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

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October 1, 2018

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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 (1)	2005-2009 ACS (2)	2010-2014 ACS (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 (1)	Assigned Non-missing PIK (2)	Non-duplicated PIK (3)	Matched to ACS (4)	Individual Characteristics Match (5)	Non-allocated demographic and work information (6)	Worked Full-Time, Full-Year in 2000 (7)	59 or younger when in ACS (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 (1)	Non-allocated work information (2)	PIKed/Matched (3)	PIKed/Matched and non-allocated work information (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

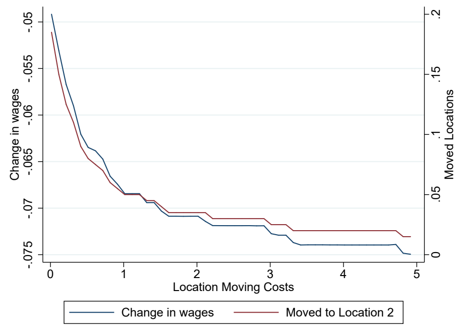
	Age in 2000				
	25-30	30-35	35-40	40-45	45-50
	(1)	(2)	(3)	(4)	(5)
Fixed Location Moving Costs	-4.037	-4.311	-4.366	-4.650	-4.616
	(9.87E-07)	(1.24E-06)	(1.29E-06)	(1.79E-06)	(2.36E-06)
Marginal Location Moving Costs per 100-miles	-0.101	-0.112	-0.111	-0.094	-0.117
	(9.77E-09)	(1.40E-08)	(1.51E-08)	(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.

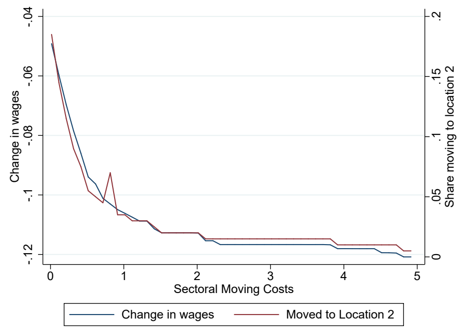
E Appendix Figures

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

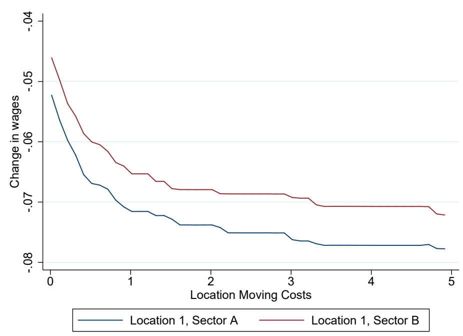
(a) Average: By Location Moving Costs ($s^J = 0$)



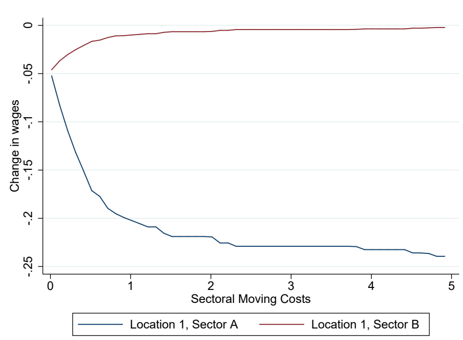
(b) Average: By Sectoral Moving Costs ($s^L = 0$)



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

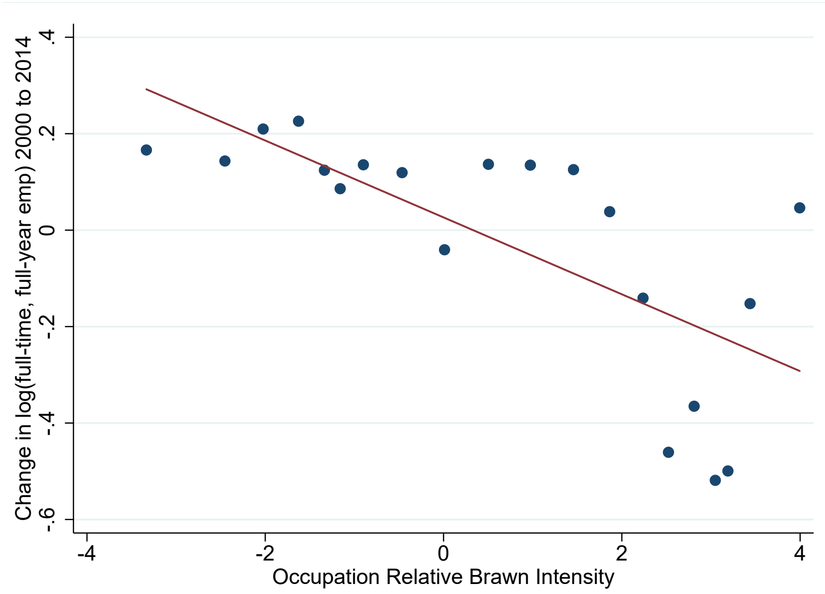


(d) By Type: By Sectoral Moving Costs ($s^L = 0$)



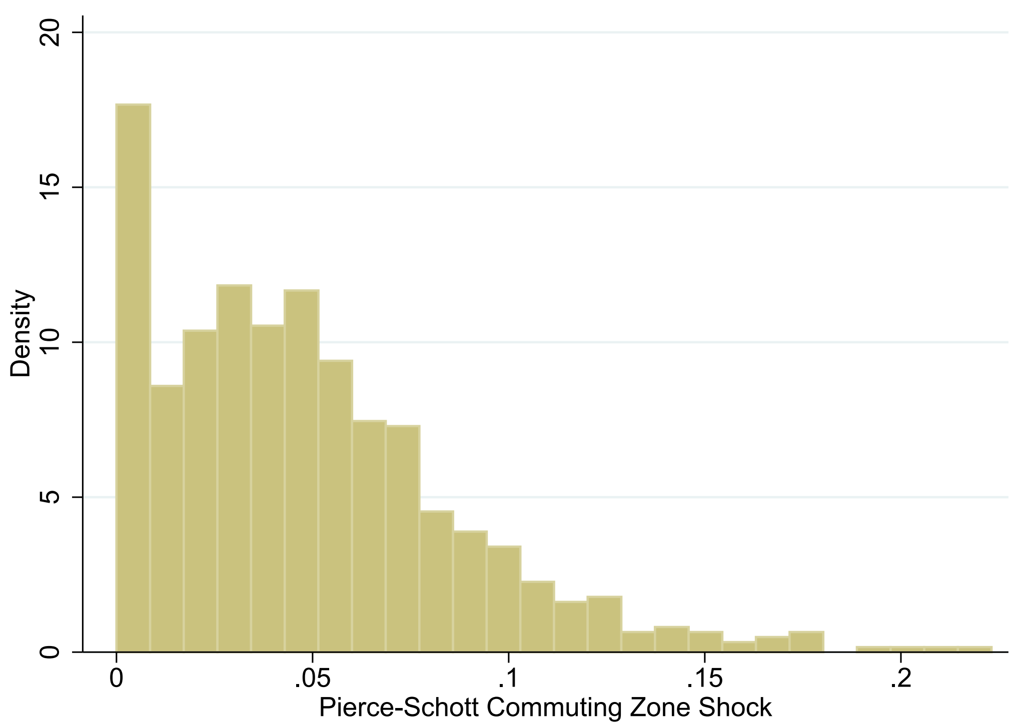
Notes: These figures plot simulations of the effect of a decline in productivity in Location 1, Sector A by individual's original location sector. In both figures, the x-axis is location moving costs and the y-axis is the change in wages. Panel A plots the relationship between location moving costs and 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.

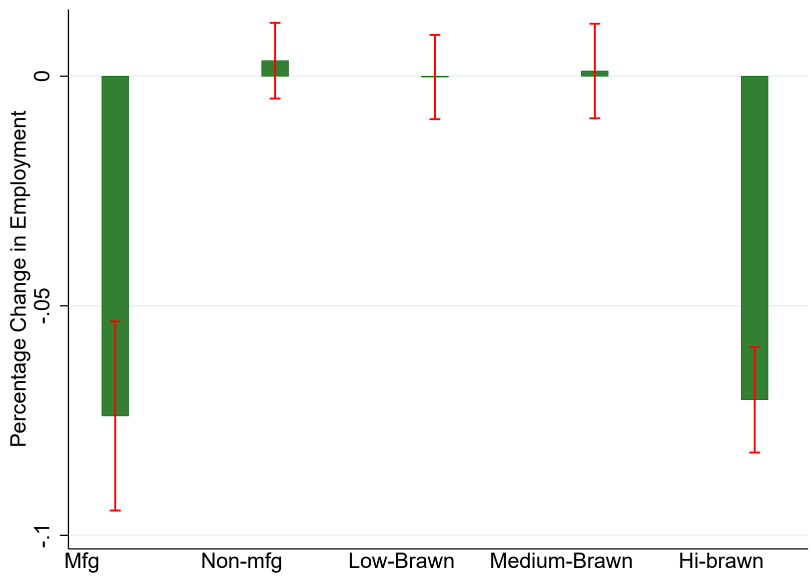
Appendix Figure E.3: Histogram of Pierce and Schott (2016) based manufacturing decline exposure measure



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

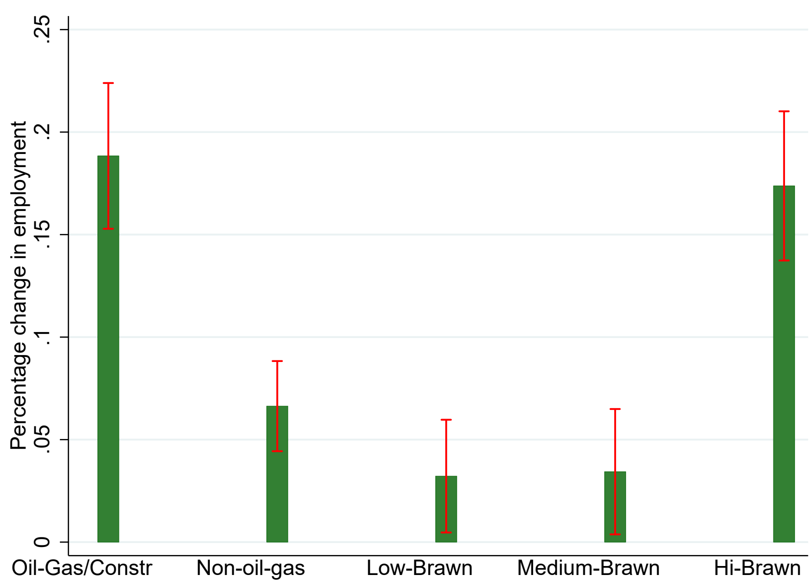
(a) Change in log(employment)



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.