	1.326	-.806	1.613
	CR	NM	0.877	0.399	0.872	0.590	0.958	1.598	0.997	2.126
Post x Attribute x Cty Gap	CR	NM	.296	.936	–1.382	-.093	–1.059	–2.188	–2.349	3.285
	CR	NM	1.346	1.939	1.277	1.310	0.811	1.371	1.545	2.173
Post x Attribute x Cty Up Gap	CR	NM	11.06**	–13.63**	2.529	1.834	2.546	5.357	3.787	–13.23**
	CR	NM	4.950	6.221	4.481	5.012	2.519	4.293	5.000	6.051
Post x Attribute x Cty Down Gap	CR	NM	–4.276**	2.819	2.92	-.259	.726	2.499	3.673	–1.153
	CR	NM	1.923	3.755	1.911	1.777	2.292	2.191	2.509	3.226
Post x Attribute x Ind Gap	CR	M	.056	-.084	-.149	-.386	.089	-.236	-.192	.026
	CR	M	0.227	0.203	0.246	0.282	0.317	0.288	0.348	0.273
Post x Attribute x Ind Up Gap	CR	M	.239	1.065	.669	2.091	1.595	-.749	–1.325	.545
	CR	M	0.963	0.663	0.868	1.881	2.103	1.040	1.194	1.334
Post x Attribute x Ind Down Gap	CR	M	-.498	-.28	-.412	-.116	.722	.735	-.214	-.376
	CR	M	0.407	0.438	0.459	0.503	0.641	0.619	0.678	0.584
Post x Attribute x Cty Gap	CR	M	-.262	–2.211	-.984	–1.913	–4.052**	–6.008**	–2.343	2.293
	CR	M	1.522	2.345	1.999	2.119	1.822	2.501	1.993	1.664
Post x Attribute x Cty Up Gap	CR	M	8.164	1.548	3.377	.205	2.343	27.06***	20.98**	–16.42**
	CR	M	5.674	7.521	7.351	6.748	4.894	8.464	8.697	6.658
Post x Attribute x Cty Down Gap	CR	M	–1.776	3.224	.604	–1.649	1.803	–1.652	–7.021*	1.222
	CR	M	2.536	3.484	3.498	3.076	3.492	4.729	3.812	3.219

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays the DID coefficients of interest for the OLS panel estimation of equation 5 that includes triple interactions with initial (1999) worker attributes for the noted earnings transformation. Only the coefficients of the triple interactions are reported. The first column in each panel notes the DID exposure term of the triple interaction, while the column header indicates the demographic attribute with which the exposure term is interacted. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.8 reports corresponding F-statistics for the joint significance of these exposure terms.

Table A.6: Triple-Interaction Demographic Regressions (E>0,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Attribute x Ind Gap	$E > 0$	NM	0	0	0	0	0	0	0	0
	$E > 0$	NM	0	0	0	0	0	0	0	0
Post x Attribute x Ind Up Gap	$E > 0$	NM	0.210*	0.152*	–0.264***	0.165***	0.173*	–0.241	–0.105	–0.041
	$E > 0$	NM	0.116	0.087	0.099	0.058	0.092	0.195	0.111	0.202
Post x Attribute x Ind Down Gap	$E > 0$	NM	–0.151*	0.019	0.085	–0.093**	–0.099	0.090	–0.099	0.160
	$E > 0$	NM	0.078	0.036	0.066	0.042	0.073	0.158	0.084	0.161
Post x Attribute x Cty Gap	$E > 0$	NM	–0.021	0.088	–0.121	–0.016	–0.121*	–0.200*	–0.199	0.265
	$E > 0$	NM	0.122	0.182	0.110	0.110	0.070	0.116	0.131	0.178
Post x Attribute x Cty Up Gap	$E > 0$	NM	1.075**	–1.343**	0.340	0.208	0.408**	0.380	0.294	–0.994**
	$E > 0$	NM	0.429	0.601	0.404	0.411	0.207	0.372	0.422	0.494
Post x Attribute x Cty Down Gap	$E > 0$	NM	–0.362**	0.292	0.275	–0	0.092	0.316*	0.374*	–0.237
	$E > 0$	NM	0.179	0.349	0.167	0.156	0.193	0.189	0.213	0.274
Post x Attribute x Ind Gap	$E > 0$	M	0.018	–0.006	–0.009	–0.036	–0.011	–0.025	–0.017	0.004
	$E > 0$	M	0.019	0.020	0.022	0.024	0.023	0.026	0.030	0.022
Post x Attribute x Ind Up Gap	$E > 0$	M	–0.023	0.100	0.084	0.174	0.165	–0.063	–0.125	0.039
	$E > 0$	M	0.082	0.066	0.069	0.135	0.146	0.091	0.102	0.106
Post x Attribute x Ind Down Gap	$E > 0$	M	–0.043	–0.020	–0.038	–0.019	0.051	0.064	–0.025	–0.043
	$E > 0$	M	0.037	0.044	0.041	0.041	0.047	0.055	0.060	0.051
Post x Attribute x Cty Gap	$E > 0$	M	0.015	–0.166	0.027	–0.190	–0.373**	–0.421*	–0.098	0.133
	$E > 0$	M	0.138	0.215	0.161	0.178	0.146	0.237	0.180	0.141
Post x Attribute x Cty Up Gap	$E > 0$	M	0.830	0.118	0.139	0.033	0.194	1.827**	1.401*	–1.020*
	$E > 0$	M	0.506	0.684	0.605	0.566	0.375	0.796	0.791	0.576
Post x Attribute x Cty Down Gap	$E > 0$	M	–0.270	0.259	–0.022	–0.012	0.316	–0.198	–0.758**	0.136
	$E > 0$	M	0.231	0.326	0.307	0.254	0.298	0.444	0.358	0.288

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays the DID coefficients of interest for the OLS panel estimation of equation 5 that includes triple interactions with initial (1999) worker attributes for the noted earnings transformation. Only the coefficients of the triple interactions are reported. The first column in each panel notes the DID exposure term of the triple interaction, while the column header indicates the demographic attribute with which the exposure term is interacted. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.8 reports corresponding F-statistics for the joint significance of these exposure terms.

Table A.7: Triple-Interaction Demographic Regressions (LN,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Attribute x Ind Gap	LN	NM	0	0	0	0	0	0	0	0
	LN	NM	0	0	0	0	0	0	0	0
Post x Attribute x Ind Up Gap	LN	NM	0.706**	0.745***	–0.951**	–0.201	–0.598	–0.774**	–0.505	–0.246
	LN	NM	0.322	0.189	0.442	0.282	0.372	0.332	0.375	0.854
Post x Attribute x Ind Down Gap	LN	NM	–0.400*	–0.135	0.714**	0.423***	0.617**	0.420*	0.030	0.396
	LN	NM	0.227	0.125	0.316	0.157	0.255	0.223	0.240	0.420
Post x Attribute x Cty Gap	LN	NM	0.504*	0.293	–0.100	0.157	–0.500**	–0.208	–0.315	0.654
	LN	NM	0.257	0.300	0.382	0.257	0.203	0.297	0.298	0.426
Post x Attribute x Cty Up Gap	LN	NM	0.542	–0.780	–0.381	–1.492	–0.019	1.558*	1.180	–3.899***
	LN	NM	0.916	1.193	1.160	0.990	0.517	0.871	1.143	1.445
Post x Attribute x Cty Down Gap	LN	NM	–0.649*	–0.301	–0.294	0.065	0.722	–0.785	–0.426	1.549***
	LN	NM	0.355	0.599	0.604	0.381	0.481	0.582	0.559	0.594
Post x Attribute x Ind Gap	LN	M	–0.106*	–0.068	–0.099	0.050	0.321***	–0.014	–0.077	0.025
	LN	M	0.058	0.044	0.063	0.070	0.105	0.068	0.075	0.073
Post x Attribute x Ind Up Gap	LN	M	0.324	0.054	–0.073	0.290	–0.191	0.034	0.029	0.056
	LN	M	0.265	0.185	0.265	0.423	0.465	0.315	0.351	0.367
Post x Attribute x Ind Down Gap	LN	M	–0.055	–0.019	0.025	0.094	0.147	0.109	0.040	0.046
	LN	M	0.094	0.088	0.103	0.117	0.152	0.167	0.155	0.126
Post x Attribute x Cty Gap	LN	M	–0.295	–0.369	–1.476***	0.040	–0.648*	–1.446***	–1.151***	1.015**
	LN	M	0.314	0.517	0.541	0.436	0.365	0.477	0.397	0.431
Post x Attribute x Cty Up Gap	LN	M	–0.249	0.246	3.106	–1.196	1.087	8.798***	7.884***	–7.360***
	LN	M	1.067	1.630	2.007	1.393	0.909	1.450	1.358	1.523
Post x Attribute x Cty Down Gap	LN	M	0.444	0.520	0.768	–0.868	–0.228	–0.883	–0.954	0.350
	LN	M	0.626	0.796	0.757	0.917	0.679	0.907	0.730	0.702

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays the DID coefficients of interest for the OLS panel estimation of equation 5 that includes triple interactions with noted initial (1999) worker attribute dummies. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.8 reports F-statistics for the joint significance of these exposure terms, by group.

Table A.8: F-Statistics for Joint Significance of Triple Interaction DID Terms

		High-Tenure	
	LHS	NM	M
Female vs Male	CR	7.25***	1.02
Non-White vs White	CR	2.25**	1.65
Age Below 30 vs Older	CR	2.34**	.25
Bachelors vs Less	CR	1.14	1.28
Highest Earner vs Less	CR	6.61***	10.7***
Small Firm vs Larger	CR	1.01	2*
Trading vs Non-Trading Firm	CR	.99	2.38**
Diversified Firm vs M	CR	1.19	1.32
Female vs Male	LN	4.27***	1.14
Non-White vs White	LN	2.82***	.54
Age Below 30 vs Older	LN	2.47**	3.27***
Bachelors vs Less	LN	2.23**	2.57**
Highest Earner vs Less	LN	4.09***	31.79***
Small Firm vs Larger	LN	2.82***	6.56***
Trading vs Non-Trading Firm	LN	.81	6.99***
Diversified Firm vs M	LN	2.02*	6.11***
Female vs Male	$E > 0$	6.05***	1.71
Non-White vs White	$E > 0$	1.43	1.18
Age Below 30 vs Older	$E > 0$	1.89*	.5
Bachelors vs Less	$E > 0$	2.69**	1.44
Highest Earner vs Less	$E > 0$	18.69***	14.62***
Small Firm vs Larger	$E > 0$	1.06	1.27
Trading vs Non-Trading Firm	$E > 0$	1.14	2.29**
Diversified Firm vs M	$E > 0$	1.03	.73

Source: LEHD, LBD, Feenstra et al. (2002), and authors' calculations. Table displays the F-statistics of the triple-interaction industry and county exposure terms for noted worker or firm characteristic. There are six exposure terms for M and 5 for NM. Each panel reports F-stats for the earnings transformation noted in the second column: CR=Chen-Roth, LN=natural log; and E>0=linear probability model for earnings greater than zero. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels.