Moving Costs and Worker Adjustment to Changes in Labor Demand: Evidence from Longitudinal Census Data

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Abstract

Real wage growth for non-college educated workers varied greatly across US local labor markets during the 2000s. This paper investigates the extent to which this variation in local wage growth reflects workers' incomplete arbitrage of job opportunities in different locations, industries, and occupations. I combine novel data linking individuals between the 2000 Census and the 2010-2014 American Community Survey with labor demand shocks from exposure to trade with China and hydraulic fracturing. Without moving costs, worker adjustment to these shocks would eliminate differential earnings effects between directly exposed workers and others in the same skill group. I find evidence against the full-mobility benchmark, estimating that exposure to trade with China reduces earnings of incumbent workers in exposed Commuting Zones (CZs) by 4%, and fracking increases earnings of incumbent workers in exposed CZs by 7%. I estimate a model of location, sector, and occupation choice to quantify the costs that rationalize this incomplete arbitrage and find average moving costs of several times annual income for changing labor markets, sectors, and occupations. Halving these moving costs would have reduced the local effect of exposure to trade with China by 35%, underscoring the role that immobility plays in the earnings difficulties of the non-college educated.

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1 Introduction

Since 2000, median weekly real wages for full-time, non-college educated workers have declined by roughly 3%. As shown in Figure 1, this decline has varied greatly across different local US labor markets, with real wages for non-college educated workers rising by over 10% in the best performing labor markets, and declining by more than 7% in the worst performing labor markets. Workers facing shocks to local labor demand may have to change location, occupation, industry, or all three to take advantage of new wage opportunities or avoid wage losses. In canonical labor market models (Rosen (1979), Roback (1982)), workers would make these moves across locations, occupations, and industries until utility was equalized across space and job-types. In such models, measured differences in real wage changes across different labor markets would reflect mismeasurement of the true change in wages per efficiency unit of labor. Such mismeasurement could be due to changes in labor force composition, direct scarring effects of negative demand shocks on exposed workers, or changes to local or job amenities. But, alternatively, workers may face substantial moving costs across locations, occupations, or sectors that are assumed away by these models. These moving costs may prevent workers from arbitraging these wage opportunities, leading to divergence in real outcomes across workers by their original location, sector, or occupation (Topel (1986), Moretti (2010a)).

In this paper, I investigate the quantitative importance of moving costs across locations, sectors and occupations in the adjustment of less-educated workers to changes in labor demand during the 2000s. I leverage novel data linking individuals across the 2000 Census and the 2010-2014 American Community Survey (ACS), allowing me to track people based on their original location, occupation, and industry, while also providing detailed information regarding workers' education and demographics. These unique data allow me to construct constant cohorts of workers within narrow demographic and skill-groups, avoiding compositional biases that confound cross-sectional analyses. I combine these data with quasi-experimental variation in labor demand from changes in trade policy with China and the development of hydraulic fracturing, isolating changes in wages due to shifts in local labor demand rather than labor supply (such as might result from changes in local amenities or local tax rates faced by workers).

In the absence of moving costs, workers switch locations and jobs until utility is equalized across space, industry, and occupation within skill-group (Rosen (1979) and Roback (1982)). In this view[1], changes in labor demand across locations, industries, and occupations during the 2000s would have translated into nationwide declines in outcomes for non-college educated workers rather than concentrated losses for workers originally in particular locations, industries, or occupations. In practice, workers may fail to arbitrage wage opportunities in different locations or sectors because of pecuniary costs of changing locations, occupations, or industries, such as the cost of renting a truck and taking time off of work or retraining costs in learning new skills, non-pecuniary costs

[1] See e.g. Autor et al. (2016) for a discussion.

because of attachments to family or friends or idiosyncratic preferences for local amenities or job characteristics, or frictions such as liquidity constraints, search costs, or limited information. In the presence of these moving costs, some workers may bear the incidence of labor demand shocks to particular locations, industries, or occupations (Topel (1986), Moretti (2010b)).

I find evidence of the existence of barriers to mobility inhibiting labor market adjustment among workers living in Commuting-Zones (CZs) more exposed to trade with China. I construct a CZ measure of exposure to trade with China using the reduction in uncertainty regarding potential tariffs resulting from the US granting China Permanent Normal Trade Relations (PNTR), which reduced manufacturing employment in particular industries (Pierce and Schott (2016), Handley and Limao (2017)). More exposed CZs experience large declines in manufacturing employment. Non-college educated workers originally living in labor markets at the 75th percentile of CZ exposure to PNTR with China saw their earnings decline by 4.4% relative to demographically similar workers at the 25th percentile of CZ exposure to PNTR with China. These losses are similar for workers originally working inside and outside manufacturing, suggesting that worker losses are not primarily driven by loss of industry specific capital or rents but rather by location-wide declines in labor demand for particular skills.[2] This interpretation is supported by my finding that the earnings declines are higher for non-college educated workers originally working in brawn-intensive occupations, i.e. those requiring high amounts of physical strength and dexterity, which were the occupations that had the largest drop in employment. Despite the large drop in local employment and wages, out-migration rises only .4 percentage points.[3]

One concern with these estimates is that they may reflect idiosyncratic features of manufacturing shocks or direct effects of negative shocks rather than barriers to changing locations or occupations. For example, negative local labor demand shocks may cause drops in local wealth that reduce migration or may cause direct scarring from unemployment. Alternatively, workers originally in manufacturing may lose industry-specific human capital.[4] I address these concerns by also studying fracking, a positive labor demand shock to non-college educated workers.

Fracking has led to large increases in employment of non-college educated workers in exposed areas, resulting in an earnings rise of 6.7% for the original residents relative to demographically similar workers within the same region. As in the case of exposure to PNTR with China, these gains are spread throughout a number of sectors, but are concentrated amongst non-college educated workers originally working in manual intensive occupations. Despite these large increases in potential earnings, out-migration declines at most 2.6 percent and in-migration rises by at most 0.5 percentage points.

Combined, these two sets of findings suggest that there are moving costs making it difficult for workers to

[2] However, this is only suggestive evidence, because there may be direct effects on employment in construction, transportation, and other industries through input-output matrices and aggregate demand spillovers. Consequently, workers outside of manufacturing may lose their jobs and lose industry-specific human capital. A full investigation of this will require the use of input-output tables to measure exposure to the shock, rather than just whether an individual is in manufacturing.

[3] Out-migration rates would not need to change a lot for the incidence of the shock to not be borne by the original residents if gross migration rates were sufficiently high or in-migration rates sufficiently high.

[4] Although, my finding that workers originally outside of manufacturing experience earnings losses suggests that industry specific human capital is unlikely to be the entire explanation.

move across locations and occupation and allow us to put a lower bound on these moving costs of at least $16,000 for changing locations, $11,000 for changing occupations, and $1,230 for changing sectors. These reduced form patterns motivate a discrete choice model of worker location, sector, and occupation choice that allows estimates of the distribution of moving costs and computation of counterfactual choices. My preferred estimates imply that non-college educated men ages 25-30 face moving costs to an arbitrary alternative of over $600,000 for moving locations, and around $150,000 for moving sectors or occupations. These costs grow steadily with age, rising 60% by ages 45-50. Location moving costs are almost 40% higher for longer-term residents, consistent with social ties being an important driver of location moving costs. I use this model to simulate how lower moving costs would have changed the incidence of exposure to PNTR with China. I find that halving all moving costs would have reduced the effects of exposure to PNTR with China by 35%. However, $10,000 relocation subsidies - similar to the size of proposed policies- would have a negligible impact.[5]

This paper makes three contributions to the literature. First, I provide additional evidence against the null of no moving costs across locations and industries, supporting evidence from Autor et al. (2014) and Walker (2013), who find that negative shocks to workers' industries have substantial effects on exposed workers, and Yagan (2014) and Yagan (2016) who finds that the original residents bore much of the incidence of the Great Recession, using different sources of variation and different data. My findings strengthen this literature's conclusions by also rejecting the zero-moving costs benchmark for a positive local demand shock.[6] This rules out the possibility that the observed patterns are driven mostly by direct scarring from job-displacement, industry specific human capital, or other features of negative shocks.[7]

Second, I take advantage of unique panel data on occupations to explore the role that occupation moving costs play in the adjustment to changes in local labor demand. I find that workers' original occupation matters: workers in more manual-intensive occupations gain the most from fracking and lose the most from PNTR with China, even when those workers are not working in directly affected industries. Conversely, workers' original sector matters less. Despite the fact that job losses from PNTR with China are concentrated primarily in manufacturing, earnings losses are similar for workers both inside and outside manufacturing.[8] Furthermore, even though fracking

[5]For example, Ludwig and Raphael (2010) propose a "mobility-bank", which would provide $10,000 income-contingent loans to individuals who move to better labor markets. Moretti (2013) proposed modifying unemployment insurance to encourage workers to move to better labor markets.

[6]Research in Germany (Dauth et al. (2014)) and Brazil (Dix-Carneiro and Kovak (2015)) also finds substantial effects of geographic trade shocks on the original residents of exposed locations. In related work, the displaced workers literature has found substantial effects of firm shocks on the outcomes of exposed workers. For example, see Ruhm (1991) and Jacobson et al. (1993)

[7]Yagan (2014), Yagan (2016) is the most closely related work to this paper, so the relationship between his and my findings bears greater discussion. He exploits longitudinal tax data to study the incidence of the Great Recession and finds that originally living in a CZ that experienced a larger downturn has large effects on workers' employment rates and earnings. My paper shows that long-term shocks generate similarly large effects on the original residents. However, my study differs from Yagan in several respects. First, by studying a positive as well as a negative shock, I can rule out that my results are driven by direct scarring from job displacement, industry specific human capital, or other features of negative shocks. Second, I focus on two shocks that workers would likely expect to have permanent effect on local communities. Consequently, we might expect mobility to play a larger role in response to these shocks than business cycle fluctuations that workers may expect to be transient. Third, I take advantage of unique data on occupations, education, and demographics to explore the role that worker skills, occupation-specific human capital and occupational moving costs play in the adjustment to changes in local labor demand.

[8]These findings are consistent with the findings in Müller et al. (2015), who study the effects of local industry mix on the effects of worker industry-level exposure to PNTR with China using German employer-employee data. They first estimate measures of

job gains are concentrated in industries such as oil and gas, earnings gains in fracking-exposed areas are similar for workers both inside and outside the oil and gas industry.

Third, I estimate a structural model of worker job-choice that incorporates location, sector, and occupation moving costs. This differs from the existing structural literature, which has focused on estimating one type of moving costs, ignoring others. Bayer et al. (2009), Kennan and Walker (2011), and Bishop (2012) estimate location moving costs, Diamond (2016) estimates costs for moving away from the state of birth, Artuç et al. (2010) and Dix-Carneiro (2014) estimate sector moving costs, and Artuç and McLaren (2015), and Traiberman (2015) estimate sector and occupation moving costs. However, when there are different distributions of industries and occupations across space, geographic moving costs and sector or occupation moving costs interact: individuals may have to change industries to move locations and vice-versa. Consequently, a full picture of the relative role of moving costs in worker adjustment requires consideration of location, sector, and occupation moving costs simultaneously. I find substantial moving costs across locations, sectors, and occupations, even when the other types of costs are incorporated, highlighting the importance of both types of moving costs in the incidence of local labor demand shocks.

More broadly, this paper is related to a number of other literatures. A large literature has investigated the effects of local labor demand shocks and worker migration responses, in part to test whether the utility-equalization assumptions of spatial-equilibrium models are borne out in practice. In the US, this literature has documented significant population responses to changes in local wages (Topel (1986), Bartik (1991), Blanchard and Katz (1992), Moretti (2010b)). Blanchard and Katz (1992) find that negative shocks to local employment result in elevated unemployment and reduced wages, but that declines in net-migration lead unemployment rates and wages to converge in five-to-seven years and ten years respectively, which has often been interpreted as lending support to the view that, at least in the medium run, migration equalizes worker utility across space. Subsequent research has investigated the role of migration in local labor markets, including differential migration rates by different types of workers (Bound and Holzer (2000), Malamud and Wozniak (2012), Cadena and Kovak (2016)), the relative importance of in-migration compared to out-migration (Monras (2015)), and the influence of asymmetric housing price responses to negative and positive demand shocks (Glaeser and Gyourko (2005) and Notowidigdo (2011)).

A related literature studies the effects of particular shocks to local labor demand, including environmental regulations (Greenstone (2002)), natural resource booms (Carrington (1996), Black et al. (2005), Allcott and

the "closeness" of different sectors to manufacturing based on the transition probabilities of workers displaced from manufacturing. They then construct a measure of "labor-market flexibility" based on local industry-mix that measures how plentiful jobs "close" to manufacturing are in different labor markets. They find that workers exposed to industry-level trade shocks experience smaller earnings losses in labor markets with more "labor-market flexibility." They interpret this evidence as consistent with manufacturing workers having occupation specific human capital in certain types of jobs. This evidence is consistent with my finding that the effects of both fracking and PNTR with China are concentrated among workers originally in high-brawn occupations. Interestingly, Müller et al. (2015) find that the oil and gas sector is one of the "closest" to manufacturing, which is consistent with my finding that the benefits of fracking shocks are particularly high amongst workers originally in manufacturing. However, this interpretation is somewhat muddied by the fact that fracking also has direct effects on manufacturing firms through local input-output linkages.

Keniston (2014)), trade (Topalova (2010), Kovak (2013), Autor et al. (2013), and Hakobyan and McLaren (2016)), and technological change (Autor et al. (2015), Acemoglu and Restrepo (2017)). However, given the potential for selective in-migration and out-migration, these results for the cross-sectional effects of local demand shocks are consistent with positive, negative, or zero long-run impacts on the original residents, and do not necessarily provide evidence for or against utility equalization across space.

This paper also contributes to the recent literature on local labor markets, which has incorporated moving costs in estimating the incidence of place-based policies (Busso et al. (2013), Kline and Moretti (2014)), corporate taxes (Zidar and Suraez-Serrato (2014)), and government spending (Suárez Serrato and Wingender (2011)). My finding that changes to local labor demand have substantial effects on the earnings of original residents highlights the importance of incorporating moving costs. However, my findings that the effects on earnings of contemporaneous residents differ from the original residents does suggest caution in using effects on local wages to infer the effects on the original residents.

Finally, my findings that the effects of both shocks are concentrated amongst workers originally in the most affected occupations rather than industries is consistent with an important role for occupation or task-specific human capital, adding further evidence to a large literature on industry, occupation, and task-specific human capital (Shaw (1984), Shaw (1987), Neal (1995), Gibbons and Waldman (2004), Kambourov and Manovskii (2009), Gathmann (2010)).[9]

This paper proceeds as follows. In the next section, I present a conceptual framework for thinking about how adjustment costs affect the responsiveness of workers to changes in labor demand in particular locations, sectors, and occupations. This conceptual framework highlights the importance of data linking individuals across time, and in Section 3 I introduce the novel census data that I exploit for this purpose. Section 4 introduces my two sources of variation in labor demand for less educated workers and explains my empirical strategy. In Section 5, I present reduced form results testing for moving cost in worker adjustment to China being granted PNTR and the advent of fracking. Section 6 presents back of the envelope bounds of moving costs and introduces a model of worker choice of location, sector, and occupation, while Section 7 presents the estimates and uses them to simulate the effects of reducing moving costs on the incidence of exposure to PNTR with China. Section 8 concludes.

2 Conceptual Framework

How do changes in productivity in a particular sector and labor market affect different types of workers? In canonical spatial equilibrium models (Rosen (1979), Roback (1982)), workers will migrate across locations (and

[9]However, it must be noted that these findings are also consistent with workers selecting into occupations prior to the shock based on their skill endowments. In this case, workers in more manual intensive occupations could be negatively impacted even if there were no occupational moving costs or specific human capital that workers learned over time.

sectors) until real wages are equalized. Negative (positive) labor demand shocks will result in nationwide declines (increases) in the wages of particular skill-groups, but, within skill-groups, will not cause heterogeneous effects on workers based on their original locations, sectors, or occupations. Topel (1986) and, more recently, Moretti (2010b) highlight that moving costs alter this prediction, leading to heterogeneous incidence of local labor demand shocks on directly exposed workers. In this section, I discuss types of moving costs workers may face in changing locations, occupations, or sectors, present a conceptual framework that illustrates the role these moving costs play in the incidence of local labor demand shocks, and discuss challenges in empirically investigating the role of moving costs.

2.1 Sources of moving costs

Location moving costs There are three main classes of location moving costs. First, there are the pecuniary costs of moving. These include the direct costs of renting a truck, opportunity cost of spending time moving, and costs of getting established in a new location. Second, moving entails non-pecuniary costs of living farther from family, friends, and other social ties and adjusting to a new setting. Descriptive statistics suggest these costs may be substantial: 73% of non-college educated workers lived in their state of birth in 2010.[10] Third, location moving costs may include market failures, such as lack of information or liquidity constraints, and behavioral biases, such as aversion to change.[11] This third category differs substantively from the first two because because it suggests there may be welfare gains from inducing people to move. Conversely, moving costs driven by the first two sources are "true costs" that must be paid when workers move. For example, subsidizing someone to move when they get significantly greater consumption value from their original location may yield small (or no) welfare gains.

Sector or occupation moving costs Drivers of sector and occupation moving costs can be classified into the same three categories. First, there are pecuniary costs of retraining and acquiring skills necessary for the new job. These costs could take the form of direct costs of retraining - i.e. if I have to pay to take a class - and indirect costs through receiving lower wages while new skills are acquired on the job.[12] These costs may also include licensing or certification processes required for many jobs. Anecdotal evidence suggests that these costs may be large. For example, Carpenter et al. (2012) collected evidence on occupational licensing requirements for entering all 102 low and middle-wage occupations that require occupational licenses in at least one state. They found that

[10] Workers may also have persistent, unobserved preference heterogeneity for the characteristics of ones' original location. In a two-location model, this will yield similar predictions to large moving costs. However, when there are many locations persistent, unobserved preference heterogeneity may imply different substitution patterns than moving costs.

[11] For example, in an online experiment Levitt (2016) provides suggestive evidence that individuals who are randomly encouraged to make significant life changes experience sizable gains in self-reported well-being, including quitting ones job. However, it must be noted that his experiment has no first-stage on the decision to move and so the results may not necessarily translate to location decisions.

[12] Note that if workers have comparative advantage in their original sector or there is a worker-firm-specific match component, then this will observationally show up as moving costs as well.

obtaining a license in the average occupation required 9 months of training, passing one exam, and $209 in fees. Additional pecuniary costs may include time and monetary costs of searching and applying for jobs. Second, there may be non-pecuniary costs of changing sectors or occupations, such as hassle costs of changing employers or physical place of work, altering routines to meet new work hours, and adjusting to a new work environment or culture. Third, their may be market failures - such as lack of information about new jobs or liquidity constraints - that prevent people from taking advantage of job opportunities in different occupations or sectors.

2.2 Setup

I illustrate the role played by location or occupation/sector moving costs in the effects of local labor demand shocks using a model of an economy with two locations, 1 and 2, and two sectors, A and B.[13] This model builds on the canonical Roback model (Roback (1982)) by incorporating individual heterogeneity in preferences over locations as in Kline (2010) and Moretti (2010a). This model closely follows the setup of Kline (2010) and Moretti (2010a), with the main difference being the incorporation of sector moving costs in addition to location moving costs.[14]

Worker i has indirect utility over locations l and sectors j given by:

$$v_{ilj} = \ln w_{lj} - \beta \ln r_l + \epsilon_{ilj} \tag{2.1}$$

Where w_{lj} are wages, r_l are rents, β is the share of income spent on housing, and ϵ_{ilj} captures moving costs, which I model as a function of the workers' original location, l_0, and sector, j_0:

$$\epsilon_{ilj} = -s^L c_i^L \times 1(l \neq l_0) - s^J c_i^J \times 1(j \neq j_0) \tag{2.2}$$

Where c_i^L and c_i^J are idiosyncratic moving cost draws that vary across individuals and s^L and s^J measure the importance of these draws.[15] In the limit, when s^L and $s^J = 0$, moving costs are 0 for all workers and we have the canonical Roback case. If s^L and s^J are both infinite, workers are completely immobile.

Workers choose locations and sectors to maximize their utility, i.e. they solve

$$\max_{l,j} v_{ilj} = \ln w_{lj} - \beta \ln r_l - s^L c_i^L \times 1(l \neq l_0) - s^J c_i^J \times 1(j \neq j_0) \tag{2.3}$$

Let c_i^L and c_i^J have some joint-distribution F. Then labor supply to each location/sector will depend on the

[13] Note that for simplicity I will refer to "sectors" but I could also have used occupations or industries. The important point is that A and B capture some feature segments labor markets within locations.

[14] I omit complications that arise from amenities, the existence of many locations and sectors, as well as idiosyncratic match-shocks that would make gross migration higher than net-migration. The structural model presented in Section 6.3 relaxes these assumptions.

[15] Below, I will assume that c_i^L and c_i^J have independent exponential distributions. In this case, s^L and s^J will be both the mean and the standard deviation of the moving cost distribution.

vector of wages and rents, on the number of workers originally in each location and sector, N_{l_0,j_0}, and on function G, related to F, that assigns probabilities of choosing each location sector:

$$LS_{l,j}(\mathbf{w},\mathbf{r}) = \sum_{l_0,j_0} N_{l_0,j_o} G(F(s^L, s^J), \mathbf{w}, \mathbf{r}) \tag{2.4}$$

Let σ_{lj} be the inverse labor-demand elasticity, and $\alpha_{l,j}$ be a labor productivity shifter in location l, sector j. Inverse-labor demand in a given location-sector is then given by:

$$w_{lj} = \alpha_{lj} LD_{lj}^{-\sigma_{lj}} \tag{2.5}$$

Let κ_l be the inverse housing-supply elasticity, and γ_l be a housing productivity shifter in location l. Inverse-housing supply in a given location-sector is then given by:

$$r_l = \gamma_l HS_l^{-\kappa_l} \tag{2.6}$$

In spatial equilibrium, housing and labor markets will clear:

$$LD_{l,j}(w_{lj}) = LS_{l,j}(\mathbf{w},\mathbf{r}) \quad \forall l, j \tag{2.7}$$

$$HS_l(r_j) = \sum_j LS_{l,j}(\mathbf{w},\mathbf{r}) \quad \forall l \tag{2.8}$$

2.3 Effects of productivity shock

I now use this setup to study how a negative shock to labor demand in location 1, sector A affects worker outcomes and how these impacts depend on moving costs.[16]. I model productivity changes as a decline in α_{1A} by Δ.[17]. I assume that c_i^L and c_i^S are independent and distributed exponentially. For positive location and sector moving costs, i.e. $s^L > 0$ and $s^J > 0$, there are not always analytical solutions for equilibrium wages. Instead, I simulate the equilibrium wages and location choices after a change in location 1, sector A productivity of Δ, and show how they vary with the magnitude of moving costs as measured by s^L and s^J. In these simulations, I make the simplifying assumptions that housing is supplied perfect elastically at a rental price of $r_1 = r_2 = r$, and that time 0 wages, population, and production function parameters are the same in all locations and sectors.[18]

The results of these simulations of the relationship between moving costs and worker location switching, sector switching, and wage changes are presented in Figures 3, 4, and 5. Figure 3 shows how these outcomes vary by

[16] A positive shock has symmetric effects in this model.

[17] Alternatively, it could reflect a decline in the national price of the tradable good produced in the sector, which could be driven by changes in trade policy or commodity prices.

[18] Specifically, I study the effects of a 25% reduction in productivity in Location 1, Sector A, assuming that their are 5000 individuals in each location/sector at baseline and that labor demand elasticities are $-.145$. Moving cost parameters s_L and s_J are shown in units of wages. For example, $s_L = .5$ means that average location moving costs are approximately 50% of average wages.

location moving costs when there are no sector moving costs. Figure 4 shows how these outcomes vary by sector moving costs when there are no location moving costs. Finally, Figure 5 shows how these outcomes vary by location moving costs when there are moderate sector moving costs. Average outcomes are reported separately by workers' original locations and sectors.[19,20] Four special cases help illustrate the roles played by these moving costs in the incidence of labor demand shocks:

Case 1, No-moving Costs ($s^L = s^J = 0$): All workers affected equally This case is shown at the far left of the x-axis of Figure 3. With no-moving costs, all workers choose the location-sector with the highest wage[21]. Workers move out of location 1, sector A into the other three location/sectors and some workers move out of location 1, sector B into location 2 until wages are equalized. The result is that wages drop by a common amount for all workers, regardless of their original location or sector.

Case 2, Location Moving Costs Only ($s^L > 0, s^J = 0$): Heterogeneous impacts by original location This case is shown in Figure 3, which plots how worker migration and wage outcomes change with location moving costs, with sector moving costs fixed at $s^J = 0$. With no costs to changing sectors, workers switch sectors until wages are equalized in sectors A and B. However, positive location moving costs mean that the marginal worker from Location 1 is willing to accept lower wages to avoid paying moving costs, leading wages to decline by more in Location 1 than Location 2, resulting in declines in average wages for workers originally in Location 1 compared to Location 2. To see this analytically, take the simple case where location 2 has perfectly elastic labor demand, so $\ln w_2$ is unaffected by the shock. Let $\Delta \bar{\ln y}_{j_0}$ be the average change in wages for workers living in location j at time 0. The difference in the average change in outcomes between workers originally in Location 1 and 2 can be written as:

$$\begin{aligned}\Delta \bar{ln y}_{1_0} - \Delta \bar{ln y}_{2_0} = \quad & (1-\mu_{1,1_0})\Delta \ln w_2 + \mu_{1,1_0}\Delta \ln w_1 - \Delta \ln w_2 \\ = \quad & \underbrace{\exp\left[\frac{\Delta \ln \alpha_{A,1}}{2s^L+\sigma}\right]}_{\text{share of workers staying}} \times \underbrace{\left(\Delta \ln \alpha_{A,1} \frac{s^L}{2s^L+\sigma}\right)}_{\Delta\text{change in wages per efficiency unit}}\end{aligned} \tag{2.9}$$

This expression illustrates the two-channels through which higher moving costs lead to larger losses for workers originally in Location 1 relative to other workers. First, the higher moving costs, the fewer workers move into Location 2 and take advantage of the higher wages. Second, the higher are moving costs, the larger is the effect on wages in Location 1 (recall that $\Delta \ln_{A,1}$ is negative). In the extreme case when location moving costs are infinite, Location 2 will be unaffected and workers originally in Location 1 will all experience earnings declines of

[19] These figures plot outcomes against the mean moving costs, s^L or s^J, but that the moving costs for any individual will depend on their draw c_i^J and c_i^L.

[20] Note that because of the properties of the exponential distribution, s^L and s^J are both the mean and standard deviation of the distribution and consequently both average moving costs and the dispersion of moving costs are increasing in s^L and s^J.

[21] Because housing is supplied perfectly elastically in both locations at a price of $r_1 = r_2 = \bar{r}$, I omit discussion of housing prices for now. My full structural model allows for changes in housing prices.

$\frac{\Delta \ln \alpha_{A,1}}{2}$, or half the decline in productivity.[22]

Case 3, Sector (Occupation) Moving Costs Only ($s^L = 0, s^J > 0$): Heterogeneous impacts by original sector This case is shown in Figure 4, which plots the relationship between sector moving costs and labor market outcomes when location moving costs are 0. Because location moving costs are zero, real wages must be equalized within sectors across locations. However, positive sector moving costs mean that the marginal worker moving from sector A to sector B is willing to accept lower wages in sector A to avoid paying moving costs. Consequently, in this case the incidence of the shock does not depend on original location, but rather on original sector. An analogous expression to Equation 2.9 also holds, showing that moving costs increase the effect of the shock on workers in the shocked sector both by reducing out-migration, but also by increasing the negative impact on wages in the shocked sector.

Case 4, Sector (Occupation) and Location Moving Costs ($s^L > 0, s^J > 0$): Heterogeneous impacts by original location-sector This case is illustrated in Figure 5, which shows the relationship between average location moving costs and worker outcomes when $s^J = .75$. Panel C shows that when both location and sector moving costs are positive, the drop in labor demand in Location 1, Sector A has different effects on wages for workers in each original location/sector cell. The relative magnitudes of these impacts depends on the relative magnitude of location and sector moving costs, as well as the elasticity of labor demand.[23] Starting on the left of the figure, where location moving costs are low, we see that the shock mostly impacts workers originally in Sector A. As moving costs increase, the effects on wages for workers originally in Location 2, Sector A fall, and the effects on workers originally in Location 1 rise in both sectors. Panels A and B illustrate why this pattern emerges. As location moving costs rise, workers originally in Location 1, and Sector A are less likely to change locations (raising wages in Location 2, Sector A), and more likely to change sectors within the same location (reducing wages in Location 1, Sector B).

Returning to Panel C, as location moving costs rise, the negative effects of the shock become increasingly concentrated amongst workers originally in location 1, sector A. At the limit, when both location and sector moving costs are infinite, the shock would entirely be borne by workers originally in the directly affected location and sector.

2.4 Empirical challenges in studying role of moving costs

The model above shows that moving costs across locations, sectors, and occupations generate heterogenous incidence on incumbent workers in directly exposed locations, sectors, and occupations. An extensive literature

[22]The effect on earnings is half the productivity decline rather than the full amount because the productivity shock only happens in location 1, sector A, while the earnings losses are split between Location 1 workers originally both in sector A and location B.

[23]In settings with non-perfectly elastic housing supply, the elasticity of housing supply will affect the effects on workers by their original location as well.

has explored the distributional effects of local labor market shocks on wage, employment, and population using cross-sectional data.[24]. However, changes in average earnings include both changes in wages per efficiency unit of labor, baseline differences in the local workforce, and changes in the composition of the local workforce. As a result, similar changes in average earnings are compatible with both large and small moving costs and large and small welfare impacts on directly affected workers.

To see this, let average wages in location l for workers in skill-group g be $\ln \bar{y}_{il}$ and s_l^g denote the share of residents of location l in skill group g. The effects of a shock, Z_l, on average earnings within location l are:

$$\frac{\partial \ln \bar{y}_l}{\partial Z} = \underbrace{\sum_j \frac{\partial \ln \bar{y}_{lg}}{\partial Z} \times s_{lg}}_{\Delta \text{ wages per efficiency unit}} + \underbrace{\sum_g \ln \bar{y}_{lg} \times \frac{\partial s_{lg}}{\partial Z}}_{\Delta \text{ composition}} \tag{2.10}$$

The effects on average wages in Location 1 compared to Location 2 are:

$$\frac{\partial \ln \bar{y}_1}{\partial Z} - \frac{\partial \ln \bar{y}_2}{\partial Z} = \underbrace{\sum_j \left[\frac{\partial \ln \bar{y}_{1g}}{\partial Z} - \frac{\partial \ln \bar{y}_{2g}}{\partial Z}\right] \times s_{1g}}_{\Delta \text{average skill-group wages}} + \underbrace{\sum_g \frac{\partial \ln \bar{y}_{2g}}{\partial Z}\left[s_{1,g} - s_{2,g}\right]}_{\Delta \text{national price for skills}} \tag{2.11}$$

$$+ \underbrace{\sum_g \ln \bar{y}_{1g} \times \left[\frac{\partial s_{1g}}{\partial Z} - \frac{\partial s_{2g}}{\partial Z}\right]}_{\Delta \text{ composition}} \tag{2.12}$$

The effect of a shock on relative earnings is composed of three terms. First, the shock changes wages per efficiency unit of labor for each skill-group. Second, if the two locations have different distributions of skill-groups, then a change in the national price for those skill-groups will lead to different effects on average cross-sectional wages. Third, workers move locations, altering the composition of the local labor force.[25] This decomposition highlights that identical changes in average earnings could result from quite different patterns of economic adjustment. For example, if moving costs are low and there is significant out-migration of individuals in particularly affected skill-groups and those skill-groups have higher (lower) earnings than others, then there may be a large decline (rise) in average earnings, even though wages per efficiency unit may change very little if at all. In this scenario, one could estimate large effects on local earnings even though workers in originally exposed location lost

[24]For examples, see: Carrington (1996), Black et al. (2005), Topalova (2010), Notowidigdo (2011) Kovak (2013), Autor et al. (2013), Bartik et al. (2016), and Hakobyan and McLaren (2016)

[25]The expression below focuses on a discrete number of (potentially) observable skill types. In practice, workers may vary in their unobserved ability, i.e. average local wages may be: $\ln \bar{w}_{l,g} = \ln \omega_{l,g} + \ln \bar{\lambda}_{ig}$ where $\ln \omega_{l,g}$ are local efficiency wages and $\ln \bar{\lambda}_{g,l_l}$ is the average ability of group-g workers in location l. Workers may selectively migrate depending on their unobserved ability, which would generate an additional term depending on the changes in average unobserved ability in each location within each skill-group:

$$\underbrace{\frac{\partial \ln \bar{y}_{Ag}}{\partial Z} - \frac{\partial \ln \bar{y}_{Bg}}{\partial Z}}_{\Delta \text{average skill-group wages}} = \underbrace{\frac{\partial \omega_{Ag}}{\partial Z} - \frac{\partial \omega_{Bg}}{\partial Z}}_{\Delta \text{wages per efficiency-unit}} + \underbrace{\frac{\partial \ln \bar{\lambda}_{iAg}}{\partial Z} - \frac{\partial \ln \bar{\lambda}_{iBg}}{\partial Z}}_{\Delta \text{unobserved ability}}$$

This expression highlights that even with granular education and demographic information, cross-sectional estimates can lead to a misleading picture of the effects of local labor demand shocks on the original residents.

very little relative to other workers.[26]

2.5 Discussion

The model above highlights three aspects of the role played by moving costs in adjustment to changes in labor demand. First, moving costs determine differences in the effects of shocks on workers in directly exposed locations, sectors, or occupations compared to other workers. As a result, estimating the effect of shocks by original location, sector, and occupation provides evidence on the relative importance of moving costs in adjustment across these three margins.

Second, focusing on location or occupation/sector moving costs at the exclusion of the other may both miss important dimensions of the response to a shock or result in mis-attributing occupation/sector moving costs to location moving costs or vice-versa. Comparing Figures 3 and 5, highlights that when location moving costs are large, the average impact on workers originally living in affected locations are similar, regardless of whether sector moving costs are large. However, when sector moving costs are also large, these losses are concentrated amongst workers originally in the affected sector.[27]

Third, differences in baseline composition of locations or sectors and changes in composition induced by demand shocks make cross-sectional estimates of the effects of local demand shocks potentially misleading regarding the incidence of local shocks and the magnitude of moving costs.

3 Data Sources and Summary Statistics

The conceptual framework above clarifies the data required to study the role of moving costs in the incidence of changes in labor demand. First, the data must be longitudinal and allow for construction of a constant cohort of workers over time to avoid biases from compositional changes. Second, the data must included detailed information on location, occupation, and industry to allow location, sector, and occupation moving costs to be distinguished from one another. Third, the data must include detailed demographic and education information to facilitate comparisons of comparable skill groups.

[26] Furthermore, for small shocks, the envelope theorem implies that welfare only depends on the change in wages per efficiency unit rather than on the equilibrium responses.

[27] Focusing on only one type of moving cost may not only mask heterogeneity, it may even lead to misleading inferences regarding the sources of moving costs. For example, in Appendix Section A.1 I present an extension of the model to the case when Location 1 and Location 2 have different industrial compositions. In the extreme case, Location 2 may only have Sector B. Consequently, when there is a shock to Location 1, Sector A, workers who want to move to a better labor market must change both locations and sectors. This difference in industrial composition leads to similar average mobility patterns and wage effects for either high sector or location mobility costs. Consequently, one could mistakingly infer that there are high location moving costs when really heterogeneous incidence is being driven by high sectoral moving costs or vice-versa.

3.1 Linked Census Data

I construct a novel panel dataset of rich economic information by linking the 2000 decennial census with the 2005-2014 ACS.[28] In 2000, one-in-six housing units[29] were sent the long-form, which includes detailed questions on educational attainment, work and labor market outcomes, income, housing details, and family background and history. After 2000, the long-form was replaced by the ACS, which is sent to approximately 3% of households per year.[30] I link individuals across these two datasets using unique identifiers (called Protected Identification Keys (PIKs)) created by the Center for Administrative Records Research and Applications (CARRA) at the US Census Bureau. Each survey observation is matched to a reference file based on the Social Security Administration (SSA) numident file using address, names, date-of-birth. A PIK is assigned to each survey observation (Wagner and Layne (2010)).[31] This PIKing process results in unique PIKs being assigned to between 87 and 89 percent of observations in the Decennial Census and the American Community Survey.[32]

I make several sample restrictions in the analysis. First, I focus on workers without college degrees.[33] Second, I restrict the sample to workers ages 25 to 50 in 2000 who were no older than 59 when interviewed in the ACS to ensure that individuals have completed their education in the base period and avoid complications related to retirement decisions. Third, I restrict the sample to workers working full-time, full-year in 2000, defined as working at least 40 weeks during the previous year and working at least 35 hours during the usual week. In all of my analysis, I restrict my sample to observations that have non-allocated observations and do not have implausible values of outcome variables. I discuss these decisions and how they affect my ultimate sample more in Appendix Sections B.1.3.

The restriction of the sample to linked observations with non-allocated labor market information means that my ultimate sample may not be fully representative of the 25-50 year old full-time, full-year working population. I account for this non-representativeness by estimating propensity-score models for having being linked to a unique PIK and having non-allocated labor market information for both the 2000 Census and the 2010-14 ACS. I then reweight observations using the inverse-propensity-score weights from these models. I discuss the estimation of the propensity scores in more detail in Section B.1.4.

Table 1 reports summary statistics for all Census 2000 respondents (Column (1)), the un-reweighted linked sample (Column (2)), and the re-weighted, linked sample (Column (3)). Three features of this table are notable. First, in Panel A, which shows individual characteristics in the 2000 census, we see that the un-reweighted sample differs along several dimensions from the re-weighted sample. In particular, individuals in the linked sample are

[28] This is the first paper that I am aware of that takes advantage of this linkage between the 2000 decennial long-form and the ACS.

[29] Ultimately, the vast majority of households respond to the decennial census, resulting in a sample of approximately 15% of US housing units.

[30] The ultimate response rate for the ACS is lower than that for the decennial census, so only about 2% of households ultimately complete the ACS.

[31] Each PIK corresponds to a unique SSN.

[32] See Appendix Section B.1.1 for more details on the PVS process and how I treat missing and duplicates PIK and Appendix Section B.1.3 for details on how I handle allocated variables and other details of the data cleaning process.

[33] Results for college educated workers, which are qualitatively similar, are available upon request.

less likely to be Hispanic or black and have higher incomes. The re-weighted sample matches the full 2000 census averages more closely, although Hispanics may be somewhat over-represented in the linked sample.

Second, one concern with the linked sample is that individuals who are linked may be systematically less or more mobile than other individuals. If this were the case, it would cast doubt on the external validity of my findings. Re-assuringly, we see that the share of people changing states between 1995 and 2000 are almost identical in the linked and unlinked samples.

Finally, in Panel B, we see that the average percentage change in earnings using the arc-elasticity is almost -38%. This large mean decline results from the sample condition that workers are working full-time, full-year in 2000, which means that there is a mass of workers who leave the labor force and have no earnings in the second time period without any corresponding mass of obserrvations that have no earnings in 2000 and substantial earnings in 2010/14.

3.2 Outcome definitions

I focus on two primary outcomes: percentage change in individual earnings and migration rates. I measure percentage change in wage and salary income between 2000 and the post-interview period using the arc-elasticity (Davis and Haltiwanger (1992)):

$$\Delta w_{i,t,t-1} = \frac{\Delta y_{i,t,t-1}}{\frac{1}{2}(y_{i,t} + y_{i,t-1})} \tag{3.1}$$

This measure is bounded between 2 and -2, avoids outliers with large gains in income from skewing the distribution of percentage changes, and allows inclusion of individuals with zero labor market earnings in the second time period. I winsorize wage and salary income at the 99th percentile in each year and drop observations where the implied hourly wage is less than \$2.50. I convert wage and salary income to 2010 USD using the Consumer Price Index (CPI) for all urban consumers (Bureau of Labor Statistics, U.S Department of Labor (2016)).

I measure migration as an indicator for whether an individual changed CZ of residence between 2000 and 2010/14. A CZs out-migration rate between 2000 and 2010/14 is the number of individuals leaving CZ g as a percentage of CZ g's population in 2000, while a CZs in-migration rate is the number of in-migrants as a share of the CZs 2000 population.

3.3 Aggregate Data

Because I only observe linked individuals in 2000 and 2005/14, I cannot directly examine the common trends assumption between labor markets with different exposure to labor demand shocks assumption that underlies my empirical strategy described below. I supplement the census data with annual Commuting-Zone employment data from the Quarterly Census of Employment and Wages (QCEW) to examine the plausibility of the common trends assumption (Bureau of Labor Statistics, US Department of Labor (2016)).

4 Empirical Strategy

Changes in local employment or wages may be driven by labor supply shifts - resulting from changes in local amenities, state and local personal taxes, or immigration - rather than labor demand. Consequently, to study the role moving costs have played in the response of workers to changing labor market opportunities across locations, occupations, and sectors, I need variation in local labor demand that is uncorrelated with local labor supply. For this purpose, I exploit policy variation in exposure to trade with China and geological variation in exposure to fracking. In addition to providing plausibly exogenous variation in labor demand for less-skilled workers, these two sources of variation are interesting in their own right, as they are two of the most important changes in labor demand for less-educated workers that have occurred over the last several decades. In this section, I discuss how I construct measures of CZ exposure to trade with China and fracking, and provide evidence that these measures were uncorrelated with pre-2000 labor market trends. I then detail the specifications I use to estimate the causal effect of fracking and trade with China on earnings and migration.

4.1 Labor Market Shocks

4.1.1 PNTR with China

Since 1992, China has dramatically expanded its trade with the rest of the world. One cause of China's growth in trade with the US has been changes in trade policy. Before 1980, Chinese imports faced "non-market economy" or "Column 2" tariffs. Starting in 1980, as part of Nixon's opening with China, Congress began annually granting China Normal Trade Relations (NTR), which granted China access to the lower "market-economy" or "Column 1" tariffs. However, because China's NTR status was subject to annual approval, substantial risk remained that Congress would not approve NTR in some future year. This risk was larger in industries with larger gaps between NTR and non-NTR tariffs. In 2000, the US granted China Permanent Normal Trade Relations (PNTR), meaning that NTR no longer was subject to annual congressional approval.

Pierce and Schott (2016) argue that China receiving PNTR decreased the uncertainty regarding potential tariff increases in those industries with high tariffs if NTR were not renewed, leading to increased investment in production in China and imports to the US. Pierce and Schott (2016) construct a measure of industry-level exposure to China receiving PNTR using the gap between the tariffs faced by each industry under NTR and without NTR and show that industries with a larger gap experienced larger rises in imports and declines in US employment after 2001.

I use the Pierce and Schott (2016) measure of industry exposure to China receiving PNTR to construct a CZ-level measure of the exposure of the average worker within the CZ to China receiving PNTR. Let μ_{j,g,t_0}

be the share of local employment represented by industry j in CZ g in time period t_0, and NTR $\text{gap}_{j,1999}$ = No $\text{NTR}_{j,1999} - \text{NTR}_{j,1999}$ be the difference between tariffs on industry j without normal trade relations and with normal trade relations. I then construct the following-measure of exposure to trade with China:

$$PS_g = \sum_j \mu_{j,g,t_0} \times \text{NTR gap}_{j,1999} \tag{4.1}$$

This CZ exposure measure varies from 0 to 1, with higher values corresponding to greater CZ exposure to tariff-based China-import shocks to manufacturing employment. A CZ has zero exposure if all industries within the CZ had no-difference between NTR non-NTR tariffs - i.e. an NTR gap of 0 - and an exposure level of 1 if all industries within the CZ faced 100% tariffs with NTR and 0% tariffs without NTR - i.e. an NTR gap of 1. Figure E.3 shows a histogram of the distribution of the Pierce-Schott shock, weighting by the number of workers in the CZ in 2000. The average CZ PNTR-exposure is .056 and the difference between the 25th and 75th percentile is .028. In other words, the average worker in CZs at the 75th percentile of exposure worked in an industry with an NTR gap that was 2.8pp higher than the average worker in CZs at the 25th percentile. Figure 6 shows a map of this measure of exposure to trade with China. Areas with high manufacturing shares - such as the southeast and midwest - are most exposed to PNTR with China.

4.1.2 Fracking

Hydraulic fracturing, often referred to as fracking, is the application of two existing technologies, horizontal drilling and hydraulic fracturing, to exploit shale formations that were previously prohibitively costly to develop. These technologies were adapted by Mitchel Energy and then Devon Energy in the Barnett shale in Texas between 1998 and 2002, and have since spread to shale formations throughout the US. Fracking has dramatically increased US oil and gas production, resulting in a roughly 60% rise in employment in the oil and gas sector between 2000 and 2014. Locally, fracking leads to large rises in employment in oil and gas, as well as in firms providing inputs for the oil an gas industry, including the transportation, manufacturing, and constructions sectors.

Fracking can only be applied in areas overlying shale formations. Even within shale formations, there is substantial variation in the potential profitability of fracking. A number of geological factors, including the depth, thickness, porosity, permeability, and thermal maturity of the formation, drive this variation. I measure CZ level exposure to the labor demand shock from fracking using a measure of potential oil and gas production based on the geological suitability of different CZs to shale development. I use data from Rystad Energy on the geological potential of different areas for shale development. I define a CZ as being exposed to fracking if it contains any area in the top-half of potential production within its shale formation (Rystad Energy (2014)) and that shale formation had fracking start in or before 2010.

Figure 7 shows a map of CZs with any fracking exposure. Fracking is spread across four regions: Pennsylvania and nearby areas where the Marcellus shale is located; the greater Texas/Oklahoma region, which is home to a number of shale formations, including the Barnett shale, the Permian Basin, the Woodford Shale, the Eagle Ford Shale and the Haynesville shale formation; Colorado, where the Niobrara shale formation is located, and North Dakota and Montana, where the Bakken formation is located.

4.2 Defining directly exposed, locations, sectors, and occupations

The conceptual framework above highlights that local labor demand shocks have differential affects on workers in directly exposed occupation and sectors when moving costs are large. Consequently, investigating the role of occupation or sector moving costs requires partitioning occupations and sectors into those that are "directly-exposed" - i.e. the labor demand shock reduces demand in the given sector or occupation and those that are not directly exposed.[34]

PNTR with China and fracking particularly affected employment in occupations requiring the use of physical strength and dexterity.[35] I construct a measure of occupation physical or "brawn-intensity" using measures of the brawn, people, and person content for occupations created by Lordan and Pischke (2016)[36]. Using these task measures, I create an index for the relative brawn intensity of different occupations:

$$r(\text{brawn})_o = \quad \text{brawn}_o - \text{people}_o - \text{brains}_o \tag{4.2}$$

$r(\text{brawn})_o$ captures how much occupation o uses brawn-tasks relative to people or abstract tasks[37]. I discuss this measure of brawn-intensity in more detail in the appendix, show that the brawn-intensity measure generates intuitive assignments of brawn-intensity to different occupations, and discuss descriptives on the brawn-intensity of occupational choices for different demographic groups. To facilitate comparison to other research, I also report estimates aggregating occupations to four traditional occupational categories: management and professional occupations, clerical and service occupations, production occupations, and operator/construction occupations in the appendix.

I then partition sectors into those directly exposed and indirectly exposed to PNTR with China and fracking. This is simplest for PNTR with China. I define the manufacturing sector as directly exposed to PNTR with

[34]Given input-output linkages and spillovers onto demand for non-tradable goods, this partitioning will always be imperfect. However, Appendix Figures E.4a and E.5a below suggest that the partitions I've chosen broadly capture the classes of occupations and sectors experiencing large changes in labor demand.

[35]I create consistent occupational categorizations over time using crosswalks from Dorn (2009) and Autor et al. (2013). See Appendix Section B.2 for more details.

[36]Lordan and Pischke (2016) create these measures using factor analysis of O*Net 5 task variables on "work activities" and "work-context" variables. Beaudry and Lewis (2014) construct a related task classification system by hand based on the "people", "physical", and "cognitive" content of occupations based on the Dictionary of Occupational Titles (DOT). I've received these occupation task assignments from Beaudry and Lewis (2014) and will explore the robustness of my results to defining "brawn-intensity" using the Beaudry and Lewis (2014) task assignment as well

[37]Note that the brawn, brains, and people indices's from Lordan and Pischke (2016) are already on a standardized scale so no re-scaling is necessary. I experimented with constructing a similar brawn-intensity task-measure by transforming all of the task measures to be weakly positive and then creating the brawn-intensity variable using the logged version of Equation 4.2 above. The resulting variable had a correlation of above .9 with the variable I use

China, while all other sectors are not directly exposed because PNTR with China exposure is mechanically 0 for all non-manufacturing industries. For fracking, I define directly affected sectors as oil, gas, and mining, as well as construction and transportation, which are also heavily used by oil and gas producers.[38]

Appendix Figures E.4a and E.5a show the change in cross-sectional employment for non-college educated workers by the occupation and sector groupings described above. The figures confirm that the partitioning is a good approximation of direct exposure, with both shocks primarily affecting the occupations and sectors I defined as directly affected. This pattern is particularly stark for PNTR with China, where the effects on employment are essentially zero outside of manufacturing and high-brawn occupations.

4.3 Estimation

In this section I detail the specifications I use to estimate the effect of fracking and exposure to trade with China on labor market outcomes and migration responses and discuss the required identification assumptions.

4.3.1 Labor market outcomes

I estimate how exposure to trade with China or fracking affected workers based on their location in 2000. Let $y_{i,g_0,t}$ be an outcome for individual i living in CZ g_0 in 2000, in year t, and $P_0 = 1[t > 2000]$, with individuals characteristics X_i, and define Z_{g_0} to be a measure of labor market changes in location g_0 between 2000 and 2010/14. I assume that:

$$y_{i,g_0,t} = \quad \gamma_i + \alpha_{g_0} + \lambda_{rt} X_i + \delta^O Z_{g_0} \times P_0 + \mu_{i,g_0,t}$$

Taking differences yields:

$$\Delta y_{i,g_0,t} = \quad \Delta\lambda_{rt} X_i + \delta^O Z_{g_0} + \Delta\mu_{i,g_0,t} \tag{4.3}$$

Equation 4.3 will consistently estimate the causal effect of Z_{g_0} under the assumption that individuals in different CZs exposed and not-exposed to fracking or trade with China would have had common changes in outcomes as other individuals with the same demographic characteristics living within their region (i.e. individuals

[38] In future work I plan on formalizing this partitioning by using input-output linkages between different industries to define directly exposed sectors

with the same value of X_i in the same region).[39], i.e.:

$$E[\Delta\mu_{i,g_{0(i)}} Z_{g_{0(i)}} | \Delta\beta_r X_i] = 0$$

I also report estimates from versions of Equation 4.3 using labor market exposure of worker's contemporaneous location (i.e. $Z_{g(i)_t}$ rather than $Z_{g(i)_0}$). These estimates serve three purposes. First, they provide information about the size of the shock and where its employment impacts are largest. Second, they allow me to check a version of my identification assumption that areas exposed and not-exposed to fracking and China receiving PNTR would have had common trends in the absence of the shocks occurring. Third, these estimates provide guidance on how severe the selection problems that can potentially bias cross-sectional estimates are. The models I estimate for contemporaneous residents are:

$$\Delta y_{g,t} = \quad \Delta\omega_{rt} + \delta^C Z_g + \Delta\epsilon_{g,t} \tag{4.4}$$

Estimates of δ^C then represent the effect of fracking or exposure to PNTR with China on outcomes for contemporaneous residents of exposed locations.

4.3.2 Migration

The model highlights that a key mechanism through which workers can adjust to local labor demand shocks is migration. Furthermore, as discussed in Section 6.2, estimates of the effect of shocks on migration are a key input for bounding moving costs. I observe migration between 1995 and 2000 based on responses to the Census long-form and then between 2000 and 2010/14, based on individuals' location in the ACS and their linked location in the 2000 long-form or short-form. These three observations occur at uneven time-intervals, preventing me from estimating Equation 4.3 for migration. Instead, I assume that exposure to fracking or PNTR with China exposure are independent of potential outcomes conditional on the lagged five-year migration rate. Let $\bar{m}^{10\text{yr}}_{g,2010/14}$ be the out-migration or in-migration rate from location g between 2000 and $2010-14$, $\bar{m}^{5\text{yr}}_{g,2000}$ be the out-migration or in-migration rate from location g between 1995 and 2000, and X_{g_0} be average demographic characteristics of CZ g in 2000.[40] I then estimate models of the form:

$$\bar{m}^{10\text{yr}}_{g,2010/14} = \quad \lambda_r \bar{X}_g + \delta Z_g + \gamma \bar{m}^{5\text{yr}}_{g,2000} + \mu_g \tag{4.5}$$

[39] In all specifications, X_i is a saturated vector of dummy variables, making estimates of Equation 4.3 interpretable as the variance weighted average of OLS regressions of $\Delta y_{i,g_0,t}$ on Z_{g_0} within each X_i cell ($\hat{\delta}_x$), i.e.:

$$\hat{\delta} = \sum_x \phi_x \hat{\delta_x}$$

The weights are $\phi_x = \frac{\mu_x Var(Z_{g_0}|x)}{\sum_{x'} \mu_{x'} Var(Z_{g_0}|x')}$, where μ_x is the share of total observations in cell x.

[40] Note that because migration rates are bounded between 0 and 1, estimating Equation 4.5 does not generate consistent estimates of β. Reassuringly, the estimated marginal effects are qualitatively similar when the model is estimated using logit or probit link functions instead.

Equation 4.5 will consistently estimate the treatment effect of fracking or trade with China exposure if exposure to both shocks is independent of potential outcomes conditional on the five-year migration rate, i.e.:

$$E[\mu_g Z_g | \bar{m}^{5yr}_{g,2000}, \lambda_r, X_{g,2000}] = 0$$

4.3.3 Testing plausibility of common trends assumption

Equations 4.3 and 4.4 will consistently estimate the effect of fracking or exposure to PNTR with China if areas exposed to both shocks would have had similar trends to observably similar areas in the absence of China receiving PNTR or fracking being developed respectively. I investigate the plausibility of this assumption by exploring whether employment trends prior to 2000 were related to exposure. To do so, I estimate a version of 4.4 where I fully interact Z_g with time-dummies (δ_t) and graphically explore the relationship between labor market outcomes and both shocks prior to 2001:[41]

$$y_{g,t} = \qquad \omega_{rt} + \alpha_g + \delta_t Z_g + \Delta\epsilon_{g,t} \tag{4.6}$$

Figures 8a and 8b report estimates of Equation 4.6 using log(total employment) as the outcome variable for fracking and exposure to PNTR with China respectively. Starting with Figure 8a showing trends in employment by CZ exposure to PNTR with China, we find a small downward, pre-trend prior to 2001. After 2001 employment declines rapidly in more China-exposed CZs, before flattening off around 2010.

Turning to the corresponding results for fracking shown in Figure 8b, we find that labor markets with any land suitable for fracking experienced similar pre-trends to other labor markets prior to 2001. After 2001, employment starts to grow rapidly, rising over 12 percent by 2014. Employment ticks down in 2015, after oil prices began to decline. Combined, these figures provide supporting evidence that CZs exposed to trade with China or fracking would have had similar trends in the absence of the beginning of trade with China or the advent of fracking. In the results below, I will show that my results are also robust to controlling for local trends in employment, further strengthening the case that the estimates are not due to differential pre-trends.

4.3.4 Quantifying Magnitude of Shocks

PNTR with China and fracking provide useful variation to study how individuals respond to shifts in local labor demand if they in fact cause shifts in labor demand in particular labor markets and sectors. In this section, I show that both PNTR with China and fracking had substantial labor market impacts and quantify how large the

[41]Exploring pre-trends in this equation tests the identifying assumption that outcomes for contemporaneous residents in areas exposed and not-exposed to fracking or trade with China had similar trends prior to fracking, or exposure to trade with China. Strictly speaking, estimating Equation 4.3 requires the slightly different identifying assumption that outcomes for workers originally living in areas with different exposure to fracking or trade with China would have had similar trends in the absence of fracking or trade with China. However, this modified identification assumption cannot be directly investigated using my current data because I do not have linked data on outcomes prior to 2000.

impacts were in different sectors and occupations. These estimates provide information on which occupations or sectors were directly affected by the shock.

I start by presenting estimates of the effect of exposure to PNTR with China on the change in outcomes between 2000 and 2010/14 of contemporaneous residents of affected locations. Table 2 reports estimates of Equation 4.4, where Z_g is CZ g's exposure to China being granted PNTR, which is measured as the tariff exposure in the average full-time, full-year workers' industry in 2000. To make these estimates more interpretable, I also report the effect of going from the 25th to 75th percentile of CZ-exposure, a difference of .028 in tariff exposure per–worker. Panel A reports the estimated effect on the change in log total-employment for contemporaneous residents (i.e. the change in overall CZ employment) in different sectors, while Panel B reports estimates of the effect on hourly wages of contemporaneous residents, and Panel C reports estimates on earnings-per-capita. Column (1) reports results for all workers, Column (2) for manufacturing workers, and Column (3) for non-manufacturing workers.

Starting with Panel A1, the point estimate for PNTR per worker is -1.1, which translates into an employment reduction of 3.3 percent for CZs at the 75th percentile compared to CZs at the 25th percentile. These employment losses are concentrated in manufacturing, with moving from the 25th to 75th percentile of PNTR-exposure estimated to reduce manufacturing employment by 7.4%, while leaving non-manufacturing employment essentially unchanged. Unlike the employment effects, the effects of PNTR exposure on wages extends both inside and outside manufacturing, with moving from the 25th-75th percentile of PNTR exposure estimated to reduce wages in manufacturing by 2.5 percent and outside of manufacturing by 1.4 percent. Panel $A3$ shows that these declines in local employment and hourly wages cause similarly large reductions in earnings-per-capita.

Similarly, columns (4)-(6) show that the employment effects of PNTR with China were concentrated almost entirely within high-brawn occupations, with moving from the 25th to 75th percentile of exposure to PNTR with China resulting in almost no-change in employment in low and high-brawn occupations, but a 7% decline in employment in high-brawn occupations. The effects on hourly-wages are quite different, with similar impacts of around 6% on hourly wages in low and high-brawn occupations, and smaller effects (around 4%) on hourly wages in medium-brawn occupations.

Panel B shows that fracking caused large rises in full-time, full-year employment, hourly wages, and earnings-per-capita for non-college educated contemporaneous residents of exposed locations. The rises in full-time, full-year employment and earnings-per-capita are particularly large, with earnings per-capita rising almost 9% and full-time, full-year employment rising 12%.

Moving right to the columns reporting the effects of fracking by sector and occupation, we seee that the employment gains from fracking are concentrated in oil and gas related sectors and among operator/construction occupations and in brawn-intensive occupations. Employment rises almost three times as much (19% vs. 7%) in oil and gas-related sectors compared to sectors unrelated to oil and gas. Turning to the results by occupation in Columns (3)-(9), employment in operator/construction occupations rises over 20 percent, while gains in other occupational groups are less than 3%. Similarly, employment in brawn-intensive occupations rises 17 percent, with rises of only 3% in low and medium brawn-intensity occupations. As with the case for exposure to PNTR with China above, the hourly wage gains differ much less than the employment gains, possibly reflecting selection in response to the employment shock.

5 Results

The conceptual framework in Section 2 highlights that moving costs generate differential impacts of labor demand shocks between workers originally in directly exposed locations, occupations, and sectors and other workers in the same skill group. In this section, I use this result to test for moving costs by estimating whether exposure to PNTR with China or fracking have different effects on workers originally working in directly exposed locations, occupations and sectors compared to demographically similar workers.

For each shock, I first estimate how the shocks affected the original residents of affected locations. Second, I explore heterogeneity in these impacts by workers' original occupation and sector. Finally, I estimate the migration response of workers to these labor demand changes.

5.1 Effects of shifts in labor demand by workers original location

How have these effects on cross-sectional averages of employment, wages, and earnings been reflected in effects on workers originally living in exposed areas? With sufficient worker mobility, these losses would be spread throughout workers in a particular skill group in the economy, rather than being concentrated among the original residents. The large estimated impacts on local employment outcomes could reflect selective in out-migration or in-migration for workers originally in shocked locations. As a result, the effects on the original residents could be bigger or smaller than these estimates.

Table 3 presents estimates of the effect of PNTR exposure on the percentage change in earnings between 2000 and 2010/14 where exposure is measured based on original residence in 2000 for non-college educated workers. For comparison, I also include in the table percentage change effects for average earnings per capita for for non-college educated contemporaneous residents. Panel A shows estimates for the contemporaneous residents, while Panel B reports results for the original residents. Starting with my baseline specification in Column (1), which includes region fixed effects and sex-by-age-group-by-acs year fixed effects[42], the estimated effect of moving from the 25th to 75th percentile of CZ PNTR-exposure is a -4.4% reduction in annual earnings for original residents, compared to an estimated -2.7% effect on overall per-capita earnings.

Theses results show that workers originally living in areas exposed to PNTR with China experienced large earnings losses, implying that workers face high moving costs across locations or occupations/sectors. However,

[42] The sex-by-age-group-by-acs year fixed effects are only included for the original residents. For contemporaneous residents, I only include region fixed-effects.

there are several alternative interpretations of these patterns. First, large negative shocks to the local economy may cause negative wealth effects through local housing markets that may reduce outmigration, causing more concentrated effects on original residents. Second, it's not certain that workers could improve their labor market outcomes by migrating from CZs with more exposure to PNTR with China to those with less exposure. Perhaps workers in CZs less exposed to PNTR with China are holding onto legacy jobs that may not be accessible to in-migrants. Finally, workers in manufacturing industries in CZ exposed to China may have lost industry-specific human capital, and so they may experience earnings losses regardless of whether or not they move.

I investigate whether the concentrated effects on original residents is driven by these particular features of negative shocks by also exploring a positive shock to labor demand for workers in manual-intensive occupations: hydraulic fracturing. Worker adjustment to fracking provides complementary evidence that workers' limited adjustment across geography and occupation to changes in labor demand is not driven by losses of industry specific human capital or direct effects of negative shocks.

Table 4 reports estimates of Equation 4.4 for contemporaneous residents and Equation 4.3 for the original residents of fracking exposed locations. In both panels, the sample is restricted to non-college educated workers. Different columns iteratively add fixed effects and control variables.

Panel B shows that the original residents experienced similar sized gains to the contemporaneous residents, suggesting that the rises for contemporaneous resident rises were not driven by in-migrants receiving high wages, but instead by broad local labor market gains that benefited the original residents as well. Combined, the results for both exposure to PNTR with China imply that moving costs have prevented workers from fully adjusting to changes in local labor demand.

In both Tables 3 and 4, Columns (2)-(4) include additional controls to adjust for potential confounding factors. Given that labor markets with higher PNTR and fracking exposure differ in population and urban-share from other labor markets, Column (2) adds controls for the share of the CZ-population living in urban areas and log-population in 2000. Column (3) and (4) then add controls for lagged log-employment and log-manufacturing employment growth respectively, providing an additional test for the identifying assumption of common trends in the absence of China being granted PNTR or fracking being developed[43]. None of the controls added in Columns (2)-(4) has an economically meaningful impact on the estimates or their precision, with the estimated effect on both contemporaneous and original residents rising slightly after the addition of the full-set of controls in Column (4).

5.2 Heterogeneity by original occupation and sector

The interpretation of the large effects on original residents presented in Tables 3 and 4 depends on their source. If PNTR exposure and fracking primarily impacts workers originally in directly affected industries (manufacturing

[43] The event studies in Figures 8a and 8b suggested that different pre-trends in overall employment were not a major concern.

in the case of PNTR exposure and oil and gas in the case of fracking), then these losses may reflect industry specific human capital, rents, or sector moving costs. Alternatively, if PNTR with China and fracking primarily impact workers who have particular skills or perform particular tasks (such as those in particular occupations), then the earnings losses may reflect labor market wide changes in demand for particular skills combined with moving costs across occupations. Finally, if there are location moving costs but occupation and sector moving costs are unimportant, the shocks will cause similar effects amongst all local workers. These different sources of earnings changes imply different distributional consequences, with industry or occupation concentrated declines potentially leading to very large losses for a subset of workers.

Table 5 reports heterogeneity in the effects of exposure to PNTR with China by original occupation and sector. Columns (1) and (2) show that, although PNTR exposure causes employment losses almost exclusively within manufacturing, and causes declines in hourly wages that are 60% higher within manufacturing than outside manufacturing, the estimated effect on earnings is similar for workers originally working inside and outside manufacturing. These findings suggest that earnings losses may not stem from losses of industry or sector-specific human capital but instead result from local reductions in demand for particular skills.[44]

Columns (3)-(5) explore the role played by the tasks performed by workers in 2000 by separately estimating results by terciles of the workers' 2000 brawn-intensity, which, as discussed in Section 4.2, is a crude measure of occupation exposure to PNTR with China.[45] Panel A bears this out, showing that higher PNTR exposure causes a 7% decline in employment in high-brawn occupations, and little effect on employment in other occupations.

Panel B shows that this difference translates into large differences in the estimated effects by the brawn-content of workers' original occupations, with the estimated impact on workers originally in high-brawn occupations being roughly 2.5 times the estimated effect for low-brawn workers, and the effect on workers in middle-brawn occupations being somewhat intermediary. Although the estimated effect on low-brawn workers is smaller than the estimated effect for high-brawn or medium-brawn workers, the estimate for workers originally in low-brawn occupations is precisely estimated and economically large, implying that even low-brawn workers experience earnings reductions of 1.9%.[46]

Table 6 performs the same exercise for fracking, investigating how workers' ability to take advantage of the opportunities created by fracking varied depending on their original sector and occupation. Columns (1) and (2) report results for oil and gas related sectors[47] and non-oil and gas related sectors, while Columns (3)-(5) report results by the brawn-intensity of workers' occupation in 2000. As discussed above, Panel A shows that fracking led to concentrated gains in employment in oil and gas and construction sectors and more brawn-intensive

[44] However, because there may be direct effects through input-output networks on transportation, construction, or other firms, workers outside manufacturing may experience displacement and lose industry-specific human capital as well.

[45] Appendix Section B.4 shows that the empirical patterns are qualitatively similar using alternative occupation groupings such as major occupation categories instead of measures based on brawn-intensity.

[46] Note that these large heterogeneous treatment effects in Table 6 hold even though the sample is restricted to non-college educated workers.

[47] I define the "oil and gas related" sectors as oil and gas, transportation, and construction.

occupations.

Panel B shows that pattern of effects by original sector differs from the pattern by original occupation. Specifically, despite the much larger employment gains within oil and gas related sectors, earnings effects are similar for workers originally working in an oil and gas related sector or outside of the oil and gas related sector (7.0% vs. 6.7%). Conversely, effects on original residents are concentrated among workers originally working in the occupations that experience the largest rises in employment. Earnings gains in high-brawn occupations are 8.5% compared to gains of 5% and 4% for workers in medium and low-brawn occupations respectively.

Combined, Tables 5 and 6 point to two conclusions. First, earnings changes for workers in labor markets affected by fracking and PNTR exposure are not driven entirely by industry specific human capital, but rather reflect broader declines in labor demand. Second, the heterogeneous effect on workers by the brawn-content of their original occupation suggest that the markets for brawn and non-brawn intensive jobs are not fully integrated, and that workers are not seamlessly able to move in and out of low-brawn occupations in response to changes in demand for brawn-intensive occupations.[48]

5.3 Migration Responses

The results above imply that there are sufficient moving costs to prevent workers from perfectly arbitraging shocks across locations and occupations. I now turn to quantifying the magnitude of the mobility response. Measuring the mobility respone allows me to bound moving costs for a share of the population. Intuitively, a large effect on the original residents is consistent with small (but non-zero) moving costs, coupled with a large shock (that many workers move in response to) or large moving costs and a small migration response. Studying the migration response allows us to distinguish these two explanations.

In Table 7, I present estimates of Equation 4.5 of the effect of exposure to PNTR and fracking on migration rates of non-college educated workers. Panel A reports results for exposure to PNTR with China and Panel B reports results for fracking. Different columns add additional controls. Starting with my baseline specification in Column (1), which includes lagged five-year in-migration and out-migration rates, Panel A shows that exposure to PNTR is associated with slightly higher out-migration rates and lower in-migration rates. Moving from the 25th to 75th percentile of CZ exposure is estimated to increase outmigration rates by .1 percentage points, although this change is imprecisely estimated, and in-migration by .8 percentage points. The out-migration estimates are small enough that I can rule out out-migration increases larger than .7 percent.

Turning to Panel B, the estimates imply that fracking reduces out-migration by 1.5 percentage points for non-college. This represents roughly a 7% decline relative to the baseline outmigration rate of 19%. Turning to in-migration, the estimate for non-college workers is positive and of moderate magnitude, although imprecisely

[48]Note that these barriers to moving in and out of different occupations could reflect both barriers to finding jobs in different occupations, but also difficulty in acquiring the skills or training required to succeed in a new occupation.

estimated. However, I can rule out in-migration rises larger than 1.6 percentage points. Consequently, despite the large rise in local income, fracking has not caused large long-term increases in in-migration, although the estimated decline in out-migration is moderately large in magnitude. This muted in-migration result is consistent with my-finding that fracking has large effects on earnings of the original residents of exposed locations.

Columns (2)-(4) then check the robustness of these results to controlling for migration pre-trends, employment pre-trends, and adding state-fixed effects respectively. Qualitatively, adding controls does not change the findings for either labor demand shock. Starting with Panel A for exposure to PNTR with China, for outmigration, the estimates are imprecise, but all are positive and small in magnitude, with the highest point estimate in Column (4) suggesting that moving from the 25th to 75th percentile of PNTR exposure raised out-migration only .4 percentage-points. The standard-errors are small enough that I can rule out out-migration increases larger than 0.8 percentage points, or 4 percent of the average out-migration rate of 19 percent. For in-migration, the estimates all suggest decreases between .6 and .9 percent. In Panel B, we see that adding controls does not substantially change the estimated effect of fracking on either in-migration or out-migration. The estimated effect of fracking on out-migration varies between -1.5 and -2.3 percent, while the estimated effect on in-migration varies from .5 to .1 percent.

How should we interpret these migration responses? Consider the largest out-migration effect of a negative manufacturing demand shock found here, which is a point estimate that such a shock will increase out-migration rates by 0.4 percentage points. Is this .4 percentage point out-migration response large or small relative to the earnings decline of 4.4 percent for the average non-college educated worker? In Section 6.2, I make some back of the envelope calculations and then present a model for thinking about the magnitude of the estimated .4 percentage point moving response.

6 Moving Costs

The reduced-form results above show that the impact of changes in labor demand depend both on the original location and occupation of workers. The conceptual framework highlighted that these types of patterns imply moving costs across locations and occupations. In this section, I make back of the envelope calculations of the minimum moving costs required to rationalize my reduced form findings on out-migration from locations exposed to PNTR with China. I then develop a model of location, sector, and occupation choice that I use to estimate average moving costs, allowing for more than two locations, moving costs across locations, occupations, and sectors, as well as amenities, demographic differences, and heterogeneous payoff shocks.

6.1 Moving Cost Shifters

The conceptual framework in Section 2 predicts that the effects of local labor demand shocks should, all else being equal, have larger effects on subgroups of workers who have higher moving costs.[49] I explored this prediction of the model for four frequently discussed potential moving cost shifters: homeownership, marital status, long-term resident, and age. I do so by estimating Equation 4.3, for effects on wage and salary income, and Equation 4.5, for migration, with the labor demand shock of interest, Z_{g_0}, interacted with measures of these four moving cost shifters. Estimates from these regressions are reported in Figures 10 for the effects on wage and salary income and 11 for out-migration. In both figures, Panel A reports estimates for

If these moving cost shifters are positively associated with moving costs and the model in Section 2 is correct, the magnitude of the effects of both fracking and trade with China should be larger for individuals with the higher value of the moving cost shifters. For these four shifters, this would mean that the effects would be larger for homeowners, married workers, long-term residents, and older workers. Migration rates should also be more responsive for these groups. In general, Figures 10 and 11 do not provide evidence for these claims; there is no clear pattern suggesting that individuals who we a priori think would have higher moving costs are also more affected by these shocks.[50]

Why is there no relationship between these four moving cost shifters and the effects of exposure to these two labor demand shocks? One possibility is that these variables are not actually associated with higher moving costs (on net). This may be because the shifter itself doesn't shift moving costs or because it is negatively correlated with another moving cost shifter. For example, even if all else equal being a homeowner raises moving costs, homeowners may also be less liquidity constrained and, consequently, not face higher moving costs on average. Alternatively, workers with different moving cost shifters may be more likely to work in sectors or occupations or live in locations that are more directly affected by these labor demand shocks. Finally, although the results don't provide evidence for the role of these moving cost shifters, they're not precise enough to provide evidence against the role of these moving cost shifters either. The fairly large standard errors mean that I cannot rule out that the effects of these shocks are higher for workers who we think have higher moving costs according to these shifters. The model of worker choice of location, sector, and occupation below addresses some of these issues, and I discuss the role of the estimated effect of these moving cost shifters using that model in Section 7.

6.2 Back of the envelope moving cost calculations

Workers originally living in labor markets exposed to trade with China experienced earnings changes of -4.4%, while out-migration rose .4 percent. The corresponding estimates for fracking are that earnings rose 6.7% and

[49] This prediction only holds if the labor demand shock is the same for these different groups. If some groups are more likely to be working in more exposed locations, sectors, or occupations before the shock, then the effects of the shock may differ between them even if they have the same moving costs.

[50] If anything, in some cases the pattern is the opposite from what we would predict. For example, unmarried workers seem to be more affected by trade with China than married workers

in-migration only rose .3%. What do these responses reveal about moving costs? We can make a simple back of the envelope calculation to bound moving costs for individuals who do not migrate based on these reduced form estimates. Following the conceptual framework above, assume that worker i chooses between working in location or job-type A and location/job-type B (indexed by j) and that indirect utility takes the following form:

$$v_{ij} = \ln(w_{ij}^r) + A_a - s_i 1[j \neq j(i)_{t-1}]$$

To make these calculations, I assume that there are no amenity changes, relative earnings changes for workers who do change locations or job-types are 0, earnings differences decay at a rate of .8 and workers have discount rates of .03 and make a one-time migration decisions.Given these assumptions, after an earnings shock to location or job-type A, a worker will not move if and only if $v_{iA} \geq v_{iB}$, which implies that:

$$\kappa(\Delta \ln(w_{iB}^r) - \Delta \ln(w_{iA}^r)) \leq \tilde{s}_i$$

This expression shows that for workers who do not move in response to a labor demand shock, moving costs must be at least $\kappa(\Delta \ln(w_{iB}^r) - \Delta \ln(w_{iA}^r))$, where κ depends on the decay rate of wage differences and worker discount rates. We can then plug in our reduced form estimates of the effect of labor demand shocks on real earnings of original residents (β), the migration response (γ) and the baseline migration rate (ω) to compute the lower bound on moving costs for the $1-\gamma$ share of workers who do not migrate.[51]

Plugging in our estimates for β, γ, and ω from my results using variation in exposure to PNTR with China yields lower bound location moving costs of \$9,726 for 99.6% of workres. Using the corresponding results for fracking yields moving cost estimates of at least \$16,210 for 99.9% of workers.[52].

This calculation has a number of limitations. First, it does not take into account changes in local amenities in response to these shocks. This concern looms large in this setting because recent research has suggested that many labor demand shocks also change local amenities (i.e. see Diamond (2016)). Second, it only provides a lower bound for moving costs, making it difficult to estimate counterfactual outcomes. Finally, it does not take into account economic geography, including distance between locations and potential interactions between location, occupation, and industry. I now write down a formal model of worker choice of location, sector, and occupation, which allows me to relax some of these limitations and use the parameter estimates to simulate the effects of counterfactual policies designed to encourage movement across locations, occupations, and sectors.

[51] Using these assumptions, the bound is: $4.11 \times \left(\frac{\beta}{1-\gamma-\omega}\right) \leq \tilde{s}_i$.

[52] The corresponding estimates for occupation moving costs are \$4,479 using the China shock and \$11,198 for fracking. For sector moving costs they are \$1,230 using the China shock and \$1,230 for fracking. Unfortunately, because I only observe occupation and sector in two time-periods, using my empirical strategy I am unable to estimate the effect of either shock on the mobility rate across occupations or sectors and, consequently, I am unable to estimate what share of the population these occupation and sector moving cost bounds apply to

6.3 Full model

In this section I specify and estimate a model of worker choice of location and job-type that incorporates geographic, sector, and occupation moving costs. This model accomplishes two goals. First, it quantifies the magnitude of moving costs necessary to rationalize the immobility of workers observed in the data. Second, the parameter estimates can be used to explore the role of moving costs in the incidence of local labor demand shocks like exposure to trade with China and simulate the effectiveness of policies designed to reduce moving costs such as relocation subsidies.

This model contributes to a large literature that has estimated models of local or sector/occupation choice by simultaneously allowing for moving costs across locations (as in Bayer et al. (2009), Kennan and Walker (2011), Bishop (2012), Diamond (2016), Morten and Oliveira (2016), and Shenoy (2015)), across sectors (as in Artuç et al. (2010), Dix-Carneiro (2014)), and occupations (Artuç and McLaren (2015), Traiberman (2015)).

6.3.1 Preferences

The economy consists of L labor markets and J job-types. Worker i receives flow utility in period t from consuming numeraire good, C_{iljt} and housing, H_{iljt} in labor market l and job-type j is:

$$U_{iljt} = C_{iljt}^{1-\gamma} H_{iljt}^{\gamma} \mu_{iljt} \tag{6.1}$$

Where μ_{iljt} is an individuals' idiosyncratic preferences for location l and job-type j in period t, w_{iljt} is wages received by individual i, and r_{lt} is the rental price of housing. Given wages and rents, these preferences imply an indirect flow utility function for living in labor market l and working in job-type j of:

$$u_{iljt} = (1 - \gamma_g) \ln w_{iljt} - \gamma_g \ln r_{lt} + \ln \mu_{iljt} \tag{6.2}$$

Note that this indirect utility function is only a slightly more complicated version of the one in the conceptual framework in Section 2. I then make four key assumptions to take this model to the data. First, I assume wages are determined by:

$$w_{iljt} = \omega_{ljt} \lambda_j^g \nu_i \tag{6.3}$$

Where ω_{ljt} are efficiency wages in labor market l and job-type j, λ_l^g represents group-specific ability in the given job-type, and ν_i captures unobserved individual ability. This assumption allows for group-specific comparative advantage and individual absolute advantage, but rules out individual comparative advantage.

Second, I assume that we can decompose idiosyncratic preferences into amenities in labor market l and job-type j for group g, moving costs between initial location and job-type and the new location and job-type, and an idiosyncratic location-job-type match term:

$$\ln \mu_{iljt} = \underbrace{\phi_{lt}^{g}}_{\text{location amenities}} + \underbrace{\zeta_{jt}^{g}}_{\text{job-type amenities}} - \underbrace{\tilde{c}_{l,l_{t_0},j,j_{t_0}}}_{\text{moving costs}} + \underbrace{\xi_{iljt}}_{\text{idiosyncratic prefs}} \tag{6.4}$$

This expression imposes the restriction that amenities are additively separable in locations and job-types, i.e. the amenities from being a carpenter in El Paso are the sum of the amenities for living in El Paso and working as a carpenter.[53] In Appendix Section C.2, I relax this assumption of additive separability of location and job-type amenities by instrumenting for location/job-type wages using exposure to PNTR with China and fracking. Broadly, the results allowing for endogenous location/job-type amenities are consistent with my main results. I discuss these results in more detail in Appendix Section C.2.[54]

Plugging Equations 6.3 and 6.4 into Equation 6.2 and collecting terms yields:

$$u_{iljt} = \beta_w \ln \omega_{ljt} + \ln \nu_i + (\beta_w \ln \lambda_{gj} + \zeta_{jt}^{g}) + (\phi_{lt}^{g} - \gamma_g \ln r_{lt}) + \tilde{c}_{l,l_{t_0},j,j_{t_0}} + \xi_{iljt} \tag{6.5}$$

Note that because $\ln \nu_i$ does not vary with location or job-type, it will not affect individual choices.

Third, I assume that individuals make decadal decisions about where to live and work, allowing me to map the model to the data where I observe individuals in 2000 and 2010-14.[55] Individuals make these decisions using a discount rate of δ and believe that that wage and rent differences will decay at the deterministic rate κ_w and κ_r respectively. Let $u_{iljt}(w_{ljt}, r_{ljt})$ be the indirect flow utility from living in location l and in job-type j in time t, individuals solve:

$$\max_{l,s} V_{l,j,t_0} = \sum_{t=t_0}^{t_0+10} \delta^{t-t_0} u_{iljt}(\kappa_w^{t-t_0}\omega_{ljt_0}, \kappa_r^{t-t_0} r_{lt_0})$$

Plugging Equation 6.5 for flow-utility into Equation 6.6 and re-arranging yields the workers indirect utility

[53]This restriction rules out three potentially important mechanisms. First, it rules out thick-labor market amenities. Second, it rules out firms endogenously adjusting amenities in response to local labor market conditions. In an especially tight labor market firms may not just raise wages to attract workers, they may also invest in creating a pleasant work environment. Third, this assumption rules out complementarities between location and job-types amenities. For example, perhaps a flexible work schedule is both an important job-types amenity that also allows one to take advantage of high location amenities - i.e. it's nice to be able to take a day off and relax particularly in places with nice weather or there are fun things to do. However, note that because I allow for location and job-type amenities to vary by age, sex, and education, I do allow for thick-labor market amenities for particular sex, age, and education groups within a location. For example, although my model rules out it being particularly good to work in finance in New York, it does allow for New York to be a particularly attractive place for young college graduates.

[54]Although it allows for endogenous location/job-type amenities, the approach of instrumenting for wages has limitations. Most importantly, because I only observe workers in 2000 and 2010/14, I estimate the model using decisions in one time-period: where to live/work in 2010/14 given ones location/job-type in 2000. Consequently, I have to instrument for levels of wages rather than changes in wages. This requirement is problematic because, as shown in Appendix Section 9, despite the fact that they are strong instruments for changes in wages, exposure to trade with China and fracking and weak instruments for changes in wages. These results using the control function approach should consequently be considered exploratory.

[55]In practice, workers may not make location and job-type decisions over decadal time horizons Consequently, I may overstate moving costs if some workers make multiple moves during the time period I observe, or they move and then return to their original location and job-type. In future work, I plan to bound my current estimates with different assumptions about workers' intermediate moves.

function:

$$
\begin{aligned}
V_{iljt} &= \underbrace{(\sum_{t_0}^{t_0+10} \delta^{t-t_0}\kappa_w^{t-t_0})}_{\tau} \beta_w^g \ln \omega_{ljt} + \underbrace{\sum_{t_0}^{t_0+10} \delta^{t-t_0}\phi_{lt}^g - (\sum_{t_0}^{t_0+10} \delta^{t-t_0}\kappa_r^{t-t_0})\gamma_g \ln r_{lt}}_{A_{lt_0}^g\text{: Pecuniary/non-pecuniary location amenities}} \\
&+ \underbrace{\beta_w^g(\sum_{t_0}^{t_0+10} \delta^{t-t_0}\kappa_w^{t-t_0}) \ln \lambda_j^g + (\sum_{t_0}^{t_0+10} \delta^{t-t_0}\zeta_{jt}^g)}_{B_{jt_0}^g\text{: Pecuniary/non-pecuniary job-type amenities}} - \underbrace{\sum_{t_0}^{t_0+10} \delta^{t-t_0}\tilde{c}_{l,l_{t_0},j,j_{t_0}}^g}_{c_{l,l_{t_0},j,j_{t_0}}^g\text{: Pecuniary/non-pecuniary moving costs}} \\
&+ \underbrace{\sum_{t_0}^{t_0+10} \delta^{t-t_0}\xi_{iljt}}_{\epsilon_{iljt}\text{: idiosyncratic preferences}}
\end{aligned}
$$

Letting A_{lt}^g and B_{jt}^g capture pecuniary and non-pecuniary amenities, including future option value, for group g in location l and job-type j respectively, we can rewrite this as the simplified expression:

$$
V_{ijst_0} = \tau\beta_w^g \ln \omega_{ljt_0} + A_{lt_0}^g + B_{jt_0}^g - c_{l,l_{t_0},j,j_{t_0}}^g + \epsilon_{iljt}
$$

Fourth, I assume that ϵ_{iljt} is i.i.d Extreme Value Type-1. This assumption rules out persistent, unobserved preference heterogeneity that may be correlated across space or job-type. For example, people with high preferences for living in San Francisco may also enjoy living in Boston. This will make it look like there are very low moving costs between Boston and San Francisco when in fact there is just persistent, unobserved preference heterogeneity. I attempt to address these concerns by allowing for individuals with different observable characteristics to have different preferences regarding characteristics of locations and sectors. For example, I allow young-college educated workers to have different preferences regarding San Francisco and Boston than older-non-college educated workers. Given these assumptions, the model is a standard conditional-logit model (McFadden (1973)) and we can write the probability that an individual from group g migrates from labor market l_{t_0} and job-type j_{t_0} to labor market l and job-type j as:

$$
\pi_{i,l,j,t}^{l_{t_0},j_{t_0}} = \frac{\exp\left(\tau^g\beta_w \ln \omega_{ljt} + A_{lt}^g + B_{jt}^g - c_{l,l_{t-1},j,j_{t-1}}^g\right)}{\sum_{s'}\sum_{j'} \exp\left(\tau_g\beta_w \ln \omega_{ljt} + A_{lt}^g + B_{jt}^g - c_{l,l_{t-1},j,j_{t-1}}^g\right)} \tag{6.6}
$$

Given data on worker location and job-type decisions and their original locations and job-types, wage information, and a parameter value for τ^g this expression can be estimated using MLE.

6.3.2 Parameterizing and Interpreting Moving Costs

I parametrize moving costs using a fixed and marginal costs of changing locations, and a fixed cost of moving between manufacturing and non-manufacturing jobs or between high-brawn and other types of jobs. Letting $d_{l,k}$ denote distance between location l and location k and mfg_j and brawn_j be indicators for whether job-type j is in mfg or is high-brawn respectively, and l_{t_0} and j_{t_0} denote an individuals' location and job-type in 2000, moving costs are then:

$$c_{l,l_{t_0}),j,j_{t_0}} = \alpha_0 1(l \neq l_{t_0}) + \alpha_1 d_{l,l_{t_0}} + \gamma_{mfg} 1(\text{mfg}_j \neq \text{mfg}_{j_{t_0}}) + \gamma_{\text{brawn}} 1(\text{brawn}_j \neq \text{brawn}_{j_{t_0}})$$

These moving costs include both pecuniary and non-pecuniary costs of moving. My empirical strategy does not allow me to distinguish pecuniary moving costs of renting a truck and physically moving, non-pecuniary moving costs from being away from family and friends, or market-frictions like information, liquidity constraints, social networks or costs of retraining. All of these types of moving costs will result in the same labor supply elasticities and positive predictions regarding the effects of counterfactual policies. However, they may have very different implications for the welfare impacts of counterfactual policies.

6.3.3 Expectations and Timing Complications

Equation 6.6 shows that agents' choices regarding migration decisions depend not just on the current periods' wages and rents, but also expectations regarding the stream of future wages and rents. Consequently, we would need to make assumptions about the expected wages and discount rates to interpret the parameters. In the results reported below, I use estimates from the literature, and assume that people believe current wage premia decay at a rate of $\tau_w = .8$ (ADD CITES), and have a discount factor of .97. In results available upon request, I report how different assumptions about τ_w and δ change my estimated moving costs. The reader can also easily convert the estimates herself by calculating $\tilde{\tau} = \sum_{t_0}^{t_0+10} \delta^{t-t_0} \kappa_w^{t-t_0}$ using her preferred δ and τ_w and multiplying the reported moving cost estimates by $\frac{\tilde{\tau}}{4.11}$.

6.3.4 Estimation

The data introduces one further complication. The panel of location and sectors does not come from a random sample. Instead, the Census bureau over-samples particular demographic groups and smaller geographic areas. The latter is problematic because it means that a persons' probability of being observed is a function of their choices, specifically individuals moving to rural areas will be more likely to be observed than individuals moving to urban areas. Consequently, we cannot estimate the model's parameters using basic maximum likelihood techniques.

To address this problem, I follow Manski and Lerman (1977) and use Weighted Exogenous Sample Maximum

Likelihood (WESML) to estimate the parameters. Specifically, let μ_i be the product of the sampling weights in the long-form and the ACS, I then estimate the pseudo-likelihood:

$$\ell\ell(\theta) \qquad = \sum_i \mu_i \ln \pi_{l,j,t}^{i,l_{t-1},j_{t-1}}(\theta) \tag{6.7}$$

Manski and Lerman (1977) show that this will consistently estimate the parameters of interest.

7 Quantifying moving frictions

In this section I describe the moving costs generated by my parameter estimates and discuss their implications. Appendix Section C presents the parameter estimates themselves and discusses them in more detail. I then use the models parameters to simulate the effects of lowering moving costs on the effects of exposure to PNTR with China. First, I simulate the effect that halving moving costs would have on the effects of exposure to PNTR with China. Second, I simulate the effect of $10,000 moving subsidies for moving to a higher wage location, occupation, or sector would have had on the effects of exposure to PNTR with China.

7.1 Moving cost estimates

Table 8 presents estimates of the present-value moving costs in dollars for non-college educated men using the parameters from Appendix Table 8.[56] These moving costs represent the discounted present-value of the costs of changing locations, sectors, and occupations over the workers' time horizon. Thus, they represent a combination of fixed costs of moving that workers may pay up front - such as renting a U-Haul or the hassle costs of selling a house - as well as flow costs of moving, such as living farther away from family and friends. Rows report the cost of moving to a location 500 miles away, in or out of manufacturing, and in or out of high-brawn occupations. For moving locations, I report moving costs separately based on whether individuals lived in the same location in 2000 as they did in 1995. Different columns report results for different five-year age groups. Panel A reports results for moving costs to an arbitrary location and job-type.

Starting with Panel A, Column (1), we see that estimated moving costs to an arbitrary alternative are large - over $100,000 - for moving locations, leaving or entering manufacturing, or switching between brawn and non-brawn intensive jobs. Location moving costs are particularly large, over $683,000 for individuals who lived in a different location in 2000 than in 1995. The magnitude of these moving costs indicates that they are not primarily driven by the direct, pecuniary costs of moving (such as renting a U-Haul), but instead reflect non-pecuniary costs of moving such as losing social ties and being distant from family and friends. Consistent with this explanation

[56] Parameter estimates for women are sensitive to specification choices and vary dramatically across age groups, and are often of the unexpected sign. For example, the marginal utility of income for women is often estimated to be negative. These results may be driven by the effect of childbearing and child-raising considerations for women that are not incorporated in the model.

for location moving costs, they rise about 40% - to $1 million - for individuals living in the same location in 2000 as they did in 1995, possibly reflecting greater social ties among long term residents. These large costs may also reflect market failures - such as insufficient information or liquidity constraints - that inhibit workers' ability to take advantage of job opportunities in different labor markets. Finally, the model does not allow for persistent, unobserved preference heterogeneity within age-sex-education groups. If there is such persistent, unobserved preference heterogeneity, then this heterogeneity would be estimated as a moving-cost.[57]

I estimate substantial costs to moving occupations and sectors as well - $163,000 and $135,000 respectively - roughly one-fourth to one-seventh the magnitude of location moving costs. These costs reflect a combination of the costs of retraining and obtaining new skills, search costs of finding a new job, as well as non-pecuniary costs of changing occupation-types, such as changing work schedules or types.[58]. Although these costs are large, they are consistent with anecdotal evidence regarding the difficulties workers face transitioning occupations and the monetary and time-costs of retraining. For example, Carpenter et al. (2012) find that among 102 low and middle-wage occupations, on average obtaining the appropriate license or certification required 9 months of coursework/training and taking one-exam. This cost does not include any tuition required for the training, lower wages that workers may receive while receiving on the job training, or period of unemployment while trying to find a job in one's new occupation. Consequently, costs of several times annual income for changing occupations for the average worker seem appropriate.

The costs reported above a for moves to an arbitrary choice. However, in the model workers also receive idiosyncratic preference shocks for certain choices, which in practice will substantially lower moving costs for marginal workers who actually make moves. In Panel B, I report moving costs to the next best alternative to their original choice. I compute moving costs to the next best alternative assuming that the worker does not make any other type of moves - i.e. they only move locations or only move in and out of manufacturing or high-brawn occupations. For example, for location moving costs the expected moving costs to the next best option are:

$$E[\text{moving costs}] = \quad \frac{1}{\beta_W}\left(\alpha_0 + E[\max \epsilon_{l \neq l_{t_0}, j_{t_0}}]\right) = \frac{1}{\beta_W}\left(\alpha_0 + \ln(J-1)\right)$$

In Panel B, we see that the moving costs to the next best alternative location are substantially lower - roughly a fifth of the size for workers living in their 2000 location in 1995 and actually positive for workers not living in

[57] Note that for some counterfactuals, whether or not the moving costs are driven by family ties or persistent, unobserved preference heterogeneity may not matter. For example, if workers receive random, idiosyncratic preference draws across locations that are uncorrelated, then moving costs driven by this unobserved preference heterogeneity will generate similar predictions. However, if the persistent, unobserved preference heterogeneity is correlated across locations, then the estimated counterfactuals may not appropriately reflect worker substitution patterns. For example, individuals who have persistent, unobserved preferences for Boston, MA may also have unobserved preferences for San Francisco, CA. Additionally, the welfare implications of different sources of moving costs may be different. I discuss the welfare implications of different sources of moving costs in more detail below.

[58] A number of commentators (Stevenson, 2016) have argued that men may find it costly to move from brawn to non-brawn intensive occupations because the non-brawn occupations may be socially stigmitized as "un-manly".

the same location in 1995. These lower moving costs reflect the fact that, given the large number of potential locations one can move to, there is likely an alternative location that one particularly likes. For example, you may have family members of friends who live in a particular alternative labor market. Consequently, moving costs for moves workers actually make will be lower than the moving costs reported in Panel A[59].

Moving from Column (1) to Columns (2)-(5) we see that moving costs rise with age. Between ages 25-30 and 45-50 moving costs across locations increase by roughly 60% , while moving costs across occupations and sectors more than double. These higher moving costs for older workers could reflect a number of factors. First, older workers may have more social ties to their original location (or their original occupation). Second, older workers may find retraining more costly or difficult than younger workers.[60]

In Table 10, I compare my estimates of location, occupation, and sector moving costs to others found in the literature.[61] Unlike previous work, my model incorporates location and sector/occupation moving costs into the model. Given the different distributions of occupations and sectors across locations, previously estimated location and occupation/sector moving costs were hard to interpret. When workers may have to change labor markets to change occupations/sectors, high-location costs may be estimated as high sector/occupation moving costs and vice-versa. However, my estimates suggest that this mis-attribution was not the case. Instead, my estimates of location moving costs of 19.3 times annual income are quite similar to the estimates from Kennan and Walker (2011) of 20.3 times annual income. Similarly, my estimates of sector moving costs of 4.6 times annual income for sector moving costs and 3.8 times annual income for occupation moving costs are quite close to the ranges in the literature (3.7 to 4.1 times annual income for sector moving costs and 4.9 to 5.3 times annual income for occupation moving costs).[62]. This new evidence in favor of both moving costs across locations and occupations/sectors highlights that geographic and retraining/job-changing barriers are important features of labor markets and must both be incorporated when thinking about how workers will adjust to changes in labor demand.

[59]Note that the estimated moving costs across occupations and sectors are the same to the next best alternative and an arbitrary alternative, because when there are two choices $\ln(J-1) = 0$.

[60]Alternatively, these higher costs for older workers could reflect shorter time horizons. This would reflect a failure of my assumption that workers make decisions over 10-year time-horizons (when even the oldest worker would be 60 at the end of the time-horizon). However, even if my assumed time-horizon is incorrect, given the discount factor and assumed decay rate of wage premia, expected wage premia in later years would only make younger workers slightly more sensitive to wage premia. For example, if workers made decisions of 15-year horizons instead of 10-years, the implied sensitivity to changes in the wage premium in a given location-sector would only rise by 6.2%, and would only overstate moving costs by 5.9%. Consequently, it is unlikely that most of the increase in estimated moving costs as workers age is driven by shorter time horizons.

[61]Note that the exact samples, location, sector, occupation aggregations, models, and migration definitions vary across the papers. I attempted to use the estimates that most closely corresponded to the ones in this paper. I discuss in more detail each paper in the footnote to Table 10.

[62]The one exception to this similarity is Bryan and Morten (2015), who estimate moving costs across locations of 2.5 times annual income, almost an order of magnitude lower than my estimates or those from Kennan and Walker (2011). One possible source of these differences is that Bryan and Morten estimate moving costs away from ones state of birth rather than from one's current location. If moving costs are much lower when people are young, then this may result in lower estimated moving costs when measuring migration as leaving ones state of birth. For example, individuals may have low moving costs when choosing their first job/place to live, but may have much higher moving costs later in the life-cycle.

7.2 Effects of reducing moving costs on the effects of local shocks

As the conceptual framework in Section 2 highlighted, high moving costs will result in shocks to particular locations, occupations, or sectors having substantial impacts on directly exposed workers. In this section, I use my parameter estimates to simulate how much lowering moving costs would have improved the outcomes of workers living in labor markets most exposed to PNTR with China during the 2000s. First, I simulate how the effects of exposure to PNTR with China would have changed if moving costs across locations, sectors, and/or occupations were halved. Second, I simulate the effect of a \$10,000 relocation subsidy for changing locations, occupations, or sectors, which is among the set of policies that have been proposed to help non-college educated workers adjust to changes in labor demand (Ludwig and Raphael (2010), Moretti (2013)).[63]

7.2.1 Assumptions in Simulating Effects of Lowering Moving Costs

I make three key assumptions in my counterfactual simulations. First, I maintain all the assumptions required to consistently estimate the parameters of the structure model. These assumptions include no comparative advantage within age-sex-education groups, amenities being additively separable into location and job-type amenities, and the expectations and timing assumptions.[64] Second, I simulate only the partial equilibrium effects of lowering moving costs and assume that wages and rents do not adjust to workers changing location, sector, and occupation choices.[65]. Third, I assume that the estimated moving costs are "true" moving costs, and are not generated by market failures such as liquidity constraints or limited information. If the reason workers are unresponsive to job opportunities is actually driven by liquidity constraints, then even small subsidies or loan programs that relax these liquidity constraints could have large impacts on migration decisions by some workers.

Given these assumptions, I simulate the effects of lowering moving costs as follows. Let $P^i_{l,j}(\theta, \mathbf{y_{g(i)}})$ be the probability that person i chooses to work in location l, job-type j given a vector of moving costs parameters, θ and the vector of wages across all locations and sectors for person i's demographic group, $\mathbf{y_{g(i)}}$, and y_{i,t_0} be worker i's earnings in 2000. The average predicted change in wages for individuals in group q (where q is some grouping of individuals[66]) is then:

$$\widehat{d \ln y_q}(\theta, \mathbf{y_{g(i)}}) \equiv \sum_{i \in q} \sum_{L} \sum_{J} P_{i,j}(\theta, \mathbf{y_{g(i)}}) \frac{\bar{y}_{g(i),l,j} - y_{i,t_0}}{\frac{1}{2}(\bar{y}_{g(i),l,j} + y_{i,t_0})}$$

We can then vary θ and $\mathbf{y_{g(i)}}$ to explore the effects of lowering moving costs or changing the availability of different job-opportunities on outcomes of workers in group q. For example, let $\hat{\theta}$ be the vector of estimated

[63] Ludwig and Raphael (2010) proposes a Mobility Bank, where the federal government would provide loans for workers interested in moving to better labor markets, while Moretti (2013) proposes restructuring unemployment insurance to provide higher benefits to workers who move to better labor markets.

[64] Note that this assumption does not rule out workers originally in particular locations, sectors or occupations having absolute advantage.

[65] In future work, I will incorporate general equilibrium effects of lowering moving costs into my counterfactual estimates.

[66] In the counterfactuals I discuss below, q will be the quartile of exposure to PNTR with China of the workers' labor market in 2000.

moving costs, $\hat{\theta}^m$ be a modified vector of moving costs, and $\mathbf{y^1_{g(i)}}$ be the empirically observed average wages for people in group demographic-group $g(i)$ in 2010/14. The estimated average effect of changing moving costs from $\hat{\theta}$ to $\hat{\theta}^m$ on earnings changes for workers in group q is:

$$\hat{\delta}_q(\hat{\theta}_{\frac{1}{2}}, \mathbf{y^0}) \equiv \widehat{d\ln y_q}(\hat{\theta}^m, \mathbf{y^1_{g(i)}}) - \widehat{d\ln y_q}(\hat{\theta}, \mathbf{y^1_{g(i)}}) \tag{7.1}$$

I present estimates of the effects of two modifications of moving costs (i.e. two different $\hat{\theta}^m$s in Equation 7.1). The first, $\hat{\theta}^h$, halves all moving costs, while the second, $\hat{\theta}^s$, provides a \$10,000 subsidy to workers who change locations, occupations, or sectors, i.e.:

$$\begin{aligned} \hat{\theta}^h &= \frac{1}{2}\hat{\theta} \\ \hat{\theta}^s &= \hat{\theta} + 10,000 \times 1(l, j \neq l_0, j_0) \end{aligned}$$

7.2.2 Simulated Effects of Lowering Moving Costs

Table 9 reports estimates of the effects of lowering moving costs on the average change in earnings by exposure to PNTR with China. Columns (1) - (4) reports estimates for each quartile of exposure to PNTR with China, where quartile 4 contains the most exposed labor markets and quartile 1 contains the least exposed labor markets. Column (5) reports the estimated difference in average earnings changes between the 4th and 1st quartiles of exposure for the counterfactual excercise in the given row, providing information about how lowering different types of moving cost effects the relationship between exposure to PNTR with China and workers outcomes. Panel A reports the empirical and predicted changes in earnings for reference and as a way of assessing model fit. Panel B the reports the effect of halving different types of moving costs on the average change in earnings in each group, while Panel C reports the effect of relocation or retraining subsidies on the average earnings change in each group. Note that the reported estimates in Panels B and C are relative to Panel A2, i.e. they represent the difference between the counterfactual and predicted change in earnings.[67]

Starting with Panel $A1$, we see that the model is able to match the observed earnings declines by quartile of exposure to PNTR with China quite well, with the predicted changes for each quartile all being within 1.6% of the observed changes. The model does slightly over-predict the difference in earnings changes between the 4th and 1st Quartile of exposure to PNTR (-7.8%) relative to the empirical value (-4.9%). Consequently, I'll emphasize the predicted effects of lowering moving costs on the gap between the 4th and 1st quartile of exposure to PNTR as a share of the baseline predicted gap.

Moving to Panel B, we see that halving moving costs has large impacts on worker earnings and substantially

[67] For example, Panel B1, Column (4) reports that halving location moving costs would have raised earnings by 0.5% for workers originally in labor markets most exposed to PNTR with China, meaning that the average change in earnings for these workers would have been -41.6% rather than -42.1%.

reduces the gap in earnings changes between the labor markets most exposed to PNTR with China and other labor markets. Starting with Column B1, Column (5), halving location moving costs reduces the gap between the 4th and 1st quartile of exposure to PNTR with China by 1.4 percentage points, or 18% of the baseline gap. This gain is driven by moderate earnings gains for workers in the 4th quartile of exposure to PNTR with China and, somewhat surprisingly, moderate losses for workers in the 1st quartile of exposure to PNTR with China.[68] Halving sector moving costs also reduces the earnings gap by about 1.4 percentage points. Interestingly, halving occupational moving costs has a small effect on the gap between the 4th and 1st quartiles of PNTR exposure, only reducing the difference by 0.1 percentage points. However, this small effect is not due to a small effect on earnings - the effect on worker earnings is almost 5%. Instead, the impact of reducing occupation moving costs does not vary with exposure to PNTR with China. This result may reflect the fact that there are substantial job opportunities outside of high-brawn occupations in most labor markets that workers are not currently exploiting.

Finally, B4 and B5 report the effects of simultaneously lowering different types of moving costs, with B4 reporting the effects of halving both sector and occupation moving costs and B5 reporting the effects of halving all moving costs. Lowering all moving costs reduces the gap between the earnings changes of labor markets in the 4th compared to 1st quartile of exposure to PNTR with China by 2.7 percentage points, or roughly 35%. The estimates suggest that reducing different types of moving costs are neither substitutes nor complements, with the sum of the estimated impacts of lowering each moving costs alone (2.67%) almost exactly equaling the effect lowering them all simultaneously (2.65%).

The results in Panel B highlight the central role that moving costs play in generating the large impacts of exposure to PNTR with China on the original residents that we observe in the data. However, given the magnitude of estimated moving costs, halving moving costs would be extremely costly. How effective would more feasible policies for assisting workers to change locations or job-types be at reducing the impacts of exposure to PNTR with China? Panel C explores this question, reporting estimates of the effects of $10,000 subsidies for changing locations, sector, and occupations. None of these subsidies reduces the gap between the 4th and 1st quartile of exposure to PNTR by more than .004%. Additionally, the estimated impacts on the earnings changes in each quartile are quite small, never rising above .019% in absolute value, even when subsidizing changing locations, occupations, and industries simultaneously (i.e. giving a $10,000 for each type of move, resulting in a $30,000 subsidy for individuals who change locations, occupations, and sectors). These small effects are despite the fact that relocation subsidies have a non-trivial impact on location decisions. For example, a $10,000 subsidy for moving from the 4th quartile of exposure to PNTR to the 1st quartile is estimated to increase migration from the 4th to 1st quartile by 2 percentage points, or roughly 50% over the baseline migration rate. However, this small change is insufficient to offset the large differences in wage opportunities in the different regions.[69].

[68] These earnings losses may reflect workers in the 1st - 3rd quartiles of exposure to PNTR with China choosing to move to high-amenity, low-wage locations when moving costs are lower. This finding makes the broader point that workers maximize utility, not earnings, and that lowering moving costs will not necessarily lead to earnings increases.

[69] It would be interesting to explore whether the effect of relocation or retraining subsidies grow once general equilibrium forces are

8 Conclusion

This paper investigates the role played by moving costs across locations, occupations, and industries, in the labor market outcomes of non-college educated workers during the 2000s. I exploit novel data linking individuals across decennial censuses, allowing me both to avoid compositional biases that confound cross-sectional analyses and to separate the roles of workers' original locations, occupations, and industries in their ability to adjust to changes in labor demand. I combine these data with variation from two large shocks to local labor demand for non-college educated workers: PNTR with China and hydraulic fracturing. Examining these two shocks allows me to isolate the effects of local labor demand shifts from changes in local labor supply, while also providing essential information about two of the most important local labor demand shocks during the 2000s.

I have three main findings. First, long-term local labor demand shocks have large effects on the earnings of the original residents of exposed locations relative to demographically similar workers within the same region. I find this large incidence on original residents both for a large negative shock (PNTR with China) and a positive shock (hydraulic fracturing), implying that my findings are not driven by losses of industry specific human capital or other particular features of negative shocks, but rather workers' imperfect ability to move locations in response to changes in labor demand.

Second, the effects of both shocks are concentrated amongst workers originally working in brawn-intensive occupations rather than in directly exposed industries, suggesting that moving costs across occupations and other costs of acquiring new skills are an important determinant of the incidence of local labor demand shocks. These results imply that workers are exposed to risks from shocks not just to their own industries, but to all local industries that use a similar set of skills.

Third, I estimate a structural model of job choice that incorporates moving costs across location, sector, and occupations to quantify the importance of these costs. This extends the previous literature, which has primarily focused on estimating location or sector/occupation moving costs in isolation. I estimate large moving costs for making all three types of moves, implying that previous research was not spuriously attributing location moving costs to sector moving costs and vice-versa. I use these moving costs to simulate how reductions in moving costs would have affected the outcomes of workers living in labor markets more exposed to PNTR with China. I find that halving all types of moving costs would have reduced the effects of exposure to PNTR with China by 35%. However, more modest relocation subsidies of the magnitude that have been proposed - $10,000 - would have little impact on the effects of exposure to PNTR with China, because such modest subsidies would only modestly affect moving probabilities across locations, occupations, and sectors.

More broadly, the combination of my reduced form finding that changes in local labor demand have large effects on directly exposed workers, and my structural estimates of large moving costs across locations, occupations, and

incorporated. With downward sloping labor demand, migration will raise wages in regions exposed to PNTR with China and reduce wages in regions less exposed, further reducing the gap in outcomes between workers in the 4th and 1st quartile. In future work, I plan on incorporating these general equilibrium effects and exploring their sensitivity to the elasticity of labor demand.

sectors, suggest that workers in directly exposed occupations and locations bear much of the incidence of changes in local labor demand, and that economists should re-consider the no-moving cost benchmark when thinking about shocks to local labor markets or particular occupations. Furthermore, workers' limited mobility response and my simulated estimates of the effect of relocation subsidies suggest that pecuniary incentives or assistance to move is unlikely to have a substantial effect on workers' responsiveness to changes in local labor demand unless the high estimated moving costs are driven by market failures.

The key question for future research is to open up the black box of "moving-costs". To what extent are these measured moving costs driven by true utility losses from moving versus: market failures, such as liquidity constraints or information problems; behavioral mistakes, such as men's aversion to working outside of traditionally male occupations; or policy induced costs, such as occupational licensing. Such research will answer whether moving costs are something that can be fixed or whether they are an indelible feature of even the fluid US labor market.

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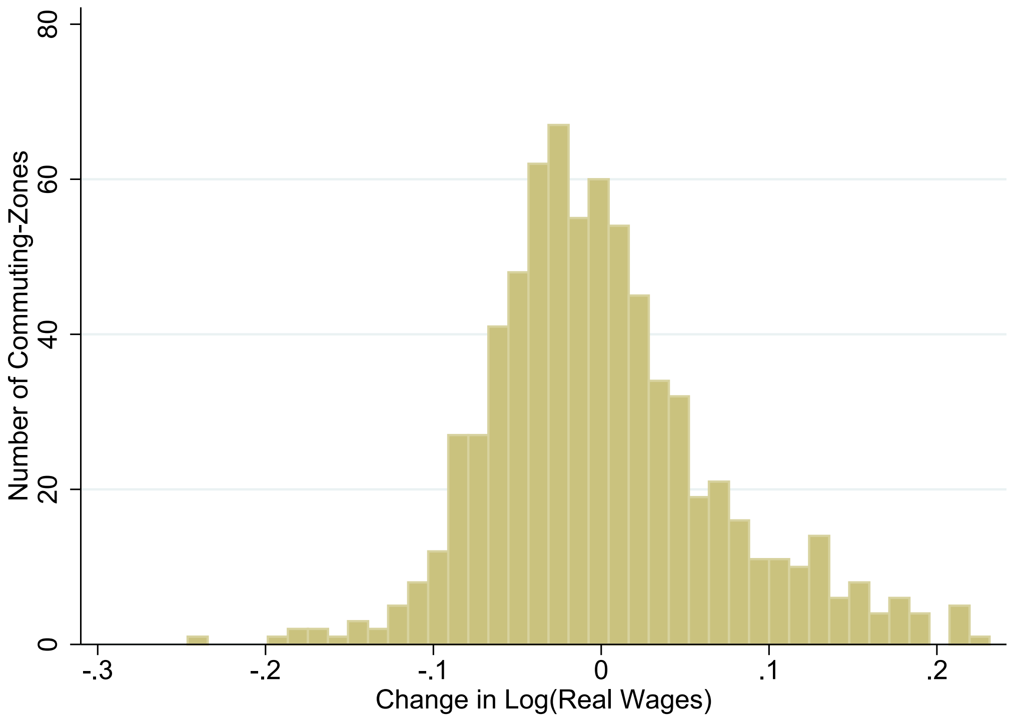
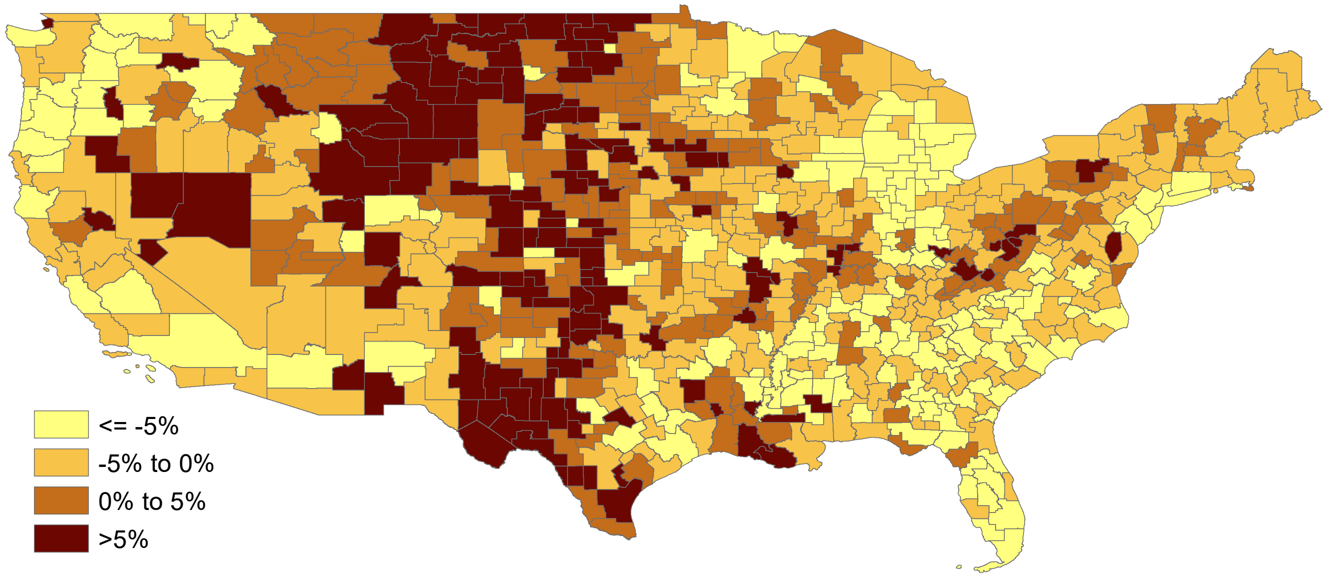
9 Figures

Figure 1: Histogram of Commuting-Zone Change in Log(Real-Wages) 2000 to 2010/14



Notes: This figure shows a histogram of the change in log(real-wages) between 2000 and 2010/14 across Commuting Zones. Real wages are computed assuming that workers spend 33% of their income on housing. Data come from the 2000 Decennial Census and the 2010-14 American Community Survey.

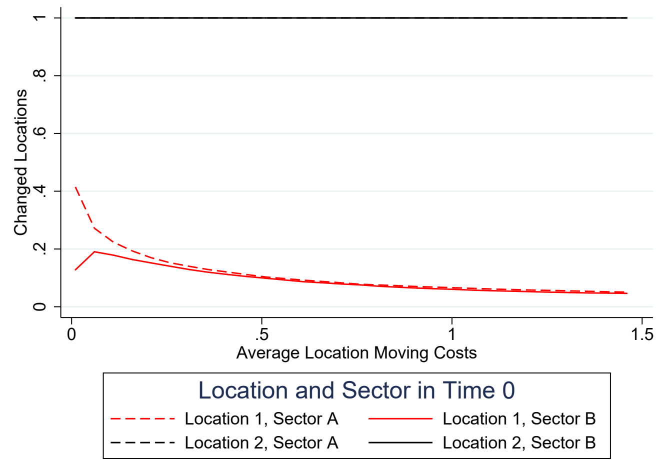
Figure 2: Commuting-Zone Change in Log(Real-Wages) for Non-College Educated Workers 2000 to 2010/14



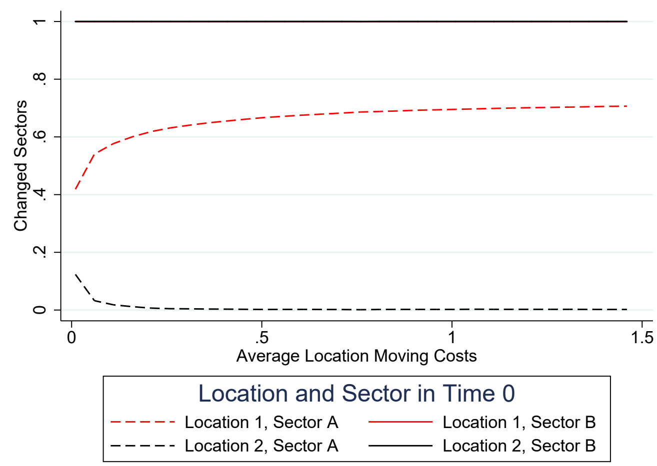
Notes: This figure shows the change in log(real-wages) between 2000 and 2010/14 by Commuting-Zone. Real wages are computed assuming that workers spend 33% of their income on housing. Data come from the 2000 Decennial Census and the 2010-14 American Community Survey.

Figure 3: Effects of Labor Demand Shock in Location 1 and Sector A:
Case 2: Positive Location Moving Costs and Zero Sectoral Moving Costs ($S^L > 0$ and $s^J = 0$)

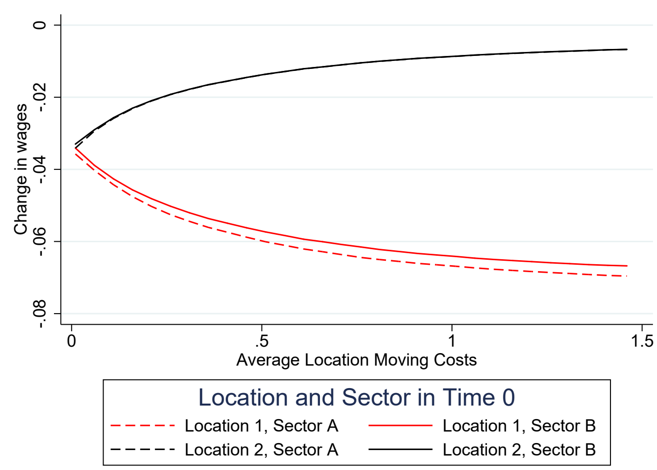
(a) Changed Locations



(b) Changed Sectors



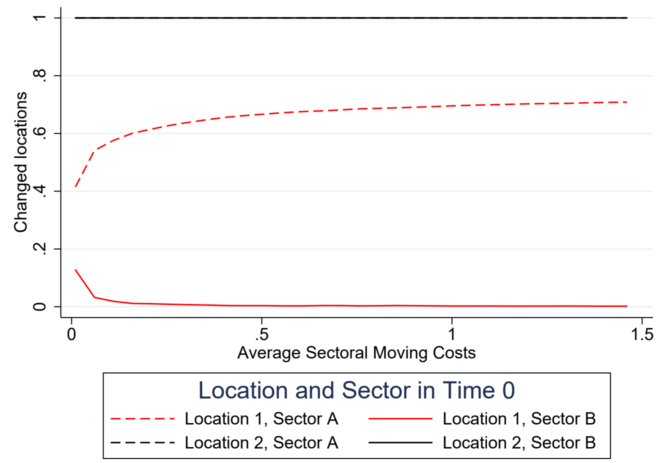
(c) Average Change in Wages



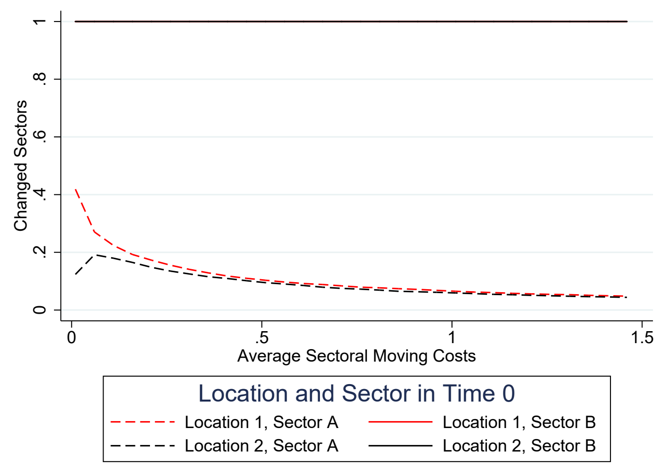
Notes: These figures plot simulations of the effect of a decline in productivity in Location 1, Sector A on average labor market outcomes for workers in different original locations and sectors by location moving costs when there are no sector moving costs (($s^J = 0$). In all Panels, the x-axis is location moving costs while different panels plot different outcomes. Panel A reports the relationship between location moving costs and the share of individuals who change locations. Panel B reports the relationship between location moving costs and the share of individuals who move sectors. Panel C plots the relationship between location moving costs and the average change in wages.

Figure 4: Effects of Labor Demand Shock in Location 1 and Sector A:
Case 3: Positive Sectoral Moving Costs and No Location Moving Costs ($s^L = 0$ and $s^J > 0$)

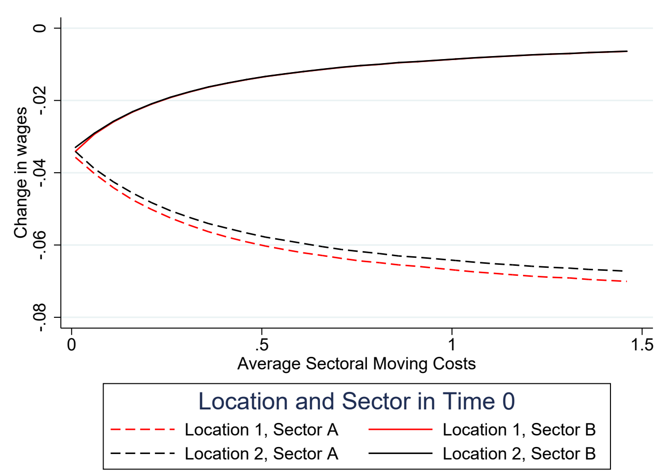
(a) Changed Locations



(b) Changed Sectors



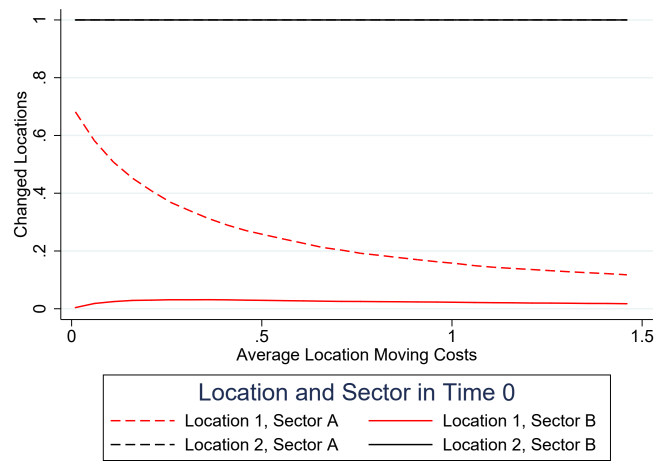
(c) Average Change in Wages



Notes: These figures plot simulations of the effect of a decline in productivity in Location 1, Sector A on average labor market outcomes for workers in different original locations and sectors by sector moving costs when there are no location moving costs (($s^L = 0$). In all Panels, the x-axis is sector moving costs while different panels plot different outcomes. Panel A reports the relationship between sector moving costs and the share of individuals who change locations. Panel B reports the relationship between sector moving costs and the share of individuals who move sectors. Panel C plots the relationship between sector moving costs and the average change in wages.

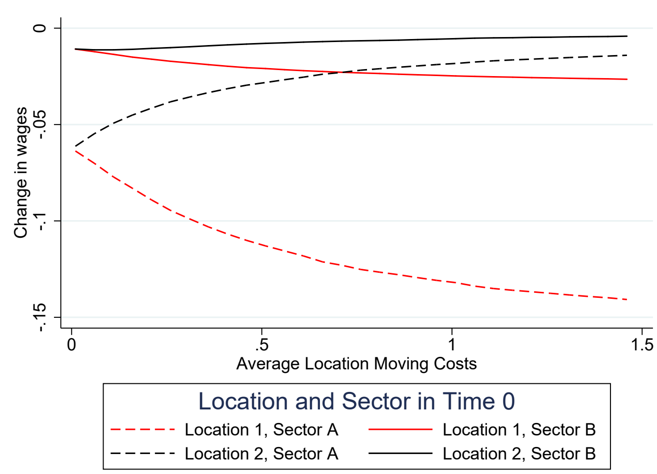
Figure 5: Effects of Labor Demand Shock in Location 1 and Sector A:
Case 4: Positive Location and Sectoral Moving Costs ($s^L > 0$ and $s^J = .75$)

(a) Changed Locations



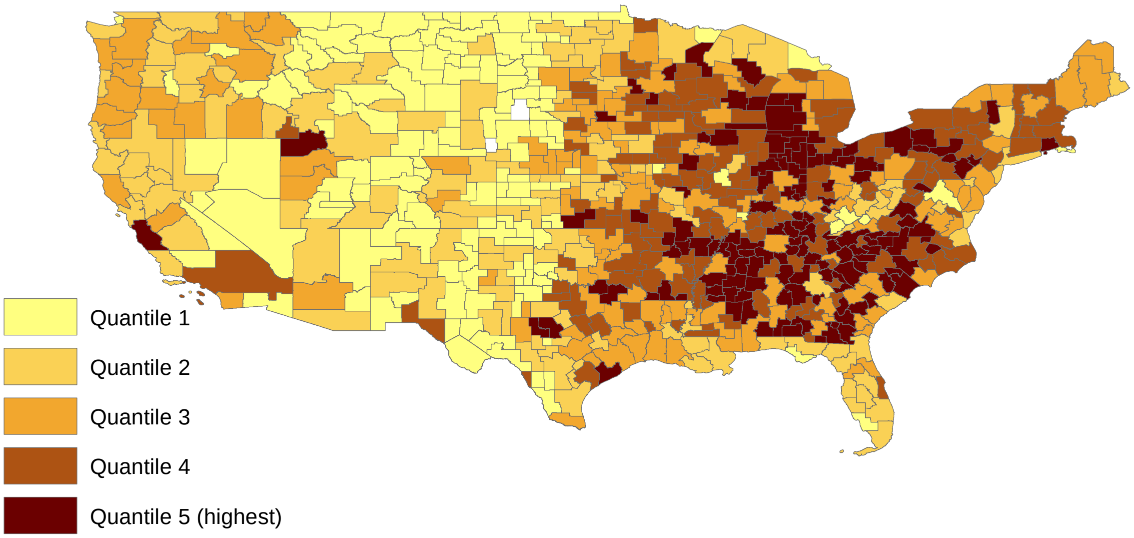
(b) Changed Sectors

(c) Average Change in Wages



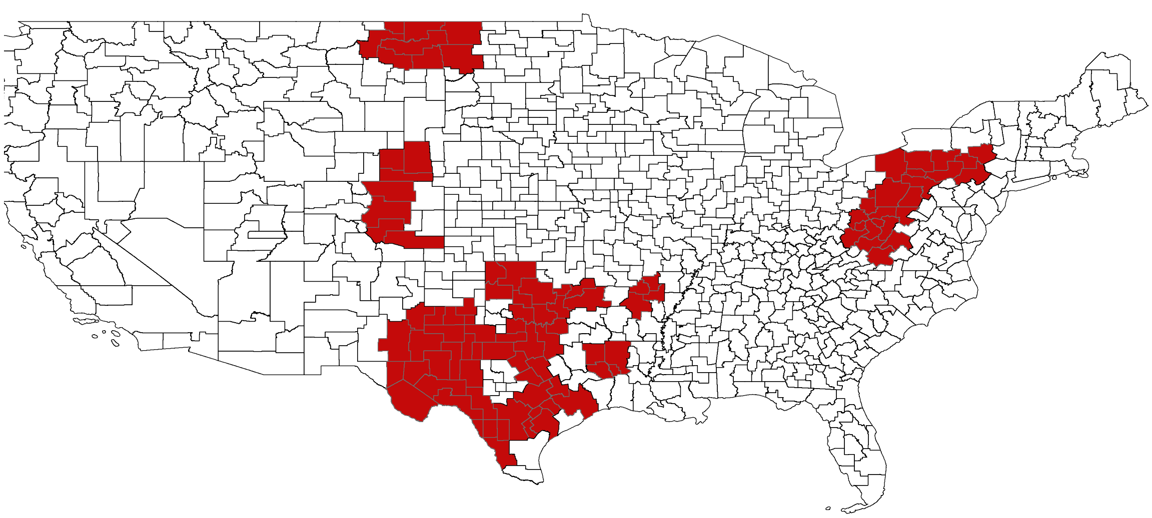
Notes: These figures plot simulations of the effect of a decline in productivity in Location 1, Sector A on average labor market outcomes for workers in different original locations and sectors by location moving costs when there are positive sector moving costs (($s^J = .75$). In all Panels, the x-axis is location moving costs while different panels plot different outcomes. Panel A reports the relationship between location moving costs and the share of individuals who change locations. Panel B reports the relationship between location moving costs and the share of individuals who move sectors. Panel C plots the relationship between location moving costs and the average change in wages.

Figure 6: Map of Pierce and Schott (2016) manufacturing decline exposure measure



Notes: This map shows the Pierce and Schott (2016) based measure for exposure to the decline of manufacturing based on the the gap between the Normal Trade Relations and non-Normal Trade Relations tariffs for the average worker in the commuting zone.

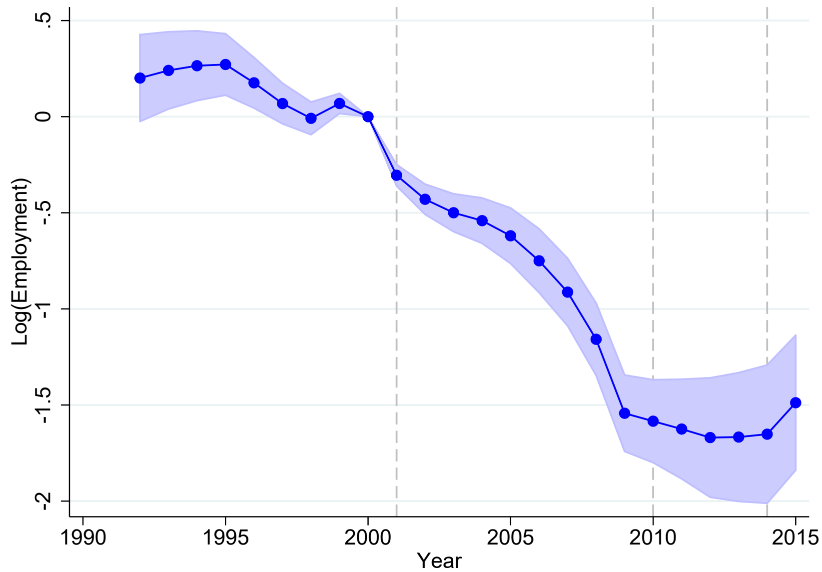
Figure 7: Map of indicator for any fracking exposure



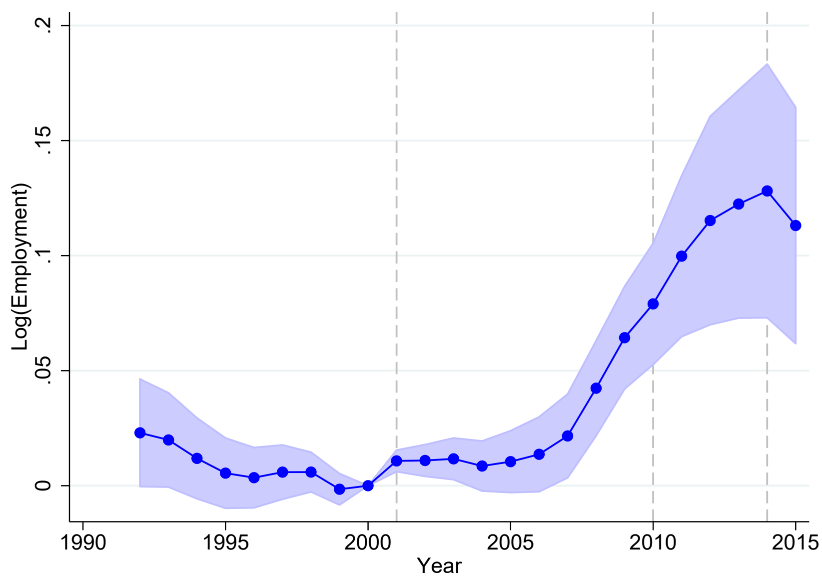
Notes: This map shows an indicator for whether or not the given commuting zone has any exposure to fracking, measured by having any area in the top half of Rystad prospectivity within the shale play of the given commuting-zone.

Figure 8: Labor market trends and exposure to PNTR with China and fracking

(a) Log(total employment) and exposure to PNTR with China



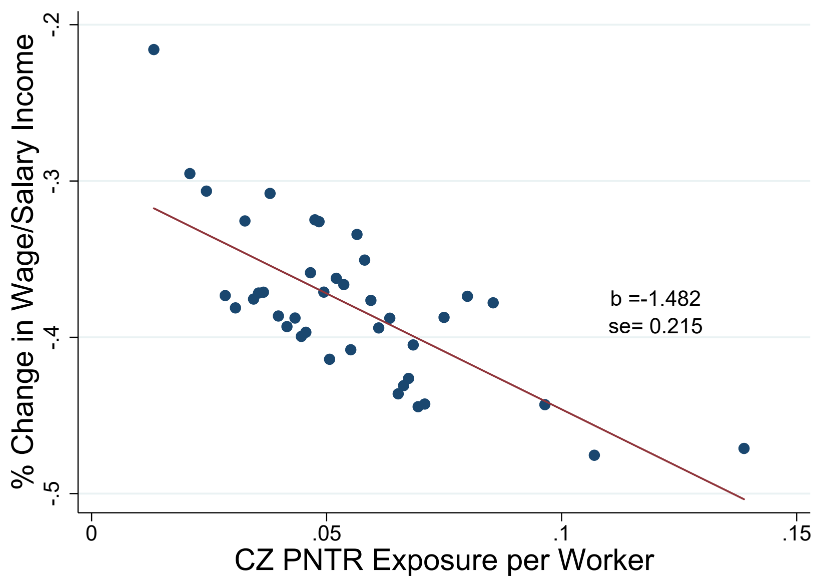
(b) Fracking exposure and log(employment)



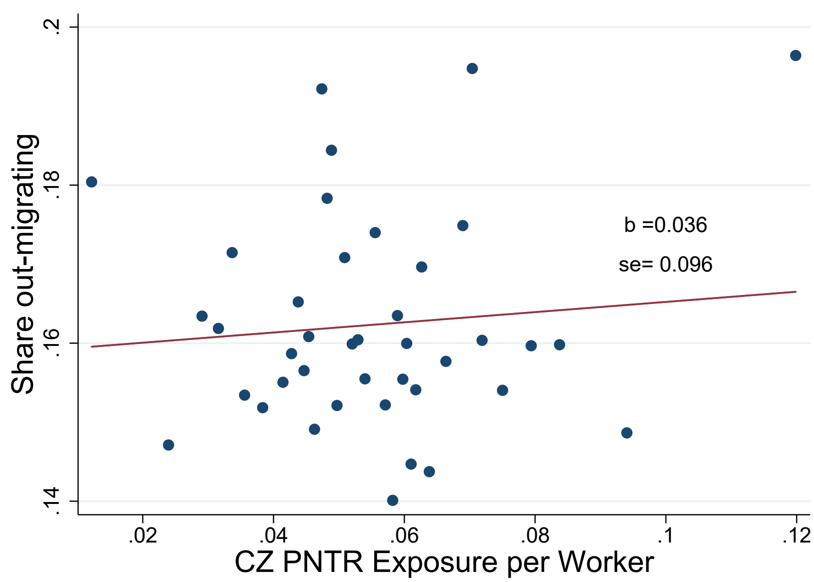
Notes: This figure plots estimates of the relationship between exposure to PNTR with China or fracking and log(total employment) over time. The reported coefficients come from fitting a modified version of Equation ?? where we interact Z_g with a vector of calendar year indicators, $delta_t$. Panel A reports results for PNTR with China where Z_g is exposure to China receiving PNTR per worker. Panel B reports results for fracking where Z_g is an indicator for the Commuting-Zone having any exposure to fracking. These coefficients measure the difference in outcomes between more and less exposed Commuting-Zones by calendar year. The model also includes region-year fixed effects. Data on log(total employment) from 1992 to 2015 come from the QCEW (Bureau of Labor Statistics, U.S Department of Labor (2016)). The shaded blue region shows 95 percent confidence intervals calculated using standard errors clustered at the commuting-zone level.

Figure 9: Exposure to China Receiving PNTR and Labor Market Outcomes

(a) Outcome: Percentage Change in Earnings



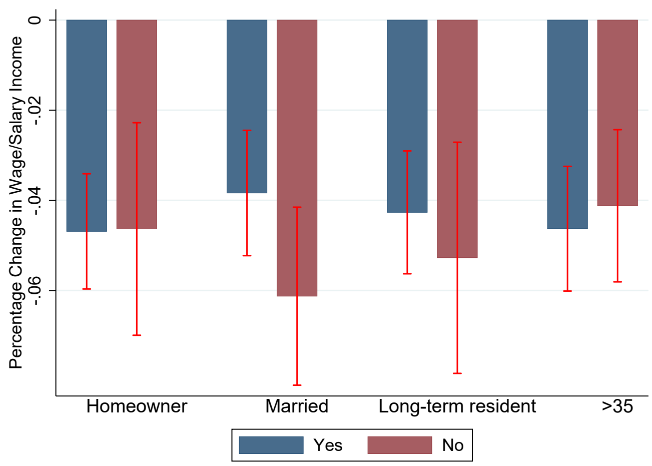
(b) Outcome: Share out-migrating to different CZ



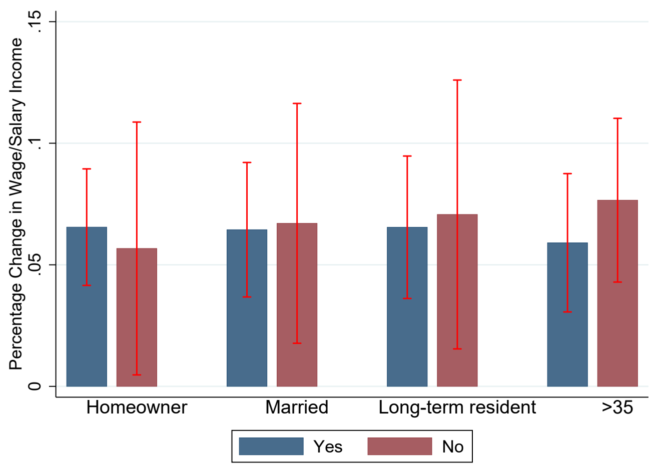
Notes: Panel A plots the mean value of the percentage change in wage and salary income between 2000 and 2010/14 by bins of exposure to PNTR with China, after partialling out region-by-year-by-age-by-sex fixed effects for non-college educated workers. The best-fit line plots the coefficient corresponding to Equation 4.3, and the corresponding coefficient is reported in Table 3, Panel B. Panel B plots estimates of the relationship between CZ out-migration and bins of exposure to PNTR with China, after partialling out region fixed effects and controls for lagged in-migration rates, lagged out-migration rates, lagged CZ population and lagged CZ share urban. The best-fit line plots the coefficient corresponding to Equation 4.5 and the corresponding coefficient is reported in Table ??.

Figure 10: Effects of Labor Demand Shocks on Wage and Salary Income by Moving Cost Shifters

(a) Effects of Exposure to PNTR with China



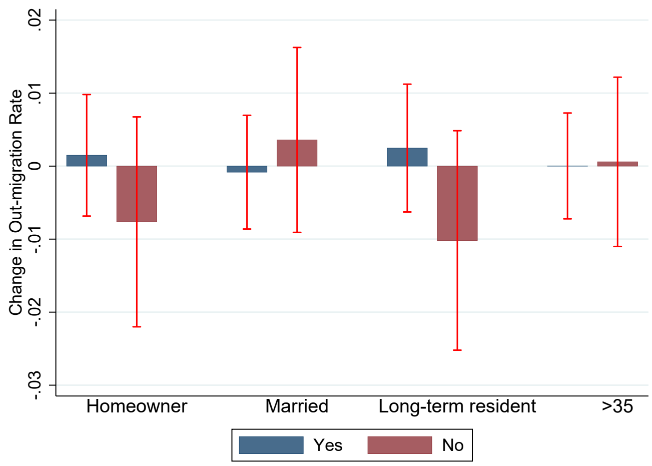
(b) Effects of Exposure to Fracking



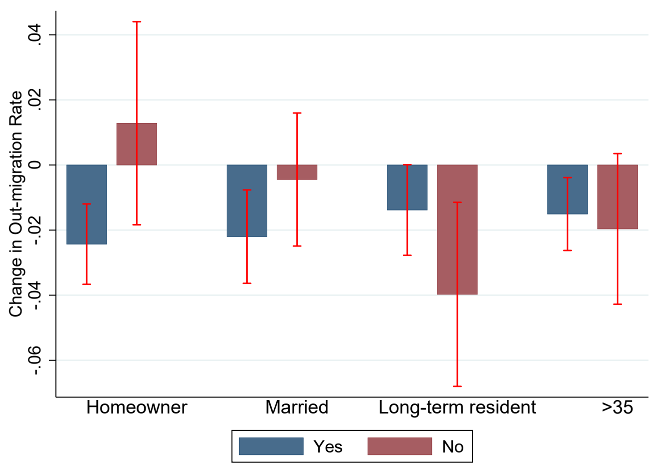
Notes: These figures plot estimates how how the effects of exposure to PNTR with China (Panel A) or fracking (panel B) on the change in wage and salary income between 2000 and 2010/14 for workers originally living in more exposed commuting zones vary with several moving cost shifters. The estimates are from versions of Equation 4.3 where the Z_{g0} is interacted by the given labor market shifter. Exposure to PNTR with China is scaled by the effect of moving from the 25th-75th percentile. 95% confidence intervals are shown using the red bars.

Figure 11: Effects of Labor Demand Shocks on Outmigration by Moving Cost Shifters

(a) Effects of Exposure to PNTR with China



(b) Effects of Exposure to Fracking



Notes: These figures plot estimates how how the effects of exposure to PNTR with China (Panel A) or fracking (panel B) on Commuting-Zone outmigration between 2000 and 2010/14 for workers originally living in more exposed commuting zones vary with several moving cost shifters. The estimates are from versions of Equation 4.5 where the Z_{g0} is interacted by the given labor market shifter. Exposure to PNTR with China is scaled by the effect of moving from the 25th-75th percentile. 95% confidence intervals are shown using the red bars.

10 Tables

Table 1: Comparison of Linked Panel Summary Statistics to Overall Population

	2000 Census	Linked 2000 to 2010/14 ACS	Linked 2000 to 2010/14 ACS
	(1)	(2)	(3)
Panel A: Characteristics in 2000 Census			
Age in 2000	36.6	36.8	36.4
Female	0.40	0.421	0.394
Black	0.12	0.091	0.127
Hispanic (any race)	0.12	0.109	0.169
Wage and Salary Income in 2000	41,752	45,954	44,935
Hourly wages: full-time, full-year workers in 2000	18.9	20.6	20.2
Panel B: Characteristics in 2010/14 ACS			
Worked last year in 2010/14	-	0.863	0.861
Worked full-time, full-year in 2010/14	-	0.732	0.730
Wage and Salary Income in 2014	-	40,118	39,218
Hourly wages: full-time, full-year workers in ACS	-	23.1	22.6
% Change in Wage/Salary Income 2000 to 2010/14	-	-0.054	-0.053
% Change in Wage/Salary Income 2000 to 2010/14 (Davis-Haltiwanger measure)		-0.376	-0.379
Changed CZs between 2000 and 2010/14	-	0.198	0.195
N	2,027,211	291,345	291,345

Notes: This paper shows sumary statistics for individuals in the 2000 Census and 2010/14 ACS for different samples and weighting schemes. The sample in all columns is invdividuals without college degrees who were ages 25 to 50 and worked full-time, full-year in 2000. Column (1) shows summary statistics for the 2000 Census public use sample, Column (2) shows summary statistics for the 2000 Census files that are assigned a unique Protected Identification Key (PIK) and matched to an observation in an ACS between 2010-2014. Column (3) then reweights the Column (2) observations using the production of inverse propensity score weights for being linked in 2000 to a unique PIK and linked in 2010/14 to a unique PIK. The propensity scores for being linked to a unique PIK are estimated on the full sample of 2000 Census and ACS respectively using age, race, sex, education, and hispanic origin. Panel A shows characteristics in 2000 while Panel B shows 2010/14 ACS characteristics or changes between 2000 and 2010/14. All columns use the ACS and Census sampling weights.

Table 2: Effects of Labor Demand Shocks on Employment and Earnings of Contemporaneous Residents: Non-College Educated Workers

	All Workers	Sector		Brawn-Intensity of Occupation		
		Directly Exposed	Not-Directly Exposed	Low-Brawn	Medium-Brawn	High-Brawn
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CZ Exposure to PNTR with China		Manufacturing	Non-Manufacturing			
Panel A1. Change in Log(total full-time, full-year employment)						
Tariff Exposure per Worker	-1.106***	-2.492***	0.114	-0.006	0.038	-2.374***
	(0.143)	(0.354)	(0.142)	(0.158)	(0.177)	(0.197)
Effect of moving from 25th - 75th pctile of exposure	-0.033***	-0.074***	0.003	0.000	0.001	-0.070***
	(0.004)	(0.011)	(0.004)	(0.005)	(0.005)	(0.006)
Panel A2. Change in Log(hourly wages for full-time, full-year workers)						
Tariff Exposure per Worker	-0.506***	-0.834***	-0.462***	-0.586***	-0.387***	-0.660***
	(0.055)	(0.097)	(0.056)	(0.056)	(0.067)	(0.107)
Effect of moving from 25th - 75th pctile of exposure	-0.015***	-0.025***	-0.014***	-0.017***	-0.011***	-0.020***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Panel A3.Change in Log(earnings per-capita)						
Tariff Exposure per Worker	-1.152***	-	-	-	-	-
	(0.120)	-	-	-	-	-
Effect of moving from 25th - 75th pctile of exposure	-0.034***	-	-	-	-	-
	(0.004)	-	-	-	-	-
Panel B: CZ Exposure to Fracking		Oil/Gas Related Sectors	Non-Oil and Gas Related Sectors			
Panel B1. Change in Log(total full-time, full-year employment)						
1(Any Fracking Exposure)	0.118***	0.188***	0.066***	0.032*	0.034*	0.174***
	(0.018)	(0.022)	(0.013)	(0.017)	(0.019)	(0.022)
Panel B2. Change in log(hourly wages)						
1(Any Fracking Exposure)	0.018	0.068***	0.007	0.006	0.018***	0.019***
	(0.012)	(0.009)	(0.006)	(0.005)	(0.005)	(0.007)
Panel B3: Change in log(earnings-per-capita)						
1(Any Fracking Exposure)	0.087***	-	-	-	-	-
	(0.015)	-	-	-	-	-
Commuting-Zones	722	722	722	722	722	722
Region FE	Y	Y	Y	Y	Y	Y

Notes: This Table reports estimates of Equation 4.2 of regressions of changes in local economic outcomes between 2000 and 2010/14 on Commuting-Zone exposure to China receiving PNTR (Panel A) or fracking (Panel B). Exposure to China receiving PNTR is measured as the gap between NTR and non-NTR tariffs for the industry of the average worker in the CZ in 2000. Fracking exposure is measured as an indicator for having any land within the Commuting-Zone which is the in the top half of fracking potential of all land within the given shale play. In each sub-panel of Panel A, the first two rows report the point estimates for the PNTR gap, while the second two-columns rescale these point estimates to reflect the change in trade exposure for a county at the 75th percentile compared to the 25th percentile of exposure, which is a difference in the tariff gap for the average worker of .028 percentage point . The sample is restricted to workers ages 25 to 59. For each Panel, sub-panel 1 shows log(total employment), sub-panel 2 reports results for hourly wages, and sub-panel 3 reports results for log(earnings per-capita). All regressions include region fixed-effects.

Table 3: Effects of Exposure to PNTR with China on Earnings by Workers' Place of Residence in 2000: Non-College Educated Workers

	(1)	(2)	(3)	(4)
Panel A. CZ Exposure Based on Contemporaneous Location (CZ Level Specification)				
Panel A: Change in Log(Earnings-per-Capita) between 2000 and 2010/14				
Tariff Exposure per Worker	-0.925***	-0.985***	-1.025***	-1.082***
	(0.253)	(0.143)	(0.260)	(0.249)
Effect of moving from 25th - 75th pctile of exposure	-0.027***	-0.029***	-0.030***	-0.032***
	(0.008)	(0.004)	(0.008)	(0.007)
Commuting Zones	722	722	722	722
Panel B. CZ Exposure Based on Original Location in 2000 (Individual Level Specification)				
Panel B. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 2010/14				
Tariff Exposure per Worker	-1.482***	-1.416***	-1.515***	-1.557***
	(0.215)	(0.264)	(0.262)	(0.260)
Effect of moving from 25th - 75th pctile of exposure	-0.044***	-0.042***	-0.045***	-0.046***
	(0.006)	(0.008)	(0.008)	(0.008)
N	291,317	291,317	291,317	291,317
N in highly exposed location	83,479	83,479	83,479	83,479
Panel A: Region FE	Y	Y	Y	Y
Panel B: ACS Year*Region*Age Group*Sex*Education	Y	Y	Y	Y
CZ Urban Share and Log(population) in 2000		Y	Y	Y
Change in log(employment) from 1990 to 2000			Y	Y
Change in log(mfg employment) from 1990 to 2000				Y

Notes: This table compares estimates of the relationship between exposure to China receiving PNTR on the change in labor market outcomes for contemporaneous residents and the original residents of exposed locations. The sample is restricted to non-college educated workers. In each panel, the first two rows report the point estimates for the PNTR gap, while the second two-columns rescale these point estimates to reflect the change in trade exposure for a county at the 75th percentile compared to the 25th percentile of exposure, which is a difference in the tariff gap for the average worker of .028 percentage point . In both panels, different columns add different control variables. Column (1) reports the base-specification without any controls other than region-demographic groups fixed effects. Column (2) adds the 2000 CZ Urban Share and Log(population). Column (3) adds the change in log-employment in the CZ between 1990 and 2000. Column (4) adds the change in log(manufacturing employment) from 1990 to 2000. Panel A reports estimates of Equation 4.3 of the change in log(average earnings per capita) of contemporaneous CZ residents on CZ exposure to China receiving PNTR. The specification includes region fixed-effects. The sample in Panel A is restricted to workers ages 25 to 59 in the given year. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to PNTR with China. These specifications include region-by-year-by-age-group-by-sex-by-education fixed effects. The sample in Panel B is restricted to workers ages 25 to 50 in 2000 who are less than 59 when surveyed ini the ACS. Standard errors in Panel B are clustered at the commuting-zone level.

Table 4: Labor Market Effects of Exposure to Fracking on Contemporaneous and Original Residents: Non-College Educated Workers

	(1)	(2)	(3)	(4)
Panel A. CZ Exposure Based on Contemporaneous Location (CZ Level Specification)				
Panel A1. Change in log(total full-time, full-year employment) between 2000 and 2010/14				
1(Any Fracking Exposure)	0.118***	0.104***	0.105***	0.104***
	(0.018)	(0.018)	(0.017)	(0.017)
Panel A2. Change in log(hourly wages)				
1(Any Fracking Exposure)	0.018	0.013	0.015**	0.014*
	(0.012)	(0.008)	(0.007)	(0.007)
Panel A3: Change in log(earnings-per-capita)				
1(Any Fracking Exposure)	0.087***	0.077***	0.078***	0.073***
	(0.015)	(0.013)	(0.012)	(0.012)
Commuting-Zones	722	722	722	722
Region FE	Y	Y	Y	Y
Panel B. CZ Exposure Based on Original Location in 2000 (Individual Level Specification)				
Panel B1. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 201(				
1(Any Fracking Exposure)	0.067***	0.057***	0.061***	0.058***
	(0.016)	(0.017)	(0.016)	(0.016)
N	291,345	291,345	291,345	291,345
Highly-Exposed N	37,609	37,609	37,609	37,609
Region*ACS Year*Age Group*Sex*Education	Y	Y	Y	Y
CZ Urban Share and Log(population) in 2000		Y	Y	Y
Change in log(employment) from 1990 to 2000			Y	Y
Change in log(mfg employment) from 1990 to 2000				Y

Notes: This table compares estimates of the relationship between exposure to fracking on the change in labor market outcomes for contemporaneous residents and the original residents of exposed locations. The sample is restricted to non-college educated workers. Fracking exposure is measured as an indicator for having any land within the Commuting-Zone which is the in the top half of fracking potential of all land within the given shale play. In both panels, different columns add different control variables. Column (1) reports the base-specification without any controls other than region-demographic groups fixed effects. Column (2) adds the 2000 CZ Urban Share and Log(population). Column (3) adds the change in log-employment in the CZ between 1990 and 2000. Column (4) adds the change in log(manufacturing employment) from 1990 to 2000. Panel A reports estimates of Equation 4.2 of the change in log(average earnings per capita) of contemporaneous CZ residents on CZ exposure to fracking. The specification includes region fixed-effects. The sample includes all individuals ages 25 to 50 in the given year. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to fracking based on the workers original location in 2000. These specifications include region-by-year-by-age-group-by-sex-by-education fixed effects. The sample in Panel B includes all individuals ages 25 to 50 in 2000 who were less than 59 when survyed in the ACS. Standard errors in Panel B are clustered at the commuting-zone level.

Table 5: Heterogeneity in Effects of Exposure to PNTR with China by Original Sector & Occupation: Non-College Educated Workers

	Sector in 2000		Brawn-intensity of occupation in 2000		
	Manufacturing	Non-Manufacturing	Low-Brawn	Medium-Brawn	High-Brawn
	(1)	(2)	(7)	(8)	(9)
Panel A. CZ Exposure measured based on contemporaneous location (CZ Level Specification)					
Panel A1. Change in log(total full-time, full-year employment) between 2000 and 2010/14					
Tariff Exposure per Worker	-2.492***	0.114	-0.006	0.038	-2.374***
	(0.354)	(0.142)	(0.158)	(0.177)	(0.197)
Effect of moving from 25th - 75th pctile of exposure	-0.074***	0.003	0.000	0.001	-0.070***
	(0.011)	(0.004)	(0.005)	(0.005)	(0.006)
Panel A2. Change in log(hourly wages) between 2000 and 2010/14					
Tariff Exposure per Worker	-0.834***	-0.462***	-0.586***	-0.387***	-0.660***
	(0.097)	(0.056)	(0.056)	(0.067)	(0.107)
Effect of moving from 25th - 75th pctile of exposure	-0.025***	-0.014***	-0.017***	-0.011***	-0.020***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Commuting-Zones	722	722	722	722	722
Region Fixed Effects	Y	Y	Y	Y	Y
Panel B. CZ Exposure measured based on original location in 2000 (Individual Level Specification)					
Panel B1. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 2010/14					
Tariff Exposure per Worker	-1.404***	-1.321***	-0.655**	-1.204***	-1.699***
	(0.276)	(0.278)	(0.285)	(0.340)	(0.254)
Effect of moving from 25th - 75th pctile of exposure	-0.042***	-0.039***	-0.019**	-0.036***	-0.050***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.008)
N	74,500	216,816	62,728	87,700	140,889
Highly-exposed N	17,037	52,032	15,201	21,069	35,422
ACS Year*Region*Age Group*Sex	Y	Y	Y	Y	Y

Notes: This table compares estimates of the relationship between exposure to China receiving PNTR on the change in labor market outcomes for non-college educated contemporaneous residents and non-college educated original residents of exposed locations separately for different original sector and occupation groups. In each panel, the first two rows report the point estimates for the PNTR gap, while the second two-columns rescale these point estimates to reflect the change in trade exposure for a county at the 75th percentile compared to the 25th percentile of exposure, which is a difference in the tariff gap for the average worker of .028 percentage point . Panel A reports estimates of Equation 4.2 of the change in log(total full-time, full-year employment) or change in wage and salary income of contemporaneous CZ residents on CZ exposure to China receiving PNTR. The specification includes region fixed-effects. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to PNTR with China. These specifications include region-by-year-by-age-group-by-sex-by fixed effects. Standard errors in Panel B are clustered at the commuting-zone level.

Table 6: Heterogeneity in Effects of Fracking by Original Sector & Occupation: Non-College Educated Workers

	Sector		Brawn-Intensity of Occupation in 2000.		
	Oil/Gas Related Sectors	Non-Oil and Gas Related Sectors	Low-Brawn	Medium-Brawn	High-Brawn
	(1)	(2)	(7)	(8)	(9)
Panel A. CZ Exposure Based on Contemporaneous Location					
Panel A1. Change in log(employment) between 2000 and 2010/14					
1(Any Fracking Exposure)	0.188***	0.066***	0.032*	0.034*	0.174***
	(0.022)	(0.013)	(0.017)	(0.019)	(0.022)
Panel A2. Change in log(hourly wages) between 2000 and 2010/14					
1(Any Fracking Exposure)	0.068***	0.007	0.006	0.018***	0.019***
	(0.009)	(0.006)	(0.005)	(0.005)	(0.007)
Commuting-Zones	722	722	722	722	722
Panel B. CZ Exposure Based on Original Location in 2000					
Panel B1. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 2010/14					
1(Any Fracking Exposure)	0.070***	0.067***	0.040*	0.050*	0.085***
	(0.025)	(0.016)	(0.021)	(0.027)	(0.017)
N	55,838	235,301	62,733	87,706	140,906
Highly-Exposed N	7,866	30,124	8,123	11,332	18,154
ACS Year*Region*Age Group*Sex			Y	Y	Y

Notes: This table compares estimates of the relationship between exposure to fracking and the change in labor market outcomes for non-college worker contemporaneous residents and non-college worker original residents of exposed locations separately for different original sector and occupation groups. Fracking exposure is measured as an indicator for having any land within the Commuting-Zone which is the in the top half of fracking potential of all land within the given shale play. Panel A reports estimates of Equation 4.2 of the change in log(total full-time, full-year employment) or change in wage and salary income of contemporaneous CZ residents on CZ exposure to fracking. The specification includes region fixed-effects. The sample in Panel A includes all individuals ages 25 to 50 in the given time period. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to fracking. These specifications include region-by-year-by-age-group-by-sex fixed effects. The sample in Panel B includes all non-college educated workers ages 25 to 50 in 2000 who are 59 or younger when interviewed in the ACS. Standard errors in Panel B are clustered at the commuting-zone level.

Table 7: Migration Response to Exposure to PNTR with China and Fracking: Non-College Educated Workers

	(1)	(2)	(3)	(4)
Panel A. Exposure to PNTR with China				
A1. Out-migration rate between 2000 and 2010/14 (as a share of the 2000 population)				
Effect of moving from 25th - 75th pctile of exposure	0.001	0.002	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.002)
A2. In-migration rate between 2000 and 2010/14 (as a share of the 2000 population)				
Effect of moving from 25th - 75th pctile of exposure	-0.008***	-0.007***	-0.006**	-0.009***
	(0.002)	(0.003)	(0.003)	(0.002)
Panel B. Exposure to Fracking				
B1. Out-migration rate between 2000 and 2010/14 (as a share of the 2000 population)				
1(Any Fracking Exposure)	-0.015**	-0.015**	-0.023***	-0.023***
	(0.006)	(0.006)	(0.006)	(0.007)
B2. In-migration rate between 2000 and 2010/14 (as a share of the 2000 population)				
1(Any Fracking Exposure)	0.003	0.005	0.001	0.001
	(0.009)	(0.006)	(0.006)	(0.006)
Commuting-Zones	722	722	722	722
Region FE	X	X	X	
State FE				X
2000 CZ Share Urban and Log(CZ pop controls)	X	X	X	X
1995-2000 Out-Migration Rate	X	X	X	X
1995-2000 In-Migration rate	X	X	X	X
1990-2000 Change in 5-year Out-Migration rate		X	X	X
1990-2000 Change in Log-Employment			X	X

Notes: This table presents estimates of Equation 4.5 of the relationship between exposure to China receiving PNTR or fracking and in-migration and out-migration rates (as a share of the CZ 2000 population). Panel A reports results for exposure to trade with China, while Panel B reports results for exposure to Fracking. In Panel A, I report rescaled point estimates to reflect the change in trade exposure for a county at the 75th percentile compared to the 25th percentile of exposure, which is a difference in the tariff gap for the average worker of .028 percentage point . In Panel B, I report the effects of haivng any exposure to fracking. In both panels, different columns add different control variables. Column (1) reports the base-specification including region fixed effects, lagged in-migration and out-migration shares, and controls for the share of the CZ population living in an urban area in 2000 and the log(cz population in 2000). Column (2) adds controls for the change in-migration rate between 1990 and 2000. Column (3) adds the change in log-employment in the CZ between 1990 and 2000. Column (4) replaces the region-fixed effects with state fixed-effects. The sample includes individuals ages 25 to 50 in 2000.

Table 8: Moving costs in multiples of annual income

	Lived in Same Labor Market in 1995	Age in 2000				
		25-30	30-35	35-40	40-45	45-50
		(1)	(2)	(3)	(4)	(5)
Panel A. Moving to arbitrary alternative						
Costs of moving 500 miles	Yes	-$1,015	-$1,089	-$1,165	-$1,607	-$1,638
	No	-$683	-$779	-$817	-$1,138	-$1,159
Cost of switching into/out of manufacturing	-	-$163	-$197	-$241	-$332	-$352
Costs of moving between manual/non-manual jobs	-	-$135	-$177	-$185	-$266	-$273
Panel B. Moving to next best alternative						
Costs of moving 500 miles	Yes	-$202	-$224	-$267	-$404	-$431
	No	$131	$86	$81	$65	$47
Cost of switching into/out of manufacturing	-	-$163	-$197	-$241	-$332	-$352
Costs of moving between manual/non-manual jobs	-	-$135	-$177	-$185	-$266	-$273

Notes: This table reports moving costs across locations, sectors, and occupations from the model for non-college educated men. For each age group, I report both the moving cost to a randomly selected location and the average moving costs to the workers next best option. Panel A reports moving costs to an arbitrary alternative, while Panel B reports moving costs to the worker's next best alternative. All moving costs are shown in thousands of dollars.

Table 9: Effects of lowering moving costs on relationship between PNTR with China and earnings

	1st Quartile (1)	2nd Quartile (2)	3rd Quartile (3)	4th Quartile (4)	Difference: 4th - 1st Quartile (5)
Panel A: Empirical and Predicted Earnings Changes					
A1. Empirical	-35.6%	-35.6%	-39.6%	-40.5%	-4.9%
A2. Predicted	-34.3%	-36.0%	-38.6%	-42.1%	-7.8%
Panel B: Effects of Halving Moving Costs on Earnings Changes (relative to Panel A)					
B1. Location Moving Costs	-0.9%	-2.2%	-1.9%	0.5%	1.4%
B2. Sector Moving Costs	3.6%	4.0%	4.1%	5.0%	1.4%
B3. Occupation Moving Costs	4.9%	4.8%	4.8%	5.0%	0.1%
B4. Sector/Occ Moving Costs	8.2%	8.5%	8.7%	9.6%	1.4%
B5. All Moving Costs	7.4%	6.3%	6.9%	10.1%	2.7%
Panel C: Effects of $10,000 Relocation Subsidies on Earnings Changes					
C1. Location Moving Costs	-0.011%	-0.010%	-0.011%	-0.012%	-0.001%
C2. Sector Moving Costs	-0.004%	-0.002%	-0.007%	-0.008%	-0.004%
C3. Occupation Moving Costs	-0.006%	0.002%	0.000%	-0.002%	0.004%
C4. Sector/Occ Moving Costs	-0.010%	-0.001%	-0.006%	-0.008%	0.002%
C5. All Moving Costs	-0.019%	-0.010%	-0.015%	-0.017%	0.002%

Note: This table reports estimates of the effect of reductions in moving costs on earnings changes of 25-30 year old non-college educated men. Columns (1) - (4) report estimates by quartile of exposure to PNTR of workers' original labor market of residence (i.e. labor market in 2000), while Column (5) reports the difference between the 4th quartile (highest exposure to PNTR with China, Column (4)), and the 1st Quartile (lowest exposure to PNTR with China (Column (1)). Percentage change in income is measured using the Arc-Elasticity (Davis and Haltiwanger, 1992). Panel A reports the average empirical and predicted changes in income. Predicted income is computed using the average earnings in the individual's age, gender and education cell in each labor market-occupation-sector combination. Panel B reports the change in the average predicted earnings change for each quartile when moving costs of different types of halved.For example, row B5, Column (1) shows that halving all moving costs increases the predicted change in income by 7.4% relative to the model's predictions with full moving costs, which are shown in A2. Different rows report results for different types of moving costs. Panel C reports the change in the average predicted earnings change for each qquartile when $10,000 subsidies for changing locations, occupations, or sectors are implemented. When more than one move is subsidied, the worker receives the sum of the subsidies. For example, a worker who changed occupatoins, locations, and sectors woudl receive a $30,000 subsidy in row C5.

Table 10: Comparison of Moving Cost Estimates to Literature

Paper	Setting	Data	Moving Costs as Share of Annual Income		
			Location	Sector	Occupation
(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Moving cost estimates					
This paper[a]	US	Linked Census Long-Form/ACS	19.3	4.6	3.8
Panel B. Estimates of Location Moving Costs					
Kennan and Walker (2011)[b]	US	NLSY	20.3	-	-
Bryan and Morten (2016)[c]	US	Census Long-Form and ACS (migration from place of birth)	2.5	-	-
Panel C. Estimations of Occupational and Sectoral Moving Costs					
Artuc, Chaudhuri, and McLaren (2010)[d]	US	CPS	-	3.7	-
Artuc, Chaudhuri, and McClaren (2015)[e]	US	CPS	-	4.0	4.9
Traiberman (2016)[f]	Denmark	Danish Employer-Employee Data	-	4.1	5.3

Notes: This table compares the present-value of moving costs estimated in this paper to those that have been estimaed in the literature. I include the most prominent recent papers that have estimated moving costs using data from industrialized countries. This excludes several prominent studies such as Morten and Oliveira (2016) and Dix-Caneiro (2014) that focus on less-wealthy countries. I report moving costs as a share of annual income. The moving cost results from this paper reported in Panel A are for non-college educated men ages 25-30. For other papers, I report estimates for samples that are as close to this sample as possible, although this is not completely possible in several cases. in the notes below on each paper I discuss where I drew the estimates from and any transformations I made to compare the estimates to mine, the sample the estimates correspond to, and the definitions of location, sectors, and occupations used in each paper.

[a] Bartik (2017) estimates moving costs using a discrete choice model of location, sector, and occupation choice. Discount and wage decay rates are calibrated to transform estimates into prevent-value terms. The sample of these estimates is non-college educated men ages 25-30 who did not live in the given location five-years before. Locations are defined as an aggregated version of local labor market areas (discussed more in the data appendix), resulting in 225 locations. Sectors are defined as manufacturing and non-manufacturing. Occupations are divided into high-brawn and low-brawn groups based on the brawn-task intensity of the occupation. Location moving costs are reported to a location 500-miles away.

[b] Kennan and Walker (2011) estimates taken from parameters reported in Table 2. Locations are defined as states. Reported estimates are for a 27.5 year-old male with a high school degree who did not live in their current location previously and correspond to moving to a non-adjacent state 500 miles away.

[c] Bryan and Morten (2016) estimates taken from the bottom of page 26 of the June 22, 2015 working paper draft. Locations are defined as states. Reported estimates are for all w orking age adults. Migration is defined based on current location and state of birth. They report moving costs in terms of flow-utility. To convert these costs to present value, I use a discount rate of 3% and assume that workers receive the benefits of their move for 30 years.

[d] Artuc, Chaudhuri, and McClaren (2010) estimates taken from Table 8, Column (1) on page 1036. Sectors are defined as Agriculture/Mining, Manufacturing, Construction, Transportation/Utilities, Trade, and Services. Reported estimates are for young workers withinout a college degree.

[e] Artuc, Chaudhuri, and McClaren (2015) estimates taken from Table 6, Column (1) on page 284. Sectors are defined as Manufacturing, Construction, Traded and Non-traded. Occupations are defined as Management and Professional, Services and Sales, Office, Others, including extraction, construction and repair occupations, and Production. Reported estimates are for workers without a college-degree. The authors estimate separate moving costs by sector. I report the unweighted average of these costs. The authors also allow for a "pecking order" of occupations where moving costs are higher for workers switching into higher-status occupations. I report estimates without including these pecking order effects, so they correspond to changing occupations but not switching to a higher status occupation.

[f] Traiberman (2016) estimates taken from Table 11 of the November 7, 2016 version of the paper. Sectors are defined as Manufacturing, FIRE and R&D, Services, and Health/Education. Occupations are defined as 24 2-digit occupations. However, he allows occupations to only exist within one sector, consequently, there are only 38 unique occupation-sector pairs. Reported estimates are for all-workers in the sample. The author allows for fixed moving costs across occupations and sectors, as well as marginal costs that vary with the task differences of different occupations. Additionally, sectoral moving costs are allowed to vary between different sectoral pairs. The reported costs are for the average occupational (without changing sectors) or sectoral move (without changing occupations).

Appendix for Worker Adjustment to Changes in Labor Demand: Evidence from Longitudinal Census Data

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A Conceptual Framework Appendix

A.1 Conceptual Framework Appendix: Effects of Productivity Shocks when Industrial Composition Differs

Location and sectoral moving costs can generate similar average patters, disguising different sources and effects on subpopulations. Appendix Figure E.1 shows the effects of a shock in Location 1 and Sector A when location 2 only has jobs in Sector B. As a result, to change locations, individuals also have to change sectors. Panel A shows the effects of increasing location moving costs on wages and migration decisions of workers originally in location 1 (when sectoral moving costs are 0), while Panel B shows the effects of increasing sectoral moving costs (when location moving costs are 0). Increasing either cost reduces out-migration and increases the magnitude of the impact on average wages. However, turning to Panels C and D, we see that these similar average effects hide heterogenous effects. These panels, which show how the effects of raising each type of moving costs affects workers originally in location A broken down by their original sector, shows that raising location moving costs hurts both workers originally in Sector A and Sector B. Conversely, increasing sectoral moving costs hurts workers in Sector A, while actually helping those originally in Sector B. Furthermore, costs of changing locations versus sectors or occupations are likely driven by different factors and may have different policy solutions. Consequently, exploiting data that allows me to distinguish these two types of costs is essential.

B Data Appendix

B.1 Linked Census Data

B.1.1 Details of the PVS System for Assigning PIKs

The Center for Administrative Records Research and Applications (CARRA) a the US Census Bureau has developed their Personal Identification Verification System (PVS) to link survey data to a unique identifier, a Protected Identification Key (PIK), that can then used to link individuals across different surveys or with administrative records.

The PVS works as follows. First, a Personal Reference File (PRF) is constructed based on the Social Security Administration (SSA) numident file, but also incorporating other federal sources of information on name, date of birth, and address. Each unique individual in the PRF is assigned a unique PIK (this essentially amounts to assigning each Social Security Number (SSN) in the numident a unique PIK). Given an input survey, such as the ACS, the PVS then attempts to match each individual survey record with a unique individual in the PRF based on a combination of name, date of birth, address, gender, and other information. The PVS proceeds iteratively through different modules that involve "blocking" or direct matching on different variables. The first-module is the "Geo-Search" module, which blocks on address information (starting through exact address match, and matching on increasingly coarse address measures, with the coarsest being matching on the households ZIP3) and then attempts to match individuals based on name, date-of-birth and gender. Each potential match is assigned a score based on how well the variables match and each observation in the survey is assigned to the PIK in the PRF with the highest match above some threshold. Survey observations not assigned a PIK in the "Geo-Search" module are then put through the "Name-Search", "DOB-Search", and "Household Composition-Search" modules, where the algorithm blocks on parts of name, date-of-birth, and household respectively. As in the "Geo-Search" module, an observation only proceeds to the next module if it has not yet been assigned a PIK. In each successive module, the PIK-assignment threshold is lowered.

Appendix Table 1 summarizes information on the assignment of PIKs to observations in different surveys. Different Columns report information on PIK rates for different survey year combinations, i.e. the 2000 long-form, the 2005-2009 ACS and the 2010-2014 ACS. In the panels, I then report progressively more stringent restrictions on PIKs that I decide to keep. Panel A shows the number of observations 25-50 in each survey year. Turning to Panel B, we see that between 90 and 93% of observations are assigned a PIK in all years. However, note that although the PVS ensures that each survey observation is only assigned to one PIK, a given PIK may be assigned to multiple survey observations. Within a given survey year, these duplicates likely reflect errors - an individual should only be surveyed once in each survey-year[1]. Consequently, I exclude all observations with duplicated PIKs with a survey year. Panel C reports the share of observations that are assigned a unique PIK within the given survey-year. This reduces the share of PIKed observations by about 1% for the 2000 long form to roughly 92%. Panel C, Column (1) imposes that each long-form observation does not have a duplicate PIK in the short-form (i.e. there is not an observation in the short form survey that is assigned the same PIK as an observation in the long-form survey), dropping the share of observations assigned a unique PIK a further 5 percent to about 87%.

Turning to Columns (2) and (3), we see that there are fewer duplicates within each survey-year in the ACS, about 1 to 1.5%, reducing the unique PIK rate to roughly 92%. However, although there are fewer within survey-year duplicates in the ACS, there are a number of duplicates across survey-year. These duplicates are problematic because given the ACS sampling design, each housing unit is only in the sampling frame once every five years. Consequently, unless an individual moves housing unit and their new housing unit is also sampled, an individual should not be surveyed multiple times except in five year intervals. Consequently, these duplicates may possibly be in error. In Panel D, I drop all ACS duplicates that are less than five years apart, reducing the ACS PIK rate by an additional 3 percentage points, resulting in an overall rate very similar to the rates for 2000 and 2010 censuses of around 89%. In Appendix Section B.1.4, I discuss the representativeness of this matched

[1] Although, it is possible that in some cases someone who maintains residence in multiple places could end up being listed in both households.

sample and my usage of a inverse-propensity score weighting procedure to reweight this matched sample to make it representative of the overall population.

B.1.2 Sample Construction

I make several sample restrictions in the analysis. First, I focus on workers without college degrees Second, I restrict the sample to workers ages 25 to 50 in 2000 who were no older than 59 when interviewed in the ACS. I make this restriction so that individuals have completed their education in the base period and to avoid complications related to retirement decisions. Second, I restrict the sample to workers working full-time, full-year in 2000, defined as working at least 40 weeks during the previous year and working at least 35 hours during the usual week. Additionally, in all of my analysis, I restrict my sample to observations that have non-allocated observations and do not have implausible values of outcome variables. I discuss these decisions and how they affect my ultimate sample more in Appendix Sections B.1.3.

Appendix Table 2 illustrates how the linkage process and sample restrictions affect the resulting sample. Starting with all individuals that were 25 to 50 in the 2000 Long Form, I restrict myself to observations with unique, non-duplicated PIKs. Of these, around 1 in 12 is matched to an ACS and around a third of those observations have non-allocated work and demographic information in 2000, worked full-time, full-year in 2000 and were 59 or younger when surveyed in the ACS. This results in a sample of 291,345 individuals in the linked data-set who are interviewed in the ACS between 2010 and 2014. This represents a sample of roughly .38% of all individuals working full-time, full-year who were ages 25-50 in 2000. As a result of the non-trivial share of observations that are either not-PIKed or have allocated labor market variables, the resulting sample is not representative of the population. The next section discusses an inverse-propensity score reweighting procedure to reweight the PIKed and non-allocated sample to be representative on observables to the overall sample.

B.1.3 Allocated Variables

I take several steps to clean the census variables. Most notably, I do not use observations with allocated values for main independent and dependent variables of interest. The Census Bureau allocates variables where the respondent does not report an answer or reports an impossible response or one inconsistent with the respondents other responses. I do not use allocated values for the following variables: age, sex, education, race, worked at all last year, weeks worked, hours hours, total income, wage and salary income, public support income, industry, or occupation. Note that for some of these variables, I do use values of variables for which only minor consistency edits were made. For example, in some cases the total reported income does not equal the sum of the individual income components, and minor edits are made to make these values consistent.

Allocation is a non-trivial issue, with about 80% of observations having one of their work variables allocated and around 75% of observations having any of the major variables listed above allocated. Furthermore, variables are more likely to be allocated for low-income individuals and minorities.

B.1.4 Reweighting Linked Sample

As discussed above, a sizable share of observations are not PIKed and matched to another survey and additionally many observations have allocated variables. Consequently, the panel I construct of non-missing observations that are observed in both the 2000 long-form and the 2010-2014 ACS may not be representative of the overall population. Appendix Table 3, Column (1) reports summary statistics in the 2000 long-form for all individuals in ages 25 to 50 in 2000. Column (2) reports the summary statistics for the sub-sample of observations that have non-missing work information. The variables are fairly similar, although blacks and are less likely to have non-allocated work observations, while college-educated individuals are more likely to have non-allocated values. Column (3) reports means for observations that are PIKed and matched to an observation in the 2010-2014 ACS. This column exhibits more substantial differences with Column (1), with blacks, hispanics, immigrants, HS drop-outs being markedly less likely to be PIKed and matched to the ACS, while higher income individuals are more likely to be matched. Column (4), which shows summary statistics for observations that are both PIKed and matched to the ACS and have non-allocated work information, is qualitatively similar to Column (3), with most of the differences with Column (1) increasing in magnitude. These patterns are similar to those found in the Bond et al. (2014) study of the representativeness of linked observations in the 2010 ACS.

Following Meyer and George (2011), I estimate the propensity score for being in the linked sample and then use the resulting predictions to construct inverse-propensity score weights to reweight the sample to be representative of the overall population. Specifically, define D_i to be an indicator for whether observation i is PIKed and has non-allocated work variables in either the ACS or 2000 Census respectively both 2000 and in the ACS, and let $X_{i,2000}$ be a saturated vector of covariates[2]. I then estimate the following model separately for both the 2000 census and the ACS using OLS[3]:

$$D_i \qquad = X_i\beta + \epsilon_i \tag{B.1}$$

Using the predicted value from this regression, I then construct inverse propensity weights, i.e. $\widehat{\omega}_{\text{survey},i} = \frac{1}{\widehat{D_{\text{survey},i}}}$ where survey $\in$ (ACS, 2000 Census). I then use these weights in conjunction with the 2000 long-form sampling weights and the ACS to reweight observations to be representative of the overall population. In my preferred specifications, I then use the weights defined below, where pwt_i^{ACS} and pwt_i^{LF} are the ACS and Census Long-Form

[2]Included covariates are: age (groups are 25-30, 30-35, 35-40, 40-45, 45-50), education (high school dropout, high school-grad, college-grad), Hispanic, black, immigrant

[3]Note that because I am saturating in covariates the predictions from this model will be identical to those that I would estimate using a Probit

person weights:

$$\lambda_i \quad = \text{pwt}_i^{ACS} \times \text{pwt}_i^{LF} \times \hat{\omega}_{2000\text{ Census},i} \times \hat{\omega}_{\text{ACS},i} \tag{B.2}$$

B.2 Occupations

I use David Dorn's croswalks (Dorn (2009) and Autor et al. (2013)) to standardize occupations and industries across different decennial census and ACS years into the "occ1990dd" and "ind1990dd" classification schemes respectively, which are modifications of the Integrated Public Use Microdata Series (IPUMS) consistent occupation and industry schemes (Ruggles et al. (2015)). Starting with the 2010 ACS, the Census started basing its occupation classification scheme on the 2010 Standard Occupation Classification (SOC) rather than the 2002 SOC. I used the Census provided crosswalk from the 2002 to 2010 SOC (United States Census Bureau (2011)) to create a crosswalk from the 2010 and later ACS occupation codes to occ1990dd. Finally, I used the IPUMS crosswalks from the census industry codes in each year to the IPUMS standardized ind1990 variable to create a crosswalk from the census industry codes in each year to ind1990dd.

B.3 Occupations Measures

B.3.1 Creating Consistent Occupation Codes

Because both labor demand shocks I study particularly affect employment in industries and occupations requiring the use of physical strength and dexterity, I use data on the brawn, people, and person content for the occ1990dd occupations from Lordan and Pischke (2016) to construct a measure of task-intensity that is closely related to the physical taxes that we think for a-priori reasons would be particularly affected by fracking or the decline of manufacturing. Lordan and Pischke (2016) construct brain, brawn, and people task measures using factor analysis from O*Net 5 task variables on "work activities" and "work-context"[4].

I create an index for the relative brawn intensity of different occupations:

$$r(\text{brawn})_o = \quad \text{brawn}_o - \text{people}_o - \text{brains}_o \tag{B.3}$$

$r(\text{brawn})_o$ captures how much occupation o uses brawn-tasks relative to people or abstract tasks[5]. To get a sense for the task assignments, Appendix Table 4 lists 30 least and most brawn-intensive occupations, amongst

[4] Beaudry and Lewis (2014) construct a related task classification system by hand based on the "people", "physical", and "cognitive" content of occupations based on the Dictionary of Occupational Titles (DOT). I've received these occupation task assignments from Beaudry and Lewis (2014) and will explore the robustness of my results to defining "brawn-intensity" using the Beaudry and Lewis (2014) task assignment as well

[5] Note that the brawn, brains, and people indices from Lordan and Pischke (2016) are already on a standardized scale so no re-scaling is necessary. I experimented with constructing a similar brawn-intensity task-measure by transforming all of the task measures to be weakly positive and then creating the brawn-intensity variable using the logged version of Equation B.3 above. The resulting variable had a correlation of above .9 with the variable I use

occupations that employed at least .05 percent of workers in 2000. The assignments are broadly intuitive, with the high-brawn occupations involving construction, operating heavy machinery, farming, and other occupations involving substantial manual labor. Similarly, the low-brawn intensity occupations are also intuitive, involving a number of occupations requiring interactions with other people or abstract thinking. Appendix Table 5 then summarizes how the share of people working in occupations in the top-tercile of brawn-intensity varies by demographic group and major occupational categories. Unsurprisingly, non-college educated men are the workers most concentrated in high-brawn occupations, with over sixty percent of them working in high-brawn occupations in 2000. An important share, roughly a quarter, of non-college educated women also work in high-brawn occupations. Unsurprisingly, a much smaller share of college-educated workers work in high-brawn occupations, with college-women being particularly unlikely to work in high-brawn occupations.

B.4 Effects of Labor Demand Shocks by Occupation using Alternative Occupation Categories

Tables 5 and 6 showed that the effects of labor demand shocks were concentrated among workers originally in more brawn-intensive occupations. One concern regarding these results is that they may reflect particularities of how relative brawn insensitivity groups occupations rather than a real moving costs of moving into occupations with different task compositions. In Appendix Tables 6 and 7 below, I report how the effects of exposure to PNTR with China and fracking vary with the standard, major occupation categories. Columns (3)-(6) report results by major occupational category in 2000 and Columns (7)-(9) report results by the "brawn-intensity" of workers' occupations in 2000 (as shown in Tables 5 and 6).

Starting with Appendix Table 6, Panel A shows that the employment effects of PNTR-exposure are concentrated in operator/construction and production occupations. The wage effects for contemporaneous residents, however, are evenly spread across different occupations. In Panel B, we see that these employment losses are largest in operator/construction occupations, which are the occupations that experience the largest contemporaneous employment decline. The results in Columns (3)-(6) are consistent with those by the brawn-intensity categories, suggesting that the type of tasks performed by workers in 2000 were an important determinant of the effects of exposure to PNTR.

Appendix Table 7 performs the same exercise for fracking, investigating how using alternative occupation definitions affects the heterogeneity in the results by occupation. Columns (3)-(6) report results by major occupation category in 2000. For comparison, Columns (7)-(9) report results by the brawn-intensity of workers' occupation in 2000, as in Table . As discussed above, Panel A shows that fracking led to concentrated gains in employment in oil and gas and construction sectors and more brawn-intensive occupations.

Panel B shows that pattern of effects by original sector differs from the pattern by original occupation.

Specifically, despite the much larger employment gains within oil and gas related sectors, earnings effects are similar for workers originally working in an oil and gas related sector or outside of the oil and gas related sector (7.0% vs. 6.7%). Conversely, effects on original residents are concentrated among workers originally working in the occupations that experience the largest rises in employment. Earnings gains are almost 10% for operator construction occupations, followed by clerical/service occupations at 5%. Workers originally in management occupations and production occupations experience only small changes in earnings. The patterns by brawn-intensity of workers' original occupations are similar, with workers originally in high-brawn occupations experiencing earnings gains of 8.5% compared to gains of 5% and 4% for workers in medium and low-brawn occupations respectively.

Combined, Tables 5 and 6 suggest that the results above were not due to some idiosynchratic feature of grouping occupations by brawn-intensity, but instead reflect heterogeneity in the effects of these labor demand shocks by workers original occupation.

C Model Appendix

In this section, I describe the parameter estimates in more detail and explore the robustness of my results to relaxing the assumption of additive separability of location and job-type amenities and allowing for location/job-type amenities that are correlated with local wages.

C.1 Parameter Estimates

Appendix Table 8 reports the parameter estimates from estimating Equation 6.6 for non-college educated men. Results for women are currently not very robust, particularly for women of child-bearing age, so I focus on the results for men.[6]. Different columns show results separately for different age groups. All moving costs are estimated to be negative - i.e. moving is estimated to reduce utility for all demographic groups. The marginal utility of annual wage and salary income is estimated to be positive for all age groups and is decreasing in age. This may reflect either higher utility of income in the utility function, or lower variance of idiosyncratic location-sector preferences for older workers compared to younger workers.

C.2 Relaxing additive separability of location/sector amenities

As Section 6.3.1 describes, identification of the parameters in Table 8 depends on the strong assumption that location/job-type amenities are additively separable into location amenities, job-type amenities, and an i.i.d.

[6] This fact may reflect women with children working part time or other decisions around child-bearing that my model fails to fully capture For example, if relative wages in different sectors differ between part time and full-time work, then this would cause mis-estimation of the marginal utility of income.

individual preference shock. Specifically, recall from Section 6.3.1 that indirect utility was given by:

$$V_{ijs} \quad = \tau^g \beta_w \ln \omega_{ljt} + A^g_{l,t} + B^g_{j,t} - c^g_{l,l_{t_0},j,j_{t_0}} + \epsilon_{iljt} \tag{C.1}$$

I then assumed that $\epsilon_{iljt} \sim$ EV-1. This assumption rules out thick-market externalities within location/job-types, firms endogenously adjusting amenities in response to local labor market , and complementarities between location and job-type amenities.

These assumptions on local amenities may not hold and could bias my estimates of moving costs. In this section, I explore this possibility by using exposure to PNTR with China and fracking as instruments for location/job-type wages and then using a control function for the wage residual to control for potential endogeneity of wages following Heckman and Robb (1985), Blundell et al. (2006), and Imbens and Newey (2009). More recently, Shenoy (2015) and Agarwal (2016) also use control functions to account for the potential endogneity of wages in related settings. Let $Z_{l,j,t}$ denote the vector of labor market exposure to trade with China and fracking interacted with job-type dummies. I assume that location/job-type average wages for demographic-group g can be written as:

$$\ln \bar{w}^g_{l,j,t} = \quad \lambda^g_{l,t} + \gamma^g_{j,t} + \beta^g Z_{l,j,t} + \nu^g_{l,j,t} \tag{C.2}$$

I then assume that location/job-type preferences can be decomposed into a part that is correlated with wages and an i.i.d. error term:

$$\epsilon_{iljt} = \quad \iota \nu_{l,j,t} + \omega_{i,l,j,t} \tag{C.3}$$

where $\omega_{i,l,j,t} \sim$ EV-1. Given these assumptions, I estimate the model's parameters in two-steps. First, I estimate Equation C.2 using OLS. We can then plug the estimated residuals, $\hat{\nu}^g_{l,j,t}$, into Equation C.3 and estimate the model using MLE as described in Section 6.3.4.

Appendix Table 9 reports estimates of Equation C.2, the first-stage relationship between location/job-type wages and the intruments, fracking and exposure to trade with China. The first-stage F-statistic is small - only 4.3. This weak first-stage may seem surprising in light of the strong reduced form relationship between fracking and trade with China and changes in local labor market outcomes described above. This difference results from the fact that because the structural model only using one time period, 2010/14, estimating Equation C.2 involves using racking and exposure to PNTR with China as instruments for wage levels rather than changes. Both instruments are much weaker for wage levels than changes because the effect of both instruments on wage changes is negatively correlated with the pre-period wage levels[7] This negative correlation explains the curious

[7]i.e. places exposed to fracking had lower wages, on average, than other labor markets prior to fracking, and places exposed to

result that the signs for some of the instruments are wrong-signed. For example, exposure to trade with China is associated with higher manufacturing wages, even though it represents a negative shock to local manufacturing.[8] This weak first-stage, combined with the point-estimates being the "wrong-side" suggests that the results using these instruments must be interpreted cautiously.

Table 10a reports estimates of C.3 for non-college educated men. I focus discussion on the estimates of the marginal utility of income, which is the parameter that we are concerned may change due to the endogeneity of location/job-type wages. The estimated marginal utilities of income using the control function for the endogenous part of wages are quite similar to the estimates without instruments reported in Table 8 for ages 30-35, 35-40, and 40-45, with the estimated marginal utilities of income differing by less than 10%. Estimates for men ages 45-50 are also somewhat higher using the control function, .244 versus .177, but are qualitatively similar. The estimates diverge substantially only for ages 25-30, for whom the estimated marginal utility of income without the control function is .235, but only .045 with the control function included.

Overall, the results using a control function approach to relax the assumption of additive separability of location and job-type amenities provides support for the validity of the main estimates, matching the estimated marginal utility of income without the control function for 4 of 5 age-groups. However, the weakness of the first-stage casts doubt on the validity of these results and consequently I do not emphasize them in the main text.

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China had higher wages than other places prior to China receiving PNTR.

[8]This problem would be alleviated if there were an additional time period before 2000, so I could use the fracking and China-exposure measures interacted with post-2000 dummies as instruments.

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D Appendix Tables

Appendix Table 1: PIK Rates

	2000 Long-Form	2005-2009 ACS	2010-2014 ACS
	(1)	(2)	(3)
Panel A. Individuals 25-50 in 2000			
N	16,430,057	8,353,867	9,286,406
Share	1.00	1.00	1.00
Panel B. Assigned PIK			
N	15,294,960	7,659,560	8,539,102
Share	0.93	0.92	0.92
Panel C. Unique PIK within Year			
N	15,178,722	7,647,319	8,518,748
Share	0.92	0.92	0.92
Panel D. No unexpected duplicates across other surveys			
	14,216,323	7,413,004	8,266,826
	0.87	0.89	0.89

Notes: This table reports the share of observations who were age 25-50 in 2000 who are assigned a PIK, have non-duplicated PIK, or have any unexpected duplicates.

Appendix Table 2: Linked Sample

Observations 25-50 in 2000 without college degrees	Assigned Non-missing PIK	Non-duplicated PIK	Matched to ACS	Individual Characteristics Match	Non-allocated demographic and work information	Worked Full-Time, Full-Year in 2000	59 or younger when in ACS
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(6)
Panel A: 2005-2009 ACS							
10,915,079	10,168,800	9,452,476	735,957	690,706	473,436	330,602	329,790
	0.93	0.57	0.04	0.04	0.03	0.02	0.02
Panel B: 2010-2014 ACS							
10,915,079	10,168,800	9,452,476	816,562	764,347	489,441	341,002	291,345
	0.93	0.57	0.05	0.05	0.03	0.02	0.02

Notes: This Table reports information on the number of observations and the share of observations in the 2000 long-form that are linked to the ACS, have matching individual characteristics, and non-allocated work information .

Appendix Table 3: 2000 Long-form and ACS 2010/2014 Linked Panel Summary Statistics

	All	Non-allocated work information	PIKed/Matched	PIKed/Matched and non-allocated work information
	(1)	(2)	(3)	(4)
Age	37.69	37.73	38.36	38.35
	(7.25)	(7.25)	(7.17)	(7.18)
Female	0.510	0.513	0.524	0.524
	(0.500)	(0.500)	(0.499)	(0.499)
Black (non-hispanic)	0.115	0.100	0.086	0.075
	(0.319)	(0.301)	(0.280)	(0.264)
Hispanic	0.124	0.117	0.081	0.078
	(0.330)	(0.321)	(0.273)	(0.268)
Immigrant	0.151	0.144	0.105	0.102
	(0.358)	(0.351)	(0.306)	(0.303)
HS Dropout	0.146	0.129	0.105	0.093
	(0.353)	(0.336)	(0.306)	(0.290)
HS Grad	0.577	0.571	0.590	0.581
	(0.494)	(0.495)	(0.492)	(0.493)
College	0.276	0.299	0.305	0.326
	(0.447)	(0.458)	(0.460)	(0.469)
Total Income	33,599	34,274	35,782	36,372
	(47,146)	(47,304)	(48,711)	(48,851)
Wage/Salary Income	28,208	28,947	30,392	31,009
	(40,194)	(40,453)	(41,556)	(41,747)
Worked Last Year	0.861	0.852	0.883	0.878
	(0.346)	(0.356)	(0.322)	(0.328)
N	14,722,803	12,095,937	2,068,051	1,746,461

Appendix Table 4: High and Low-Brawn Occupations

30 Lowest Relative Brawn Intensity Occupations				30 Highest Relative Brawn Intensity Occupations			
occ1990dd code	Occupation Name	Relative Brawn Intensity	Total employment in 2000	occ1990dd code	Occupation Name	Relative Brawn	Total employment in 2000
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
99	Occupational therapists	-3.723	60,612	595	Roofers and slaters	4.314	150,952
15	Managers of medicine and health occupations	-3.705	378,792	844	Operating engineers of construction equipment	4.001	287,337
84	Physicians	-3.547	677,280	585	Plumbers, pipe fitters, and steamfitters	3.943	441,292
14	Managers in education and related fields	-3.461	647,604	848	Crane, derrick, winch, hoist, longshore operators	3.841	73,426
174	Social workers	-3.413	582,038	563	Masons, tilers, and carpet installers	3.807	336,421
7	Financial Managers	-3.338	887,492	779	Machine operators, n.e.c.	3.769	1,115,931
207	Licenses practical nurses	-3.298	526,876	597	Structural metal workers	3.754	91,487
178	Lawyers and judges	-3.263	881,023	869	Construction lagborers	3.748	915,398
8	Human resources and labor relations managers	-3.073	419,401	756	Mixing and blending machine operators	3.666	88,781
98	Respiratory therapists	-3.048	80,360	516	Heavy equipement and farm equpment mechanics	3.603	204,833
29	Buyers, wholesale, and retail trade	-2.960	194,074	573	Drywall installers	3.602	137,215
13	Managers and specialists in marketing, advertisement, PR	-2.958	1,230,062	889	Laboerers, freight, stock, and material handlers, n.e.c.	3.599	1,208,516
167	Psychologists	-2.931	158,505	719	Molders and casting machine operators	3.583	77,186
26	Management analysts	-2.926	491,757	567	Carpenters	3.534	1,130,795
418	Police and detectice, public service	-2.861	787,632	887	Vehicle washers and equipment cleaners	3.489	191,456
158	Special education teachers	-2.797	164,930	706	Punching and stamping press operatorives	3.466	115,267
253	Insurance sales occupations	-2.686	447,713	508	Aircraft mechanics	3.422	189,109
177	Welfare service workers	-2.644	226,804	875	Garbage and recyclable material collectors	3.396	67,101
23	Accountants and auditors	-2.617	1,622,348	588	Concrete and cement workres	3.353	67,955
188	Painters, sculptors, craft-artists, and print-makers	-2.431	196,445	783	Welders, solderers, and metal cutters	3.339	518,940
27	Personnel, HR, training, and labor relations specialists	-2.388	813,435	888	Packers and packagers by hand	3.284	273,628
97	Dieticians and nutritionists	-2.369	69,228	709	Grinding, abrading, buffing and polishing workers	3.261	68,349
256	Advertising and related sales jobs	-2.278	180,469	747	Clothing pressing machine operators	3.196	71,999
33	Purchasing managers, agents, and buyers, n.e.c.	-2.270	428,539	479	Farm workers, including nursery farming	3.183	471,200
229	Computer software developers	-2.226	1,238,608	734	Printing machine operators, ne.e.c.	3.144	73,427
163	Vocational and educational counselors	-2.205	482,790	657	Cabinetmakers and bench carpeters	3.099	69,707
36	Inspectors and compliance officers, outside	-2.199	100,126	579	Painters, construction, and maintenance	3.075	430,072
55	Electrical engineers	-2.198	349,343	859	Stevedores, and misc material moving occupatoins	3.066	75,394
22	Managers and adminstrators, n.e.c.	-2.128	5,209,907	829	Ship crews and marine engineers	3.044	58,649
83	Medical scientists	-2.111	76,283	789	Painting and decoration occupations	3.033	145,155

Notes: This table reports the occupations with the 30-highest and the 30-lowest relative brawn-intensities among occupatoins which employed at least .05% of the population in 2000. Relative brawn intensity is measured using the brawn, people, and brains task data from Lordan and Pishke (2016) and is computed as: task_brawn - task_brains - task_people.

Appendix Table 5: Share of workers in top-tercile brawn-occupations by demographic and major occupational category

All	Major Occupation Group			
	Management, Professional	Services, Clerical	Production	Operator, Construction
(1)	(2)	(3)	(4)	(5)
Panel A: All workers				
0.37	0.04	0.30	0.55	0.96
Panel B: Non-college educated men				
0.63	0.09	0.46	0.61	0.96
Panel C: Non-college educated women				
0.28	0.03	0.25	0.47	0.97
Panel D: College educated men				
0.10	0.02	0.18	0.31	0.88
Panel E: College educated women				
0.06	0.02	0.16	0.22	0.90

Notes: This table shows the share of workers in different demographic groups and major occupational groups who worked in occupations in the top-tercile of brawn intensity in 2000. Data come from the 2000 decennial census. Brawn intensity is constructed using the task-measures from Lordan and Pishke (2016).

Appendix Table 6: Heterogeneity in Effects of Exposure to PNTR with China by Original Sector & Occupation (Non-College Educated Workers): Additional Occupation Classifications

	Sector in 2000		Major Occupation Class in 2000				Brawn-intensity of occupation in 2000		
	Manufacturing	Non-Manufacturing	Management	Clerical, Services	Production	Operator, Construction	Low-Brawn	Medium-Brawn	High-Brawn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. CZ Exposure measured based on contemporaneous location (CZ Level Specification)									
Panel A1. Change in log(total full-time, full-year employment) betweeen 2000 and 2010/14									
Tariff Exposure per Worker	-2.492***	0.114	-0.028	-0.137	-0.827**	-2.294***	-0.006	0.038	-2.374***
	(0.354)	(0.142)	(0.156)	(0.161)	(0.383)	(0.232)	(0.158)	(0.177)	(0.197)
Effect of moving from 25th - 75th pctile of exposure	-0.074***	0.003	-0.001	-0.004	-0.025**	-0.068***	0.000	0.001	-0.070***
	(0.011)	(0.004)	(0.005)	(0.005)	(0.011)	(0.007)	(0.005)	(0.005)	(0.006)
Panel A2. Change in log(hourly wages) between 2000 and 2010/14									
Tariff Exposure per Worker	-0.834***	-0.462***	-0.518***	-0.834***	-0.462***	-0.586***	-0.586***	-0.387***	-0.660***
	(0.097)	(0.056)	(0.063)	(0.097)	(0.056)	(0.056)	(0.056)	(0.067)	(0.107)
Effect of moving from 25th - 75th pctile of exposure	-0.025***	-0.014***	-0.015***	-0.025***	-0.014***	-0.017***	-0.017***	-0.011***	-0.020***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Commuting-Zones	722	722	722	722	722	722	722	722	722
Region Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Panel B. CZ Exposure measured based on original location in 2000 (Individual Level Specification)									
Panel B1. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 2010/14									
Tariff Exposure per Worker	-1.404***	-1.321***	-0.717**	-1.258***	-0.971**	-1.974***	-0.655**	-1.204***	-1.699***
	(0.276)	(0.278)	(0.306)	(0.336)	(0.478)	(0.256)	(0.285)	(0.340)	(0.254)
Effect of moving from 25th - 75th pctile of exposure	-0.042***	-0.039***	-0.021**	-0.037***	-0.029**	-0.059***	-0.019**	-0.036***	-0.050***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.014)	(0.008)	(0.008)	(0.010)	(0.008)
N	74,500	216,816	76,558	95,039	19,018	100,701	62,728	87,700	140,889
Highly-exposed N	17,037	52,032	18,501	27,073	4,467	23,866	15,201	21,069	35,422
ACS Year*Region*Age Group*Sex	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table compares estimates of the relationship between exposure to China receiving PNTR on the change in labor market outcomes for non-college educated contemporaneous residents and non-college educated original residents of exposed locations separately for different original sector and occupation groups. In each panel, the first two rows report the point estimates for the PNTR gap, while the second two-columns rescale these point estimates to reflect the change in trade exposure for a county at the 75th percentile compared to the 25th percentile of exposure, which is a difference in the tariff gap for the average worker of .028 percentage point . Panel A reports estimates of Equation 4.2 of the change in log(total full-time, full-year employment) or change in wage and salary income of contemporaneous CZ residents on CZ exposure to China receiving PNTR. The specification includes region fixed-effects. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to PNTR with China. These specifications include region-by-year-by-age-group-by-sex-by fixed effects. Standard errors in Panel B are clustered at the commuting-zone level.

Appendix Table 7: Heterogeneity in Effects of Fracking by Original Sector & Occupation (Non-College Educated Workers): Additional Occupation Classifications

	Sector		Major Class of Occupation in 2000				Brawn-Intensity of Occupation in 2000.		
	Oil/Gas Related Sectors	Non-Oil and Gas Related Sectors	Management	Clerical, Services	Production	Operator, Construction	Low-Brawn	Medium-Brawn	High-Brawn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. CZ Exposure Based on Contemporaneous Location									
Panel A1. Change in log(employment) between 2000 and 2010/14									
1(Any Fracking Exposure)	0.188***	0.066***	0.036**	0.042**	0.039	0.213***	0.032*	0.034*	0.174***
	(0.022)	(0.013)	(0.017)	(0.017)	(0.041)	(0.025)	(0.017)	(0.019)	(0.022)
Panel A2. Change in log(hourly wages) between 2000 and 2010/14									
1(Any Fracking Exposure)	0.068***	0.007	0.008	0.012**	0.006	0.018**	0.006	0.018***	0.019***
	(0.009)	(0.006)	(0.005)	(0.006)	(0.009)	(0.007)	(0.005)	(0.005)	(0.007)
Commuting-Zones	722	722	722	722	722	722	722	722	722
Panel B. CZ Exposure Based on Original Location in 2000									
Panel B1. Percentage Change in Earnings (Davis-Haltiwanger Arc-Elasticity) between 2000 and 2010/14									
1(Any Fracking Exposure)	0.070***	0.067***	0.014**	0.060***	-0.019***	0.097***	0.040*	0.050*	0.085***
	(0.025)	(0.016)	(0.006)	(0.003)	(0.006)	(0.008)	(0.021)	(0.027)	(0.017)
N	55,838	235,301	76,486	94,979	19,007	100,657	62,733	87,706	140,906
Highly-Exposed N	7,866	30,124	10,044	12,558	2,258	13,130	8,123	11,332	18,154
ACS Year*Region*Age Group*Sex			Y	Y	Y	Y	Y	Y	Y

Notes: This table compares estimates of the relationship between exposure to fracking and the change in labor market outcomes for non-college worker contemporaneous residents and non-college worker original residents of exposed locations separately for different original sector and occupation groups. Fracking exposure is measured as an indicator for having any land within the Commuting-Zone which is the in the top half of fracking potential of all land within the given shale play. Panel A reports estimates of Equation 4.2 of the change in log(total full-time, full-year employment) or change in wage and salary income of contemporaneous CZ residents on CZ exposure to fracking. The specification includes region fixed-effects. The sample in Panel A includes all individuals ages 25 to 50 in the given time period. Panel B report estimates of Equation 4.1, which are individual level regressions of the percentage change in wage and salary income for individual workers on CZ exposure to fracking. These specifications include region-by-year-by-age-group-by-sex fixed effects. The sample in Panel B includes all non-college educated workers ages 25 to 50 in 2000 who are 59 or younger when interviewed in the ACS. Standard errors in Panel B are clustered at the commuting-zone level.

Appendix Table 8: Parameters of structural model of location/sector choice

	Age in 2000				
	25-30	30-35	35-40	40-45	45-50
	(1)	(2)	(3)	(4)	(5)
Fixed Location Moving Costs	-4.037	-4.311	-4.366	-4.650	-4.616
	(9.87E-07)	(1.24E-06)	(1.29E-06)	(1.79E-06)	(2.36E-06)
Marginal Location Moving Costs per 100-miles	-0.101	-0.112	-0.111	-0.094	-0.117
	(9.77E-09)	(1.40E-08)	(1.51E-08)	(1.96E-08)	(3.04E-08)
Fixed Costs of leaving manufacturing	-1.084	-1.235	-1.452	-1.493	-1.578
	(3.23E-07)	(3.01E-07)	(2.80E-07)	(3.00E-07)	(4.20E-07)
Fixed Occupation moving costs	-0.898	-1.109	-1.112	-1.195	-1.223
	(2.09E-07)	(2.10E-07)	(1.79E-07)	(2.02E-07)	(2.70E-07)
Fixed value of place 5 years ago	-1.815	-1.791	-1.549	-1.636	-1.705
	(1.09E-06)	(1.88E-06)	(1.31E-06)	(2.22E-06)	(1.36E-06)
Marginal value of being 100 miles farther from place five years ago	-0.079	-0.080	-0.078	-0.073	-0.078
	(9.50E-09)	(2.14E-08)	(1.26E-08)	(1.96E-08)	(1.42E-08)
Marginal utility of annual wage/salary income	0.235	0.250	0.266	0.208	0.177
	(3.57E-07)	(6.06E-07)	(3.36E-07)	(5.68E-07)	(2.82E-07)
N	34217	44414	59021	65041	68241

Notes: This table presents MLE estimates of a structural model of location, occupation, and sectoral choice allowing for moving costs across sectors. Standard errors are reported in parentheses.

Appendix Table 9: First-stage of location/sector/occupation wages and Trade with China/Fracking Instruments

	(1)
1(Any Frack)*1(Hi-brawn, in mfg)	-0.069
	(0.030)
1(Any Frack)*1(Low-brawn, in mfg)	-0.034
	(0.030)
1(Any Frack)*(Hi-brawn, outside mfg)	-0.072
	(0.030)
1(Exposed to trade with China)*1(Hi-brawn, in mfg)	0.242
	(0.207)
1(Exposed to Trade with China)*1(Low-brawn, in mfg)	0.714
	(0.207)
1(Exposed to Trade with China)*(Hi-brawn, outside mfg)	-0.102
	(0.207)
Number of commuting-zone/industry/occ groups	900
F-stat	4.3
Instruments	6
Location FE	Y
Job-Type FE	Y

Notes: This table reports regressions of labor market-by-sector-by-occupation fixed effects for non-college educated workers on instruments for labor demand interacted with industry/occupation dummies. Labor market-by-sector-by-occupation fixed effects are computed by regressing log wages on location-by-sector-by-occupation fixed effects, controlling for age-group by gender by race fixed effects. All regressions include location and occupation-by-sector fixed effects.

Appendix Table 10: Parameters of structural model of location/sector choice

(a) Estimates using instruments

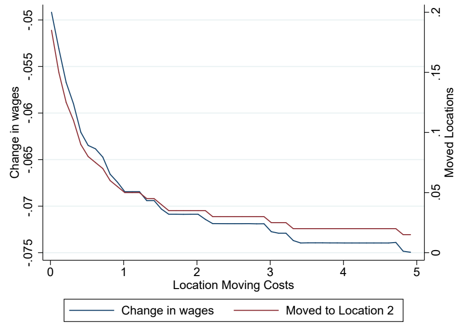
	Age in 2000				
	25-30	30-35	35-40	40-45	45-50
	(1)	(2)	(3)	(4)	(5)
Fixed Location Moving Costs	-4.037	-4.311	-4.366	-4.650	-4.616
	(9.87E-07)	(1.24E-06)	(1.29E-06)	(1.79E-06)	(2.36E-06)
Marginal Location Moving Costs per 100-miles	-0.101	-0.112	-0.111	-0.094	-0.117
	(9.77E-09)	(1.40E-08)	(1.51E-08)	(1.96E-08)	(3.04E-08)
Fixed Costs of leaving manufacturing	-1.088	-1.235	-1.452	-1.493	-1.578
	(3.24E-07)	(3.01E-07)	(2.80E-07)	(3.00E-07)	(4.20E-07)
Fixed Occupation moving costs	-0.897	-1.109	-1.112	-1.195	-1.223
	(2.09E-07)	(2.10E-07)	(1.79E-07)	(2.02E-07)	(2.70E-07)
Fixed value of place 5 years ago	-1.816	-1.549	-1.705	-1.814	-1.756
	(1.09E-06)	(1.31E-06)	(1.36E-06)	(1.85E-06)	(2.38E-06)
Marginal value of being 100 miles farther from place five years ago	-0.079	-0.078	-0.078	-0.059	-0.078
	(9.50E-09)	(1.26E-08)	(1.42E-08)	(1.76E-08)	(2.79E-08)
Marginal utility of annual wage/salary income	0.045	0.226	0.274	0.221	0.244
	(8.92E-07)	(8.17E-07)	(6.58E-07)	(6.10E-07)	(5.37E-07)
N	34217	44414	59021	65041	68241

Notes: This table presents MLE estimates of a structural model of location, occupation, and sectoral choice allowing for moving costs across sectors. In an attempt to account for potential endogeneity of location/sector ameities, this version uses a control function approach where controls for the residual of regressions of wages on exposure to trade with China and Fracking are included in the regressions as well. Standard errors are reported in parentheses.

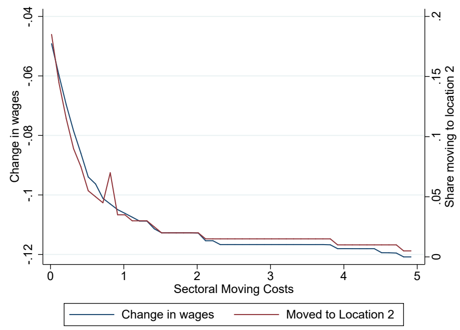
E Appendix Figures

Appendix Figure E.1: Effects of Labor Demand Shock in Location 1 and Sector A by Location and Sectoral Moving Costs

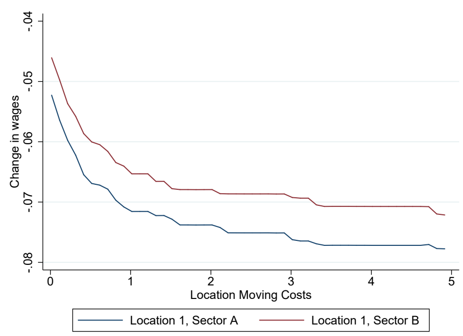
(a) Average: By Location Moving Costs ($s^J = 0$)



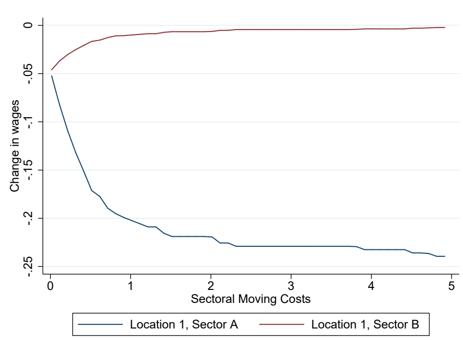
(b) Average: By Sectoral Moving Costs ($s^L = 0$)



(c) By Type: By Sectoral Moving Costs ($s^L = 0$)

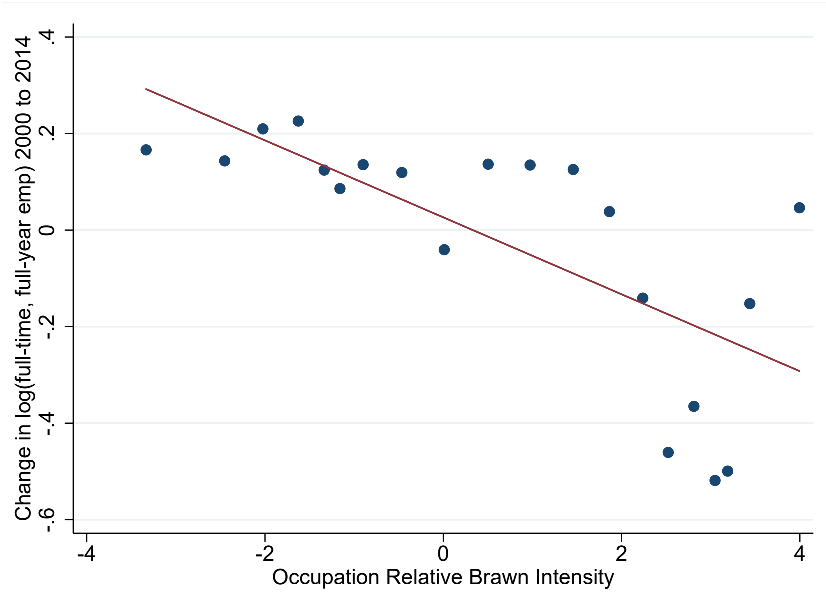


(d) By Type: By Sectoral Moving Costs ($s^L = 0$)



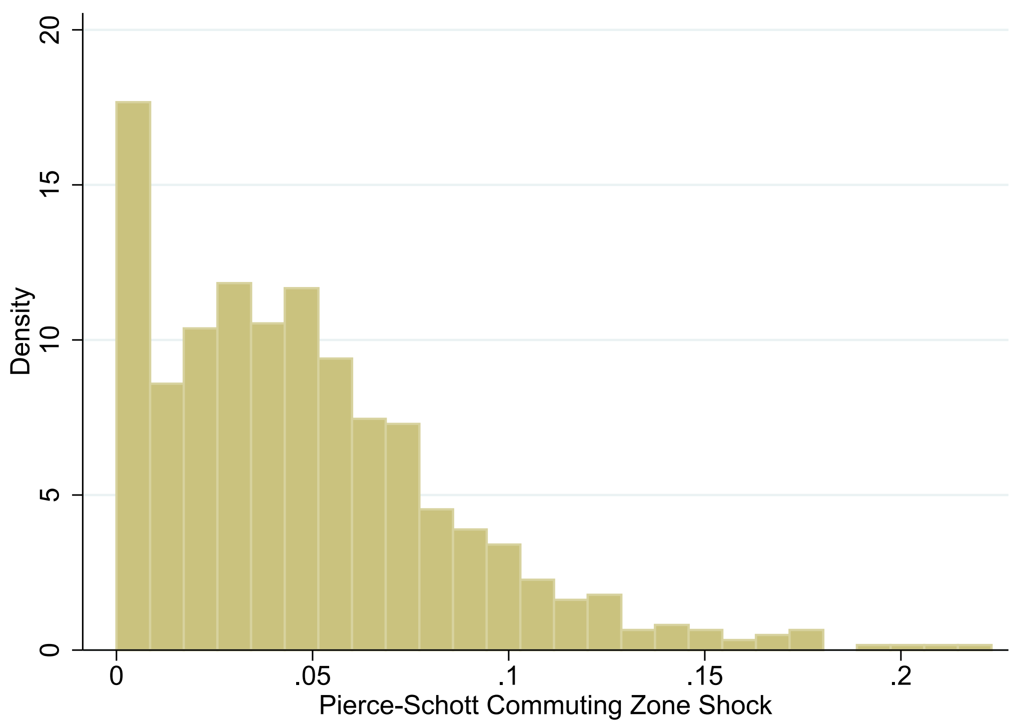
Notes: These figures plot simulations of the effect of a decline in productivity in Location 1, Sector *A* by individual's original location sector. In both figures, the x-axis is location moving costs and the y-axis is the change in wages. Panel A plots the relationship between location moving costs and the change in wages when there are 0 sectoral moving costs. Panel B plots the relationship between location moving costs and the change in wages when there are moderate sectoral moving costs ($s^J = .75$)

Appendix Figure E.2: Change in log(employment) between 2000 and 2010/14 by occupation brawn-intensity



Notes: This figure shows the change in employment by occupation brawn-intensity in 2000 for binned groups of occupations. The figure is based on 2000 Decennial Census and 2014 ACS data.

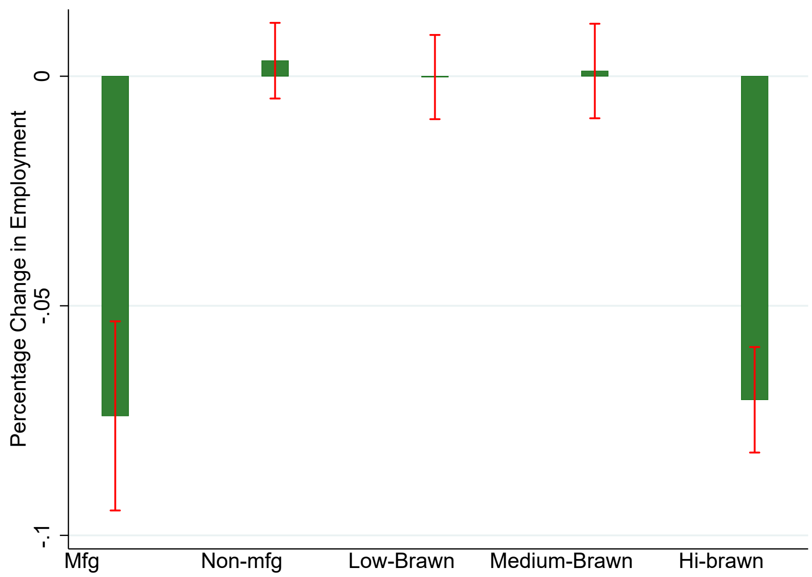
Appendix Figure E.3: Histogram of Pierce and Schott (2016) based manufacturing decline exposure measure



Notes: This histogram shows the distribution of the Pierce and Schott (2016) based measure for exposure to the decline of manufacturing based on the the gap between the Normal Trade Relations and non-Normal Trade Relations tariffs for the average worker in the commuting zone.

Appendix Figure E.4: Occupations and Sectors by Direct Exposure to PNTR with China

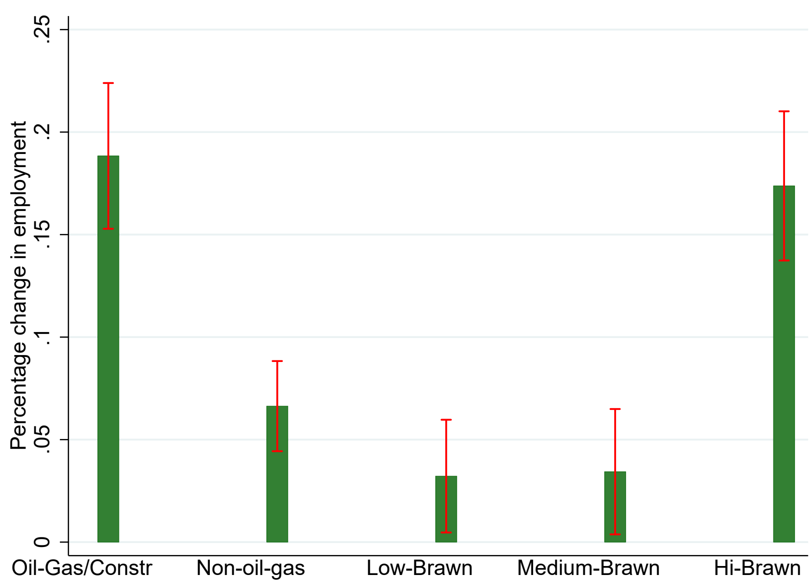
(a) Change in log(employment)



Notes: This figure shows the change in employment by the occupation and sector partitions used to measure direct exposure to PNTR with China.

Appendix Figure E.5: Occupations and Sectors by Direct Exposure to PNTR with China

(a) Change in log(employment)



Notes: This figure shows the change in employment by the occupation and sector partitions used to measure direct exposure to fracking.