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

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Comments Welcome!

Abstract

We examine US workers' earnings after trade liberalization with China using a novel approach that considers industry and geographic exposure to the shock both directly and via input-output linkages. In contrast with the literature, we find evidence of relative earnings *gains* from the "China Shock" among workers initially employed outside manufacturing due to increased competition in input markets. Workers initially employed in manufacturing, by contrast, exhibit substantial and persistent relative declines in earnings that are exacerbated by downstream exposure. Across these estimates, we find that spatial exposure is more influential for workers' earnings outcomes than industry exposure.

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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; Hakobyan and McLaren, 2016), 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. This paper shows that after considering a worker's industry and geographic exposure, and allowing for effects through input-output linkages, most workers outside manufacturing experience relative earnings gains after the liberalization. As such, it provides long-suspected but previously missing empirical evidence of relative benefits of the China Shock, consistent with the input-output mechanisms put forward in theoretical models such as Caliendo et al. (2019). By contrast, for manufacturing workers, we find that exposure via the value chain exacerbates the relative earnings losses documented in earlier research.

Our approach requires detailed information on each worker's industry and county of employment. Toward that end, we make use of the matched employer-employee data from the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. The LEHD is well-suited to our inquiry in two ways. First, it tracks the earnings of nearly all workers—manufacturing and nonmanufacturing—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 higher levels of aggregation, such as across industries or regions.

To set ideas, we provide the first decomposition of long-run US worker transitions during the period of sharp manufacturing employment decline at the turn of the century. This decomposition focuses on workers initially employed in manufacturing in 2000 and reports employment flows and nominal earnings growth from 2000 to 2007 for workers depending on whether they remain in manufacturing or switch to one of 18 other non-manufacturing sectors. Even with the substantial decline in manufacturing employment during this period, the most common outcome is for workers to remain in the manufacturing sector, and these workers experience median nominal earnings growth of 27 percent. In raw terms, the three largest nonmanufacturing destinations for workers switching sectors are administration and support, wholesale, and retail.[1] Workers transitioning to the most common destination sector, administration and support—which is dominated by temporary staffing agencies—experience outright nominal earnings *declines* of 22 percent from 2000 to 2007. Those

[1] When adjusting for the initial size of the destination sector—i.e., accounting for the fact that the utilities sector is much smaller than the retail sector—the most popular destinations are wholesale, mining (which includes oil and gas drilling and extraction), and management. The least popular are education; accommodation and food; and arts, entertainment, and recreation.

switching to retail see nominal earnings remain roughly flat from 2000 to 2007, substantially lagging their counterparts who remain in manufacturing. Those switching to wholesale experience nominal earnings gains that modestly outpace those who remain in manufacturing.

In the second part of the paper, we use a series of worker-level difference-in-differences (DID) regressions to examine 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.[2] Given that earnings can be zero, we consider three transformations of earnings as 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, subject to the usual caveats.

Our DID regressions provide a reduced form assessment of the relative importance of sectoral versus spatial exposure to trade liberalization, as well as the salience of "direct" versus "input-output" (or "IO") exposure to the shock via supply-chain linkages. In this sense, our results provide empirical evidence that can be compared with the model-based estimates in Caliendo et al. (2019). For direct exposure, we consider two forms of susceptibility: the industry of the establishment at which the worker is initially employed, and, as in Hakobyan and McLaren (2016), 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 tables to construct workers' industry and spatial up- and downstream "IO" exposures. The up- and downstream exposures for a worker in industry i are the input-output-coefficient weighted averages of the exposures of all industries used by i as inputs, 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 exposure via their industry or county.

To aid comparison with approaches that do not account for input-output linkages, we first report results from the "direct" specification that includes only own-county and -industry DID exposure terms. Among M workers, we find a negative and statistically significant relationship between earnings and own-county exposure, but a statistically insignificant relationship with respect to own-industry exposure. These results are notable: while higher industry exposure among M workers has been

[2] We compare our baseline results to those using a lower threshold of tenure in Section 6.

shown to be associated with employment contraction *in those industries* (Pierce and Schott, 2016), our estimates here indicate that a *worker's* labor market outcomes after PNTR depend primarily on the extent of exposure in their location. In this specification, we find a similar negative relationship between earnings and own-county exposure among NM workers.

Results from our "IO" specification highlight the importance of accounting for up- and downstream linkages in evaluating the effects of trade and other labor-demand shocks, and provide novel evidence of the effect of the China Shock on worker earnings. 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 DID coefficients for the two groups of workers. In particular, positive coefficients for county upstream exposure are large and precisely estimated for NM workers—indicating that they benefit from higher competition in input markets—while they are not statistically significant for M workers. Estimates for county downstream exposure are negative for workers in both sectors but are larger in absolute value for M 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. This aspect of our empirical results provides the first empirical evidence for the China Shock consistent with the mechanism and model-based estimates in Caliendo et al. (2019), in which lower intermediate input costs associated with import competition from China boost productivity, leading to welfare gains for many US workers. Indeed, the elasticities we estimate offer new inputs that can be useful in calibration of a broad variety of trade models (Caliendo et al., 2019), and more broadly in macro-labor models, where identification of labor demand shocks is often a challenge.

Summarizing the combined economic significance of the own, up- and downstream DID estimates using the traditional metric of an interquartile increase in exposure is complicated by their high dimensionality and correlation. As an alternative, we use these 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.[3] For M workers, the distribution of "IO" predictions lies to the left of the distribution of "direct" predictions, indicative of the underestimation of relative earnings losses for M workers under the simpler model discussed above. By contrast, the "IO" county-industry predictions for NM workers lie to the right of the "direct" predictions, implying overestimation of relative losses in the simpler model. In fact, under the "IO" specification, nearly all NM county-industry pairs are predicted to have relative earnings *gains*.

One explanation for why M workers are not helped by upstream exposure and are more substantially harmed by 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 sus-

[3] We are unable to release analogous predictions at the worker level due to Census disclosure restrictions.

ceptible to higher competition downstream. 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 among 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 worker outcomes outside manufacturing. While Pierce and Schott (2016) and Acemoglu, Autor, Dorn, Hanson, and Price (2016) include up- and downstream exposure in their *industry*-level studies of the impact of Chinese import competition on US manufacturing employment, neither finds evidence of any positive effect. 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.[4]

In the final part of the paper, we investigate whether responses to PNTR vary by workers' initial characteristics or their initial firms' attributes using 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. 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-diversified 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 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.[5] Among worker characteristics, we find that relative earnings outside manufacturing are predicted to be higher among women, whites, younger workers, and high earners.[6] 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 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

[4]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. Greenland, Ion, Lopresti, and Schott (2020) show that firms' reactions to PNTR vary widely within narrow industries, in part due to their access to cheaper inputs from China. **?** find similar heterogeneity among French firms' reactions to the China shock.

[5]Kovak and Morrow (2022) report a similar result among Canadian firms' response to CUSFTA.

[6]Kahn, Oldenski, and Park (2022) examine the heterogeneous effects of Chinese import competition and find that Hispanic workers exhibit greater manufacturing employment loss during the China shock.

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.[7] Hakobyan and McLaren (2016) document 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), Utar (2018), and Kovak and Morrow (2022) explore the impact of exposure to trade among Brazilian, Danish, and Canadian workers.[8] Keller and Utar (2023) examine the effects of import competition on worker polarization in Denmark, and 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, while also considering industry- and geography-level exposure to the trade shock. Our contribution relative to these efforts arises from the combination of using employer-employee data to study a US trade liberalization, assessing the effect of both industry and geographic exposure, evaluating the long-run influence of these exposures along the supply chain, explicitly examining spillovers to nonmanufacturing workers, and investigating differential responses to the shock among different types of workers with varying professional attributes.

The 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 non-manufacturing workers. Finally, in terms of results, we find geographic exposure to be a more important determinant of subsequent earnings than industry exposure, a result that may arise, in part, because our data contain 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

[7]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) illustrate how import competition results in a decline in the proportion of female employees, promotions, and earnings at firms subject to the Family and Medical Leave Act, compared to firms not subject to this policy.

[8]In the latter paper, the authors find that the bilateral trade liberalization arising from the Canada-U.S. Free Trade Agreement allowed import-competing workers to avoid long-term earnings losses by moving to industries benefiting from U.S. tariff cuts.

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 US 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.[9] 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 reports the results of robustness tests, and 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

[9] 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.

earnings are defined as the sum of gross wages, salaries, bonuses and tips.[10]

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).[11] 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.[12]

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 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.[13] 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.[14] 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.[15]

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 cap-

[10] 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.

[11] 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.

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

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

[14] 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.

[15] 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 those in the larger sample being a bit older, on average, than those in the 19-state sample.

ital prior to the change in policy, composed of workers who are continuously employed from 1993 to 1999, but not necessarily by the same firm. For computational convenience, we draw representative 5 percent samples from the population of both groups of workers for our regressions. These draws include all workers from "small" counties (i.e., those in the first size decile, with population at or below 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 to abstract away from normal-age retirement.

Within each sample, workers are classified as initially in manufacturing (M) if they are employed in an establishment whose major activity in 1999 is in NAICS industries beginning with "3". All other workers are classified as initially non-manufacturing (NM). Workers not present in the sample during some or all of the post period are classified as not employed (NE) in those years. The predominant reason for NE status is lack of employment—unemployment or labor force exit—but it may also be the result of death, movement to a state (or country) outside the sample of states for which we have data, or movement to a job that is out of scope of the UI system.[16]

3 Post-2000 US Labor Reallocation

In this section, we summarize workers' 2000 to 2007 employment 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.[17] They also provide additional evidence relating to several hypotheses regarding manufacturing worker outcomes that have appeared in the literature and provide context for existing research on the employment effects of the China Shock and broader US structural change (Ding et al., 2019).

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.[18] 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

[16]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.

[17]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 we examine.

[18]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.

(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.

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.[19] 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.[20] 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.[21]

3.2 Detailed Decomposition of Gross M Outflows

We provide a more detailed description of manufacturing workers' reallocation across sectors in Table 2, which decomposes *gross flows* 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

[19] 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 small.

[20] 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.

[21] 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.

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.

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

	Gross Flow		2000 Employment		
	(1)	(2)	(3)	(4)	(5)
Destination NAICS Sector	Flow	% of Flow	Level	% of Total	(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 reports outflows of manufacturing workers (in thousands) to 2-digit sectors between 2000 and 2007 across the 46 states. Second column reports the share of the overall flow from manufacturing going to each sector. Third column displays the distribution of initial US employment (in thousands) across the noted sectors in 2000 from the Quarterly Workforce Indicators Database (QWI) available at https://ledextract.ces.census.gov/. Fourth column reported the flows as a share of initial employment in each sector. The last column reports the ratio of columns 2 and 4.

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 may reflect 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).[22] Transitions to these sectors is consistent with workers switching industry but not necessarily occupation (Traiberman, 2019), e.g., an R&D scientist formerly located in a

[22] Appendix Figure A.7 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).

manufacturing plant might move to a research lab in a company headquarters (NAICS 55). 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.[23]

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 have found a commensurately-compensated haven in this sector during the post-2000 housing boom, and Caliendo et al. (2019) highlight employment shifts from manufacturing to construction arising from import competition with China. 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

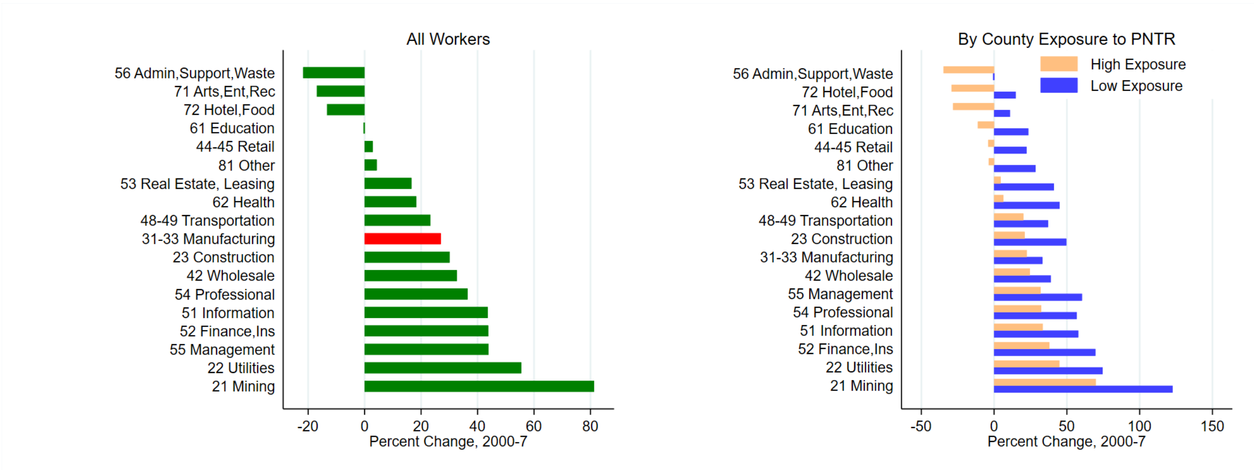
We investigate how the nominal earnings of workers initially employed in manufacturing evolve depending upon whether they remain in that sector or migrate to another by calculating the ratio of their 2007 to 2000 nominal earnings. We then take the quasi-median across all workers moving to each destination (including those that stay in manufacturing), subtract 1, and report the corresponding median cumulative percent changes in Figure 1.[24]

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., 2021). It is also negative

[23] 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).

[24] 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.

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



Source: LEHD, LBD and authors' calculations. Figure displays quasi-median 2000 to 2007 growth in nominal earnings across workers moving from manufacturing to the noted 2-digit NAICS sector between 2000 and 2007 in the 46 states for which information is available in the LEHD for these years (Alabama, Arkansas, New Hampshire Mississippi and the District of Columbia are excluded). Left panel displays growth for all workers. Right panel displays quasi-median growth for workers in the first (low) versus fourth (high) quartile of county exposure to PNTR, defined in Section 4.

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).[25] 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.[26] 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. Interestingly, these earnings declines for workers moving to local-facing service industries could be indicative of negative

[25]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.

[26]Appendix Section E provides an analogous decomposition of worker flows.

spillover effects from manufacturing to services, e.g. former factory workers no longer patronizing local restaurants.

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 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), 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.[27] 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. The measure of geographic exposure to trade liberalization could also be calculated at a higher level of aggregation. Pierce and Schott (2020) show that measures based on Public Use Microdata Areas—which contain a minimum population of 100,000 and are larger even than Commuting Zones—yield similar effects to those based on counties.

Figure 2 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.[28] In some instances below we calculate the economic significance of the estimated impact of PNTR using interquartile shifts in exposure, which are 20.5 and 7.7percent for industry and county, respectively.

Trade liberalization episodes such as PNTR may also affect US workers' earnings via their supply chains, i.e., the upstream industries from which their firms purchase inputs or the downstream industries to which they sell their outputs.[29] 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,

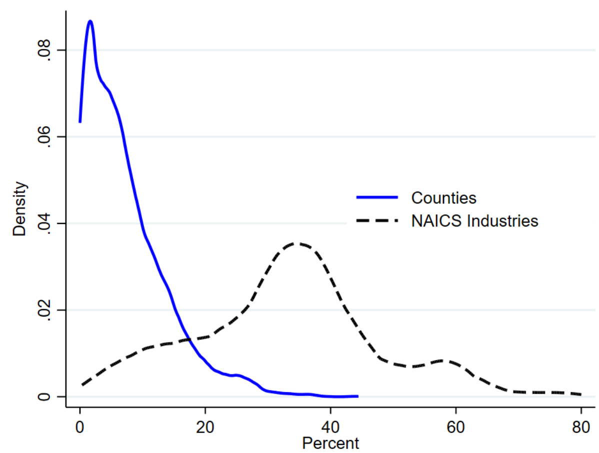
$$Industry\ Gap_i^{up} = \sum_k \omega_{ik}^{up}\ Industry\ Gap_k. \tag{3}$$

[27] 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.

[28] 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.

[29] 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).

Figure 2: 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.

$Industry\ Gap_i^{down}$ is the analogous weighted average for all the downstream industries outside i's 3-digit root that use industry i.[30]

We compute $County\ Gap_c^{up}$ and $County\ Gap_c^{down}$ by taking employment-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.[31]

Industries vary intuitively in terms of their up- and downstream gaps.[32] Hospitals (NAICS 622), for example, has above-median upstream exposure (0.08) as a result of sourcing from Chemicals (NAICS 325), which includes pharmaceuticals, Plastics and Rubber (NAICS 326), and Miscellaneous Manufactures (NAICS 339), which includes medical devices and scientific equipment. As its sales are mostly to final consumers, it has negligible downstream exposure. General Warehousing and Storage (493110), by contrast, has below-median upstream exposure (0.04) but above-median downstream exposure (0.11), as Chemicals (NAICS 325), Electronics (NAICS 334), and Transport Equipment (NAICS 336) are among its most important customers. Software Publishing (NAICS 511210) is an interesting case in that its up- and downstream exposure are both high (0.08 and 0.26) because it has substantial purchases *and* sales to Computer and Electronics (NAICS 334).

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

[31] 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.

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

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.

To set a baseline, and ease comparison with approaches that do not account for input-output linkages, our first, "direct," specification examines whether employment outcomes 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),

$$\begin{aligned} d_{jfcit} &= \delta_1 Post \times County\ Gap_c + \delta_2 Post \times Industry\ Gap_i + \delta_3 Post \times MSH_{c,1999} + \\ &\quad Post \times \mathbf{X_{j,1999}} \beta_\mathbf{j} + Post \times \mathbf{X_{f,1999}} \beta_\mathbf{f} + Post \times \mathbf{X_i} \beta_\mathbf{i} + \\ &\quad \gamma_1 Post \times MSH_{c,1999} + \gamma_2 Post + \mathbf{X_{it}} \gamma_\mathbf{i} + \alpha_j + \alpha_t + \epsilon_{jfcit}. \end{aligned} \tag{5}$$

Examining the effects on employment of workers' industry- and geographic-level exposure is justified by a range of trade models. Support for a similar regression for wages is found in Caliendo et al. (2019), where local labor markets are defined at the sector-state-level, and workers face "substantial and heterogeneous costs" to switching either sector or state, which prevents instantaneous adjustment of wages to shocks. Equation 5 represents a reduced form approach to capturing both industry- and geography-level exposure, and it has been used by Hakobyan and McLaren (2016) and Autor et al. (2014) in their analyses of labor market outcomes in response to NAFTA and Chinese import growth, respectively. Moreover, we note that our data and identification strategy could be adapted to estimate parameters relevant to a range of models in international trade, including those estimating worker-level frictions associated with switching sectors or regions.

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 or 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 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 combination of the intensive- and extensive-margin responses[33],

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

With ARC, the implied elasticity of earnings with respect to county or industry exposure is equal 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 a key county-level characteristic, county c's 1999 manufacturing share ($MSH_{c,1999}$), which is interacted with the post dummy, $Post$. With this term, the county gap reflects exposure to PNTR conditional on the county's manufacturing share and addresses the issue of "incomplete shares" in exposure (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 $Post$, $Post \times \mathbf{X_{j,1999}}$ 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.

[33] An important caveat associated with the ARC transformation is that estimates are sensitive to the units in which the dependent variable is expressed, e.g., dollars versus thousands of dollars (Bellemare and Wichman, 2020). For this reason, we report results for all three transformations throughout the paper. One concern with the log earnings measure is that it may be sensitive to initially low-earning workers who experience large percentage changes in earnings post-PNTR. This concern is allayed by our focus on high-tenure workers in the baseline.

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 are 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) and Pierce and Schott (2020); 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 than NM workers to be female, American born, and have advanced educational attainment.

5.1 Own-Industry Exposure ("Direct" Specification)

Table 4 reports our findings for this "direct" specification. 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, respectively.[34] 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.

The main message of the "direct" specification in Table 4 is that PNTR affects both M and NM workers through their geographic exposure. For M workers, for which both industry and county

[34] 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.

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 geographical, 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. We find similar results for county-level exposure for NM workers but, as we will see in the next section, overall outcomes for NM workers change substantially when accounting for up- and downstream exposure.

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 (000s)	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 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 relative 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 a specification with spatial exposure only), or one that is *positive* and marginally significant (in an alternate specification with both industry and spatial exposure).[35]

The negative relationship for 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 accounting for workers' exposure to PNTR via up- and downstream industries provides a potential explanation for this result.[36]

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.

Results are reported in Table 5. The top panel reports estimates for the six DID terms of interest. The bottom panel assesses 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.

[35] 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.

[36] 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 A.8 of the appendix. These figures reveal that industry exposure coefficients remain close to zero and statistically insignificant, county exposure terms are near zero until 2001, at which time they drop substantially, and that the negative effect of county exposure is persistent.

Table 5: "IO" Specification

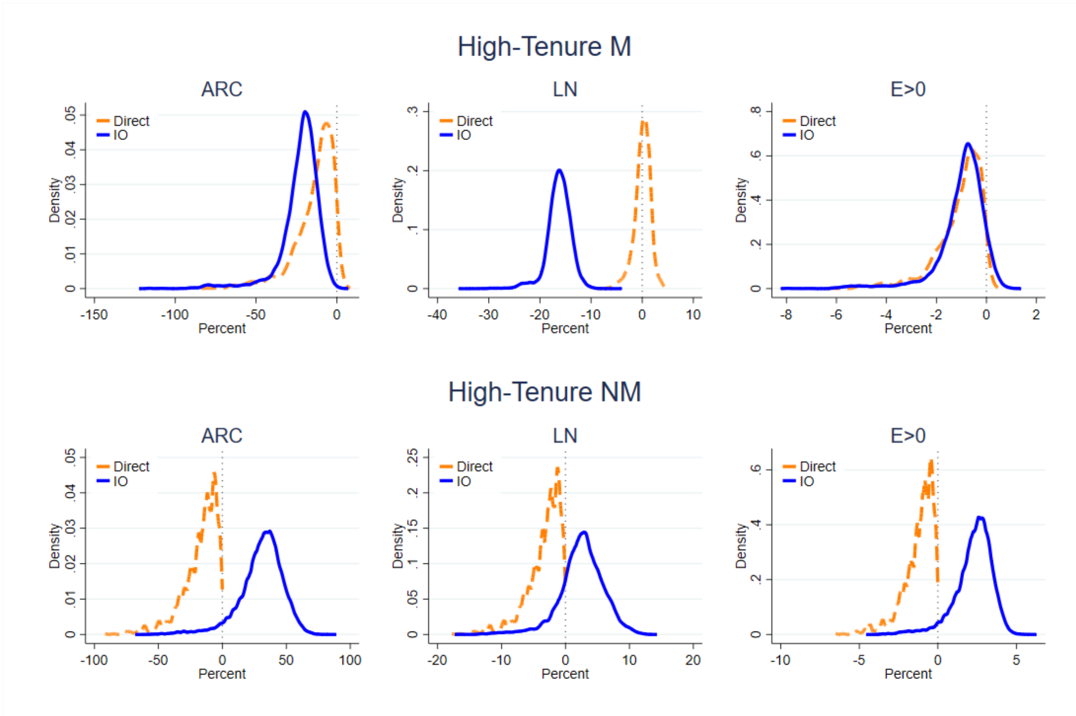
	High-Tenure M			High-Tenure NM		
	ARC	LN	E>0	ARC	LN	E>0
Post x Industry Gap	0.120	0.091	0.006			
	0.203	0.059	0.015			
Post x Industry Upstream Gap	0.258	–0.336	0.037	2.567*	0.737**	0.141
	1.276	0.310	0.093	1.480	0.292	0.122
Post x Industry Downstream Gap	–0.413	–0.211*	–0.021	–1.096	–0.194	–0.075
	0.398	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 (000s)	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.

The results in Table 5 reveal novel information on how Chinese import competition affects workers, particularly by uncovering novel sources of relative *gains* for NM workers. As shown in the table, we continue to find that NM workers experience relative earnings losses associated with higher exposure to PNTR in their own county. Moreover, we find further relative earnings losses for NM workers via their county's downstream exposure, i.e. the exposure of the manufacturing industries to which they sell. But importantly, we now find sources of relative earnings *gains* for NM workers that come through higher upstream exposure, which increases import competition in input markets. Relative gains via higher upstream exposure are most apparent for workers in counties whose industries purchase inputs from exposed industries, but also via higher exposure to the worker's industry in the ARC and LN specifications. For M workers, we continue to find relative earnings losses associated with PNTR, with the effect loading on county-level downstream exposure, and the effect of own-county exposure losing statistical significance, a finding that we discuss in greater detail below.

Importantly, the results for NM workers represent the first empirical evidence consistent with the mechanism in Caliendo et al. (2019), in which lower intermediate input costs boost welfare for most US workers. More generally, the elasticities presented in Tables 4 and 5 can be of use in calibration of a broad variety of trade and macro-labor models. Here, our examination of multiple margins of earnings adjustment, and use of a plausibly exogenous shock, offer information useful for consideration of a wide variety of labor-adjustment mechanisms.

Figure 3: Distribution of County-Industry Predictions, "Direct" vs "IO" Specifications



Source: LEHD, LBD, and authors' calculations. Panels display distributions of predicted relative county-industry earnings 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. 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.

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, thus yielding estimates of relative changes in outcomes for workers in each industry-county bin.[37]

[37] 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

Figure 3 reports 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. 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, predicted relative earnings growth under the "direct" specification lies to the right of the "IO" specification, with 25^{th} and 75^{th} percentiles of -19 to -5 percent, and -27 to -15 percent, respectively. The relative placement of these distributions indicates that ignoring "IO" linkages leads to an *underestimation* of 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 point estimates for industry and county upstream as well as downstream exposure are all negative. There is no difference 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.

By contrast, county-industry predictions for NM workers under the "IO" specification lie to the right of those from the "direct" specification, and are generally positive along both intensive and extensive margins. This relative placement indicates that ignoring exposure to trade liberalization along the supply chain leads to an *overestimation* of relative earnings losses among NM workers.[38] Indeed, PNTR induces relative NM earnings *gains* among a substantial share of county-industry pairs: the interquartile range under the ARC transformation is -23 to -7 percent under the "direct" specification versus 23 to 42 percent under the "IO" specification.[39]

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, is home to 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).[40] 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 4, which re-plots Figure 3 for just these two counties. While M workers in both counties exhibit predicted relative earnings losses, they are less negative for Napa, owing to its relatively high upstream exposure and relatively low downstream

workers is not defined.

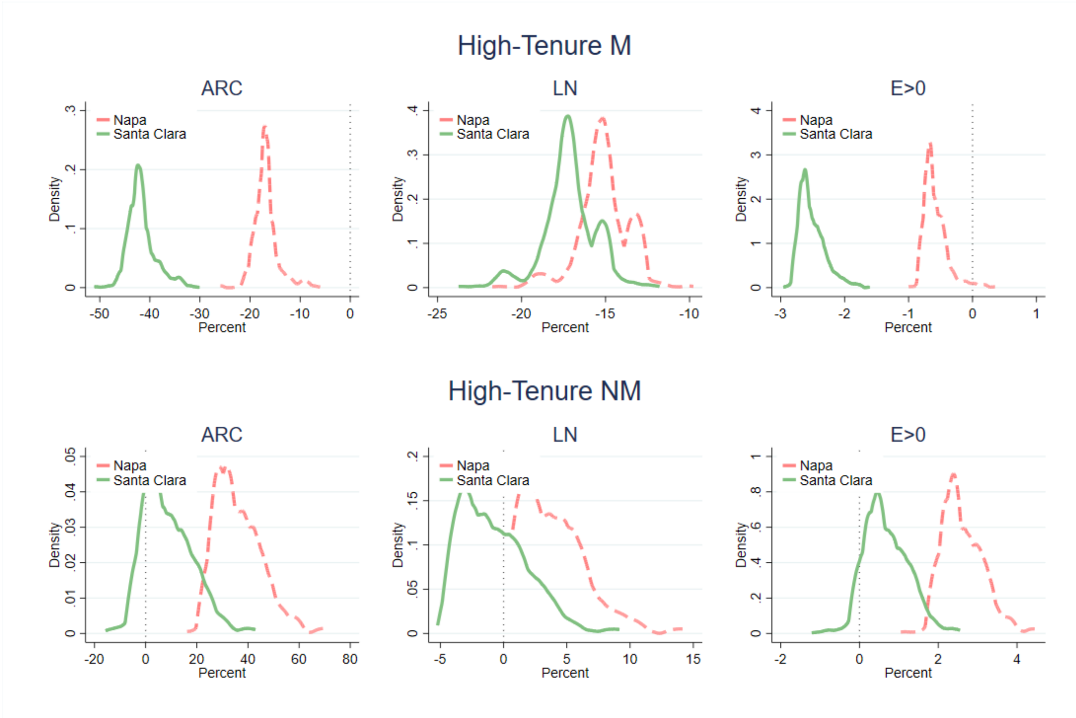
[38] NM worker predictions are all negative under the "direct" specification because of the negative point estimates in Table 4.

[39] In Appendix Figure K we demonstrate that the differences between M and NM workers' predictions are driven almost entirely by the differences in the coefficient estimates, and not by underlying variation in exposure.

[40] Appendix Figure A.3 compares 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.

exposure *vis à vis* Santa Clara. At the same time, while relative earnings predictions for both counties are positive for NM, they are more positive for Napa than for Santa Clara.

Figure 4: Napa and Santa Clara "IO" Predictions



Source: LEHD, LBD, and authors' calculations. Figure displays county-industry relative earnings growth predictions under the "IO" specification for high-tenure initial M and NM workers in Napa and Santa Clara counties after PNTR versus before. "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 Table 5 for further description of the underlying regressions.

One potential explanation for M workers' negative (LN) and lower (ARC, E>0) responsiveness to both upstream and downstream county exposure in Table 5 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. This process of co-offshoring is also a potential explanation for why downstream exposure is more important than own exposure for determining labor market outcomes for M workers.[41] For services, such co-migration may not be possible, e.g., hospitals must stay within reach of their patients, and hotels

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

must remain close to their guests.[42]

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 trading versus non-trading firms; and workers at "diversified" (have both M and NM establishments) versus non-diversified firms.[43]

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.[44] 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 5 and 6 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, with separate distributions for M and NM workers. 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

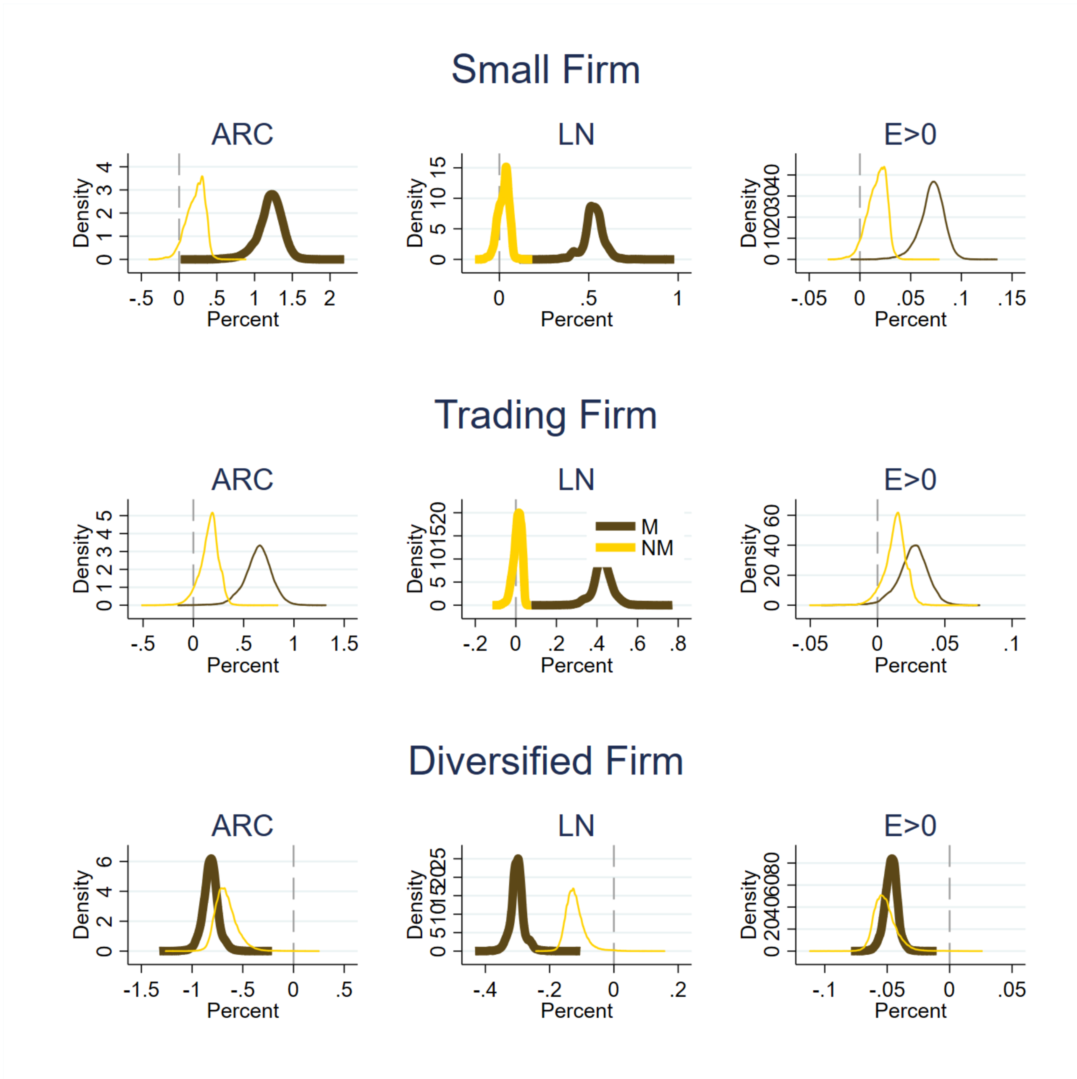
[42]PNTR may also benefit NM workers by inducing entry of "factoryless goods producers" like Fitbit and Roku that take advantage of a greater ability to outsource and offshore the physical transformation stages of goods production (Fort, 2023). While difficult to identify using existing BEA input-output 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.

[43]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.6 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.

[44]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.

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. Distributions for M workers are dark (brown) while those for M workers are light (yellow).

Figure 5: 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 5, 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 5, we find that M workers initially employed at small firms perform relatively better than those employed at large firms. This result is consistent with Holmes and Stevens (2014)'s argument that small firms are more likely to produce customized output that is less substitutable with Chinese imports. Second, as shown in the bottom row of the figure, M workers employed at diversified firms perform relatively worse than those employed at firms that also have NM plants (i.e., diversified firms). This result is somewhat surprising, as transitioning from M to NM might in principle be easier for workers at firms that span both sectors, and allow for retention of firm-specific human capital, even if those activities are in different locations. On the other hand, a strict focus on manufacturing activities may contribute to firms' ability to produce the kinds of goods Holmes and Stevens (2014) have in mind.[45] 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).

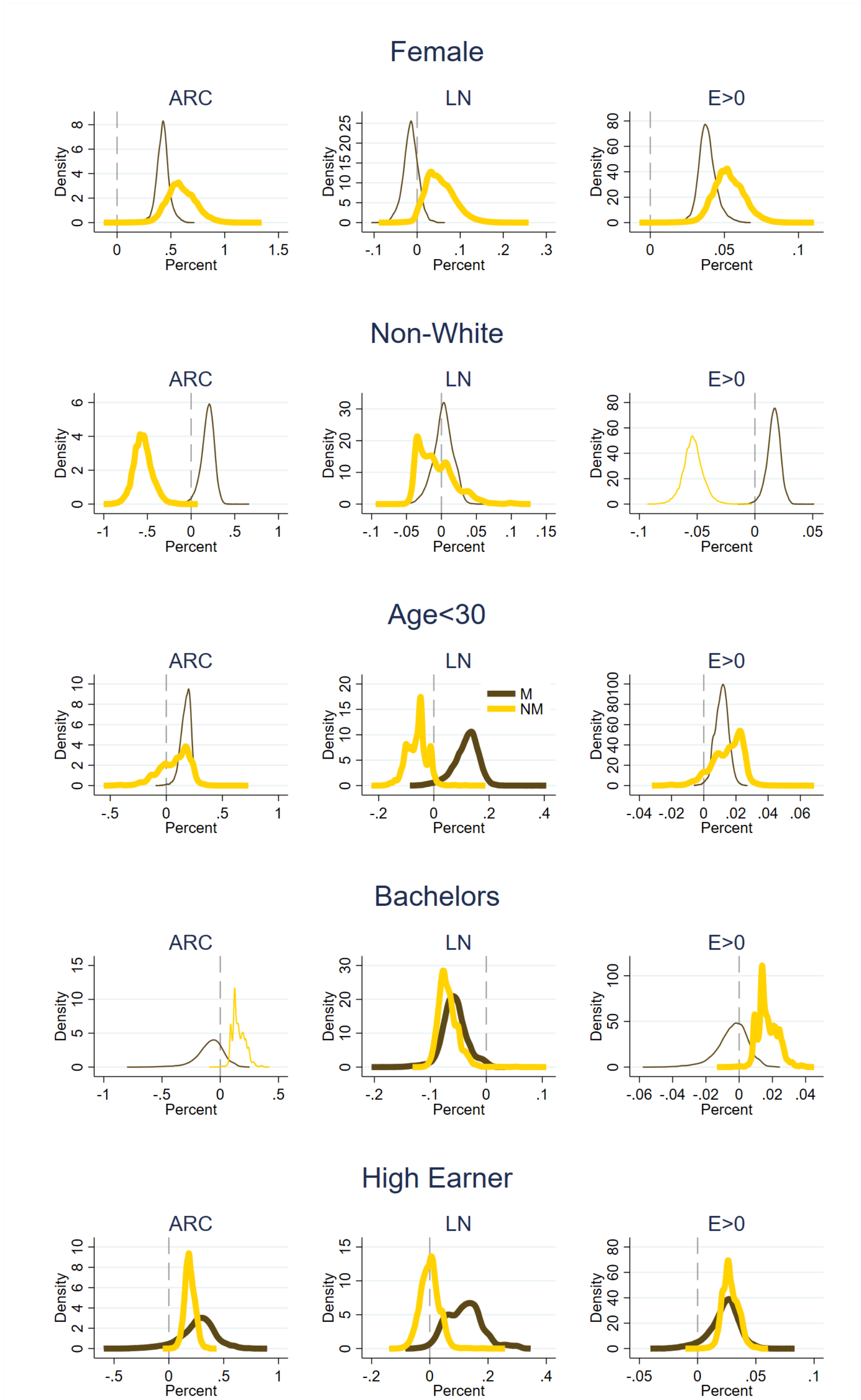
Next, we examine heterogeneous responses by demographic characteristics, as displayed in Figure 6. First, in terms of gender, we find that female NM workers experience relatively better labor market outcomes than males, in terms of all three outcomes. With respect to race, NM workers who are not white 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.[46]

Lastly, perhaps the most widespread heterogeneous response we find among worker attributes relates to initial earnings. As shown in the bottom row of Figure 6, 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.

[45] 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.

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

Figure 6: Triple-Interaction County-Industry Predictions by Worker Demographic

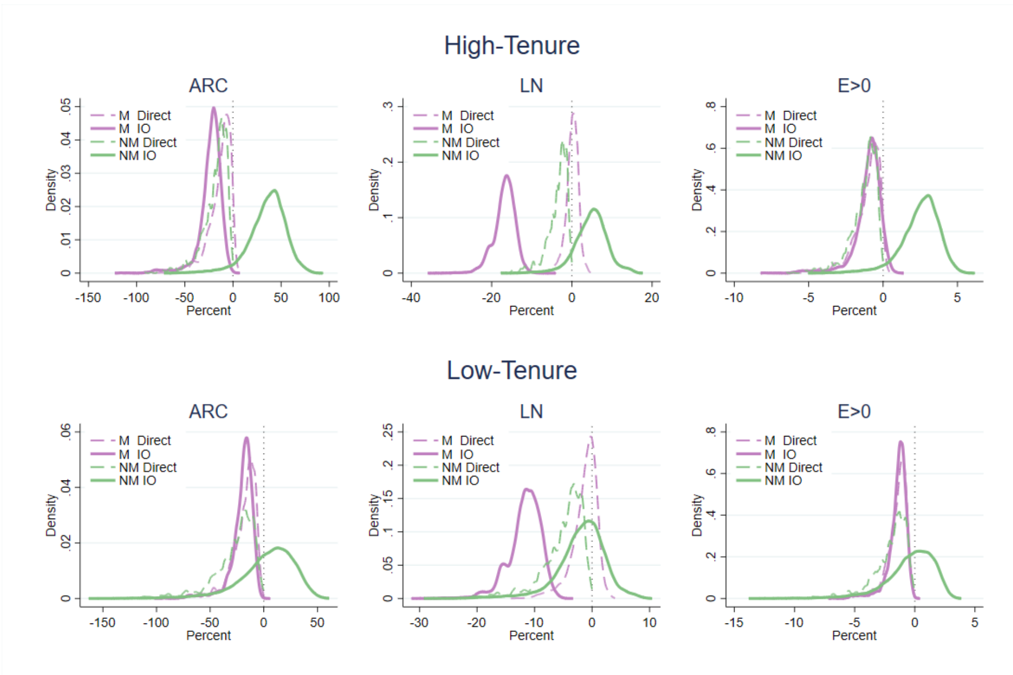


Source: LEHD, LBD, and authors' calculations. Figure displays county-industry predictions of relative earnings growth for noted worker demographic attribute versus those not possessing that attribute using the triple-interaction DID coefficients discussed in the text and reported in Appendix Tables A.10 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 their pre-PNTR firm, and to an alternate definition of county exposure that is specific to each worker.

Figure 7: Direct and IO Predictions for High- vs Low-Tenure Workers



Source: LEHD, LBD, and authors' calculations. Figure displays the distributions of predicted relative earnings growth from the "direct and "IO" 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

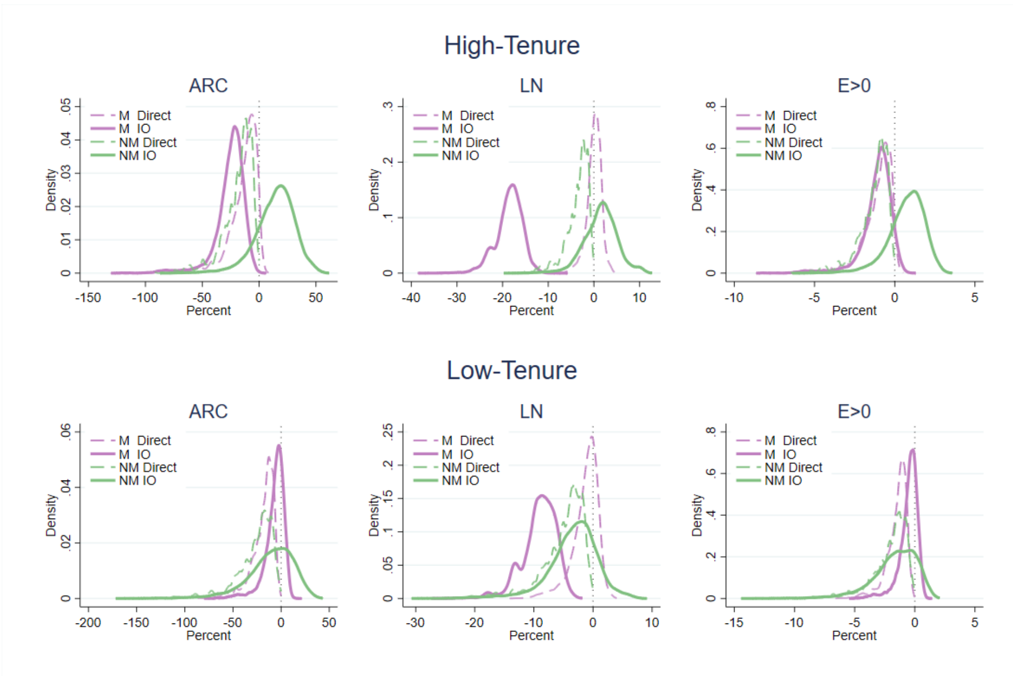
The "high-tenure" workers in our baseline sample were employed by the same firm over the entire 1993 to 1999 period. We define a second sample referred to as "low-tenure" that lowers this threshold to include workers with positive earnings in every year from 1993 to 1999 but not necessarily from the same employer.[47] Figure 7 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 distributions of predicted relative earnings growth under the "direct" and "IO" specifications across all county-

[47] Construction of weaker levels of attachment is feasible so long as we observe workers' industry and county prior to PNTR.

industry pairs in our 19 state sample.[48]

As indicated in the figure, the predicted relative earnings gains for low-tenure NM workers are not as strong as those displayed for high-tenure NM workers. 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 (e.g. restaurants, retail), or a "last-in-first-out" approach to layoffs among firms.

Figure 8: Direct and IO Predictions using Alternate County Exposure



Source: LEHD, LBD, and authors' calculations. Figure displays the distributions of predicted relative earnings growth from the "direct and "IO" 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. One concern with this approach is that in counties that are highly concentrated in terms of industries, workers' industry exposure may be highly correlated with their county exposure. An alternate approach is to exclude workers' own industries from computation of geographic exposure.

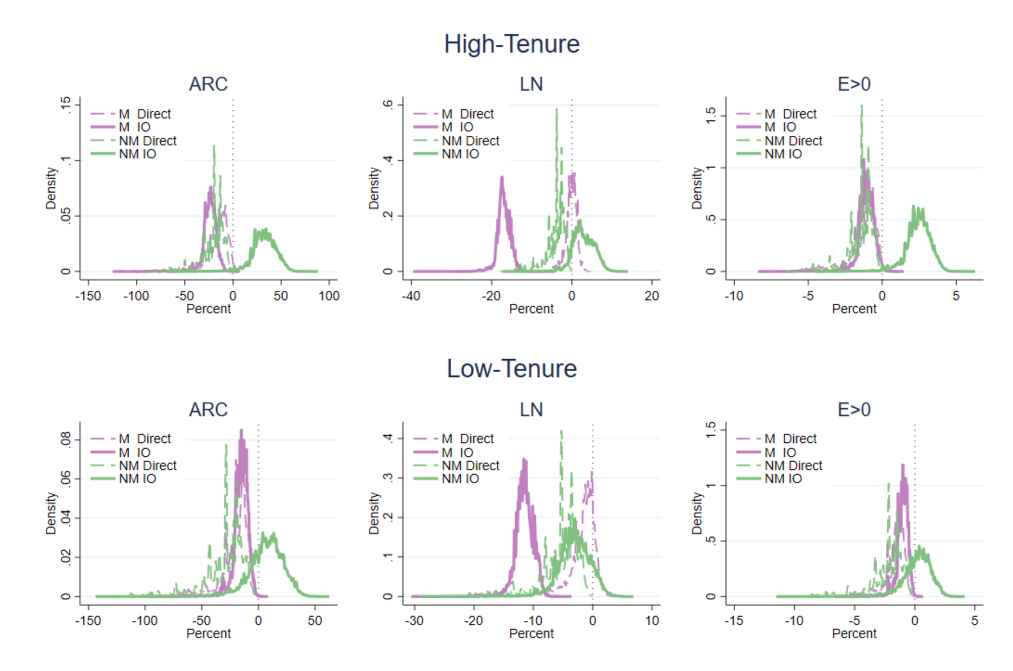
In Figure 8 we report the differences between predicted relative earnings growth under the "IO" versus "direct" specifications across all county-industry pairs in our 19 state sample using these alternate measures of county exposure.[49] Comparison of this figure with our baseline Figure 7 reveals that the results are qualitatively similar: it remains the case that the "direct" specification *underestimates*

[48] Regression results for low-tenure workers are reported in Appendix Tables A.5 and A.6.

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

the relative earnings losses among M workers, and *overestimates* the relative earnings loss of NM workers.

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



Source: LEHD, LBD, and authors' calculations. Figure displays the distributions of predicted relative earnings growth from the "direct and "IO" 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

All worker-level regressions reported in the paper are unweighted, meaning that each worker is treated equally in the regression, regardless of their earnings level. In reporting the economic significance of our baseline results we use the county-industry as a unit of analysis, and treat 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 9, using the same format of the previous two figures, reports the results of this exercise, by reporting the weighted distributions of predicted relative earnings growth from the "direct" and "IO" specifications across all county-industry pairs.[50] These distributions are less smooth than those above precisely because the number of workers varies across county-industry pairs. Even so, we obtain qualitatively similar results.

[50] 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 US 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 vary according to workers' demographic and firm characteristics.

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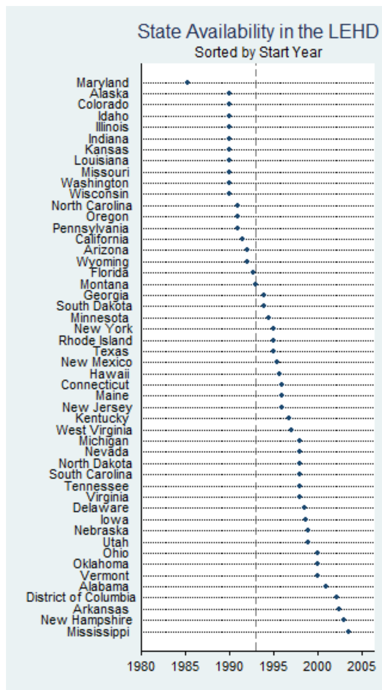
Online Appendix (Not for Publication)

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

A State Coverage in the LEHD

The set of states included in the LEHD varies over time as summarized in Figure A.1. We use the 46 states available as of 2000 in examining worker movement between M and NM sectors in Section 3, and the 19 states present from 1993 to 2014 for our regression analysis.

Figure A.1: State Availability in the LEHD



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

B Industry Variable Construction

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

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

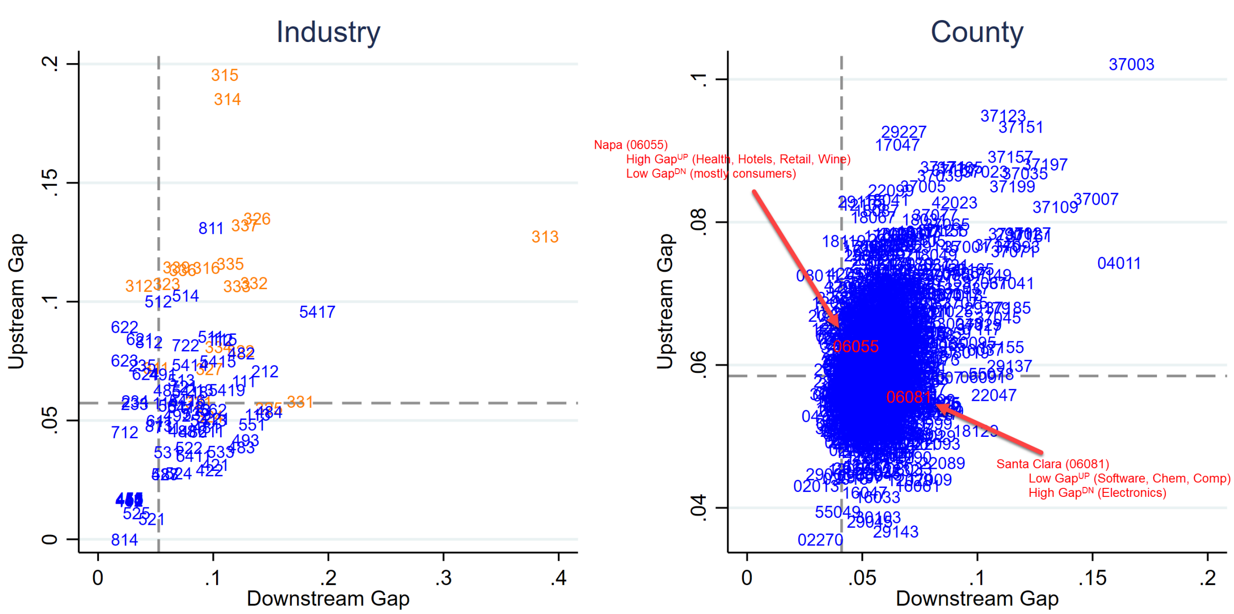
> The [MFA] and its successor, the Agreement on Textile and Clothing (ATC), grew out of quotas imposed by the United States on textile and clothing imports from Japan during

> the 1950s. Over time, it evolved into a broader institution that regulated the exports of clothing and textile products from developing countries to the United States, European Union, Canada and Turkey...Bargaining over these restrictions was kept separate from multilateral trade negotiations until the conclusion of the Uruguay Round in 1995, when an agreement was struck to eliminate the quotas over four phases. On January 1, 1995, 1998, 2002, and 2005, the United States was required to remove textile and clothing quotas representing 16, 17, 18 and the remaining 49 percent of their 1990 import volumes, respectively.

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

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

Figure A.2: Average Up- and Downstream Gaps

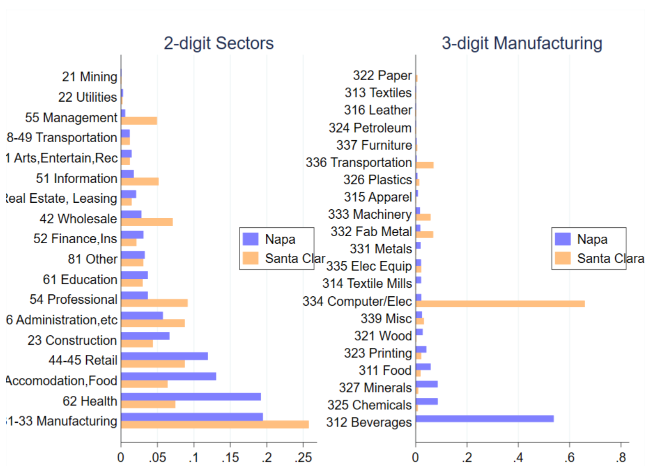


Source: CBP, BEA, Feenstra, Romalis, and Schott (2002), and authors' calculations. Left panel displays mean industry up- and downstream NTR gap, $Industry\ Gap_i^{up}$ and $Industry\ Gap_i^{down}$, across 3-digit NAICS sectors, except for 541, which is broken out by 4-digit sectors. Manufacturing industries are highlighted. Right panel reports up- and downstream gaps for each county in our 19 state regression sample, $County\ Gap_c^{up}$ 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: China instituted a number of policy changes as part of its accession to the WTO, and for which we control including reducing import tariff rates and production subsidies. As in Pierce and Schott (2016), we use product-level data on Chinese import tariffs from 1996 to 2005 from Brandt, Van Biesebroeck, Wang, and Zhang (2017) to compute industry-level changes in Chinese import tariffs. We use data from the Annual Report of Industrial Enterprise Statistics published by China's National Bureau of Statistics (NBS) as a measure of changes in production subsidies. We construct county-level measures of exposure to each of these policy changes using labor share weights and then interact these measures with an indicator for post-PNTR years. See Appendix D of Pierce and Schott (2020) for additional details.

Up- and Downstream NTR Gaps: The left panel of Figure A.2 reports the average up- and downstream NTR gaps by 3-digit NAICS industry, while the right panel of the figure reports the up- and downstream gap for all counties in our 19 state sample. Manufacturing sectors are highlighted in the left panel, while Napa and Santa Clara, California, 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 Computers and Electronics (NAICS 334). Within manufacturing, Napa is concentrated in production at Wineries (NAICS 312130).

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.

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. As indicated in the table, relative to nonmanufacturing workers, manufacturing workers are disproportionately male, somewhat less likely to be American-born, less likely to have completed college, a bit older, and have higher earnings, on average.

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 (2000) and Wage Growth (2000 to 2007) (Public BLS Data)

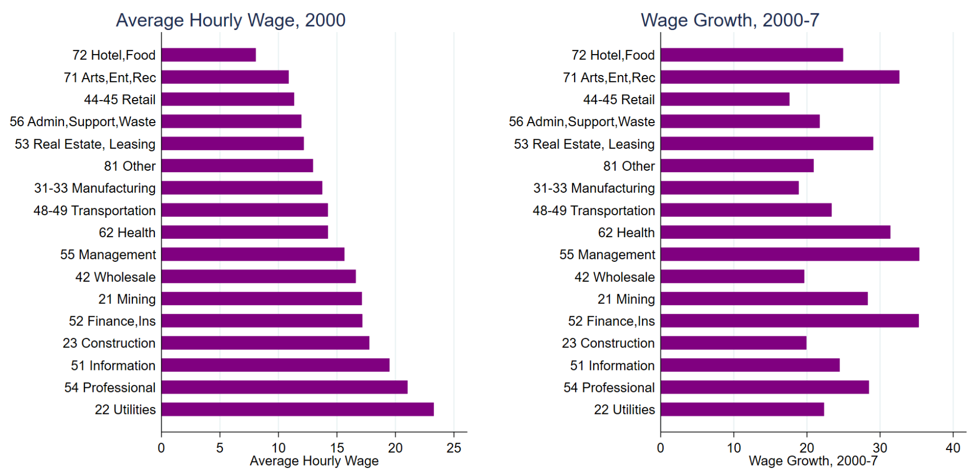
Using publicly available data from the US Bureau of Labor Statistics, Figure A.4 reports the average hourly wages as of 2000, of production and non-supervisory workers, as well as wage growth from 2000-2007, by major sector. As indicated in the figure, the average hourly wage for production and non-supervisors 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.

E Initial M Gross Outflows by PNTR Exposure

For completeness, Figure A.5 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.[51] The scatterplot on the right 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,

[51] Fifty-eight percent of all M workers in 2000 are still in that sector in 2007. The analogous shares for workers in counties with high and low exposure are 63 and 49 percent, respectively.

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.

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.

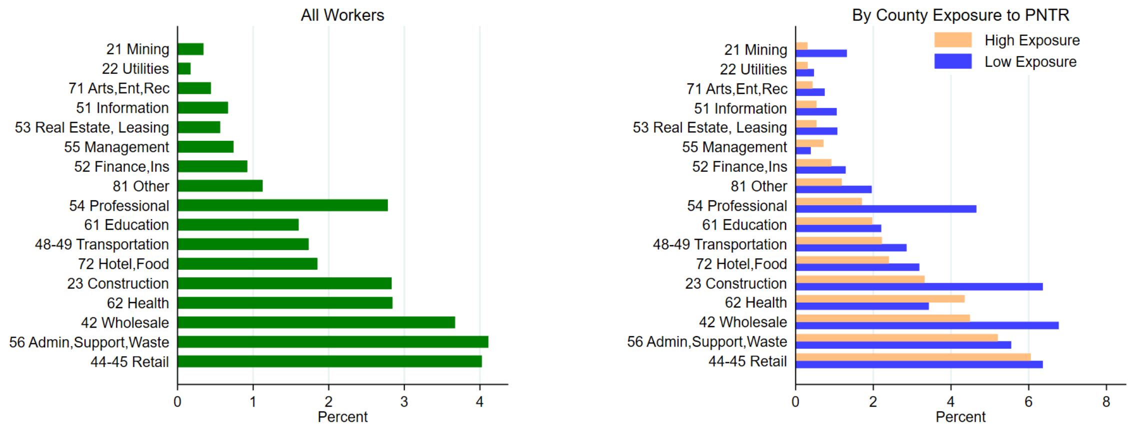
F Demographic Characteristics of Workers, by Sector

Figure A.6 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.

G 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 2011, as opposed to the results reported in Table 1 in the main text, for

Figure A.5: 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 reported in percentage terms, such that displayed percentages plus the share remaining in manufacturing (not displayed) add to 100. In the left panel, the shares match those reported in Table 2. In the right panel, these shares are computed separately for High and Low exposure counties.

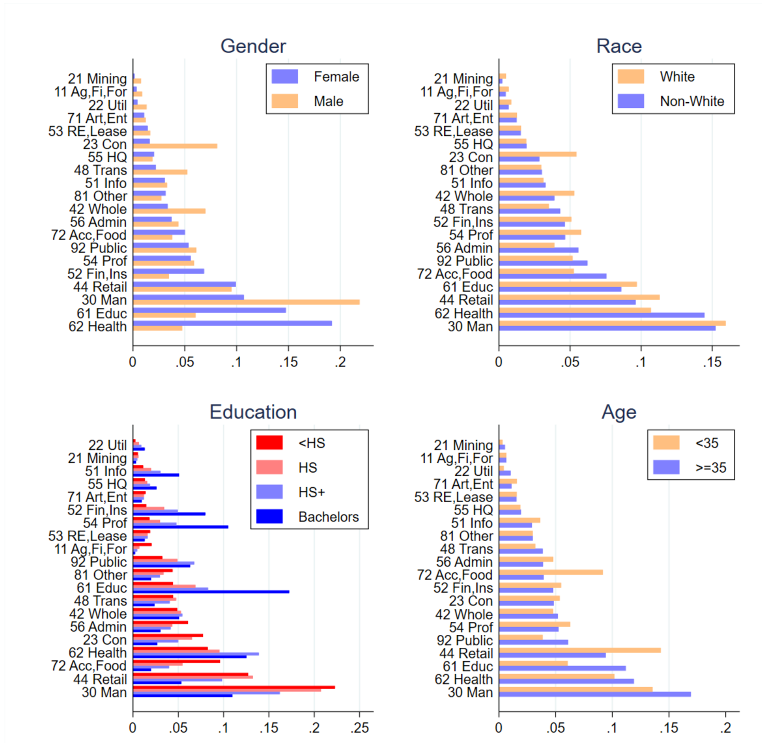
2000 to 2007. As in Table 1, the top and bottom panels report transitions in terms of millions of workers and percentages of initial levels, respectively. As indicated in the figure, gross flows out of initial sectors are lower for 2000 to 2005 than for 2000 to 2007, but substantially higher for 2000 to 2011 due to the intervening Great Recession. This is true when flows are measured in number of workers or as a share of the initial level.

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: Worker Demographics in 2000 (Public LEHD Data)



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

Table A.3 and Figure A.7 provide 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 outflows from manufacturing employment are 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, Accommodation 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)

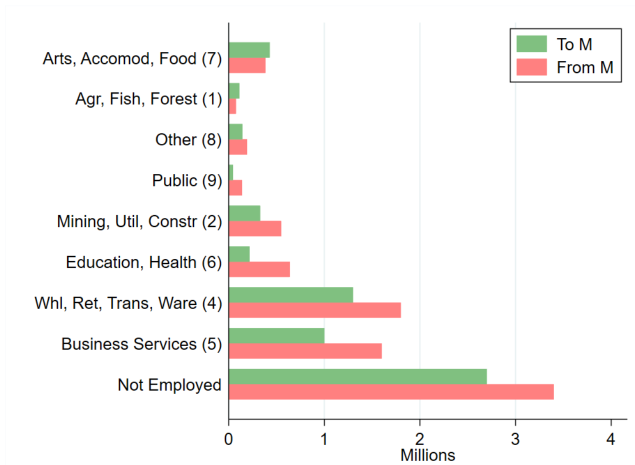
	Sector in 2005										Total in
Sector in 2000	1	2	3	4	5	6	7	8	9	NE	2000
Agriculture, Forestry, Fishing and Hunting(1)	0.57	0.09	0.11	0.13	0.11	0.05	0.06	0.02	0.01	0.62	1.79
Mining, Utilities, Construction (2)	0.04	5.43	0.33	0.59	0.83	0.30	0.21	0.11	0.18	2.49	10.49
Manufacturing (3)	0.08	0.55	8.94	1.78	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) to 2005 (column) by 1-digit NAICS sector (in parentheses) for the 46 states whose information is available in the LEHD starting in 2000. Alabama, Arkansas, New Hampshire and Mississippi as well as the District of Columbia are excluded. Upper panel reports levels in millions of workers. Lower panel reports shares of initial levels.

Figure A.7: Gross Flows Into and Out of M, 2000-5



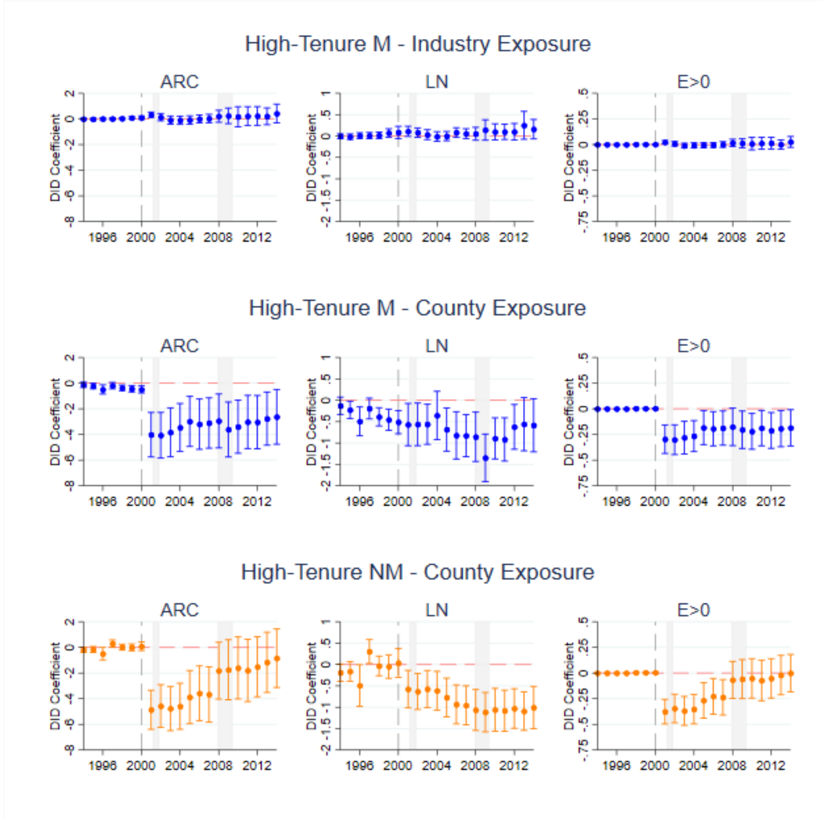
Source: LEHD, LBD and authors' calculations. Figure displays the grows inflows into and gross outflows out of manufacturing between 2000 and 2005, in millions, by 1-digit NAICS sector (noted in parentheses) other than the diagonal. The full transition matrix (including the diagonal) is reported in Appendix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

H Annual "Direct" Specification for High-Tenure Workers

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 A.8. 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.[52] 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.

[52] Note that E>0 is equal to one by definition in the pre-period, and industry switching is minimal given the requirement that workers be employed by the same firm from 1993 to 2000 to be included in the high-tenure sample.

Figure A.8: 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 A.8 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.

I 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, while not statistically significant, 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 Finnish-Soviet bilateral trade agreement.

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

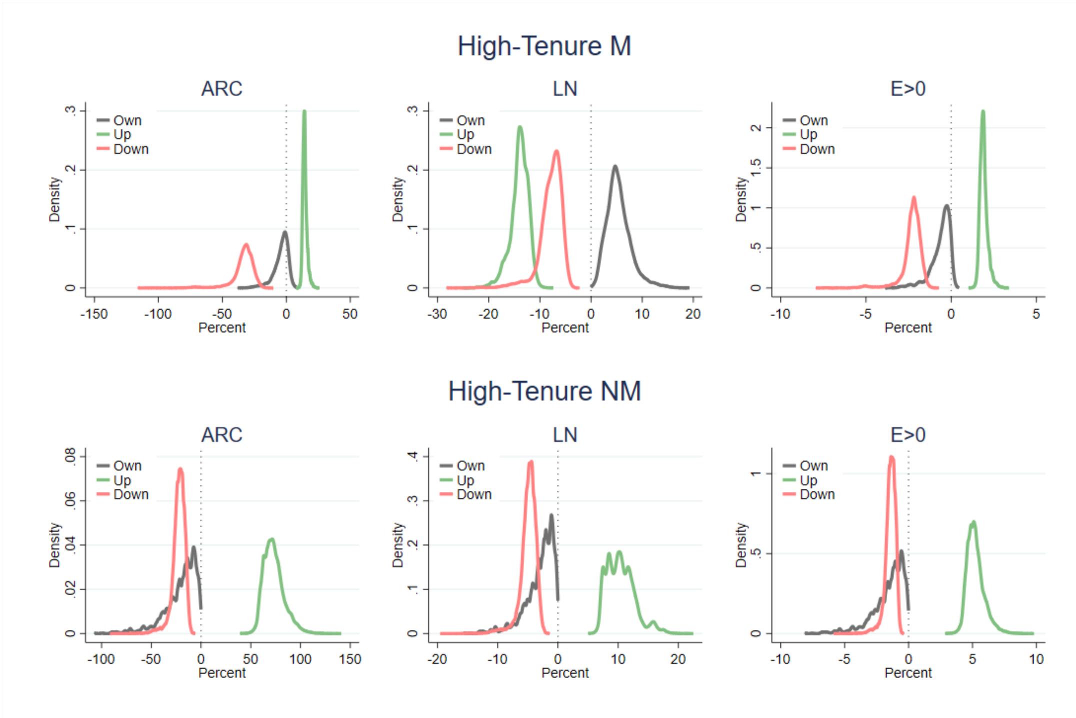
	High-Tenure M		
	ARC	LN	E>0
Post x Industry Gap	0.090	0.145	–0.001
	0.300	0.088	0.023
Post x County Gap	–3.334***	0.079	–0.285***
	1.134	0.332	0.091
Post x Industry Gap * County Gap	0.293	–1.189	0.103
	2.501	0.794	0.195
R-sq	0.439	0.558	0.408
Observations (000s)	1,520	1,378	1,520
Fixed Effects	j,f,t	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.

J Decomposition of "IO" Specification Predictions

Figure A.9 provides a breakdown of the county-industry relative earnings predictions for the "IO" specification reported in Figure 3 by the own, up- and downstream dimensions. Each distribution records the sums of the products of the "own" industry and county coefficients from Table 5 with their actual exposures. As indicated in the figure, the own and downstream portion of the relative earnings predictions lie below zero, and the upstream contributions lie above zero, except for the LN specification for high-tenure M workers.

Figure A.9: Breakdown of "IO" Specification County-Industry Predictions



Source: LEHD, LBD, and authors' calculations. Panels display the constituent components of the county-industry relative earnings predictions for noted groups of workers from noted specifications reported in Figure 3. Each distribution records the sums of the products of the noted industry and county coefficients from Table 5 with their actual exposures. See notes to Tables 4 and 5 for further description of the underlying regressions.

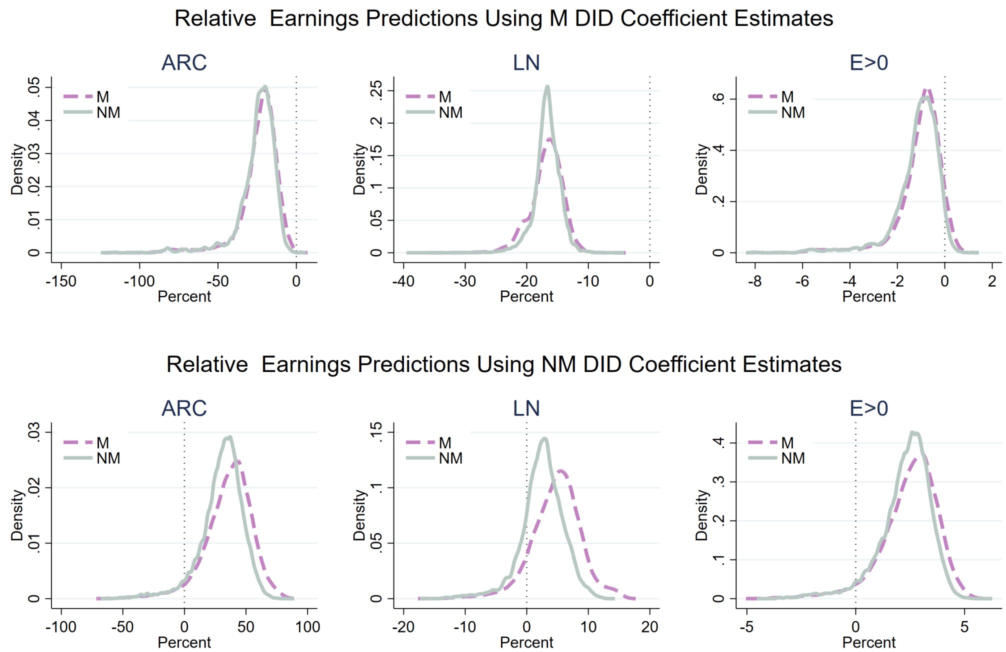
K Using M Estimates to Predict NM Outcomes, and *Vice Versa*

In this section we show that the relative county-industry earnings predictions for the "IO" specification (reported in Figure 3 of the main text) are due to the coefficient estimates and not the underlying relative exposures of M versus NM industries by computing alternate predictions for each group of workers using the DID coefficient estimates for the *other* group. Results are displayed in Figure A.10.[53] The top panel computes predictions for both groups of workers using the M coefficient estimates from Table 5. The lower panel computes them using the NM coefficient estimates. The top panel, therefore, repeats the results in Figure 3 for M workers, while the bottom panel duplicates them for NM workers.

As indicated in the Figure, actual and alternate distributions are very similar. In the top panel, they lie over one another almost exactly, while in the bottom panel, the alternate results for M workers lie slightly to the right of those for NM workers. These results suggest it is the earnings outcomes conditional on exposure that drive the coefficient estimates, consistent with the co-offshoring mechanism described in the main text.

[53] When using the M coefficient estimates to compute NM predictions, we assume own industry exposure is zero. M predictions using NM coefficient estimates do not account for M industries' own exposure, as there is no corresponding NM coefficient estimate.

Figure A.10: Alternate "IO" Relative Earnings Predictions



Source: LEHD, LBD, and authors' calculations. Figure displays county-industry "IO" specification relative earnings growth predictions for initial M and NM workers using the DID coefficient estimates from Table 5 for the *other* group of workers. The top panel uses M worker estimates, while the bottom panel employs NM worker estimates. 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.

L 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 A.6 contains estimates for "IO" specification. Results are very similar, qualitatively, to those for high-tenure workers presented in the main text.

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 (000s)	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.

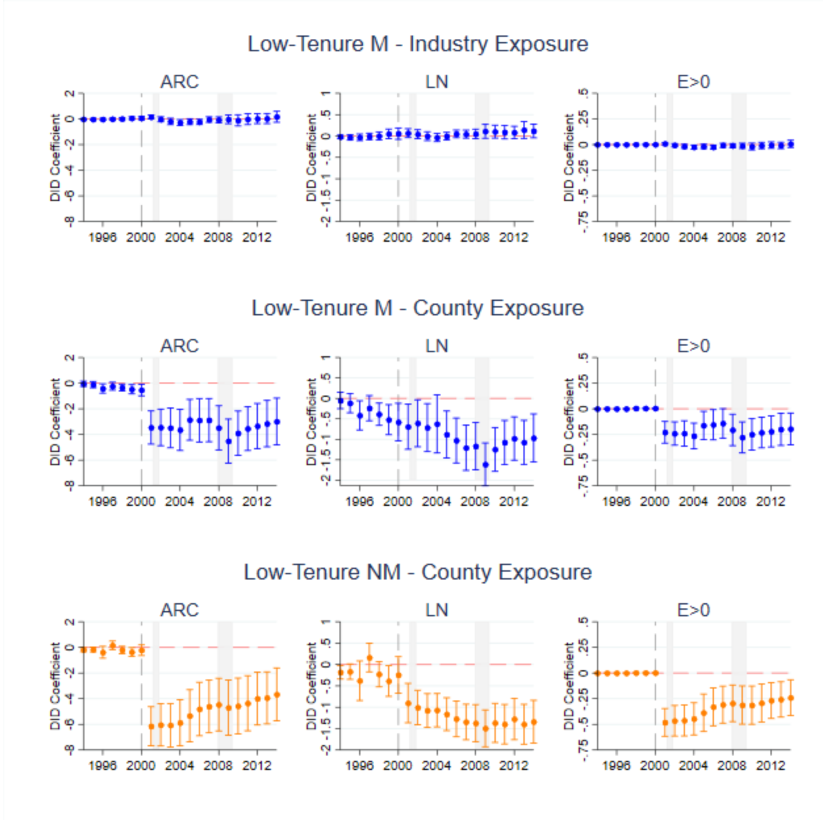
Table A.6: "IO" Specification for Low-Tenure Workers

	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 (000s)	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.11 replicates Figure A.8 for low-tenure M and NM workers.

Figure A.11: "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.

M 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, as 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 (000s)	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 (000s)	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 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.

N Results for Triple-Interaction Demographic Specifications

This section 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 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 transformations using the approach discussed in the main text. The last four columns report the share of county-industry predictions that are greater than 0, i.e., which exhibit relative income gains. The asterisks in this table correspond to the significance of the underlying triple interactions, 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 that also 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 A.13 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. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.13 reports F-statistics for the joint significance of these exposure terms, by group.

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. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.13 reports F-statistics for the joint significance of these exposure terms, by group.

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. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels. Table A.13 reports F-statistics for the joint significance of these exposure terms, by group.

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.