Trade Liberalization and Labor-Market Gains: Evidence from US Matched Employer-Employee Data*

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Comments Welcome!

Abstract

We use employer-employee data to follow US workers' long-run employment flows and earnings after trade liberalization with China. Descriptive results indicate that manufacturing workers in more exposed counties flow disproportionately into low-skill services such as retail and temp agencies, and are more likely to exhibit nominal wage *declines* after seven years. Difference-in-differences analysis reveals that exposure to a trade shock operates predominantly through workers' labor market versus industry, that greater *upstream* exposure via suppliers can offset the adverse impact of own and downstream exposure, and that this positive upstream exposure generally dominates among workers initially employed outside manufacturing, leading to relative earnings *gains*.

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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). One specific area of interest has been the reaction of US workers (Autor et al., 2014), industries (Pierce and Schott, 2016) and regions (Autor et al., 2013; Bloom et al., 2019) to US trade liberalization with China. While this research finds that Chinese import competition induced a steep decline in US manufacturing employment, its impact on earnings inside and outside of that sector, especially among service workers that might be expected to benefit from greater upstream exposure to China, is unclear.

We use detailed data from the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program to provide greater resolution on these outcomes. The LEHD is well-suited to our inquiry in two ways. First, it tracks the earnings of nearly all workers among US states participating in the program, permitting investigation into variation in 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 the higher levels of aggregation typically examined in the "China Shock" literature, e.g., across industries or regions.

In the first part of the paper, we provide the first decomposition of long-run US worker sector transitions following an important change in U.S. trade policy, the extension of Permanent Normal Trade Relations (PNTR) to China in 2000. We find that the most popular destination among workers leaving manufacturing between 2000 and 2007 is Wholesale (NAICS 42), with those following this path exhibiting median nominal earnings growth slightly higher than those staying in manufacturing, at 33 versus 27 percent over the 7-year period. This reallocation may reflect a switch of industry but not occupation (Traiberman, 2019), or the growth of factoryless goods producers that focus on the design and marketing of goods rather than their physical production (Fort, 2017; Ding et al., 2019; Bloom et al., 2019).

Consistent with anecdotal reports (Scott et al., 2022), we find that former manufacturing workers' median nominal earnings growth is markedly lower among the large number of workers transitioning towards more consumer-service-oriented sectors such as Retail (NAICS 44-5) and Accommodation and Food (NAICS 72), and lowest – at -22 percent – among those moving to Administrative and Support Services (NAICS 56), which is dominated by temporary staffing agencies. Workers flowing into that sector likely capture some manufacturing firms' outsourcing of workers to third parties (Dey et al., 2012), potentially related to a decline in union power (Charles et al., 2021a). The flow from manufacturing to Construction (NAICS 23), posited by Charles, Hurst, and Notowidigdo (2016) as a potential haven for displaced factory workers, while also large, is disproportionately smaller in counties with greater exposure to PNTR. Overall, we find that manufacturing workers initially employed in counties with the highest sensitivity to PNTR exhibit smaller earnings growth along *all* transition paths.

In the second part of the paper, we use a series of worker-level difference-in-differences (DID) regressions to examine, formally, how earnings evolve after versus before PNTR based on workers' exposure to the change in policy and their observable attributes. Our main regressions focus on "high-tenure" manufacturing (M) and non-manufacturing (NM) workers, which we define as workers initially employed in M or NM by the same firm during the entire 1993 to 1999 pre-PNTR period. Consistent with current best practice, we consider three transformations of earnings—which can take the value zero—as the left-hand side outcomes of interest: log earnings (LN), which, because it excludes zeros, yields estimates conditional on remaining employed (the "intensive" margin); a dummy for earnings greater than zero (E>0), which tracks employment (the "extensive" margin); and the arcsin of earnings (ARC), which offers an estimate of the combined impact of the intensive- and extensive-margin responses.

Our DID regressions are designed to assess the relative importance of sectoral versus spatial frictions, as well as the salience of "direct" versus "input-output" (or "IO") exposure to the shock via supply-chain linkages. For the former, we consider two forms of susceptibility: the industry of the establishment at which the worker is initially employed, and the county in which this establishment is located. The first is derived directly from the US tariff schedule but defined only for M workers. The second is a Bartik-style employment-weighted-average across industries produced in the county and is applicable to workers both inside and outside manufacturing.

In addition to these "direct" county and industry exposures, we use data from the US input-output table to construct up- and downstream "IO" exposures. The up- and downstream exposure for industry i is the input-output-coefficient weighted average of the exposures of all industries used by i, and all industries to which i sells, respectively. Likewise, county up- and downstream exposures are constructed as the average up- and downstream exposures of the industries initially produced in a county, weighted by the latter industries' initial employment. Upstream exposure is expected to be beneficial to the extent that PNTR reduces input prices or otherwise positively affects productivity upstream (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011). Downstream exposure, by contrast, may worsen outcomes if it leads difficult-to-replace customers to contract or exit. Including these measures is especially useful for workers outside manufacturing, as they have no "own" industry exposure, but can have up- and downstream industry exposure.

In our "direct" specification, which includes only own-county and -industry DID exposure terms, we find that own-county exposure is negative and statistically significant among both M and NM workers, and that industry exposure is statistically insignificant among M workers. These results suggest geographic frictions to reallocation are most binding for both types of workers, providing support for the assumptions made in recent theoretical contributions (Artuc et al., 2010; Kovak, 2013; Caliendo et al., 2019). Coefficient estimates from this specification also indicate that M and NM workers respond similarly to PNTR: interquartile increases in county exposure reduce overall post-period relative earnings for M and NM workers by -25 and -27 percent. These results suggest a local-labor-market spillover of the goods-industry shock to service sectors due to some combination of greater competition for a smaller pool of jobs and declining demand for goods and services as a result of lower aggregate income.

Results from our "IO" specification highlight the importance of accounting for up- and downstream exposure in evaluating the "China Shock". While county exposure remains most influential in determining outcomes, we find that ignoring supply-chain linkages leads to *underestimation* of relative earnings losses among M workers, and *overestimation* of these losses among NM workers. This asymmetry is driven by variation in estimated up- and downstream exposure coefficients for the two groups of workers. In particular, positive coefficients for county upstream exposure are larger for NM workers than M workers, while estimates for county downstream exposure are more negative among M workers than NM workers. A similar trend is evident with respect to upstream industry exposure, which is relatively large and more likely to be statistically significant among NM workers.

Summarizing the combined economic significance of these estimates using the traditional metric of an interquartile increase in exposure is complicated by their high dimensionality and correlation. As an alternative, we use our DID estimates to predict relative changes in post-period earnings associated with PNTR across all county-industry pairs appearing in our regression sample, i.e., the product of our estimated DID coefficients of interest and actual measures of exposure. For M workers, the distribution of these predictions shifts to the left in moving between the "direct" and "IO" specifications, indicating a worsening of relative earnings changes under the "IO" specification, with the interquartile boundaries for relative earnings growth under the ARC transformation decreasing from -19 and -5 percent to -27 and -15 percent. By contrast, the county-industry predictions for NM workers shift to the right, with the interquartile boundaries rising from -23 and -7 percent in the "direct" model to 23 to 42 percent in the "IO" specification. Indeed, under the "IO" specification, NM workers in nearly all county-industry pairs are predicted to have relative earnings *gains*.

One explanation for M workers' lower responsiveness to county upstream exposure, and greater vulnerability to county downstream exposure, is an asymmetry in manufacturing's sensitivity to supply-chain disruption *vis à vis* other sectors. 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, e.g., apparel and textiles. Outside M, such co-offshoring may not be possible, e.g., a hospital must stay near its patients, and a hotel near its guests.

Overall, the results of our "IO" specification provide the first evidence of (relative) benefits arising to downstream workers from increased Chinese import competition in input markets. They also reveal that adopting a broader input-output perspective is particularly critical for understanding outcomes outside manufacturing. Indeed, 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. Worker-level results in this paper indicate that the agglomeration of input-output effects in particular regions is an important determinant of their ultimate impact on workers.[1]

[1] Greenland, Ion, Lopresti, and Schott (2020) use equity market reactions to the passage of PNTR to identify market

In the final part of the paper, we investigate whether responses to PNTR vary by workers' initial characteristics or their initial firms' attributes using a version of our "IO" specification that includes triple interactions of these traits and our six "IO" measures of exposure. Consistent with our main results, we find that the county exposure triple interactions are more likely to be statistically significant at conventional levels than the industry triple interactions, and that this significance is most prevalent along the intensive margin of earnings changes.

These "triple-interaction" estimates also reveal that *firm* as well as worker attributes are important determinants of worker outcomes. For example, we find that manufacturing workers at smaller and non-diversifed firms—i.e. those engaged solely in manufacturing or non-manufacturing activities—have relatively better earnings outcomes than workers at firms that are larger or have both manufacturing and non-manufacturing establishments. The former result provides the first 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 second suggests that a focus on manufacturing may contribute to this ability. Among worker characteristics, we find that relative earnings outside manufacturing are predicted to be higher among women, whites, younger workers and high earners.[2] That last of these relationships also holds among those initially employed in manufacturing, suggesting workers in both sectors with high earnings before the shock possess skills that are more easily transferable to other industries, areas or firms, or that they have savings that may allow them to be more selective in accepting a new position after the shock.

Our characterization of worker earnings and employment before and after PNTR contributes most directly to the literature using individual-level data to investigate 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 alternate approach to identifying "mass layoffs".

Building on this work, a rapidly expanding line of research exploits the labor demand shocks associated with international trade to consider effects on a wide range of employment responses, with recent research increasingly employing worker-level data.[3] Hakobyan and McLaren (2016) document

participants' assessment of firms that will gain and lose from greater integration with China. A more recent set of papers including Flaaen and Pierce (2019), Bown, Conconi, Erbahar, and Trimarchi (2020), Goswami (2020), and Handley, Kamal, and Monarch (2020) does find effects of *increases* in input tariffs on downstream industries when examining the US-China trade war or US antidumping duties.

[2] Kahn, Oldenski, and Park (2022) find that Hispanic workers exhibit greater manufacturing employment loss during the China shock.

[3] This literature is surveyed in McLaren (2017), McLaren (2022), and Caliendo and Parro (2022). 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) illustrates 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 decline in wages of 8 percentage points among M and NM workers in US industries and regions with greater exposure to NAFTA. Outside the United States, Dix-Carneiro (2014), Krishna et al. (2014) and Kovak and Morrow (2022) explore the impact of exposure to trade among Brazilian and Canadian workers, respectively, while Deng, Krishna, Senses, and Stegmaier (2021) investigate differences in the impact of industry- versus occupational exposure to import competition on 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. Our contribution relative to these efforts is to use employer-employee data to study a US trade liberalization, to assess the effect of both industry and geographic exposure, to evaluate the long-run influence of these exposures along the value chain, and to investigate differential responses to the shock among different types of workers with varying professional attributes.

The two papers most closely related to ours are Autor et al. (2014) and Carballo and Mansfield (2023). Autor et al. (2014) use individual-level US Social Security Administration (SSA) earnings data and find that over the period examined in this paper, workers initially employed in import-competing manufacturing industries exhibit disproportionately large losses in cumulative earnings. The data we use, the approach we take, and the findings we report differ from this paper in several ways. First, because the LEHD data link employees to the rich Census Bureau data on establishments and firms, we are able to control for a rich set of firm characteristics including size, scope, and trade activity, which can be important determinants of earnings (Bernard and Jensen, 1999; Song et al., 2018). Second, our approach accounts for the implications of trade shocks passed through input-output linkages, which we find to be a key determinant of worker-level outcomes, especially for nonmanufacturing workers. Finally, in terms of results, we find geographic exposure to be a more important determinant of subsequent earnings than industry exposure, a result which may arise, in part, because our data contain complete information on a worker's location of employment, as opposed to the less precise geographical information in the SSA data, which typically requires imputation.

Carballo and Mansfield (2023) use data from the LEHD in an assignment model to examine the incidence on workers of the trade shock described in Pierce and Schott (2016). Relative to earlier work examining the labor market consequences of this trade shock, Carballo and Mansfield (2023) allow for potential effects of competition from China in export markets served by U.S. firms, as well as increased access to imports, which is measured based on observed firm-level direct importing. Like in this paper, Carballo and Mansfield (2023) find large negative effects of the import competition channel on labor market outcomes for manufacturing workers; the export competition and import access effects, though substantive, offset one another. While Carballo and Mansfield (2023) find that negative effects of import competition on manufacturing workers spill over to those in other sectors, we find that nonmanufacturing workers often experience relative *gains* in earnings from trade liberalization via increased competition in manufactured input markets. We note that our approach – using input-output tables – allows for this higher competition to be present for firms that source inputs from domestic suppliers or purchase imported inputs via wholesalers, not just those that are direct importers. In addition, we allow these input-output linkages to have effects via either industry or county-level aggregation.

Our results also 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), for example, find that overall employment growth conditional on own-region exposure is positive in skill-abundant commuting zones and negative in those that are skill-scarce.[4] While we also find that workers – particularly NM workers – in some geographic areas benefit from increased import competition, we identify a mechanism that operates through input-output linkages. We also find that for the workers that are (relatively) harmed by PNTR, the negative effects on earnings are more long-lived than reported in Bloom et al. (2019), 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. Section 3 provides a detailed accounting of gross manufacturing employment in- and outflows between 2000 and 2007. Section 4 describes the trade liberalization we study. Section 5 presents our main results with respect to high-tenure M and NM workers. Section 6.1 compares these results to an alternate low-tenure sample. Section 7 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.[5]

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).[6] 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.[7]

[4] Evidence regarding the impact of trade liberalization outside manufacturing is mixed. Also using commuting-zone-level data, Autor, Dorn, and Hanson (2013) find that greater own-region exposure to imports from China reduces US manufacturing employment but has no impact on non-manufacturing employment, while the reverse is found for wages. Hakobyan and McLaren (2016) find that own-industry and own-county exposure to NAFTA is associated with substantial wage declines among less educated workers in both manufacturing and non-manufacturing.

[5] 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.

[6] 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.

[7] Note that educational attainment is imputed for the vast majority (92 percent) of PIKs in the LEHD. See Vilhuber

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 plant and firm in the Longitudinal Business Database (LBD), which tracks employment and other attributes of virtually all privately owned firms in the United States. Via the LBD, we are able to measure the size of a worker's firm as well as whether the firm has multiple establishments.

In any given year a worker may be employed by more than one firm. We adopt the convention among LEHD users 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.[8] We 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 3, we use information from the 46 states whose data are in the LEHD starting in 2000.[9] In the difference-in-differences estimations we present in Section 5, we use data from the 19 states whose information is available for our full pre- and post-PNTR sample period, 1993 to 2014.[10]

Our regression analysis focuses on "high-tenure" workers, i.e., those who are employed continuously by the same firm in the 1993 to 1999 "pre-period" prior to implementation of PNTR. In Section 6.1 we compare results for these workers to a "low-tenure" sample with less firm-specific human capital prior to the change in policy. This sample is defined as those who are continuously employed from 1993 to 1999, but not necessarily by the same firm. For computation 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 5327 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). Note that all of our regressions are weighted by the inverse of the probability of being in the sample. Finally, we eliminate workers from this draw who will be older than age 64 in 2014 so that they are not influenced by 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

and McKinney (2014) for more details.

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

[9]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.

[10]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. They represent 47 percent of US overall and manufacturing employment in 2000. Appendix Table A.1 compares worker attributes in the 19- and 46-state samples as of 2000. As noted in that table, the M and NM workers in the two samples are similar, with with those in larger sample being a bit older, on average, than those in the 19-state sample.

the result of death, movement to a state (or country) outside the sample of states for which we have data, or movement to a job that is out of scope of the UI system.[11]

3 Post-2000 US Labor Reallocation

In this section, we provide context for existing research on the employment effects of the China Shock, and, more generally, on US structural change (Ding et al., 2019), by summarizing workers' 2000 to 2007 transitions among sectors, and the earnings growth associated with these moves. While straightforward, these descriptions provide – to our knowledge – the first detailed accounting of sector-to-sector flows for manufacturing workers during this period, and therefore offer a more complete view of the labor market transitions of manufacturing workers at the onset of the steep increase in import competition from China.[12] They also provide additional evidence relating to several hypotheses regarding manufacturing worker outcomes that have appeared in the literature.

3.1 Transitions Among M, NM and NE

Table 1 offers a broad overview of workers' gross flows among manufacturing (M), non-manufacturing (NM) and non-employment (NE) from 2000 to 2007 using the 46-state sample described in the previous section.[13] The left panel reports these flows in millions of workers, while the right panel expresses them as percentages of origin sectors' initial levels. As indicated in the left panel, the number of M workers declines from 18.3 million in 2000 (row 2, final column) to 15.4 million in 2007 (column 2, final row), while NM employment increases from 118.6 to 133.1 million.

Table 1: Gross Flows to and from Manufacturing, 2000-7

	Employment							
	Millions				Percent of Initial Level			
	Sector in 2007			Total in	Sector in 2007			Total in
Sector in 2000	NM	M	NE	2000	NM	M	NE	2000
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
Total in 2007	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. Appendix Table 1 reports analogous statistics for 2000 to 2005 and 2000 to 2011.

[11] Workers in our regression sample that move to one of the 46 states available in the LEHD after 2000 remain in the regression sample and are not classified as NE.

[12] While the US Census Bureau's J2J Explorer (`https://j2jexplorer.ces.census.gov/`) can be used to analyze US workers' transitions across space and industries, movement can be examined only quarter by quarter, i.e., not across the seven-year interval investigated below.

[13] The analysis ends in 2007 to focus on worker reallocation prior to the Great Recession. In Appendix Table A.2 we find that while the general pattern of movement is similar for the periods ending in 2005 and 2011, there is, intuitively, greater transition away from initial sector over longer intervals.

Table 1 reveals two novel and interesting features of labor-market adjustment in the post-PNTR period. First, we see that even as many workers left manufacturing, employment declines were partially offset by sizable gross inflows from industries outside the sector.[14] From 2000 to 2007, 3.9 million workers move from NM to M, and 3.2 million transition from NE to M, with the result that 46 percent (7.1/15.4) of workers employed at a manufacturing establishment in 2007 were not at such a plant in 2000.[15] Thus, there is substantial switching *into* manufacturing, even in a time of precipitous net decline.

The second noteworthy trend in Table 1 is that, despite the steep decline in manufacturing employment and associated negative socioeconomic implications discussed in the literature (Feler and Senses, 2017; Autor et al., 2019; Pierce and Schott, 2020), the share of year-2000 employees transitioning to non-employment in 2007 is similar for manufacturing and non-manufacturing. As shown in the lower panel of Table 1, 23 percent of 2000 M workers transitioning to NE in 2007, versus 25 percent for NM workers.[16]

3.2 Detailed Decomposition of Gross M Outflows

We provide a more detailed description of worker reallocation *away* from manufacturing in Table 2, which decomposes manufacturing workers' $gross\ outflows$ from 2000 to 2007 by two-digit NAICS category. The first two columns, which report the level and share of outflows by destination sector, reveal that the largest outflows are towards Administration, Support, and Waste Management (NAICS 56), Retail (NAICS 44-5), and Wholesale (NAICS 42), accounting for 4.1, 4.0 and 3.7 percent of the total gross outflow. Hereafter, we refer to Administration, Support, and Waste Management as ASW.

In column 5, we divide the outflow shares (in column 2) by destination sectors' initial employment as a share of the total (in column 4) to assess the $relative$ likelihood of former manufacturing workers entering a particular sector. Values of this ratio above unity indicate flows into a sector that are greater than their initial size, in percentage terms. Staying in manufacturing remains the most prevalent outcome, and the only destination for which the ratio exceeds 1, at 3.28. This persistence likely reflects the importance of sector-specific human capital (Neal, 1995; Artuc et al., 2010; Ebenstein et al., 2014; Caliendo et al., 2019). Adjusted for initial size, Wholesale (NAICS 42) becomes the most popular non-manufacturing destination, followed by Mining (NAICS 21), Management (NAICS 55), and ASW (NAICS 56).[17] Transitions to each of these sectors is consistent with workers switching industry but

[14] Worker industry transition without plant transition is possible if a worker's plant switches industry codes (Bernard et al., 2006). Though Bloom et al. (2019) report a high correlation between M plants' industry switching and import competition from China, Ding, Fort, Redding, and Schott (2019) show that the actual employment associated with these switches is very small.

[15] One source of flows from NE to M could be the first-time entry of young workers to the labor force. Given how we construct our regression samples, such workers will not appear in the difference-in-differences estimations later in the paper.

[16] Manufacturing and non-manufacturing workers had different rates of transition to non-employment in the pre-PNTR period, so that a convergence to similar rates post-PNTR represents a change. Unfortunately, we cannot extend the 46-state sample backwards in time as this large number of states is only available in the LEHD starting in 2000.

[17] Appendix Figure A.6 reports *net* outflows from the manufacturing sector at the one-digit NAICS level for 2000 to 2005, ranked as follows: Not Employed (-.70 million), Business Services (-.60 million), Wholesale, Retail, Transportation and Warehousing (-.50 million), Education and Health (-.42 million), and Mining, Utilities, and Construction (-.22 million).

not necessarily occupation (Traiberman, 2019). Except for mining, they may also represent the growth of factoryless goods producers (Fort, 2017; Ding et al., 2019; Bloom et al., 2019; Fort, 2023).

One area of interest in Table 2 is the flow of 745 thousand workers from M to ASW (NAICS 56), the largest component of which is staffing services, e.g., temp agencies. Dey, Houseman, and Polivka (2012) use other data sources to provide a comprehensive analysis of manufacturers' use of staffing services over time, and estimate that the number of staffing-service workers edged down, on net, from 1.4 million in 2000 to 1.3 million in 2006. However, given that direct manufacturing employment—i.e., employment by manufacturing establishments—plunged over the same period (see Table 1), staffing services' share of manufacturing employment rose from 8 to 9 percent. Our finding that a relatively large number of workers transitioned from M to ASW is consistent with this proportional rise in staffing services.[18]

Table 2: 2000 to 2007 Manufacturing Outflows (46-States)

	Gross Outflow		2000 Employment		
Destination NAICS Sector	(1) Flow	(2) % of Flow	(3) Level	(4) % of Total	(5) (2) / (4)
11 Agriculture,Fish,Forest	74	0.4	1,649	1.3	0.33
21 Mining	62	0.3	596	0.5	0.75
22 Utilities	31	0.2	757	0.6	0.30
23 Construction	513	2.8	8,093	6.2	0.46
31-33 Manufacturing	8,281	45.7	18,300	13.9	3.28
42 Wholesale	665	3.7	6,106	4.6	0.79
44-45 Retail	729	4.0	17,450	13.3	0.30
48-49 Transportation	314	1.7	4,436	3.4	0.51
51 Information	121	0.7	3,908	3.0	0.22
52 Finance, Insurance	167	0.9	5,797	4.4	0.21
53 Real Estate, Leasing	102	0.6	2,248	1.7	0.33
54 Professional	504	2.8	7,217	5.5	0.51
55 Management	134	0.7	1,487	1.1	0.65
56 Admin, Support,Waste Mgmt	745	4.1	9,789	7.5	0.55
61 Education	290	1.6	11,400	8.7	0.18
62 Health	515	2.8	13,880	10.6	0.27
71 Arts, Entertain, Recreation	80	0.4	2,270	1.7	0.26
72 Accomodation, Food	335	1.8	11,590	8.8	0.21
81 Other	204	1.1	4,406	3.4	0.34
Not Employed	4,250	23.5			
Total	18,116	100	131,379	100.0	

Source: LEHD, LBD, QWI and authors' calculations. First column displays the distribution of initial US employment across the noted sectors in 2000 from the Quarterly Workforce Indicators Database (QWI) available at https://ledextract.ces.census.gov/static/data.html. Second column reports outflows of manufacturing workers to those sectors between 2000 to 2007 across the 46 states for which information is available in the LEHD in those years (Alabama, Arkansas, New Hampshire Mississippi and the District of Columbia are excluded). Columns 3 and 4 report the flows as a share of initial employment and as a share of the overall outflow from manufacturing. Last column reports the ratio of columns 2 and 4.

Also noteworthy in Table 2 is the gross flow from M to Construction (NAICS 23). Charles, Hurst, and Notowidigdo (2016) suggest workers displaced from manufacturing in the early 2000s may

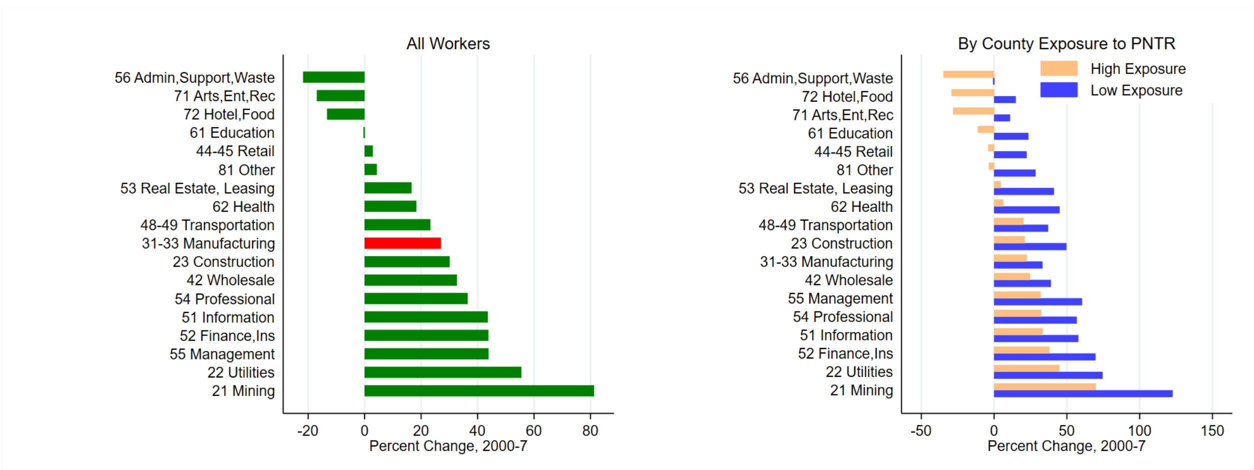
[18] Even so, Dey, Houseman, and Polivka (2012) estimate that outsourcing activity did not materially change the trend in overall manufacturing employment (see their Figure 3).

have found a commensurately compensated haven in this sector during the post-2000 housing boom. While the flow of 513 thousand manufacturing workers to construction ranks relatively high – fifth and seventh – in columns 2 and 4, we show below that this shift predominantly occurs in counties that were *less* exposed to PNTR.

3.3 Initial M Earnings Growth by Gross Outflow and PNTR Exposure

We investigate how the nominal earnings of workers initially employed in manufacturing evolve depending upon whether they remain in that sector or migrate to another by calculating the ratio of their 2007 to 2000 nominal earnings. We then take the quasi-median across all workers moving to each destination (including those that stay in manufacturing), subtract 1, and report the corresponding median cumulative percent changes in Figure 1.[19]

Figure 1: Median Nominal Earnings Growth Among Initial M Workers, by Transition Path (46 States)



Source: LEHD, LBD and authors' calculations. Figure displays 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 median growth for workers in the first (low) versus fourth (high) quartile of county exposure to PNTR, defined in Section 4.

The left panel of the figure displays results for all workers making each transition. It reveals that initial M workers experience dramatically different nominal earnings growth depending on their destination sector. For workers who remain in manufacturing (indicated by the highlighted bar), cumulative median earnings growth is 27 percent, right in the middle of the pack. Growth is most positive among workers moving to Mining (NAICS 21), Utilities (NAICS 22), and Professional Services and Management (NAICS 54-55), sectors that are intensive in their use of either physical or human capital and generally have higher wages than manufacturing. Median nominal earnings growth is lowest, and *negative*, for those transitioning to ASW (NAICS 56), consistent with a potential increase in outsourcing previously high-wage unionized factory workers (Charles et al., 2021a). It is also

[19] 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 below.

negative for those moving into Arts, Entertainment and Recreation (NAICS 71), and Accommodation and Food Services (NAICS 72), and essentially flat for those heading to Retail (NAICS 44-5). These outcomes are consistent with the generally lower wages paid in these sectors, the popular narrative that well-paid manufacturing workers face large drops in income when they move to service sectors with low skill requirements (Scott et al., 2022), and the heterogeneous scarring effects of job loss documented in Huckfeldt (2022).[20] Workers transitioning to Wholesale (NAICS 42), by contrast, exhibit earnings growth comparable to those that remain in manufacturing, perhaps because, as noted above, these workers are switching industries but not occupation.

In a purely descriptive preview of our regression analysis below, the right panel of Figure 1 shows how median earnings growth across workers varies among counties in the highest versus lowest quartile of exposure to Chinese import competition, defined in the next section. Two differences stand out *vis à vis* the left panel. First, earnings growth is lower along *all* paths within highly exposed counties, relative to less exposed counties. For workers remaining in M, for example, growth is about a third less, at 23 versus 33 percent. Second, *declines* in nominal earnings occur only within highly exposed areas. In those counties, workers moving to ASW (NAICS 56), Accommodation and Food Services (NAICS 72), Arts, Entertainment, and Recreation (NAICS 71), Education (NAICS 61), Retail (NAICS 44-5), and Other (NAICS 81) exhibit drops of -35, -29, -28, -11, -4, and -4 percent.

3.4 Initial M Gross Outflows by PNTR Exposure

For completeness, Figure 2 decomposes gross flows out of manufacturing by 2-digit NAICS sector for all workers (left panel) and among workers in counties with high versus low exposure to PNTR (right panel). In each case the percentages displayed are net of workers remaining in manufacturing.[21] The scatterplot on the left reveals that workers in low-exposure counties are substantially more likely to shift into Wholesale (NAICS 42), Construction (NAICS 23) and Professional Services (NAICS 54) than workers in counties with high exposure. The relatively large flows into Construction, coupled with that sector's high earnings growth in Figure 1, is consistent with research by Feler and Senses (2017) and Xu, Ma, and Feenstra (2019) which finds that higher regional exposure to import competition from China is associated with lower housing prices and demand, dampening the ability of construction to absorb former M workers unless they move geographically.

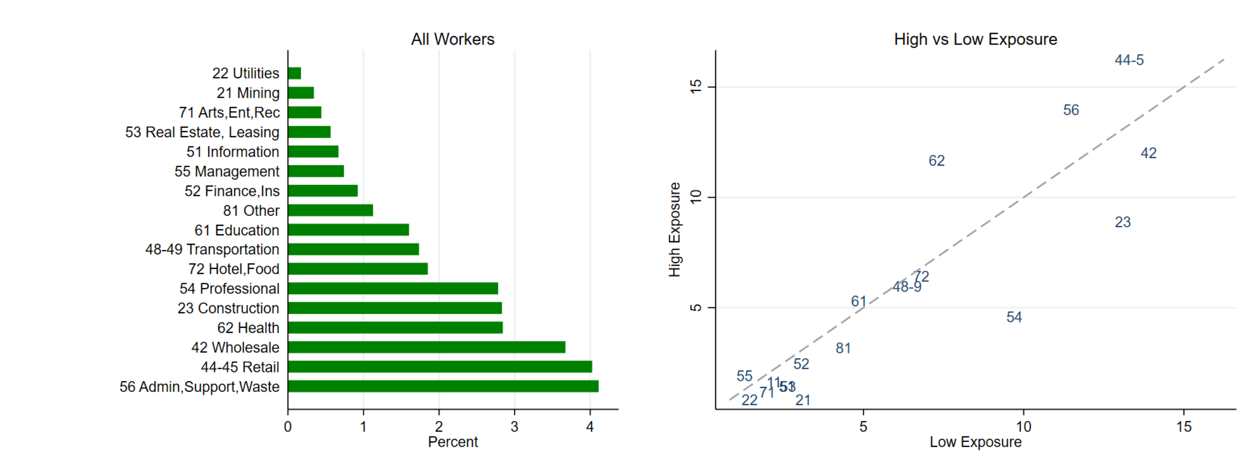
4 Defining Industry and County Exposure to PNTR

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

[20]The wage declines displayed in Figure 1 do not appear to be driven by differential wage growth across sectors. According to publicly available data from the BLS, summarized in Appendix Figure A.4, the average hourly earnings for production and non-supervisors in Manufacturing (NAICS 3) in 2000 was $13.80, versus $12.0, $11.30, $10.90 and $8.10 for ASW (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.

[21]Fifty-eight percent of all M workers in 2000 are still in that sector in 2000. The analogous shares for workers in counties with high and low exposure are 63 and 49 percent, respectively.

Figure 2: Gross Employment Flows Among Initial M Workers, by Transition Paths (46 States)



Source: LEHD, LBD and authors' calculations. Figure decomposes the 2000 to 2007 gross flows of initial manufacturing workers by 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 are excluded). Right panel further decomposes the flows according to counties with the first (low) versus fourth (high) quartile of county exposure to PNTR, defined in Section 4. In each panel, flows are computed in percentage terms net of the number of workers remaining in manufacturing, such that displayed percentages add to 100.

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 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,

$$Industry\ Gap_i = Non\ NTR\ Rate_i - NTR\ Rate_i. \tag{1}$$

We compute $NTR\ Gap_i$ for six-digit NAICS industries using a simple average of the Harmonized system (HS) level *ad valorem equivalent* tariff rates provided by Feenstra, Romalis, and Schott (2002) for the year 1999, 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 $Industry\ Gap_i$, 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 $Industry\ Gap_i$ of the industries it produces. For each US county c,

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

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.[22] In this computation, $Industry\ Gap_i$ is defined 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.

Figure 3 displays the kernel densities of $Industry\ Gap_i$ and $County\ Gap_i$, 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. $Industry\ Gap_i$ has a mean and standard deviation of 33 and 14 percent, while $County\ Gap_i$ has a mean and standard deviation of 7 and 6 percent. Intuitively, the distribution of $County\ Gap_j$ lies to the left of the distribution of $Industry\ Gap_i$, reflecting the presence of service industries with NTR gaps of zero. The correlation between $Industry\ Gap$ and $County\ Gap$ across workers in our 19-state regression sample is 0.26.[23] In some instances below we calculate the economic significance of the estimated impact of PNTR using interquartile shifts in exposure, which are 24.6 and 6.9 percent for industry and county, respectively.[24]

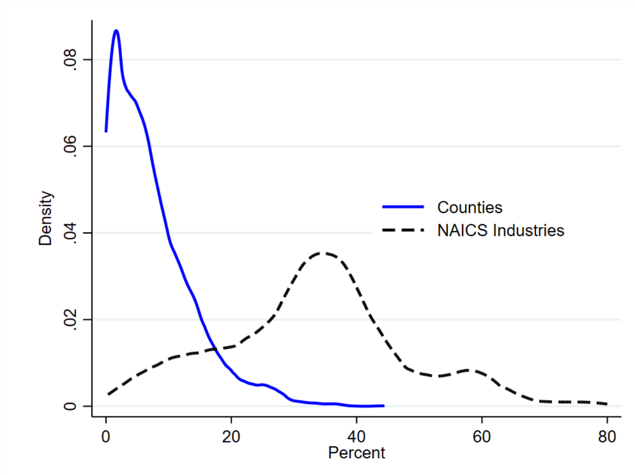
Trade liberalization episodes such as PNTR may also affect US workers' earnings via their supply chains, i.e., the upstream industries from which they purchase their inputs or the downstream

[22] 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.

[23] 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.

[24] The 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of $Industry\ Gap_i$ are .05, .20, .33, .40 and .54. The corresponding percentiles for the $County\ Gap_j$ are 0.01, 0.02, 0.06, 0.10, and .15.

Figure 3: Distribution of *Industry Gap* and *County Gap*



Source: Longitudinal Business Database, Feenstra, Romalis, and Schott (2002) and authors' calculations. Figure displays the distributions of the 1999 NTR gap across six-digit NAICS industries ($Industry\ Gap_i$) and US counties ($NTR\ Gap_c$). The former is restricted to the 473 industries that appear in the US tariff schedule. *Industry Gap* has a mean and standard deviation of 28.4 and 17.4 percent, and an interquartile range of 24.6 percent. $County\ Gap_j$ has a mean and standard deviation of 6.1 and 5.2 percent, and an interquartile range of 6.9 percent.

industries to which they sell their outputs.[25] We compute up- and downstream NTR gaps using information from the 1997 BEA input-output tables. $Industry\ Gap_i^{up}$ 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-use input-output coefficients (ω_{ik}^{up}) as weights,

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

$Industry\ Gap_i^{down}$ is the analogous weighted average for all the downstream industries outside i's 3-digit root that use industry i.[26]

We compute $County\ Gap_c^{up}$ and $County\ Gap_c^{down}$ by taking weighted averages of $Industry\ Gap_i^{up}$ and $Industry\ Gap_i^{down}$, e.g.,

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

Upstream exposure is therefore higher when the county produces more output in industries whose upstream industries have higher exposure.[27]

[25] 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).

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

[27] The means of 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.

Industries vary intuitively in terms of their up- and downstream gaps.[28] Hospitals (NAICS 622), for example, has above-median upstream exposure (0.08) as a result of sourcing from Chemicals (NAICS 325), 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 discussing our regression results in Section 5.2.

5 DID Analysis of Workers' Earnings Response to PNTR

In this section, we examine the link between PNTR and worker earnings using generalized OLS difference-in-differences (DID) specifications. This approach allows us to compare the impact of county versus industry exposure to the policy change while controlling for initial worker (j), firm (f), industry (i), and county (c) characteristics, along with worker and time (t) fixed effects, α_j and α_t.

Our first, "direct" specification examines whether the earnings (in dollars) of workers with greater industry ($Industry\, Gap_i$) and county ($County\, Gap_c$) exposure to PNTR (first difference) vary after PNTR versus before (second difference),

$$\begin{aligned} d_{jfcit} \;=\;& \delta_1 Post \times County\, Gap_c + \delta_2 Post \times Industry\, Gap_i + \delta_3 Post \times MSH_{c,1999} + \\ & Post \times \mathbf{X_{j,1999}}\beta_{\mathbf{j}} + Post \times \mathbf{X_{f,1999}}\beta_{\mathbf{f}} + Post \times \mathbf{X_i}\beta_{\mathbf{i}} + \\ & \gamma_1 Post + \gamma_1 MSH_{c,1999} + \mathbf{X_{it}}\gamma_{\mathbf{i}} + \alpha_j + \alpha_t + \epsilon_{jfcit}. \end{aligned} \tag{5}$$

The sample period is 1993 to 2014. As noted in Section 2, we focus on 5 percent samples of "high-tenure" workers initially employed inside and outside manufacturing aged 64 or younger in 2014 from the 19 states for which employer-employee data are available over the sample period. We weight observations by the inverse of the probability of being in the sample, and, consistent with best practices (Bellemare and Wichman, 2020), consider three transformations of earnings as the left-hand side outcome of interest: log earnings (LN), which yields estimates conditional on remaining employed (the "intensive" margin); a dummy (E>0) for earnings greater than zero (the "extensive" margin); and the inverse hyperbolic sine of earnings (ARC), which provides a (scale dependent) combination of the intensive- and extensive-margin responses,

$$ARC(Earnings_{jfcit}) = ln(Earnings_{jfcit} + \sqrt{Earnings^2_{jfcit} + 1}). \tag{6}$$

With ARC, the implied elasticity of earnings with respect to county or industry exposure is equal

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

to the estimated DID coefficient in equation 5 multiplied by the correction $\sqrt{\frac{Earnings^2+1}{Earnings^2}}$, which is close to 1 in our context (Bellemare and Wichman, 2020). The percent impact on earnings of an interquartile shift in county exposure for this transformation is therefore approximately equal to

$$100 \times \delta_1(County\ Gap_c^{75} - County\ Gap_c^{25}).$$

Worker, firm, industry, and county attributes are as of the final year of the pre-period, 1999. The first two terms on the right-hand side of equation 5 are the county and industry DID terms of interest, i.e. interactions of county- or industry-level exposure to PNTR with a post-PNTR dummy that takes the value 1 for years after 2000. The third term on the right-hand side represents county c's 1999 manufacturing share, $MSH_{c,1999}$. With this term, the county gap reflects exposure to PNTR conditional on the county's manufacturing share (Borusyak et al., 2021). The remaining terms on the right-hand side of equation 5 are controls for 1999 worker and firm characteristics interacted by the post dummy, $Post \times \mathbf{X_{j,1999}}$ and $Post \times \mathbf{X_{f,1999}}$, and time-varying industry characteristics, $\mathbf{X_{it}}$. We multiply the 1999 worker and firm characteristics—which do not change over time and would be completely absorbed by the worker fixed effects—by the *Post* dummy. The resulting interactions allow for the relationships between these attributes and the dependent variables to change at the same time as PNTR was granted, assisting us in isolating the impact of the policy change.

Table 3: 19-State Sample Worker Attributes in 1999

	High Tenure			High Tenure	
Attribtute	M	NM	Attribute	M	NM
Female	0.284	0.46	Less than HS	0.125	0.086
	(0.451)	(0.499)		(0.331)	(0.280)
White	0.869	0.870	HS	0.339	0.266
	(0.337)	(0.337)		(0.473)	(0.442)
Black	0.070	0.076	Some College	0.324	0.336
	(0.255)	(0.264)		(0.468)	(0.472)
American Born	0.846	0.887	College or More	0.211	0.313
	(0.360)	(0.316)		(0.408)	(0.464)
Age	37.79	37.28	Earnings	46,840	46,840
	(6.167)	(6.525)		(231,500)	(210,630)

Source: LEHD, LBD and authors' calculations. Table reports the mean and standard deviation of noted "high-tenure" manufacturing (M) and non-manufacturing (NM) workers in 1999. Samples are 5 percent stratified draws from the 19 states whose information is available in the LEHD over our regression sample period, 1993 to 2014. Workers above the age of 50 in 2000 are omitted. Age and earnings are in years and dollars; all other attributes dummy variables.

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. Industry characteristics capture other changes in policy that occur during our sample period: reductions in Chinese import tariffs, reductions in Chinese production subsidies, and 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); their construction is described in Section B of the appendix.

Table 3 summarizes the initial attributes of the high-tenure workers in our two regression samples. As indicated in the table, initial M workers are less likely to be female, American born, and have advanced educational attainment.

5.1 Own-Industry Exposure ("Direct" Specification)

We start with a "direct" specification that restricts attention to own-county and own-industry exposure to PNTR, before considering up- and downstream exposure in the next section. Table 4 reports our findings. The left and right panels focus on "high-tenure" initial M and NM, workers, respectively, while the three columns within each panel report results for the three transformations of earnings discussed above: arcsin (ARC), natural log (LN) and a dummy for earnings greater than zero (E>0), where the latter two capture the "intensive" and "extensive" margins of earnings.[29] To conserve space, we report estimates only for the DID terms of interest. Standard errors are two-way clustered by 4-digit NAICS and county.

Table 4: "Direct" Specification

	High-Tenure M			High-Tenure NM		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	0.111	0.060	0.007			
	0.196	0.058	0.015			
Post x County Gap	–3.231***	–0.337*	–0.248***	–3.537***	–0.686***	–0.251***
	0.858	0.203	0.072	0.925	0.168	0.074
R-sq	0.439	0.558	0.408	0.441	0.631	0.406
Observations	1,520	1,378	1,520	4,605	4,173	4,605
Fixed Effects	j,t	j,t	j,t	j,t	j,t	j,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
IQ Increase Industry Gap	.023	.012	.001			
IQ Increase County Gap	-.249	-.026	-.019	-.272	-.051	-.019

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5. The sample period is 1993 to 2014. The samples are high-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and County gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

The main message of the "direct" specification in Table 4 is that PNTR affects both M and

[29] We are unable to determine the extent to which earnings decline due to fewer worked hours versus lower wage per hour, as we do not observe hours worked.

NM workers through their local labor markets. For M workers, for which both industry and county exposures are defined, coefficient estimates for industry exposure are close to zero and statistically insignificant, while those for county exposure are negative, statistically significant at conventional levels, and economically meaningful. This primacy of county exposure may suggest that M workers face binding costs related to physical, as opposed to sectoral re-location in response to the shock, or it may indicate that congestion effects block inter-sector switching in counties with larger exposure to the shock. The large and precisely estimated coefficients on county exposure for NM workers reinforce this message, indicating that PNTR's shock to manufacturing spills over to workers outside that sector due to some combination of greater competition for a smaller pool of jobs and declining demand for goods and services as a result of lower aggregate income. This spillover is especially severe along the intensive margin, where the estimated coefficient for NM workers is -0.686, versus -0.337 for M workers. That is, conditional on remaining employed, earnings fall twice as much for NM workers for a given level of county exposure.

The final row of Table 4 reports the economic significance of our estimates in terms of implied impacts of interquartile shifts in county exposure. For M workers, such shifts imply a -2.6 percent decline in relative earnings along the intensive margin and a -1.9 percent drop in the probability of remaining employed along the extensive margin. Combined, in the ARC transformation, these decreases suggest an overall reduction in relative earnings of -25 percent in the post- versus pre-periods, reflecting the extreme earnings loss associated with transitions to non-employment. For NM workers, interquartile shifts in county exposure imply -5.1 and -1.9 percent reductions along the intensive and extensive margins, and -27 percent overall.

The dominance of county over industry exposure among M workers reported in Table 4 contrasts with existing studies in which both spatial and industry exposure are considered. Using worker-level data from the US Social Security Administration and the US Population Census, respectively, Autor, Dorn, Hanson, and Song (2014) and Hakobyan and McLaren (2016) find that both dimensions of exposure to greater import competition from China or Mexico, respectively have a negative relationship with wages. Autor, Dorn, Hanson, and Song (2014) also examine cumulative years in employment and, across specifications, find either no significant relationship (in their specification with spatial exposure only), or one that is *positive* and marginally significant (in their alternate specification with both industry and spatial exposure).[30]

Our finding of a spillover between M and NM is consistent with Hakobyan and McLaren (2016), but stands out with respect to the "China Shock". Using commuting-zone level data, Autor, Dorn, and Hanson (2013) find that greater spatial exposure to imports from China reduces M but not NM employment, and decreases NM but not M wages. More recent research by Bloom et al. (2019) finds that, depending on the time period and industrial classification system considered, greater spatial exposure to China can *raise* non-manufacturing employment. We show in the next section that

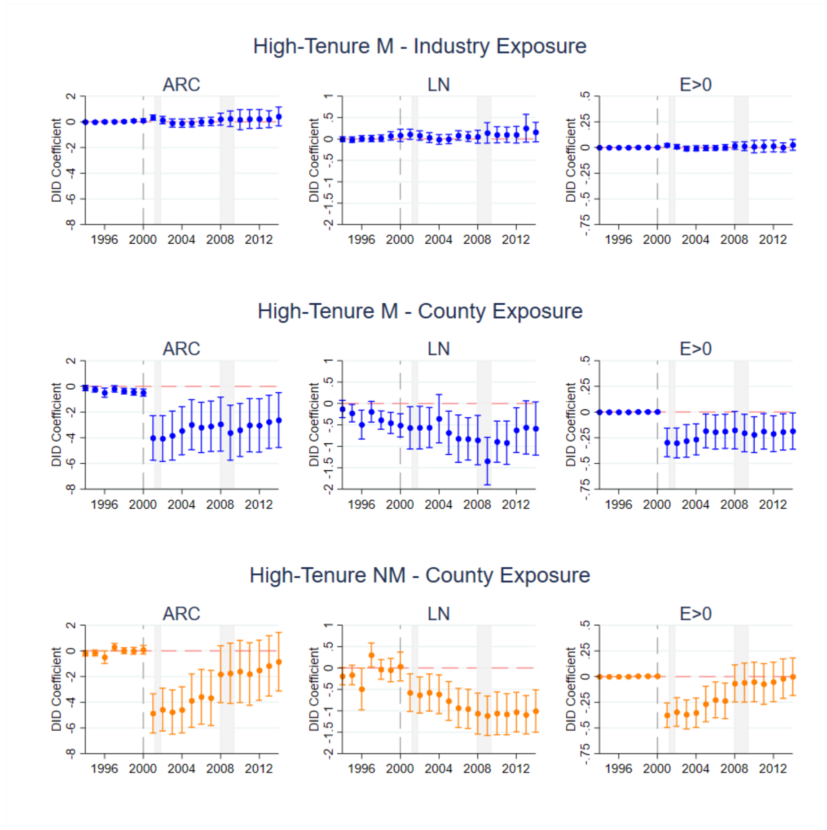
[30] In Appendix Table A.4 we add a triple-interaction DID term, $Post$ x $Industry\ Gap_i$ x $County\ Gap_c$, to equation 5 to explore whether the impact of industry exposure rises with county exposure. Coefficient estimates for this term are statistically insignificant for ARC and E>0 but negative, significant and large in absolute magnitude along the intensive margin. Costinot, Sarvimäki, and Vogel (2022) find evidence of a similar interaction in their analysis of Finnish workers' reactions to the implosion of the Soviet Union.

accounting for workers' exposure to PNTR via up- and downstream industries provides a potential explanation for this result.

Before continuing, we evaluate the timing and persistence of the relationship between worker outcomes and PNTR using an "annual" version of our "direct" specification that replaces the $Post_t$ indicator in equation 5 with a full set of year dummies, omitting 1993. Results are displayed visually in Figure 4. Three trends stand out. First, as indicated in the upper panel of the figure, industry exposure coefficients (available for M workers only) remain close to zero and statistically insignificant in both the pre- and post-periods. Second, county exposure terms for M and NM workers, displayed in the middle and lower panels, are near zero until 2001, at which time they drop substantially and become statistically significant, with some evidence of a pre-trend along the intensive margin among M but not NM workers.[31] Finally, the negative effect of county exposure is persistent. For M workers, county exposure adversely affects relative earnings through 2014. For NM workers, relative earnings remain low throughout the sample period along the intensive margin, but stage a recovery along the extensive margin in 2007.

[31] Note that E>0 is equal to one by definition in the pre-period.

Figure 4: Industry and County DID Coefficients from Annual Earnings Specification



Source: LEHD, LBD, and authors' calculations. Panels display the 95 percent confidence intervals for the industry and county exposure DID coefficients of interest from an annual version of equation 5 that replaces the $Post_t$ indicator with a full set of year dummies, omitting 1993. Industry exposure is not defined for NM workers. See notes to Table 4 for further description of the underlying regression. Standard errors are two-way clustered by four-digit NAICS and county. Shading corresponds to the 2001 and 2007 recessions.

The persistence displayed in Figure 4 is consistent with the lingering impact of trade liberalization found among workers in Brazil (Dix-Carneiro and Kovak, 2017), and *regional* responses to Chinese import competition found in the United States reported by Autor, Dorn, and Hanson (2021). Bloom et al. (2019), however, find that the latter dissipate after 2007 in high-human-capital areas, while Kovak and Morrow (2022) show that Canadian workers subject to larger tariff reductions in their industries experience higher probabilities of layoffs, but that rapid transitions to industries less exposed to import competition mean that there was little effect on long-run cumulative earnings.

5.2 Up- and Downstream Exposure ("IO" Specification)

In this section, we broaden our notion of worker exposure to PNTR to include the up- and downstream NTR gaps constructed in Section 4. Upstream exposure may benefit workers if greater openness with China results in lower input prices or otherwise affects productivity positively (Amiti et al., 2014). Downstream exposure, by contrast, may further dampen outcomes if it disrupts sales to customers. Including these additional covariates at the industry level is especially useful for NM workers, for whom direct industry exposure is not defined.

Table 5: "IO" Specification

	High-Tenure M			High-Tenure NM		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	0.120	0.091	0.006			
	0.203	0.059	0.015			
Post x Industry Upstream Gap	0.258	–0.336	0.037	2.567*	0.737**	0.141
	1.276	0.310	0.093	1.480	0.292	0.122
Post x Industry Downstream Gap	–0.413	–0.211*	–0.021	–1.096	–0.194	–0.075
	0.398	0.112	0.030	1.040	0.204	0.085
Post x County Gap	–1.465	0.501	–0.149	–4.137***	–0.604***	–0.313***
	1.486	0.327	0.115	1.173	0.203	0.095
Post x County Upstream Gap	1.984	–1.768	0.256	9.926**	1.088	0.748**
	5.164	1.131	0.388	3.828	0.712	0.303
Post x County Downstream Gap	–6.666***	–1.354**	–0.473***	–4.096***	–0.947***	–0.253**
	2.217	0.528	0.173	1.552	0.357	0.126
R-sq	0.439	0.559	0.408	0.441	0.631	0.406
Observations	1,520	1,378	1,520	4,605	4,173	4,605
Fixed Effects	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gap F-Stat	0.386	1.951	0.212	1.062	2.144	0.446
	0.763	0.128	0.888	0.366	0.096	0.721
County Gap F-Stat	5.788	3.150	5.223	8.349	9.158	6.376
	0.001	0.029	0.002	0.000	0.000	0.000

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 that also includes DID terms for up- and downstream county and industry exposure. The sample period is 1993 to 2014. The samples are high-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and county gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

Results are reported in Table 5. The top panel reports estimates for the six DID terms of interest. The bottom panel assess the joint statistical significance of the industry and county exposure terms via separate F-statistics and p-values for each dimension. As these statistics indicate, we continue to find that county exposure is most influential: the three county exposure terms are jointly significant across all specifications for both groups of workers, while those for the industry exposure terms are jointly insignificant for ARC and E>0, and marginally significant for LN.

Comparison of the estimates for M and NM workers in Table 5 reveals several differences in their reaction to exposure along the supply chain. First, the sign pattern of the county exposure terms for NM workers is as expected in all three earnings transformations – i.e., negative for own and downstream, and positive for upstream. For M workers, the sign pattern is not always intuitive:

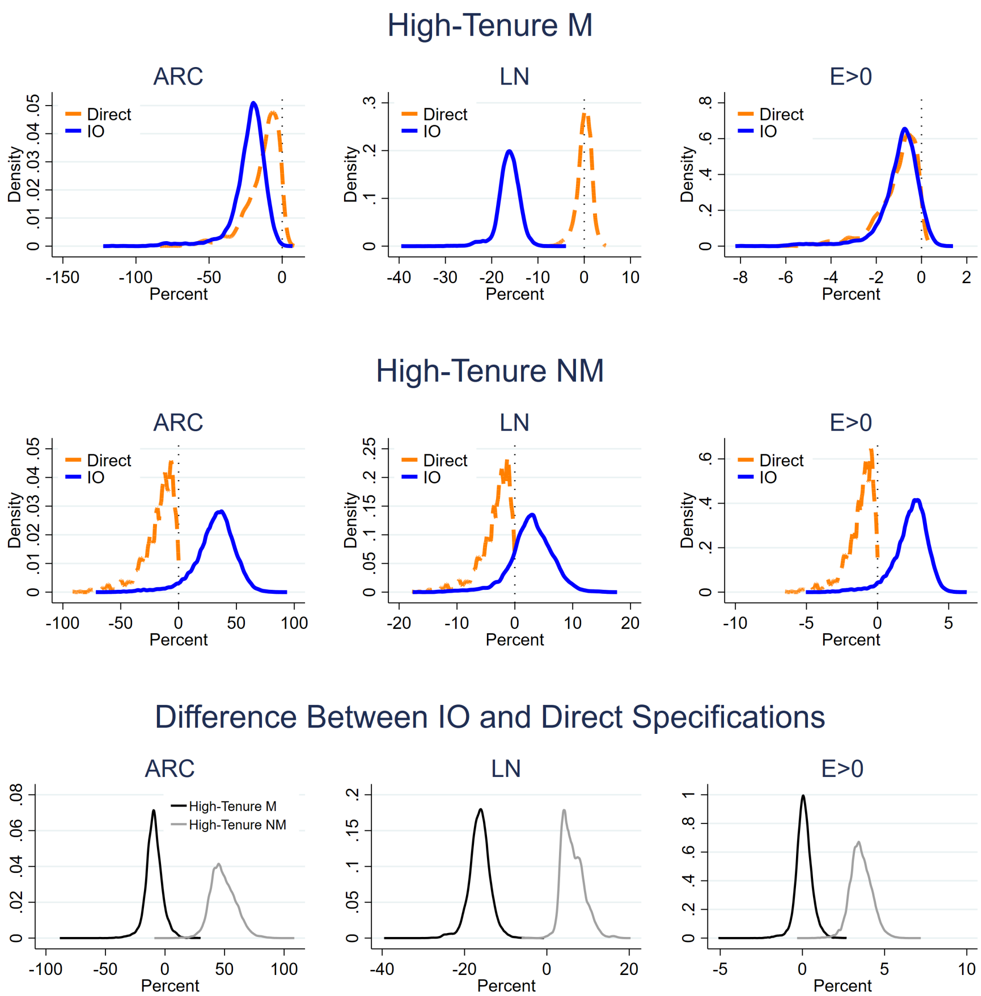
in particular, along the intensive margin, the coefficients for both county and industry upstream exposure are negative. Second, coefficients for the upstream county gap are larger for NM than M workers, while those for the county downstream gap have the opposite pattern. Finally, a similar asymmetry is evident with respect to estimates of upstream exposure, which is again relatively large and more likely to be statistically significant for NM workers.

The high dimensionality and correlation of the industry and county exposures in the "IO" specification complicate use of the traditional interquartile shift in exposure to assess economic significance. Instead, we use our coefficient estimates to *predict* relative earnings growth for each county-industry pair in our 19-state sample. These predictions are the product of the DID coefficients reported in Tables 4 or 5 and industries' and counties' actual NTR gaps.[32]

The top two panels of Figure 5 report the distributions of these county-industry predictions for each sample and earnings transformation. Dashed and solid lines map to the "direct" and "IO" specifications, respectively. To summarize these results, the bottom panel reports the difference between the predictions of the "IO" and "direct" specifications for each sample and transformation. As indicated in the figure, the asymmetry in M versus NM estimated coefficients noted in Table 5 translates into predictions that are sharply different for M and NM workers under the two specifications. For M workers, overall predicted relative earnings growth, as summarized by the ARC transformation, shifts to the left in moving from the "direct" to the "IO" specification, with the 25^{th} and 75^{th} percentiles decreasing from -19 and -5 percent to -27 and -15 percent. As highlighted in the bottom panel of the figure, this shift indicates that ignoring the "IO" linkages *underestimates* relative earnings loss among M workers. Examination of the results for the LN specification reveals that this underestimation is due almost entirely to the intensive margin, where, as noted above, point estimates for industry and county upstream as well as downstream exposure are all negative. There is no commensurate shift in predictions along the extensive margin: both the "direct" and "IO" specifications for M workers predict a similar decline in the probability of remaining employed.

[32]We are unable to report worker-level predictions due to Census disclosure guidelines. Predictions for NM workers under the "direct" specification are the same for all industries within a county, as own industry exposure for these workers is not defined.

Figure 5: Distribution of County-Industry Predictions, “Direct” vs “IO” Specifications



Source: LEHD, LBD, and authors’ calculations. Top two panels display distributions of predicted relative county-industry growth for high-tenure M and NM workers after PNTR versus before. Solid lines depict “direct” specification predictions that rely solely on estimates from Table 4. Dashed lines represent “IO” specification predictions based on estimates of own, up- and downstream exposure from Table 5. Predictions are the product of the reported coefficients and actual exposures. Bottm panel reports the difference between “IO” and “direct” specifications across county-industry pairs. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). See notes to Tables See notes to Tables 4 and 5 for further description of the underlying regressions.

By contrast, county-industry predictions for NM workers under the “IO” versus “direct” specification shift to the right, into (relative) positive territory, along both intensive and extensive margins. These shifts indicate that ignoring exposure to PNTR along the supply chain *overestimates* relative earnings losses among NM workers.[33] Indeed, PNTR induces relative NM earnings *gains* among a substantial share of county-industry pairs: the interquartile range under the ARC transformation

[33]NM worker predictions are all negative under the “direct” specification because of the negative point estimates in Table 4.

shifts from -23 to -7 percent under the "direct" specification to 23 to 42 percent under the "IO" specification.

Two California counties, Napa and Santa Clara, help illustrate the forces at work. Napa's economy is concentrated in non-tradeable services such as Health (NAICS 62), Accommodation and Food (NAICS 72), and Retail (NAICS 44-5), as well as Wineries (NAICS 312130), all of which intensively use manufactured inputs to provide services to consumers. As a result, it has relatively high county upstream exposure and relatively low county downstream exposure, at the 71^{st} and 12^{th} percentiles, respectively. By contrast, Santa Clara, the heart of Silicon Valley, focuses on M and NM industries that are important suppliers to goods producers, including Computers and Electronic Products (NAICS 334), Professional Services (NAICS 54) and Software Publishing (NAICS 511210).[34] Relative to Napa, it has low upstream exposure and high downstream exposure, at the 29^{th} and 87^{th} percentiles, respectively.

Napa's greater upstream and lower downstream exposure translate into comparatively better relative earnings predictions, as illustrated in Figure 6, which provides a scatterplot version of the distributions displayed in Figure 5. Here, each point is a county-industry pair, with Napa's and Santa Clara's industries highlighted in green and blue, respectively. Comparison of the points for each county relative to the 45 degree line reveals that Napa's predictions for M are generally better under the "IO" specification, owing to its high upstream exposure, while Santa Clara's are worse, given its high downstream exposure. NM industries do relatively better in both counties as a result of PNTR, though the relative gains are larger for Napa.

One potential explanation for M workers' negative (LN) and lower (ARC, E>0) responsiveness to both upstream and downstream county exposure is an asymmetry in M versus NM industries' 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*. In that case, the former's upstream exposure affords no benefit, and the latter's downstream exposure is particularly disruptive.[35] For services, such comigration may not be possible, e.g., hospitals must stay within reach of their patients, and hotels must remain close to their guests.[36]

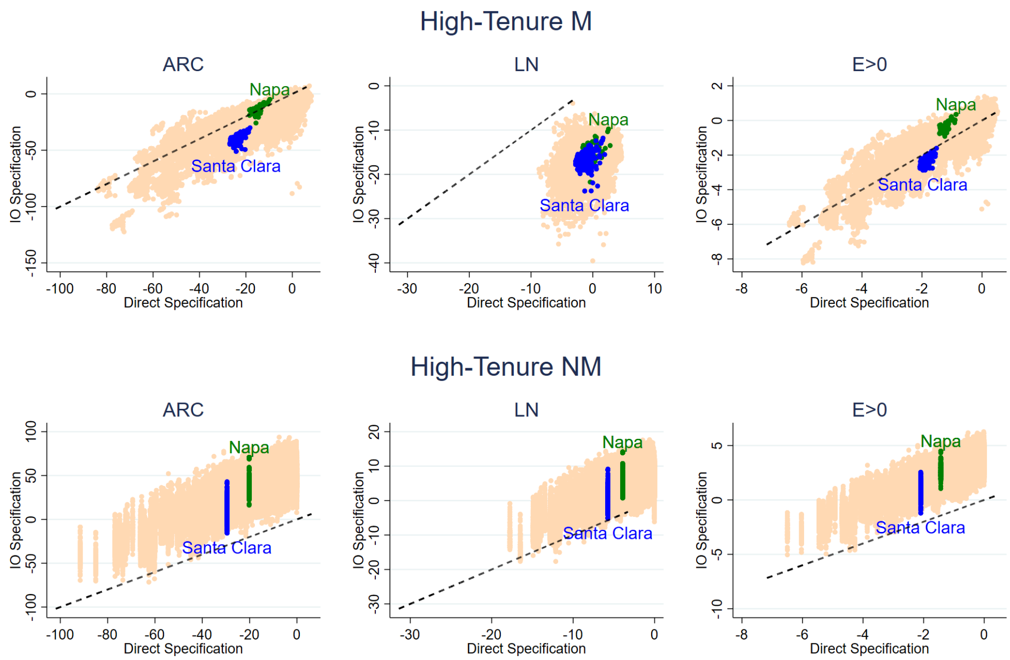
The median changes in earnings among workers leaving manufacturing in 2000 reported in Section

[34] Appendix Figure A.3 compare Napa and Santa Clara in terms of their initial employment across 2-digit NAICS sectors and 3-digit NAICS manufacturing industries. Appendix Figure A.2 illustrates the up- and downstream exposures of sectors and counties.

[35] Further 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 does 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".

[36] 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.

Figure 6: Napa and Santa Clara "IO" Predictions



Source: LEHD, LBD, and authors' calculations. Figure displays county-industry relative earnings growth predictions under the "direct" and "IO" specifications for high-tenure initial M and NM workers after PNTR versus before. County-industries for Napa and Santa Clara counties in California are highlighted. "Direct" predictions rely solely on estimates from Table 4 and are the same for all NM industries in a county. 'IO' predicitons are based on the own, up- and downstream exposure estimates from Table 5. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). See notes to Tables 4 and 5 for further description of the underlying regressions.

3 offer further intuition for this mechanism, and our results more broadly. That is, in addition to reducing M workers' likelihood of remaining employed (E>0), PNTR sharply reduces relative earnings conditional on employment (LN). These decreases along the intensive margin include M workers transitioning to service sectors such staffing agencies, hotels, restaurants and retail, with substantially lower wages as M employment falls.

Another interesting aspect of the results displayed in Figure 6 is that the over- and underestimation of M and NM workers' responses to PNTR are asymmetric along the intensive and extensive margins. That is, in the "IO" specification, M workers fare worse because of relatively lower earnings conditional on remaining employed, but their likelihood of remaining employed does not change. NM workers, by contrast, have relatively better outcomes under the "IO" specification because of both higher relative earnings conditional on remaining employed and because of higher relatively likelihood of being employed. One potential explanation for this asymmetry is unionization. That is, given that M workers are more likely to be unionized (of Labor Statistics, 2022), their adjustment may be more likely to occur through a wage concession than employment (i.e. layoffs).[37] For less-unionized NM workers, adjustment might take place more freely along both margins.

[37]That said, Charles et al. (2021b) find that higher trade competition is associated with decliens in union organizing activities.

Taken together, our findings in this section highlight the importance of considering exposure along industry supply chains when evaluating responses to trade liberalization. Such consideration is especially important for understanding outcomes outside the manufacturing sector.

5.3 Heterogeneous Outcomes By Worker Attribute

In this section, we examine whether responses to PNTR vary by workers' initial (i.e., 1999) characteristics using a version of equation 5 that includes triple interactions of these attributes with own, upstream and downstream county and industry exposure DID terms. Examining such heterogeneous responses of workers to trade liberalization is an active area of research. 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.

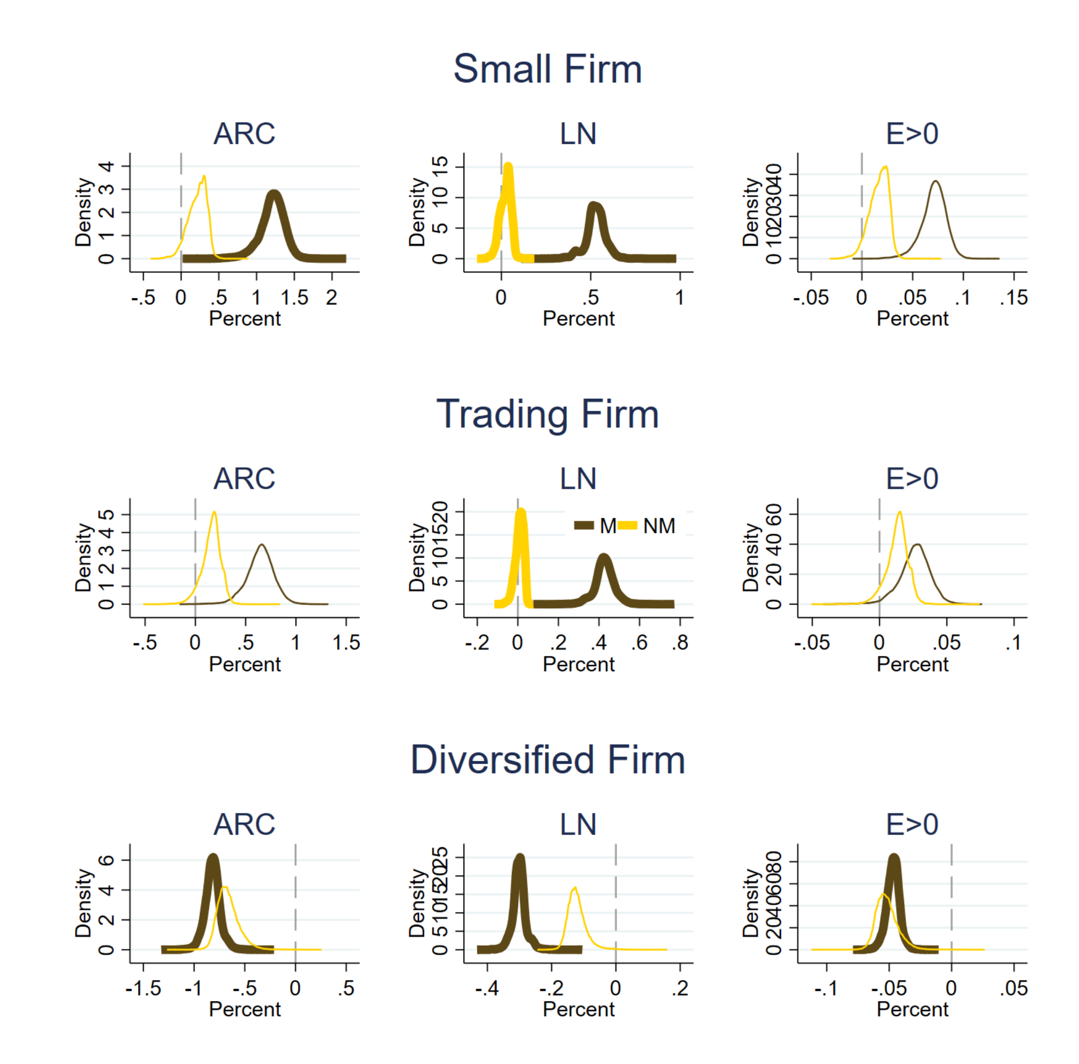
In our analysis, we run separate regressions for each earnings transformation and comparison, i.e.: females to males, non-whites to whites, workers aged 30 and below to those that are older, workers that have at least a bachelors degree to those with less educational attainment, workers in the fourth quartile of earnings ("high earners") to those in the lower quartile; workers at "small" (less than 50 employees) versus large firms, workers at traders versus non-traders; and workers at "diversified" (have both M and NM) versus non-diversified firms.[38]

To conserve space in the main text, estimated coefficients are relegated to Appendix Tables A.10 to A.12, and DID-term F-statistics associated with these estimates are reported in Appendix Table A.13. 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.

As above, we assess economic significance using predicted county-industry relative earnings growth. In this case, the predictions are the product of the triple interactions and county-industry actual exposures. As such, they represent the differential relative earnings growth associated with a noted attribute versus the left-out partner, e.g., females versus males. Figures 7 and 8 report the distributions of these differentials for workers' firm and demographic characteristics, respectively, across all of the county-industry pairs in our 19-state sample, by earnings transformation. In the figure, distributions are displayed with thick curves if the underlying F-statistic of the triple interactions from which it is computed are statistically significant at conventional levels, as summarized in Appendix Table A.13. They are reported with thin curves if the F-stats are statistically insignificant at conventional levels.

[38]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.

Figure 7: Triple-Interaction County-Industry Predictions by Workers' Firms' Attributes



Source: LEHD, LBD, and authors' calculations. Figure displays county-industry predictions of relative earnings growth 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.10 to A.12. 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.13, are jointly significant at the 10 percent level. Legend is in middle panel. See notes to Tables 4 and 5 for further description of the underlying regressions.

The figures convey several aspects of heterogeneous worker responses to trade liberalization that have not been documented before. In particular, as shown in Figure 7, we find that initial *firm* characteristics are important determinants of subsequent earnings outcomes for manufacturing *workers*. First, as shown in the top row of Figure 7, we find that manufacturing workers initially employed at small firms perform relatively better than those employed at large firms. To our knowledge, this result is the first worker-level evidence 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. Second, as shown in the bottom row of the figure, M workers employed at diversified firms perform relatively worse than those employed firms that also have NM plants (i.e., diversified firms). This result is somewhat suprising, as transitioning from M to NM might in principle be easier for workers at firms that span both sectors, even if those activities are in different locations. On the other hand, a strict focus on manufacturing activities may contribute to firms' ability to produce the kinds of goods Holmes and Stevens (2014) have in mind.[39] 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).

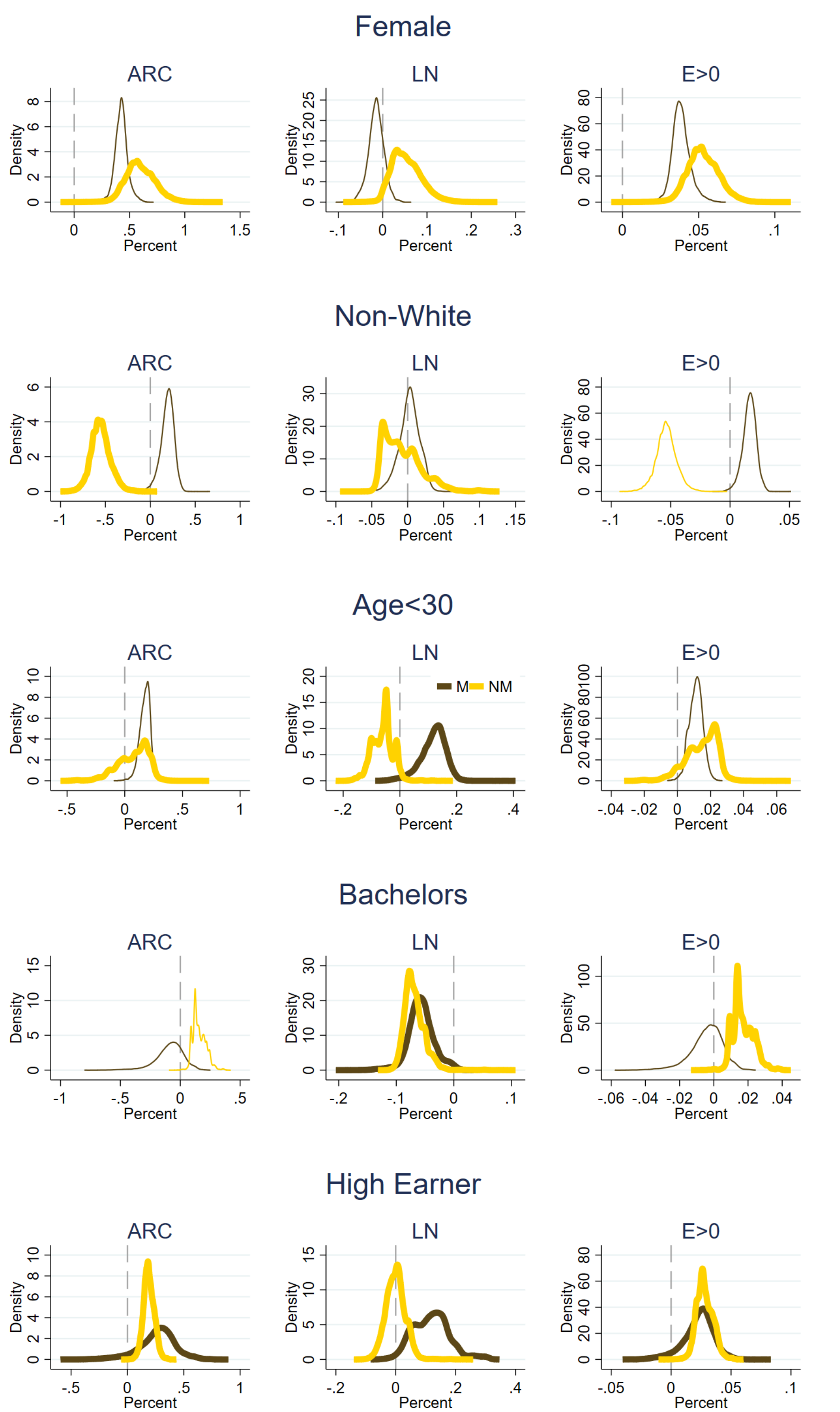
Next, we examine heterogeneous responses by demographic characteristics, as displayed in Figure 8. First, in terms of gender, we find that female NM workers experience relatively better labor market outcomes than males, in terms of all three outcomes. With respect to race, NM workers who are not white exhibit relatively worse earnings outcomes in terms of ARC, reflecting lower subsequent earnings conditional on employment and a lower but imprecisely estimated probability of being employed. For age, the typical NM worker under 30 performs modestly better than older workers when considering ARC, though this result is not universal, and depends on industry and county exposure. While we find some differences in terms of workers with or without bachelors degrees, there is no statistically significant difference in terms of ARC, which captures both probability of employment and earnings conditional on employment.[40]

Lastly, perhaps the most widespread heterogeneous response we find among worker attributes relates to initial earnings. As shown in the bottom row of Figure 8, 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—due to savings—to be more selective in accepting a new job, resulting in a better match.

[39] 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.

[40] 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. Greenland, Lopresti, and McHenry (2016) find that import competition is associated with increases in high school graduation rates. 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 8: Triple-Interaction County-Industry Predictions by Worker Demographic

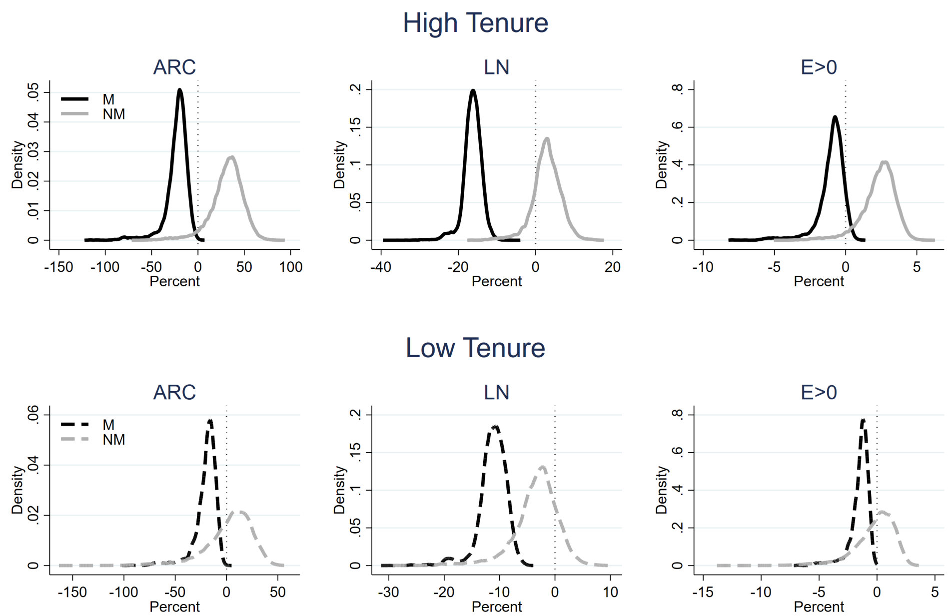


Source: LEHD, LBD, and authors' calculations. Figure displays county-industry predictions of relative earnings growth for noted worker demographic attribute versus those not possessing that attribute using the triple-interaction DID coefficients discussed in the text and reported in Appendix Tables A.10 to A.12. 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.13, are jointly significant at the 10 percent level. Legend is in middle panel. See notes to Tables 4 and 5 for further description of the underlying regressions.

6 Robustness

Our baseline results demonstrate that a "direct" specification that considers only own-county and -industry exposure to PNTR *underestimates* relative earnings losses among M workers, and *overestimates* these losses for NM workers. In this section, we show that this finding is robust to consideration of workers with less attachment to the labor force, and to an alternate definition of county exposure that is specific to each worker.

Figure 9: Difference Between IO and Direct Predictions for High- vs Low-Tenure Workers



Source: LEHD, LBD, and authors' calculations. Figure displays the distribution of the differences in predicted relative earnings growth from the "IO" versus "direct" specifications across county-industry pairs in our 19-state regression sample by initial sector and earnings transformation. High-Tenure workers are employed by the same firm during the entire 1993 to 1999 pre-period. Low-Tenure workers are employed during the entire pre-period, but not necessarily by the same firm. Predictions for each county-industry are obtained by multiplying the coefficients from main text Table 4 and Appendix Table A.6 by county-industries' actual exposures. Top panel compares differences for high-tenure workers while bottom panel focuses on low-tenure workers.

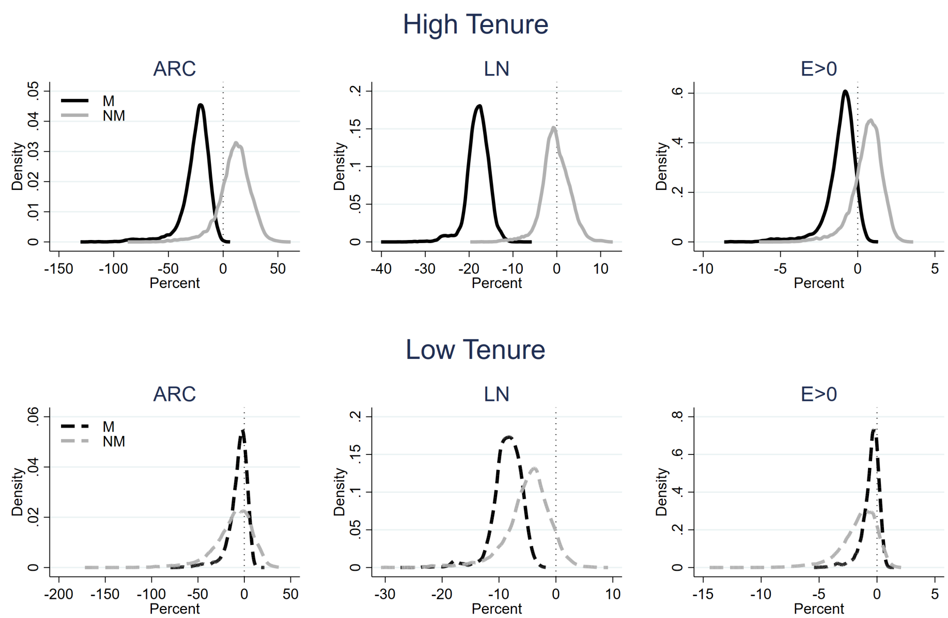
6.1 Low-Tenure Workers

The "high-tenure" workers in our baseline sample were employed by the same firm over the entire 1993 to 1999 period. We define workers as having "low-tenure" if they have positive earnings in every year from 1993 to 1999 (i.e., they have high attachment), but they are not employed by the same firm. Figure 9 compares results for low- and high-tenure workers. For each of our four samples – high- and low- tenure M and high- and low-tenure NM – the figure plots the distribution of the differences between predicted relative earnings growth under the "IO" versus "direct" specifications across all county-industry pairs in our 19 state sample, analogous to the bottom panel of Figure 5.[41]

[41] For example, in Figure 5, M workers in most county-industry pairs in the ARC specification exhibit lower predicted relative earnings under the "IO" versus "direct" specification. As a result, in the first panel of Figure 9, the distribution

As indicated in the figure, the starkest difference in results is for low-tenure NM workers (dashed gray), relative to high-tenure NM (solid gray). As discussed above, high-tenure NM workers experience relatively better earnings performance after accounting for "IO "linkages, particularly the benefit from exposure to trade liberalization on inputs. This benefit arising from "IO" linkages is shown by most of the area under the solid gray curve appearing to the right of zero. By contrast, low-tenure workers do not seem to share this benefit that occurs via "IO" linkages, as shown by the mass under the gray dashed curve being shifted closer to—or even to the left of—zero. This outcome may be driven by low-tenure NM workers' disproportionate susceptibility to labor-market competition from displaced M workers, their greater presence in NM sectors sensitive to aggregate declines in income, or a "last-in-first-out" approach to layoffs among firms.

Figure 10: Difference Between IO and Direct Predictions using Alternate County Exposure



Source: LEHD, LBD, and authors' calculations. Figure displays the distribution of the differences in predicted relative earnings growth from the "IO" versus "direct" specifications across county-industry pairs in our 19-state regression sample by initial sector and earnings transformation, using the alternate measure of county exposure described in the main text. Predictions for each county-industry are obtained by multiplying the coefficients from the relevant table by $County\ Gap_c$, $County\ Gap_c^{up}$, and $County\ Gap_c^{dn}$. Top panel compares differences for high-tenure workers while bottom panel focuses on low-tenure workers.

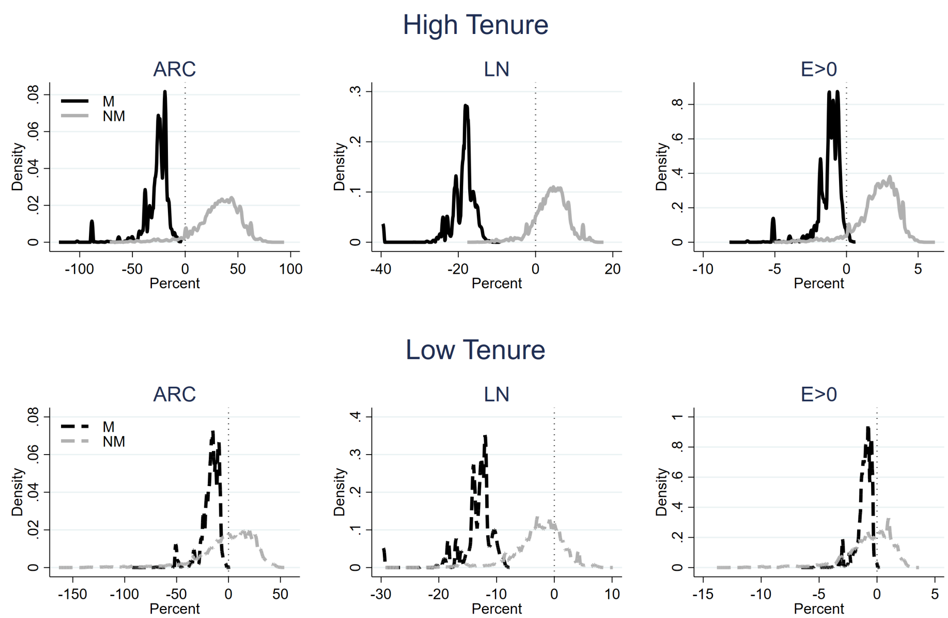
6.2 Alternate County Exposure

In our baseline results, we include workers' own industry in the computation of their county exposures. An alternate approach is to exclude workers' own industries from these computations, so that the county exposures are worker specific. In Figure 10 we report the differences between predicted relative earnings growth under the "IO" versus "direct" specifications across all county-industry pairs in our

for these workers generally lies below zero. Regression results for low-tenure workers are reported in Appendix Tables A.5 and A.6.

19 state sample using these alternate measures of county exposure.[42] Comparison of this figure with Figure 9 reveals that the results are qualitatively similar: it remains the case that the "direct" specification *underestimates* the relative earnings losses among M workers, and *overestimates* the relative earnings loss of NM workers.

Figure 11: Weighed Differences Between IO and Direct Predictions



Source: LEHD, LBD, and authors' calculations. Figure displays the weighted distribution of the differences in predicted relative earnings growth from the "IO" versus "direct" specifications across county-industry pairs in our 19-state regression sample by initial sector and earnings transformation, using 1999 county-industry employment as weights. Predictions for each county-industry are obtained by multiplying the coefficients from the relevant table by $County\ Gap_c$, $County\ Gap_c^{up}$, and $County\ Gap_c^{dn}$. Top panel compares differences for high-tenure workers while bottom panel focuses on low-tenure workers.

6.3 Weighting

In reporting the economic significance of our baseline results we use the county-industry as a unit of analysis, explicitly treating each county-industry equally despite the fact that workers are not uniformly distributed across county-industry cells. An alternate approach would be to weight each county-industry point in the distribution by its number of workers in the pre-period. Figure 11, using the same format of the previous two figures, reports the results of this exercise, by reporting the weighted differences between predicted relative earnings growth under the "IO" versus "direct" specifications across all county-industry pairs.[43] These distributions are noisier than those above precisely because the number of workers varies across county-industry pairs. Even so, we obtain qualitatively similar results.

[42]Regression results for these alternate measures of exposure for high- and low-tenure workers are reported in Appendix Tables A.7 and A.8.

[43]We note that our coefficient estimates are from worker-level regressions. As a result, there is no issue of weighting the regressions by these cell counts.

7 Conclusion

This paper provides a detailed analysis of US workers' response to a large labor market shock induced by US trade liberalization with China. Using linked employer-employee data from the US Census Bureau, we provide the first detailed accounting of manufacturing workers' movements out of that sector during the sharp decline in U.S. manufacturing employment beginning in 2000, as well as corresponding estimates of median changes in nominal earnings. The results are striking: workers leaving manufacturing to work in temp agencies or in relatively skill-scarce sectors such as retail exhibit nominal wage *declines* of up to -22 percent over seven years, which are more severe in the counties most exposed to PNTR.

In the second part of the paper, we use formal difference-in-differences analysis to examine relative earnings outcomes after versus before the change in US policy among high- and low-tenure workers initially employed both outside and within manufacturing. We find that workers' exposure to the shock via their county is more important than exposure via their industry, highlighting the salience of spatial versus sectoral frictions.

We also find that accounting for exposure along supply chains is crucial for understanding variation in outcomes across different groups of workers. Comparing results for a "direct" specification which considers only own-county and -industry exposure to an "IO" specification in which one also accounts for up- and downstream exposure, we find that the "direct" specification *underestimates* the relative earnings losses of manufacturing workers and *overestimates* the relative earnings losses of NM workers. Indeed, while workers initially employed in manufacturing have substantial and persistent predicted declines in relative earnings, those outside manufacturing are generally predicted to experience relative earnings *gains*. In the final section of the paper, we show that predicted relative earnings growth after versus before the change in policy can vary substantially according to workers' demographic and firm characteristics.

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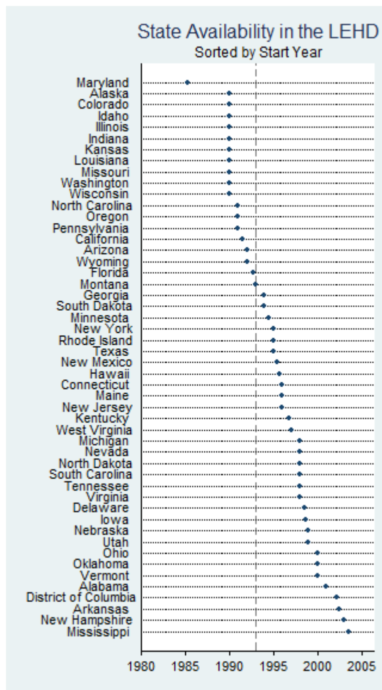
Online Appendix (Not for Publication)

This online appendix contains detailed 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 in Section 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.

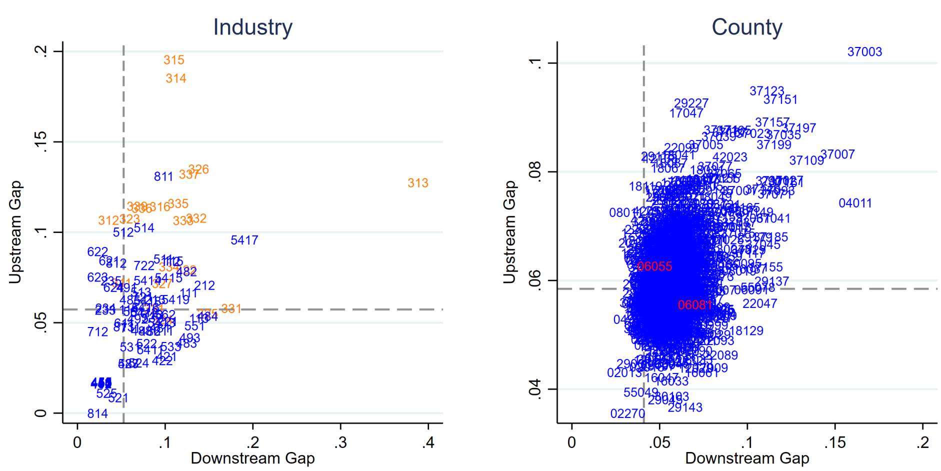
B Industry Variable Construction

In this section we describe how the time-varying industry controls referenced in Section 5 are constructed.

MFA Exposure: As discussed in greater detail in Khandelwal, Schott, and Wei (2013), 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, the MFA 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.

Computation of counties' exposure to elimination of the MFA proceeds in three steps. First, we follow Khandelwal, Schott, and Wei (2013) in measuring the extent to which MFA quotas in industry j and phase p were binding as the average fill rate of the industry's constituent import products in the year before they were phased out, $FillRate_{jp}$.[44] Specifically, for each phase, we measure an industry's exposure to MFA expiration as its average quota fill rate in the year prior to the phase's expiration. Industries with higher pre-expiration average fill rates faced more binding quotas and are therefore more exposed to the end of the MFA. Second, we compute counties' labor-share-weighted-average fill rate across industries for each phase, $FillRate_{cp}$. Finally, the county-year variable of interest, $MFA\ Exposure_{ct}$, cumulates the calculated fill rates as each phase of expiration takes place. This measure of exposure to the MFA rises over time, as quotas for additional products are removed, by phase.

Figure A.2: Average Up- and Downstream Gaps



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

Changes in Chinese Policy: As part of its accession to the WTO, China agreed to institute a

[44] As discussed in Brambilla, Khandelwal, and Schott (2010), fill rates are defined as actual imports divided by allowable imports under the the quota. MFA products for which there were no restrictions on imports (i.e., there were no quotas), have fill rates of zero.

number of policy changes that could have influenced US manufacturing employment and thereby mortality, including liberalization of its import tariff rates and reductions of production subsidies, which might increase export opportunities for US manufacturers. Following 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 the average change across those years in Chinese import tariffs across products within each US industry. For production subsidies, we use data from the Annual Report of Industrial Enterprise Statistics compiled by China's National Bureau of Statistics (NBS), which reports the subsidies provided to responding firms.[45] For both changes in Chinese import tariff rates and production subsidies, we compute the labor-share-weighted average of this change across the industries active in each US county and then interact these variables with an indicator for post-PNTR years.

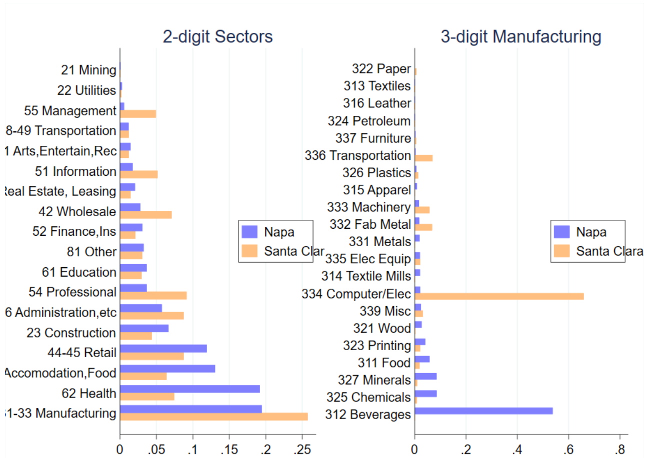
Up- and Downstream NTR Gaps: The left panel of Figure A.2 reports the average up- and downstream NTR gaps by 3-digit NAICS industry, while the right panel of the figure reports the up- and downstream gap for all counties in our 19 state sample. Manufacturing sectors are highlighted in the left panel, while Napa and Santa Clara, California, discussed in the main text, are highlighted in the right panel. Figure A.3 reports a breakdown of initial employment shares across 2-digit NAICS sectors and 3-digit NAICS industries for these counties. 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 Comnputers and Electronics (NAICS 334). Within manufacutring, Napa cocentrates on Wineries (NAICS 312130).

C Worker Characteristics in the 46-State Sample

Table A.1 reports M and NM worker characteristics in 2000 across the 46 states for which information is available in the LEHD in that year.

[45]The NBS data encompass a census of state-owned enterprises (SOEs) and a survey of all non-SOEs with annual sales above 5 million Renminbi (~$600,000). The version of the NBS dataset available to us from Khandelwal, Schott, and Wei (2013) spans the period 1998 to 2005. Following Girma, Gong, and Gorg (2009) and Aghion, Cai, Dewatripont, Du, Harrison, and Legros (2015) we use the variable "subsidy" in this dataset and compute the change in the subsidies to sales ratio for each SIC industry between 1998 and 2005 using concordances provided by Dean and Lovely (2010).

Figure A.3: Napa versus Santa Clara Employment Shares



Source: CBP, Eckert, Fort, Schott, and Yang (2020) and authors' calculations. Figure displays 1993 employment shares for Napa and Santa Clara, CA counties by 2-digit NAICS sector and 3-digit NAICS manufacturing industry, both sorted according to Napa's shares.

Table A.1: US Worker Characteristics (46-state Sample)

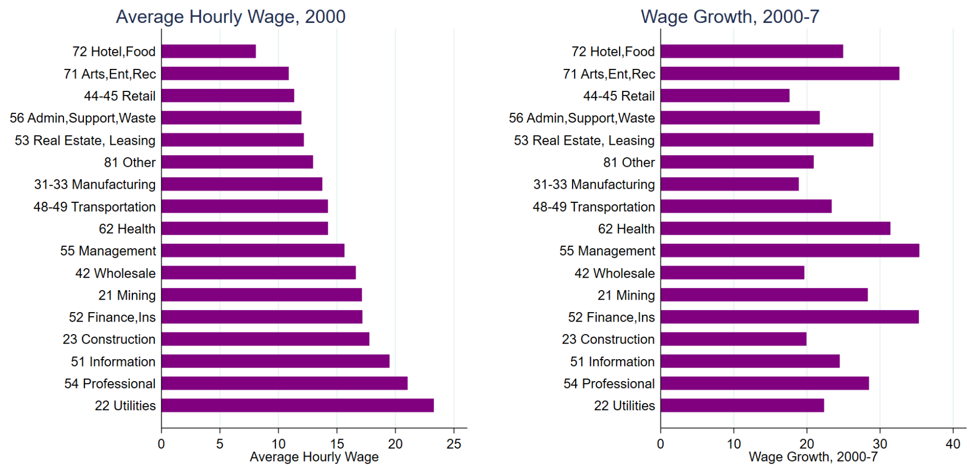
	2000			
	Manufacturing		Non-Manufacturing	
	Mean	SD	Mean	SD
Male	0.67	0.47	0.49	0.50
American Born	0.83	0.38	0.87	0.34
≤High School	0.16	0.37	0.14	0.34
=High School	0.33	0.47	0.28	0.45
Some College	0.31	0.47	0.31	0.46
≥College	0.20	0.40	0.28	0.45
Age	39.7	12.86	37.3	14.51
Earnings	36,000	200,000	27,000	130,000

Source: LEHD, LBD and authors' calculations. Table reports the mean and standard deviation of noted worker attributes in 2000 for the 46 states whose information is available in the LEHD in 2000. Alabama, Arkansas, New Hampshire and Mississippi as well as the District of Columbia are excluded. All figures are in percent except age and earnings, which are in years and dollars. Right and left panels compare workers employed in manufacturing to those initially employed outside manufacturing.

D Wages Wage Growth, 2000 to 2007 (Public BEA Data)

Using publicly available data from the US Bureau of Labor Statistics, Figure A.4 reports the average hourly wages of production and non-supervisory workers by sector. 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.4: Wages and Wage Growth, by 2-digit NAICS (Public BLS Data)



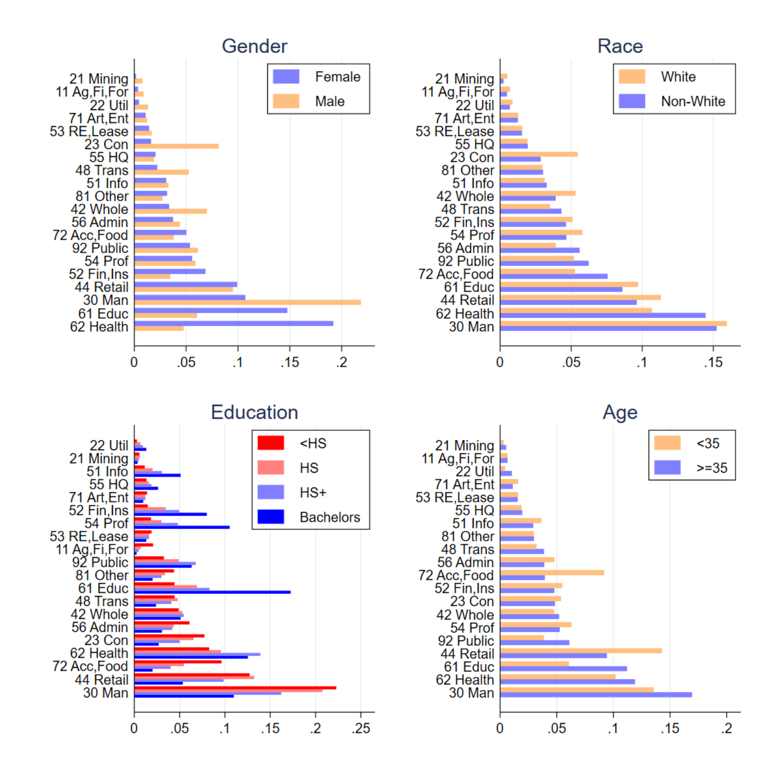
Source: BLS and authors' calculations. Left panel displays the average hourly wage of production and non-supervisory workers by 2-digit NAICS sector in 2000. Right panel displays nominal growth in these average hourly wages from 2000 to 2007.

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 lie 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 are located 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.

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

Table A.2 reports manufacturing to non-manufacturing transitions for two alternate time periods, 2000 to 2005 and 2000 to 2007, compared to the results reported in Table 1 in the main text, for 2000 to 2007. As in Table 1, the top and bottom panels report transitions in terms of millions of workers and percentages of initial levels, respectively. As indicated in the figure, gross flows out of initial sectors are lower for 2000 to 2005 than for 2000 to 2007, but substantially higher for 2000 to 2011 due to the intervening Great Recession.

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 (left panel), race, educational attainment and age in 2000 from publicly available LEHD data downloadable at https://ledextract.ces.census.gov/j2j/emp.

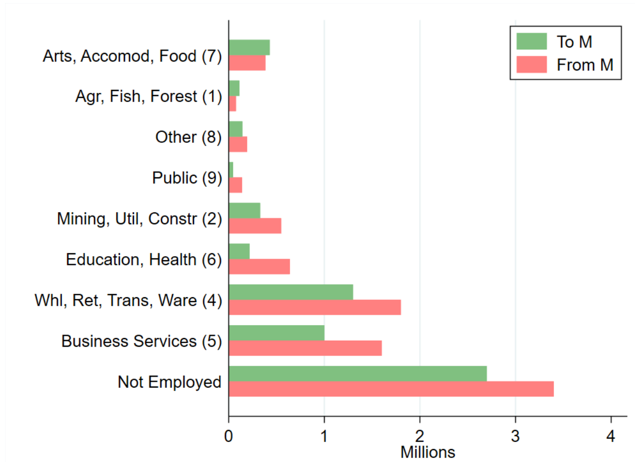
Table A.2: 2000-5 and 2000-11 $M \leftrightarrow NM$ Transitions (46-State Sample)

	2000-2005				2000-2011			
	Employment (Millions)				Employment (Millions)			
Origin/Destination	NM	M	NE	Total	NM	M	NE	Total
Not Manufacturing (NM)	89.8	3.6	25.8	119.2	73.7	3.4	40.5	117.6
Manufacturing (M)	5.3	8.9	3.4	17.7	5.8	5.8	6.0	17.5
Not Employed (NE)	34.5	2.7	.	37.1	24.4	2.1	.	26.5
Total	129.5	15.2	29.3	174.0	103.8	11.2	46.5	161.5

	Share of Initial Level (Percent)				Share of Initial Level (Percent)			
Origin/Destination	NM	M	NE	Total	NM	M	NE	Total
Not Manufacturing (NM)	75	3	22	100	62	3	34	99
Manufacturing (M)	30	51	19	100	33	33	34	99
Not Employed (NE)	93	7	.	100	66	6	.	71
Total	74	9	17	100	60	6	27	93

Source: LEHD, LBD and authors' calculations. Table reports the transition paths of employed and not-employed workers from 2000 (row, left panel) to 2005 (column, left panel), and from 2000 (row, right panel) to 2011 (column, right pane), 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.

Figure A.6: Gross Flows Into and Out of M, 2000-5



Source: LEHD, LBD and authors' calculations. Figure displays the grows inflows into and gross outflows out of manufacturing between 2000 and 2005, in millions, by 1-digit NAICS sector (noted in parentheses) other than the diagonal. The full transition matrix (including the diagonal) is reported in Appendix Table A.3. Secrtors are sorted by net flows: .05, .04, -.05, -.09, -.22, -.42, -.5, -.6, and -.7.

Table A.2 and Figure A.6 provides a more detailed version of the left panel of Table A.2 by reporting beginning and ending employment at the 1-digit NAICS sector level. As indicated in the table, the largest net losses of manufacturing employment are due to Not Employed (-.70 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, Accomodation and Food exhibit net inflows into manufacturing, of .04 and .05 million, respectively.

Table A.3: 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, Accomodation, 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, left panel) to 2005 (column, left panel) 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.

F A Triple-Interaction "Direct" Specification

Table A.4 reports the results of adding a third DID term to equation 5 – a triple interaction of $Post$ x $Industry\ Gap_i$ x $County\ Gap_c$ – to our "direct" specification. As indicated in that table, coefficient estimates for this term are small in magnitude and statistically insignificant for ARC and E>0. Along the intensive margin, however, it is negative and large in absolute magnitude, indicating relative declines in earnings are largest among those who face high levels of both county and industry exposure. That result is consistent with Costinot, Sarvimäki, and Vogel (2022), who find that labor-market outcomes are more negative among workers at highly exposed firms within highly exposed regions in their analysis of Finnish workers' reactions to the implosion of the Soviet Union.

Table A.4: "Direct" Specification with County x Industry Interaction

	High-Tenure M		
	ARC	LN	E>0
Post x Industry Gap	0.090	0.145	–0.001
	0.300	0.088	0.023
Post x County Gap	–3.334***	0.079	–0.285***
	1.134	0.332	0.091
Post x Industry Gap * County Gap	0.293	–1.189	0.103
	2.501	0.794	0.195
R-sq	0.439	0.558	0.408
Observations	1,520	1,378	1,520
Fixed Effects	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 that includes an additional, triple-interaction of *Post* with both industry and county exposures. The sample period is 1993 to 2014. The regression is restricted to high-tenure workers initially employed in manufacturing (M); it cannot be estimated on NM workers as they have no own-industry exposure. *Post* is a dummy variable for years after 2000. Industry and County gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the main text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

G Results for Low-Tenure Workers

In this section we report "direct" and "IO" specification results for low-tenure M and NM workers, defined as workers who are employed in all years of the pre-period, but not necessarily by the same firm. Table A.5 displays results for the "direct" specification, while Table **??** contains estimates for

"IO" specification.

Table A.5: "Direct" Specification for Low-Tenure Workers

	Initial M – Low Tenure			Initial NM – Low Tenure		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	–0.066	0.052	–0.010			
	0.116	0.046	0.009			
Post x County Gap	–3.174***	–0.545***	–0.229***	–5.176***	–0.956***	–0.394***
	0.673	0.183	0.059	0.927	0.153	0.079
R-sq	0.445	0.572	0.412	0.446	0.605	0.411
Observations	4,274	3,830	4,274	17,360	15,370	17,360
Fixed Effects	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Initial Attachment Sample	High	High	High	High	High	High
Initial Sector Sample	M	M	M	NM	NM	NM
IQ Increase County Gap	-.244	-.041	-.018	-.399	-.071	-.03

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5. The sample period is 1993 to 2014. The samples are low-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and County gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the main text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

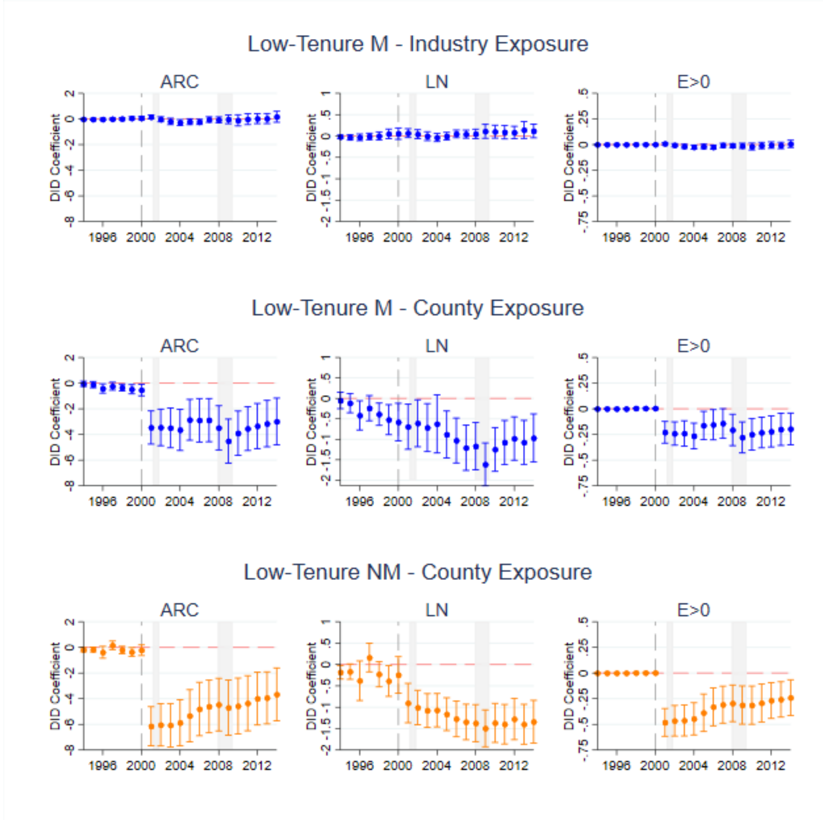
Table A.6: "IO" Specification for Low-Tenure Workers

	Initial M – Low Tenure			Initial NM – Low Tenure		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	–0.055	0.086*	–0.011			
	0.125	0.050	0.010			
Post x Industry Upstream Gap	0.104	–0.266	0.020	2.331	0.618**	0.138
	0.787	0.241	0.060	1.485	0.249	0.143
Post x Industry Downstream Gap	–0.317	–0.276**	–0.007	–1.825*	–0.137	–0.155
	0.292	0.108	0.023	1.022	0.169	0.097
Post x County Gap	–1.937	0.176	–0.156	–5.417***	–0.687***	–0.425***
	1.241	0.242	0.105	1.244	0.182	0.107
Post x County Upstream Gap	1.937	–0.817	0.124	6.507*	0.238	0.444
	4.649	1.001	0.365	3.760	0.636	0.312
Post x County Downstream Gap	–4.105**	–1.114***	–0.268*	–3.340**	–1.025***	–0.187
	1.618	0.326	0.143	1.583	0.274	0.141
R-sq	0.446	0.572	0.412	0.446	0.605	0.411
Observations	4,274	3,830	4,274	17,360	15,370	17,360
Fixed Effects	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gap F-Stat	0.449	2.964	0.468	1.068	2.253	1.002
	0.719	0.037	0.706	0.364	0.083	0.393
County Gap F-Stat	11.47	6.289	7.521	14.18	22.63	10.522
	0.000	0.001	0.000	0.000	0.000	0.000
IQ Increase Industry Own	-.004	.007	-.001			
IQ Increase Industry Up	.008	-.02	.002			
IQ Increase Industry Down	-.024	-.021	-.001			
IQ Increase County Own	-.149	.014	-.012	-.417	-.052	-.033
IQ Increase County Up	.149	-.061	.01	.501	.018	.034
IQ Increase County Down	-.316	-.082	-.021	-.257	-.076	-.014

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 that also includes DID terms for up- and downstream county and industry exposure. The sample period is 1993 to 2014. The samples are low-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and county gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the main text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

Figure A.7 and replicates Figure 4 in the main text for low-tenure M and NM workers.

Figure A.7: "Annual" Coefficient Estimates for Low-Tenure Workers



Source: LEHD, LBD, and authors' calculations. Panels display the 95 percent confidence intervals for the industry and county exposure DID coefficients of interest from an annual version of equation 5 that replaces the $Post_t$ indicator with a full set of year dummies, omitting 1993. Industry exposure is not defined for NM workers. See notes to Table 4 for further description of the underlying regression. Standard errors are two-way clustered by four-digit NAICS and county. Shading corresponds to the 2001 and 2007 recessions.

H Results for Alternate County Exposure

Tables A.7 and A.8 report "direct" and "IO" specification results using the alternate measures of county exposure that do not include workers' own industries discussed in Section 6.

Table A.7: "IO" Specification with Alternate County Exposure

	High-Tenure M			High-Tenure NM		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	0.122	0.103*	0.005			
	0.209	0.062	0.016			
Post x Industry Upstream Gap	0.279	–0.375	0.041	2.449	0.708**	0.132
	1.306	0.322	0.094	1.521	0.315	0.123
Post x Industry Downstream Gap	–0.561	–0.245**	–0.031	–1.308	–0.226	–0.090
	0.398	0.114	0.030	1.098	0.221	0.088
post_CTYg_Ind_excluded	–1.776	0.459	–0.161	–2.805**	–0.363	–0.214**
	1.575	0.322	0.125	1.332	0.249	0.107
post_CTYgUpstream_Ind_excluded	1.706	–2.120*	0.246	5.227	0.385	0.362
	6.056	1.251	0.451	4.311	0.854	0.341
post_CTYgDownstream_Ind_excluded	–6.171**	–1.149**	–0.453**	–3.532**	–0.892**	–0.197
	2.555	0.551	0.202	1.754	0.373	0.143
R-sq	0.439	0.559	0.408	0.441	0.629	0.406
Observations	1,520	1,378	1,520	4,305	3,900	4,305
Fixed Effects	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gap F-Stat	0.667	2.338	0.396	0.866	1.691	0.405
	0.574	0.079	0.756	0.460	0.170	0.749
County Gap F-Stat	7.200	3.223	6.616	4.063	6.438	2.733
	0.000	0.027	0.000	0.008	0.000	0.045
IQ Increase Industry Own	.009	.008	0			
IQ Increase Industry Up	.021	-.028	.003			
IQ Increase Industry Down	-.043	-.019	-.002			
IQ Increase County Own	-.137	.036	-.012	-.216	-.028	-.016
IQ Increase County Up	.131	-.151	.019	.402	.03	.028
IQ Increase County Down	-.475	-.085	-.035	-.272	-.066	-.015

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 using an alternate measure of county exposure that does not include workers own industry. The sample period is 1993 to 2014. The samples are low-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and County gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the main text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

Table A.8: "IO" Specification with Alternate County Measure

	Low-Tenure M			Low-Tenure NM		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	–0.074	0.089*	–0.013			
	0.127	0.051	0.010			
Post x Industry Upstream Gap	0.103	–0.287	0.020	2.486	0.624**	0.155
	0.809	0.253	0.060	1.516	0.267	0.144
Post x Industry Downstream Gap	–0.445	–0.307***	–0.016	–1.943*	–0.153	–0.161
	0.303	0.108	0.024	1.071	0.179	0.100
post_CTYg_Ind_excluded	–2.345*	0.099	–0.186	–4.550***	–0.650***	–0.346***
	1.335	0.260	0.113	1.423	0.196	0.126
post_CTYgUpstream_Ind_excluded	3.955	–0.398	0.252	2.443	–0.093	0.053
	4.709	0.919	0.376	4.494	0.676	0.391
post_CTYgDownstream_Ind_excluded	–2.979*	–0.918***	–0.170	–2.199	–0.948***	–0.073
	1.742	0.335	0.155	1.744	0.269	0.158
R-sq	0.446	0.572	0.412	0.446	0.604	0.411
Observations	4,274	3,830	4,274	17,360	15,370	17,360
Fixed Effects	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t	j,f,t
Two-way Clustering	N4,c	N4,c	N4,c	N4,c	N4,c	N4,c
Worker x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x *Post* Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Gap F-Stat	0.819	3.520	0.648	1.116	1.941	0.926
	0.487	0.019	0.586	0.344	0.124	0.429
County Gap F-Stat	9.344	3.849	6.148	10.580	27.06	7.415
	0.000	0.012	0.001	0.000	0.000	0.000
IQ Increase Industry Own	-.006	.007	-.001			
IQ Increase Industry Up	.008	-.022	.002			
IQ Increase Industry Down	-.034	-.023	-.001			
IQ Increase County Own	-.181	.008	-.014	-.35	-.049	-.027
IQ Increase County Up	.305	-.03	.019	.188	-.007	.004
IQ Increase County Down	-.229	-.068	-.013	-.169	-.07	-.006

Source: LEHD, LBD, and authors' calculations. Table displays DID terms of interest from worker-year level OLS regressions of equation 5 that also includes DID terms for up- and downstream county and industry exposure and also uses an alternate measure of county exposure that does not include workers own industry. The sample period is 1993 to 2014. The samples are low-tenure workers initially employed within (M) and outside (NM) manufacturing. *Post* is a dummy variable for years after 2000. Industry and county gaps are as defined in Section 4. Results are reported for three transformations of worker earnings: arcsin (ARC), natural log (LN), and a dummy variable for earnings greater than zero (E>0). Regressions include interactions of *Post* with the worker and firm attributes noted in the main text, as well as worker (j), firm (f) and year (t) fixed effects. Standard errors two-way clustered by 4-digit NAICS and county are noted below coefficients. Regression samples are 5 percent stratified random draws of high-tenure M and NM workers aged 50 and below in 2000 from the 19 states whose data are available in the LEHD over the sample period. Observations are weighted by the inverse probability of being in the sample. Final row of the table reports the implied impact of an interquartile increase in county exposure in percentage terms. ***, **, and represent statistical significance at the 1, 5 and 10 percent levels.

I Results for Triple-Interaction Demographic Specifications

This sections reports estimated coefficients for the triple-interaction specifications discussed in Section 5.3. Table A.9 summarizes the economic significance of the coefficient estimates reported for both both high- and low-tenure M and NM workers in Tables A.10 to A.12 in two ways. The first four columns report the median county-industry prediction for each subsample of workers and earnings transformation using the approach discussed in the main text. The last four columns report the share of county-industry predictions that are greather than 0, i.e., which exhibit relative income gains. The asterisks in this table correspond to the significance of the underlying triple interations, reported in Table A.13, which, consistent with the pattern of results reported in Sections 5.1 and 5.2 of the main text, reveal that county exposure triple interactions are more likely to be statistically significant at conventional levels than the industry triple interactions. As indicated in Table A.13, this significance is most prevalent along the intensive margin.

Table A.9: Triple-Interaction County-Industry Predictions by Worker Characteristic

		Median County-Industry Prediction				Share Predictions>0			
		High-Tenure		Low-Tenure		High-Tenure		Low-Tenure	
	LHS	M	NM	M	NM	M	NM	M	NM
Female vs Male	ARC	.42	.56***	.11*	.28***	1	1***	.98*	1***
Non-White vs White	ARC	.19	-.55*	.18*	-.07***	.98	0*	.98*	.18***
Age Below 30 vs Older	ARC	.18	.12*	-.07	-.12**	1	.76*	.09	.02**
Bachelors vs Less	ARC	-.1	.14	.37	.41*	.2	1	1	1*
Highest Earner vs Less	ARC	.26***	.19***	.19***	.26***	.94***	1***	.95***	1***
Small Firm vs Larger	ARC	1.2*	.26	.33*	.03	1*	.97	1*	.61
Trading vs Non-Trading Firm	ARC	.63**	.2	.21	-.38	1**	.97	.98	0
Diversified Firm vs M	ARC	-.81	-.69	-.15	-.07	0	0	.03	.11
Female vs Male	LN	-.02	.04***	.04	.05***	.17	.98***	.97	1***
Non-White vs White	LN	0	-.02***	.11**	-.04	.58	.29***	1**	.01
Age Below 30 vs Older	LN	.12***	-.05**	-.11***	0***	.98***	.02**	0***	.47***
Bachelors vs Less	LN	-.06**	-.07**	-.05	-.08**	.01**	0**	0	0**
Highest Earner vs Less	LN	.12***	0***	0***	-.09***	.99***	.51***	.47***	0***
Small Firm vs Larger	LN	.52***	.03***	.24*	.05***	1***	.81***	1*	.94***
Trading vs Non-Trading Firm	LN	.42***	.01	.31***	-.02	1***	.77	1***	0
Diversified Firm vs M	LN	-.3***	-.12*	-.16***	-.11	0***	0*	0***	0
Female vs Male	LPM	.04	.05***	0**	.02***	1	1***	.77**	.99***
Non-White vs White	LPM	.02	-.05	.01**	-.01**	.99	0	.73**	.18**
Age Below 30 vs Older	LPM	.01	.02*	.01**	-.01**	.99	.96*	.89**	.01**
Bachelors vs Less	LPM	0	.02**	.03	.04***	.34	1**	1	1***
Highest Earner vs Less	LPM	.02***	.03***	.03***	.05***	.95***	1***	.99***	1***
Small Firm vs Larger	LPM	.07	.02	.01**	-.01	1	.97	.84**	.07
Trading vs Non-Trading Firm	LPM	.02**	.02	-.01**	-.04	.98**	.97	.2**	0
Diversified Firm vs M	LPM	-.05	-.05	.01	.01	0	0	.82	.85

Source: LEHD, LBD, and authors' calculations. Table summarizes predicted relative earnings growth across the county-industry combinations appearing in our 19-state regression sample. Predictions are the product of actual county and industry exposures and coefficients from a specification like equation 5 which interacts the noted worker attribute with own, up- and downstream county and industry exposure. Columns 3 to 6 report the weighted median prediction across county-industries in each sample, using either M or NM employment as weights. Columns 7 to 10 report the share of county-industry predictions that are greater than zero. ***, **, and represent statistical significance of the F-statistic testing joint significance of the underlying triple-interaction exposure terms at the 1, 5 and 10 percent levels. See Appendix Table ?? for the underlying F-statistics.

Table A.10: Triple-Interaction Demographic Regressions (ARC,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Industry Gap	ARC	High-Tenure M	0.103	0.136	0.137	0.204	0.093	0.162	0.152	0.103
	ARC	High-Tenure M	0.216	0.215	0.226	0.207	0.187	0.202	0.210	0.223
Post x Ind Up Gap	ARC	High-Tenure M	0.203	0.087	0.188	–0.238	–0.049	0.403	0.589	–0.031
	ARC	High-Tenure M	1.311	1.232	1.346	0.955	0.879	1.349	1.363	0.928
Post x Ind Down Gap	ARC	High-Tenure M	–0.251	–0.370	–0.359	–0.386	–0.557	–0.526	–0.387	–0.181
	ARC	High-Tenure M	0.419	0.392	0.403	0.397	0.374	0.434	0.424	0.435
Post x County Gap	ARC	High-Tenure M	–1.385	–1.034	–1.349	–1.069	–0.732	–0.997	–1.309	–3.317**
	ARC	High-Tenure M	1.638	1.472	1.592	1.450	1.501	1.520	1.536	1.658
Post x Cty Up Gap	ARC	High-Tenure M	–0.528	1.296	1.582	1.617	2.630	–0.540	–0.518	14.69**
	ARC	High-Tenure M	5.544	5.409	5.461	4.915	4.923	5.384	5.414	5.882
Post x Cty Down Gap	ARC	High-Tenure M	–6.172***	–7.094***	–6.746***	–6.500***	–7.474***	–6.324***	–5.720**	–7.616**
	ARC	High-Tenure M	2.135	2.278	2.418	2.172	2.230	2.188	2.203	2.958
Post x Attribute x Ind Gap	ARC	High-Tenure M	0.069	–0.087	–0.156	–0.411	0.081	–0.254	–0.204	0.029
	ARC	High-Tenure M	0.239	0.217	0.261	0.298	0.332	0.306	0.368	0.289
Post x Attribute x Ind Up Gap	ARC	High-Tenure M	0.223	1.135	0.726	2.212	1.709	–0.793	–1.412	0.572
	ARC	High-Tenure M	1.018	0.707	0.915	1.974	2.203	1.101	1.262	1.407
Post x Attribute x Ind Down Gap	ARC	High-Tenure M	–0.528	–0.294	–0.438	–0.129	0.757	0.779	–0.231	–0.406
	ARC	High-Tenure M	0.432	0.469	0.487	0.531	0.673	0.656	0.719	0.619
Post x Attribute x Cty Gap	ARC	High-Tenure M	–0.252	–2.326	–0.965	–2.045	–4.310**	–6.299**	–2.411	2.385
	ARC	High-Tenure M	1.616	2.490	2.109	2.241	1.922	2.663	2.116	1.759
Post x Attribute x Cty Up Gap	ARC	High-Tenure M	8.739	1.630	3.473	0.228	2.478	28.33***	21.96**	–17.13**
	ARC	High-Tenure M	6.019	7.986	7.762	7.134	5.150	9.007	9.239	7.048
Post x Attribute x Cty Down Gap	ARC	High-Tenure M	–1.963	3.403	0.589	–1.657	2.022	–1.789	–7.546*	1.316
	ARC	High-Tenure M	2.693	3.705	3.708	3.247	3.696	5.033	4.056	3.416
Post x Ind Up Gap	ARC	High-Tenure NM	0.861	2.288	3.047*	2.064	2.484*	3.663**	3.497*	2.484*
	ARC	High-Tenure NM	1.195	1.452	1.565	1.392	1.461	1.627	1.869	1.490
Post x Ind Down Gap	ARC	High-Tenure NM	0.108	–1.088	–1.248	–0.799	–1.047	–1.319	–0.749	–1.385
	ARC	High-Tenure NM	0.879	1.042	1.076	0.997	1.044	1.029	1.185	1.078
Post x County Gap	ARC	High-Tenure NM	–4.088***	–4.245***	–3.888***	–4.112***	–4.053***	–3.202**	–2.612	–4.813***
	ARC	High-Tenure NM	1.129	1.202	1.239	1.075	1.146	1.426	1.814	1.177
Post x Cty Up Gap	ARC	High-Tenure NM	4.044	11.46***	9.461**	9.393***	10.20***	7.610*	7.472	12.54***
	ARC	High-Tenure NM	3.652	4.012	4.063	3.531	3.716	4.543	6.052	3.816
Post x Cty Down Gap	ARC	High-Tenure NM	–2.154	–4.324***	–4.573***	–4.020***	–4.528***	–4.930**	–6.374***	–3.714**
	ARC	High-Tenure NM	1.470	1.647	1.670	1.479	1.604	1.943	2.395	1.585
Post x Attribute x Ind Up Gap	ARC	High-Tenure NM	2.781**	2.288**	–3.760***	1.551*	1.126	–3.208	–1.478	–0.425
	ARC	High-Tenure NM	1.350	0.972	1.362	0.840	1.161	2.157	1.452	2.930
Post x Attribute x Ind Down Gap	ARC	High-Tenure NM	–1.930**	0.103	1.468	–0.752	–0.514	1.389	–0.875	1.724
	ARC	High-Tenure NM	0.929	0.422	0.916	0.617	1.003	1.706	1.053	2.236
Post x Attribute x Cty Gap	ARC	High-Tenure NM	0.281	0.997	–1.465	–0.105	–1.143	–2.327	–2.487	3.468
	ARC	High-Tenure NM	1.429	2.064	1.351	1.385	0.858	1.450	1.635	2.295
Post x Attribute x Cty Up Gap	ARC	High-Tenure NM	11.81**	–14.56**	2.764	1.979	2.828	5.620	3.991	–13.92**
	ARC	High-Tenure NM	5.245	6.630	4.755	5.292	2.660	4.548	5.288	6.387
Post x Attribute x Cty Down Gap	ARC	High-Tenure NM	–4.527**	3.021	3.111	–0.259	0.790	2.718	3.933	–1.317
	ARC	High-Tenure NM	2.046	3.994	2.022	1.883	2.422	2.318	2.654	3.413

Source: LEHD, LBD, 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. Second and third columns note the earnings transformation and sample, where ARC=arcsin, 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. Table **??** in the main text reports F-statistics for the joint significance of these exposure terms, by group. Table 4 reports sample sizes and notes other attributes of these refgressions, e.g., fixed effects and clustering. R-squares are available upon request.

Table A.11: Triple-Interaction Demographic Regressions (LN,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Industry Gap	LN	High-Tenure M	0.121*	0.101	0.102	0.083	0.014	0.090	0.101	0.072
	LN	High-Tenure M	0.066	0.062	0.063	0.054	0.047	0.062	0.063	0.056
Post x Ind Up Gap	LN	High-Tenure M	–0.426	–0.344	–0.325	–0.390	–0.237	–0.312	–0.311	–0.317
	LN	High-Tenure M	0.346	0.309	0.329	0.247	0.214	0.340	0.344	0.200
Post x Ind Down Gap	LN	High-Tenure M	–0.194*	–0.208*	–0.213*	–0.225**	–0.234**	–0.226*	–0.218*	–0.245**
	LN	High-Tenure M	0.115	0.113	0.116	0.111	0.103	0.117	0.115	0.120
Post x County Gap	LN	High-Tenure M	0.613*	0.573*	0.692**	0.502	0.556*	0.615*	0.578*	–0.295
	LN	High-Tenure M	0.365	0.325	0.327	0.329	0.328	0.340	0.343	0.328
Post x Cty Up Gap	LN	High-Tenure M	–1.748	–1.878	–2.145*	–1.599	–1.511	–2.542**	–2.581**	3.780***
	LN	High-Tenure M	1.210	1.171	1.136	1.062	1.109	1.151	1.144	1.142
Post x Cty Down Gap	LN	High-Tenure M	–1.468**	–1.414**	–1.439**	–1.239**	–1.387***	–1.254**	–1.217**	–1.655***
	LN	High-Tenure M	0.569	0.544	0.554	0.523	0.467	0.550	0.569	0.483
Post x Attribute x Ind Gap	LN	High-Tenure M	–0.106*	–0.068	–0.099	0.050	0.321***	–0.014	–0.077	0.025
	LN	High-Tenure 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	High-Tenure M	0.324	0.054	–0.073	0.290	–0.191	0.034	0.029	0.056
	LN	High-Tenure 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	High-Tenure M	–0.055	–0.019	0.025	0.094	0.147	0.109	0.040	0.046
	LN	High-Tenure M	0.094	0.088	0.103	0.117	0.152	0.167	0.155	0.126
Post x Attribute x Cty Gap	LN	High-Tenure M	–0.295	–0.369	–1.476***	0.040	–0.648*	–1.446***	–1.151***	1.015**
	LN	High-Tenure 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	High-Tenure M	–0.249	0.246	3.106	–1.196	1.087	8.798***	7.884***	–7.360***
	LN	High-Tenure 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	High-Tenure M	0.444	0.520	0.768	–0.868	–0.228	–0.883	–0.954	0.350
	LN	High-Tenure M	0.626	0.796	0.757	0.917	0.679	0.907	0.730	0.702
Post x Ind Up Gap	LN	High-Tenure NM	0.326	0.642**	0.853***	0.824***	0.880***	0.990***	1.060**	0.734***
	LN	High-Tenure NM	0.313	0.294	0.327	0.252	0.259	0.345	0.448	0.268
Post x Ind Down Gap	LN	High-Tenure NM	0.067	–0.166	–0.274	–0.354*	–0.378*	–0.272	–0.237	–0.254
	LN	High-Tenure NM	0.217	0.213	0.224	0.195	0.201	0.217	0.261	0.220
Post x County Gap	LN	High-Tenure NM	–0.790***	–0.636***	–0.581***	–0.642***	–0.507**	–0.495**	–0.400	–0.695***
	LN	High-Tenure NM	0.208	0.202	0.211	0.208	0.206	0.242	0.296	0.213
Post x Cty Up Gap	LN	High-Tenure NM	0.743	1.198*	1.145	1.476**	1.172	0.441	0.319	1.669**
	LN	High-Tenure NM	0.697	0.711	0.746	0.692	0.741	0.815	1.170	0.753
Post x Cty Down Gap	LN	High-Tenure NM	–0.693*	–0.921**	–0.896**	–0.965***	–1.116***	–0.641	–0.676	–1.271***
	LN	High-Tenure NM	0.360	0.355	0.376	0.366	0.359	0.444	0.517	0.367
Post x Attribute x Ind Up Gap	LN	High-Tenure NM	0.706**	0.745***	–0.951**	–0.201	–0.598	–0.774**	–0.505	–0.246
	LN	High-Tenure 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	High-Tenure NM	–0.400*	–0.135	0.714**	0.423***	0.617**	0.420*	0.030	0.396
	LN	High-Tenure NM	0.227	0.125	0.316	0.157	0.255	0.223	0.240	0.420
Post x Attribute x Cty Gap	LN	High-Tenure NM	0.504*	0.293	–0.100	0.157	–0.500**	–0.208	–0.315	0.654
	LN	High-Tenure 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	High-Tenure NM	0.542	–0.780	–0.381	–1.492	–0.019	1.558*	1.180	–3.899***
	LN	High-Tenure 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	High-Tenure NM	–0.649*	–0.301	–0.294	0.065	0.722	–0.785	–0.426	1.549***
	LN	High-Tenure NM	0.355	0.599	0.604	0.381	0.481	0.582	0.559	0.594

Source: LEHD, LBD, 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. Second and third columns note the earnings transformation and sample, where ARC=arcsin, 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. Table **??** in the main text reports F-statistics for the joint significance of these exposure terms, by group. Table 4 reports sample sizes and notes other attributes of these refgressions, e.g., fixed effects and clustering. R-squares are available upon request.

Table A.12: Triple-Interaction Demographic Regressions (E>0,High-Tenure)

	LHS	Sample	Female	Non-White	Age<30	Bachelors	High Earner	Small Firm	Diversified	Trader
Post x Industry Gap	LPM	High-Tenure M	0.001	0.007	0.007	0.013	0.007	0.010	0.009	0.004
	E>0	High-Tenure M	0.016	0.016	0.017	0.016	0.015	0.015	0.016	0.018
Post x Ind Up Gap	LPM	High-Tenure M	0.045	0.022	0.028	–0.002	0.005	0.047	0.065	0.015
	E>0	High-Tenure M	0.092	0.088	0.097	0.071	0.068	0.096	0.098	0.079
Post x Ind Down Gap	LPM	High-Tenure M	–0.008	–0.018	–0.017	–0.017	–0.031	–0.031	–0.018	0.004
	E>0	High-Tenure M	0.033	0.030	0.030	0.030	0.028	0.033	0.032	0.037
Post x County Gap	LPM	High-Tenure M	–0.155	–0.118	–0.153	–0.113	–0.084	–0.120	–0.146	–0.254*
	E>0	High-Tenure M	0.125	0.117	0.123	0.114	0.119	0.117	0.118	0.139
Post x Cty Up Gap	LPM	High-Tenure M	0.024	0.205	0.240	0.228	0.328	0.097	0.095	1.013**
	E>0	High-Tenure M	0.422	0.415	0.407	0.382	0.382	0.406	0.405	0.492
Post x Cty Down Gap	LPM	High-Tenure M	–0.401**	–0.506***	–0.472**	–0.478***	–0.569***	–0.438**	–0.379**	–0.565**
	E>0	High-Tenure M	0.163	0.178	0.188	0.170	0.182	0.168	0.167	0.257
Post x Attribute x Ind Gap	LPM	High-Tenure M	0.018	–0.006	–0.009	–0.036	–0.011	–0.025	–0.017	0.004
	E>0	High-Tenure M	0.019	0.020	0.022	0.024	0.023	0.026	0.030	0.022
Post x Attribute x Ind Up Gap	LPM	High-Tenure M	–0.023	0.100	0.084	0.174	0.165	–0.063	–0.125	0.039
	E>0	High-Tenure M	0.082	0.066	0.069	0.135	0.146	0.091	0.102	0.106
Post x Attribute x Ind Down Gap	LPM	High-Tenure M	–0.043	–0.020	–0.038	–0.019	0.051	0.064	–0.025	–0.043
	E>0	High-Tenure M	0.037	0.044	0.041	0.041	0.047	0.055	0.060	0.051
Post x Attribute x Cty Gap	LPM	High-Tenure M	0.015	–0.166	0.027	–0.190	–0.373**	–0.421*	–0.098	0.133
	E>0	High-Tenure M	0.138	0.215	0.161	0.178	0.146	0.237	0.180	0.141
Post x Attribute x Cty Up Gap	LPM	High-Tenure M	0.830	0.118	0.139	0.033	0.194	1.827**	1.401*	–1.020*
	E>0	High-Tenure M	0.506	0.684	0.605	0.566	0.375	0.796	0.791	0.576
Post x Attribute x Cty Down Gap	LPM	High-Tenure M	–0.270	0.259	–0.022	–0.012	0.316	–0.198	–0.758**	0.136
	E>0	High-Tenure M	0.231	0.326	0.307	0.254	0.298	0.444	0.358	0.288
Post x Ind Up Gap	LPM	High-Tenure NM	0.011	0.123	0.175	0.086	0.127	0.225*	0.206	0.133
	E>0	High-Tenure NM	0.091	0.119	0.127	0.122	0.128	0.133	0.143	0.125
Post x Ind Down Gap	LPM	High-Tenure NM	0.019	–0.076	–0.083	–0.039	–0.060	–0.088	–0.033	–0.102
	E>0	High-Tenure NM	0.065	0.084	0.087	0.086	0.091	0.082	0.090	0.089
Post x County Gap	LPM	High-Tenure NM	–0.290***	–0.323***	–0.293***	–0.309***	–0.310***	–0.234**	–0.191	–0.366***
	E>0	High-Tenure NM	0.093	0.098	0.099	0.088	0.095	0.115	0.144	0.097
Post x Cty Up Gap	LPM	High-Tenure NM	0.219	0.887***	0.693**	0.693**	0.790***	0.591	0.567	0.943***
	LPM	High-Tenure NM	0.298	0.322	0.318	0.287	0.303	0.363	0.471	0.307
Post x Cty Down Gap	LPM	High-Tenure NM	–0.096	–0.275**	–0.296**	–0.252**	–0.312**	–0.355**	–0.474**	–0.197
	E>0	High-Tenure NM	0.120	0.134	0.135	0.120	0.133	0.158	0.189	0.134
Post x Attribute x Ind Up Gap	LPM	High-Tenure NM	0.210*	0.152*	–0.264***	0.165***	0.173*	–0.241	–0.105	–0.041
	E>0	High-Tenure NM	0.116	0.087	0.099	0.058	0.092	0.195	0.111	0.202
Post x Attribute x Ind Down Gap	LPM	High-Tenure NM	–0.151*	0.019	0.085	–0.093**	–0.099	0.090	–0.099	0.160
	E>0	High-Tenure NM	0.078	0.036	0.066	0.042	0.073	0.158	0.084	0.161
Post x Attribute x Cty Gap	LPM	High-Tenure NM	–0.021	0.088	–0.121	–0.016	–0.121*	–0.200*	–0.199	0.265
	E>0	High-Tenure NM	0.122	0.182	0.110	0.110	0.070	0.116	0.131	0.178
Post x Attribute x Cty Up Gap	LPM	High-Tenure NM	1.075**	–1.343**	0.340	0.208	0.408**	0.380	0.294	–0.994**
	E>0	High-Tenure NM	0.429	0.601	0.404	0.411	0.207	0.372	0.422	0.494
Post x Attribute x Cty Down Gap	LPM	High-Tenure NM	–0.362**	0.292	0.275	–0.000	0.092	0.316*	0.374*	–0.237
	E>0	High-Tenure NM	0.179	0.349	0.167	0.156	0.193	0.189	0.213	0.274

Source: LEHD, LBD, 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. Second and third columns note the earnings transformation and sample, where ARC=arcsin, 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. Table ?? in the main text reports F-statistics for the joint significance of these exposure terms, by group. Table 4 reports sample sizes and notes other attributes of these refgressions, e.g., fixed effects and clustering. R-squares are available upon request.

Table A.13: F-Statistics for Joint Significance of Triple Interaction Industry and County Exposure Terms

		Industry F-Stat				County F-Stat				County-Industry F-Stat			
		High-Tenure		Low-Tenure		High-Tenure		Low-Tenure		High-Tenure		Low-Tenure	
	LHS	M	NM	M	NM	M	NM	M	NM	M	NM	M	NM
Female vs Male	ARC	.52	2.06	1.81	2.77**	1.35	7.63***	2.12*	4.77***	1.05	6.05***	1.83*	4.71***
Non-White vs White	ARC	1.27	2.15*	3.88***	6.63***	.49	2.39*	.15	1.06	1.62	1.84*	2.02*	4.25***
Age Below 30 vs Older	ARC	.38	2.55*	1.18	3.56**	.08	.87	.74	.67	.25	1.95*	1.22	2.48**
Bachelors vs Less	ARC	.87	1.8	.19	2.06	1.99	.1	1.46	1.09	1.29	1.02	.74	2.1*
Highest Earner vs Less	ARC	.97	.31	2.33*	.37	2.17*	2.63**	.61	2.73**	10.87***	6.18***	10.94***	8.63***
Small Firm vs Larger	ARC	.99	.81	3.05**	.35	3.7**	.97	.64	.47	1.95*	.85	1.97*	.32
Trading vs Non-Trading Firm	ARC	1.41	.83	2.98**	.73	2.66**	1.1	.64	1.28	2.38**	.84	1.73	.91
Diversified Firm vs M	ARC	.19	.34	1	.99	2.16*	1.78	2.61*	.15	1.29	.99	1.75	.6
Female vs Male	LN	1.23	2.5*	2.27*	1.2	.91	6.6***	1.16	6.29***	1.14	4.27***	1.64	4.45***
Non-White vs White	LN	.9	5.28***	1.4	1.73	.24	.33	2.87**	.77	.54	2.82***	2.4**	1.27
Age Below 30 vs Older	LN	1.23	1.88	.14	4.8***	4.73***	2.04	6.09***	4.69***	3.27***	2.47**	3.49***	4.97***
Bachelors vs Less	LN	1.09	2.42*	1.06	4.68***	2.51*	1.22	.96	1.22	2.57**	2.23**	1.15	2.55**
Highest Earner vs Less	LN	4.39***	1.97	3.82***	.36	1.42	2.46*	3.36**	15.32***	31.79***	4.09***	3.88***	28.5***
Small Firm vs Larger	LN	.18	2.7**	.21	3.19**	12.36***	1.86	3.33**	4.53***	6.56***	2.82***	2*	4.61***
Trading vs Non-Trading Firm	LN	.56	.62	1.31	.13	11.79***	1.05	4.76***	.2	6.99***	.81	3.2***	.12
Diversified Firm vs M	LN	.19	.33	.02	.78	10.36***	3.69***	5.76***	1.31	6.11***	2.02*	2.92***	1.14
Female vs Male	E>0	.61	1.49	3.2**	2.34*	2.21*	7.16***	3.13**	4.04***	1.71	6.05***	2.66**	4.29***
Non-White vs White	E>0	1.18	1.03	4.01***	4.05***	.37	2.41*	.4	1.06	1.18	1.43	2.17**	2.65**
Age Below 30 vs Older	E>0	.61	2.37*	1.75	2.49*	.23	1.23	2.17*	1.4	.5	1.89*	2.53**	2.16**
Bachelors vs Less	E>0	1.08	5.02***	.26	2.97**	1.7	.2	1.89	1.58	1.44	2.69**	1.02	3.15***
Highest Earner vs Less	LPM	1.09	1.23	2.16*	.45	2.4*	8.3***	1.88	12.88***	14.62***	18.69***	29.75***	33.42***
Small Firm vs Larger	E>0	1.05	.73	4.5***	.19	2.32*	1.36	.15	.13	1.27	1.06	2.53**	.15
Trading vs Non-Trading Firm	E>0	1.28	1.31	4.35***	1.37	2.23*	1.26	.2	1.97	2.29**	1.14	2.27**	1.47
Diversified Firm vs M	E>0	.29	.62	1.39	1.65	1.12	1.73	2.09	.08	.73	1.03	1.6	.9

Source: LEHD, LBD, 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: ARC=arcsin, 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.