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Abstract

This paper examines local labor market outcomes from an oil and gas boom. We examine two main outcomes across gender, race, and ethnicity: the probability of employment in the oil and gas industry and the log wages of workers employed outside the oil and gas industry. We find that men and women both gain employment in the oil and gas industry during booms, but such gains are much larger for men and are largest for black and Hispanic men. We also find positive income spillovers for workers in other industries that are similar in magnitude across demographic groups.

Keywords: Oil, Natural Gas, Employment, Gender, Race, Energy
JEL Codes: J20, Q33, Q40, R10

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1. Introduction

Oil and natural gas production in the United States expanded significantly beginning in the mid-2000s, in large part due to the implementation of hydraulic fracturing techniques and a boom in energy prices between 2000 and 2011 (Fitzgerald 2013; Economist 2014; Kelsey et al. 2016).[1,2] In 2014, the United States became the world's largest oil producer (Oyedele 2015). Based on data from the U.S. Bureau of Labor Statistics, between 2000 and 2014, employment in the oil and gas extraction sector grew 58 percent (BLS 2018). The energy sector has historically followed a boom and bust cycle, and this period of expansion was no different. Due largely to a worldwide surplus in the supply of oil, prices dropped and U.S. oil production fell beginning in mid-2014 (See Figure 1). Between June 2014 and January 2015, oil prices dropped 57 percent and between September 2014 and August 2015, U.S. oil production dropped by 120,000 barrels a day (Egan 2015; Gold 2015). The oil and natural gas price declines led to widespread layoffs throughout the industry in 2015 and 2016 (Hardzinski 2016; Hiller 2016; Miller 2016; Proctor 2016; Franklin 2015).

Although it did not last forever, the boom in oil and gas employment in the United States provided a significant opportunity for new workers to enter the industry, including women and minorities. Historically, the labor force in the oil and gas industry has been largely male and predominantly white (Price 2015). There have been accusations of widespread and on-going gender and racial discrimination in the industry, but the industry has countered that in recent

[1] Hydraulic fracturing technology refers to the combined use of existing horizontal drilling and hydraulic fracturing technologies. The combined use of these technologies led to the "shale revolution", which started in the Barnett Shale in Texas in 1998 and spread across the U.S. in the mid-2000s (Fitzgerald 2013).
[2] Hydraulic fracturing technology allowed access to previously economically inaccessible oil and natural gas reserves. The type of resources found depends largely on geology. Oil and natural gas are commonly located together in the same reservoir and natural gas is generally found during exploration for the more valuable commodity, oil. A boom in oil prices is expected to increase production of both toil and natural gas.

years diversity is increasing (Litvak 2016; Velarde 2014; Gillula and Fullenbaum 2014; Pruitt and Nethercutt 2002).[3]

Our paper examines local labor markets in Texas to explore how local growth in oil and gas employment differentially affects workers by gender, race, and ethnicity. Texas produces more crude oil than any other state, and has more than one-third of total U.S. proved reserves (EIA Texas 2018).[4] Between 2000 and 2016, Texas onshore fields produced 29 percent of the average annual U.S. oil production, this increased to 33 percent between 2011 and 2016 (EIA oil 2018). Texas is also the top natural gas producing state and has one-fourth of U.S. natural gas proved reserves (EIA Texas 2018).[5] Texas onshore production of natural gas from 2000-2016 was 27 percent of total U.S. production (EIA ng 2018). Figure 2 shows that the large employment gains in the oil and gas extraction industry during the boom were mirrored by a large increase in employment in Texas.

We first examine the probability of gaining employment in the oil and gas industry during the Texas oil and gas boom by race and gender. We find that these gains are concentrated among men, and the employment gains are especially strong for black males and Hispanic males. We find positive effects on employment for women as well. We then estimate income spillovers for workers not employed in the oil and gas industry. We find that increased oil and gas employment in the local area has positive, statistically significant, and economically important income spillovers for workers in other industries. Furthermore, the income spillovers are widespread and similar in size across gender, racial, and ethnic groups.

[3] In 2010, female workers comprised 19 percent, Hispanic workers comprised 15.7 percent, and black workers comprised 8.2 percent of total oil and gas industry jobs according to Gillula and Fullenbaum (2014).
[4]From 2000 and 2011, Texas crude oil production was higher than any other state and second only to federal offshore drilling in the Gulf of Mexico (GOM), since 2012, Texas production exceeds even GOM offshore production (EIA oil, 2018).
[5] Since 2000, Texas onshore natural gas production has exceeded all states and offshore production areas (EIA ng, 2018).

2. Background

2.1 Racial/Ethnic Diversity in the Oil and Gas Industry

Minorities have historically made up a relatively small share of the labor force in the oil and gas industry. As stated previously, some have argued that this is due largely to discrimination in the labor market in general and in the oil and gas market specifically. There have been several complaints of racial discrimination in the oil and gas industry dating back to the 1980s (Brady 2017; Litvak 2016; Pruitt and Nethercutt 2002). However, according to a forecast from the American Petroleum Institute (API), employment by black and Hispanic workers is expected to rise to 40 percent of total employment by 2035 (Gillula, Fullenbaum, and Winkel 2016). This forecast is due in large part to the expected increased demand for energy workers and the aging of the existing oil and gas field workers (Brady 2017). To meet the forecast will require a significant shift in the labor composition in the industry; in 2010 black and Hispanic workers made up approximately 24 percent of the labor force (Gillula and Fullenbaum 2014).

Economists have examined several factors that affect the employment and wages of minority workers, including discrimination (Kreisman and Rangel 2015; Lang and Manove 2011; Hellerstein, Neumark, and McInerney 2008; Hersch 2008; Bertrand and Mullainathan 2004; Reimers 1983), differences in labor force participation (Antecol and Bedard 2004), and differences in pre-labor market characteristics such as education (Black et al 2006; Carneiro, Heckman, and Dimitriy 2005; Neal and Johnson 1996). Each of these factors plays a role in the representation of minority workers across industries.

Spatial mismatch is also an important concern. Spatial mismatch theory states that in the last several decades job growth has been predominantly a suburban phenomenon while black workers reside disproportionately in urban areas relative to white workers. This mismatch of jobs in suburban areas and black workers in urban areas has been widely cited in the literature as a significant factor in higher rates of unemployment for black workers in recent decades (Holzer et al 2011; Aslund, Osth, and Zenou 2010; Partridge and Rickman 2008; Wang 2008; Johnson 2006; McQuaid 2006; Partridge and Rickman 2006; Houston 2005; Brueckner and Zenou 2003; Smith and Zenou 2003; Zenou and Boccard 2000; Holzer et al. 1994; Kain 1992; Holzer 1991; Ihlanfeldt and Sjoquist1990). In terms of the oil and gas sector, spatial mismatch theory might explain a portion of the lower share of employment for black workers in oil and natural gas fields. These jobs are typically located in rural areas as the majority of oil and gas development occurs outside metropolitan areas.

Networks may also play important roles in finding good jobs in expanding industries (Patacchini and Zenou 2012; Battu et al. 2011; Ioannides and Loury 2004; Topa 2001). Potential entrants into an industry may benefit from social connections to workers already in the industry who can provide information about job openings and serve as references. African Americans may be persistently disadvantaged by historical underrepresentation in the oil and gas industry and limited connections with workers already in the industry.

2.2 Gender Diversity in the Oil and Gas Industry

Historically, women have been underrepresented in the oil and gas industry (Brady 2015; Price 2015; Ditrrick 2014; Feltus 2008). There are many possible factors including a difficult working environment that has discouraged women, discrimination, and a skill mismatch due to women being historically underrepresented in engineering fields (AMMA 2017; API 2015; Brady 2015; GI 2015; and Price 2015). During the boom period, the increased demand for petroleum engineers required oil and gas firms to diversify their hiring in order to meet their increased demand for workers (Brady 2017; Brady 2015; Price 2015). This increased demand for engineers, however, may be offset by low numbers of women working in the oil and natural gas fields where the share of female workers was below 5% in 2010 (Brady 2015, Gillula and Fullenbaum 2014, p.21, 25).

More generally, there is a large research literature on gender differences in labor market outcomes. These include examinations of wage differentials (Autor, Katz, and Kearney 2008; Mulligan and Rubinstein 2008; Mueller and Plug 2006; Topel 1994), differences in labor force participation (Compton and Pollak 2014; Fernandez 2013; Eckstein and Lifshitz 2011; Fogli and Veldkamp 2011; Gayle and Golan 2011; Coen-Pirani, Leon, and Lugauer 2010; Aguero and Marks 2008; McKinnish 2004), and examinations of gender composition and discrimination in the workplace (Niederle and Vesterlund 2007; Buser Niederle, and Oosterbeek 2014; Bertrand and Hallock 2001). This paper builds on this literature by examining the composition of female workers in a male dominated oil and gas industry that underwent a significant period of expansion and rapid hiring across skill levels.

2.3 Oil and Gas Spillovers on Local Economies

Increased oil and gas production requires an influx of workers, particularly in rural areas where the oil and gas fields are primarily located. This may lead to increased spending on construction, accommodations and local services in communities near oil and gas development. Oil and gas companies have argued that the expansion of oil and gas development during the boom period had a significant positive impact on local economies, including increased income and job growth (API 2017). The academic literature, however, has found mixed results in terms of the local economic benefits of the post-2000 oil and gas boom (Weinstein, Partridge, and Tsvetkova 2018; Agerton et al. 2017; Feyrer, Mansur, Sacerdot 2017; Maniloff and Mastromonaco 2017; Tsvetkova and Partridge 2016; Lee 2015; Michieka and Richard 2015; Munasib and Rickman 2015; Paredes et al. 2015; Weinstein 2014; Weber 2012). Overall, the research points to local economic benefits from oil and gas development, but there is some variation by region and in terms of the magnitude of the effects. In a notable recent study, Feyrer, Mansur and Sacerdote (2017) find that new oil and gas extraction between 2005 and 2012 added 640,000 jobs in the United States and decreased the overall unemployment rate by 0.43. Locally, they find that each million dollars in oil and gas production led to an additional $80,000 in wage income within an oil and gas producing county. Nearly 40 percent of that income was due to local economic spillovers, providing income to workers outside the oil and gas industry. They also find that two-thirds of these income increases persist for two year after the initial production increase (Feyrer, Mansur and Sacerdote 2017).

3. Data and Methods

3.1 Data

The data for our analysis were obtained from IPUMS-USA (Ruggles et al. 2018). We use individual-level microdata from the year 2000 decennial census long-form questionnaire (5% sample) and the American Community Survey (ACS), 2001-2016, conducted by the U.S. Census

Bureau.[6] The data include detailed individual information on age, gender, race, ethnicity, birthplace, education, employment, and income. In order to focus on employment composition in Texas, a key oil and gas producing state, we restrict our analytical sample to persons residing in Texas who at the time of their survey were ages 18-61 and employed. We use pooled cross-sectional data to compare similar people in the same geographic areas over time, but due to data limitations, it is not possible to link individuals across time.

While Texas has 254 counties, our data are combined into 49 local geographic areas. Due to confidentiality protections, the level of geographic specificity is limited for sparsely populated areas. The finest level of geographic identification is the Census Bureau constructed Public Use Microdata Area (PUMA), and confidentiality protections require that PUMAs are defined to contain at least 100,000 residents. This allows for geographic identification for heavily populated areas, but it requires that sparsely populated areas are combined with other nearby areas until the population threshold is met. Our regression analyses are also affected by the availability of PUMA identifiers and changes in PUMA boundaries beginning in 2012.[7] PUMA boundaries were the same for 2000 and 2005-2011, but were redrawn beginning in 2012. To construct consistent PUMAs, we use the IPUMS consistent PUMA variable, CPUMA0010. The result is 49 consistent PUMAs (local areas), some of which include a single urban area and some of which include several adjacent sparsely populated counties.[8]

[6] The year 2000 sample is a five percent random sample of the U.S. population. For 2001-2004, the ACS is a roughly 0.4 percent annual sample of the population, and each year of the ACS during 2005-2016 includes a one percent sample of the population.
[7] PUMA identifiers are not available for 2001-2004, so these years are excluded from our regression analysis, but they are included in our descriptive figures showing statewide trends.
[8] We use the terms consistent PUMA and local area interchangeably.

Figure 3 provides a map of the 49 consistent PUMAs and illustrates how oil and gas employment rates varied among them in year 2000 by grouping them based on the standard deviations their energy employment is above or below the mean.[9] The energy employment share in 2000 has unweighted mean of 0.016 and unweighted standard deviation of 0.026 across consistent PUMAs. We see that there were considerable differences, some areas had very little oil and gas employment (less than one percent of total employment) and others had oil and gas employment accounting for more than 10 percent of total employment in the area in 2000. This highlights the fact that opportunities for employment in the oil and gas industry were not equally dispersed across Texas.

Figure 4 illustrates statewide trends over time in oil and gas employment rates separately for men and women. The figure shows that both saw increased employment in the oil and gas industry after 2000 that peaked in 2014 and then declined. However, the oil and gas industry employment rate was consistently higher for males and increased over time more for males than females. This suggests that males may have gained more than women from the oil and gas boom. Figure 5 illustrates time changes in oil and gas employment rates in Texas separately for the four major racial/ethnic groups. All four groups experienced increased oil and gas employment between 2000 and 2014, but there were some ups and downs along the way. White workers had the highest oil and gas employment rate in every year, and black workers had the lowest oil and gas employment rate in all but one year (2004).

3.2 Regression Model

[9] Individual oil and gas employment is defined based on responses to industry of employment. The oil and gas employment rates in Figures 3-5 are defined based on the number of workers in the oil and gas industry divided by the total number of workers; individual survey weights are used.

We estimate linear regressions using both ordinary least squares (OLS) and two-stage least squares (2SLS).[10] Our basic model is:

$$Y_{igct} = \theta_g OilGasShare_{ct} + \beta_g X_{igct} + \gamma_{gc} + \delta_{gt} + \varepsilon_{igct}$$

where Y_{igct} is one of two individual-level dependent variables for individual *i* in demographic group *g* living in local area *c* in survey year *t*. We first examine an oil and gas industry employment indicator as the dependent variable.[11] Next, we analyze the natural log of earned income during the previous 12 month as the dependent variable. Our main explanatory variable of interest is $OilGasShare_{ct}$, which measures the share of employment in area *c* and year *t* that is in the oil and gas industry.[12] The detailed individual-level data we use allows us to control for important individual characteristics, X_{igct}; these include detailed dummy variables for age, education, and state of birth (country of birth for foreign-born workers). We also control for hours worked during the previous year in regressions with log earned income as the dependent variable.[13]

Our research is fundamentally interested in how energy employment impacts vary across demographic groups, so we define four mutually exclusive racial/ethnic groups: white, black, Asian, and Hispanic. In constructing these, persons reporting Hispanic ethnicity are assigned to the Hispanic group regardless of their race; i.e., the white, black,

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[10] Our analysis is conducted in Stata using the REGHDFE command (Correia 2017).

[11] Since this dependent variable is binary and we estimate a linear model, the model is a linear probability model (LPM). LPM is warranted because we a have a large individual-level dataset and include a large number of fixed effects, which can create difficulties with estimation and accuracy for non-linear models (Greene 2004).

[12] This variable is computed in multiple steps. We first compute the oil and gas share in each local area and year based on where jobs are located, i.e., PUMAs of workplace, in order to account for the fact that some workers live and work in different places. This measure is then matched to the local areas where people live. Thus, $OilGasShare_{ct}$, is a measure of the oil and gas employment share for jobs located in the area where an individual lives.

[13] Most years of the ACS only report the number of weeks worked the previous year in intervals. We include dummies for each weeks worked interval, and we also include a continuous variables for the log of the usual number of hours worked per week.

and Asian groups are non-Hispanic. Due to data limitations and small sample sizes, we exclude from the analysis persons who are not in one of these four race/ethnicity categories.[14] We split each of these four racial/ethnic groups into gender-specific categories yielding eight groups based on combinations of gender, race and ethnicity in our analyses.

Our regressions include demographic group-specific controls for consistent PUMA fixed effects (γ_{gc}) and year fixed effects (δ_{gt}). Our inclusion of consistent PUMA fixed effects accounts for time-invariant factors that affect our dependent variables. Our inclusion of year fixed effects accounts for all aggregate factors affecting all areas and individuals in a given year, such as macroeconomic fluctuations and aggregate government policy changes. ε_{igct} is a mean zero error term. We cluster standard errors by consistent PUMA to account for the grouped nature of our main explanatory variable and possible serial correlation within areas.

In order for OLS to give accurate estimates, the error term needs to be uncorrelated with the explanatory variables. This condition may fail to hold for various reasons including measurement error in our primary variable of interest, $OilGasShare_{ct}$. If measurement error is random, it will attenuate OLS coefficient estimates toward zero, but estimates would likely still have the correct sign. However, OLS may also suffer from sampling error that induces correlation between the oil and gas employment dependent variable and the explanatory variable of interest since these come from the same source; this could cause a positive bias for OLS estimates.

[14] These excluded persons account for less than two percent of all workers ages 18-61 in Texas.

3.3 Instrumental Variables

Our preferred estimates use instrumental variables (IV) with 2SLS. 2SLS regresses the explanatory variable of interest ($OilGasShare_{ct}$) on the IV in the first stage and then forms a prediction based on the first-stage to include in the second-stage in place of the explanatory variable of interest. We examine two related instrumental variables, one that is preferred and the other as a robustness check. Our preferred instrument, IV2000, is constructed as follows:

$$IV2000_{ct} = OilGasShare_{c,2000} \times OilGasShare_{US,t}.$$

Our secondary instrumental variable is IV2014 and is constructed similarly as follows:

$$IV2014_{ct} = OilGasShare_{c,2014} \times OilGasShare_{US,t}.$$

IV2000 combines the oil and gas industry employment share in consistent PUMA *c* in year 2000 ($OilGasShare_{c,2000}$) with the oil and gas industry employment share for the rest of the United States (excluding Texas) in year *t* ($OilGasShare_{US,t}$). IV2014 follows the same idea but uses the year 2014 oil and gas share in area *c*.

Our construction of IV2000 builds on previous research using variants of the shift-share instrument strategy (Bartik 1991; Moretti 2010; Partridge et al. 2017; Charles et al. 2018). The spatial variation relies on differences in oil and gas employment across areas in 2000, which largely precedes the subsequent shale boom.[15] The temporal variation relies on the changes in oil and gas employment experienced in the rest of the U.S. outside of Texas. Our main results with IV2000 limit the analysis to the sample from the 2005-2016 ACS; i.e., we exclude the year 2000 sample when we employ IV2000 because the instrument is by construction related to $OilGasShare_{ct}$ for year 2000 observations in ways that would threaten the exogeneity of the

[15] New technologies were implemented in parts of Texas earlier than the rest of the U.S., so there was some uptick in oil and gas development in parts of Texas in 2000, but it was still small compared to later increases that began after 2005.

instrument. When we use IV2014, we exclude the 2014 sample observations from the analysis for similar reasons.

A valid instrument must be both relevant and exogenous. The relevance condition requires that the instrument be a good predictor in the first stage. We expect the relevance condition to be satisfied for IV2000 for two main reasons. First, we expect oil and gas employment shares in 2000 to be correlated with subsequent growth in oil and gas employment shares during the energy boom; i.e., areas with existing employment in oil and gas will see growth when the industry starts to boom. Second, we expect the timing of changes in oil and gas employment in the rest of the U.S. to be driven by industry conditions related to technology and prices that affect oil and gas employment in Texas around the same time. We test the relevance condition based on first-stage diagnostic tests for the strength of the instrument.

The exogeneity condition requires that the instrument be uncorrelated with the error term in the second stage. We first consider the spatial portion of IV2000, $OilGasShare_{c,2000}$. Because the spatial variation is determined at least five years before the 2005-2016 ACS samples, we can be assured that the relationship is not driven by reverse causality. Second, the timing and extent of the subsequent boom in oil and gas employment due to new technology and increased energy prices were not widely or clearly anticipated in 2000, at least not in ways that would cause workers to alter their behavior five or more years in advance. Next, we consider the temporal variation, the source of temporal variation in IV2000, $OilGasShare_{US,t}$, is due to changes in industry technology and prices that are arguably external to individual workers in Texas at the same time. Thus, we expect the IV2000 instrument should be exogenous.

IV2014 should satisfy the relevance condition for similar reasons as IV2000. However, it is intentionally constructed based on the peak of the boom, which somewhat limits the argument for exogeneity. Since IV2000 is based on spatial variation in year 2000, there is potential concern that it might miss some of the oil and gas boom from shale development in areas that did not have significant oil and gas employment prior to the shale boom. IV2014 incorporates oil and gas employment in these "new" oil and gas areas and allows us to examine whether our results are robust to a more shale-inclusive measure. IV2000 is our preferred instrument because of its stronger claim to exogeneity.

4. Regression Results

4.1 Gaining Employment in the Oil and Gas Industry

The regression results for the oil and gas industry employment dependent variable are presented in Table 1. OLS results are presented in Panel A. Our preferred 2SLS results using IV2000 are presented in Panel B. Panel C provides 2SLS results using IV2014, which we view as a robustness check. Each of the eight columns of the table corresponds to one of our eight demographic groups. Columns 1-4 are for white males, black males, Hispanic males, and Asian males, respectively. Columns 5-8 are for white females, black females, Hispanic females, and Asian females, respectively. We report the coefficients and standard errors for our main explanatory variable of interest, $OilGasShare_{ct}$, but we do not report the results for the other explanatory variables because they are too numerous and simply intended as control variables.[16] The local oil and gas share is measured as the number of oil and gas jobs divided by the total number of jobs, so a one-unit increase in this share would mean going from zero oil and gas

[16] The exact number of dummy control variables varies slightly across groups because some state/country of birth categories are completely empty for some groups. However, all groups have more than 200 dummy explanatory variables included making their results too numerous to present.

employment to all oil gas employment in the area. The oil and gas share in our analytical sample has a minimum value of zero and a maximum value of 0.268; the mean share is 0.020 and the standard deviation is 0.025.

All OLS coefficient estimates in Panel A of Table 1 are positive, and all but the estimates for Asian males and Asian females in Columns 4 and 8 are statistically different from zero at the one percent level of significance. However, the magnitudes vary quite a bit across the eight groups. In particular, the magnitudes are generally larger for men than women, but even within each gender, there is some variation across racial/ethnic groups. The coefficient estimate is largest for Hispanic males (1.19), followed by black males (0.95) and then white males (0.65). The coefficient is smallest for black females (0.09) and no female group has an OLS coefficient larger than 0.3. These results suggest that local increases in oil and gas employment increase the likelihood of getting a job in the oil and gas industry for most groups of workers, but the impact varies across demographic groups. Hispanic males and black males seem to gain the most in terms of obtaining oil and gas employment, while black females gain the least.

OLS estimates may suffer from measurement error and other sources of endogeneity. Our preferred estimates in Table 1 are those in Panel B from 2SLS using IV2000. Our first-stage diagnostic tests indicate that IV2000 is a strong instrument in all cases except for in Columns 4 and 8 for Asian males and Asian females, respectively. According to Stock and Yogo (2005), the weak instrument test critical value based on a 5% size distortion of a 5% Wald test is 16.38 for our case. In Panel B, the first stage Kleibergen-Paap Wald F statistics (Kleibergen and Paap 2006) exceed 16.38 in Columns 1-3 and 5-7 but fall below 16.38 in Columns 4 and 8, so we should be cautious in interpreting the results in Columns 4 and 8 .[17]

[17] For brevity, we do not report the first-stage coefficients on the instrument, but they were positive and statistically significant in all cases as expected.

Interestingly, the pattern of results is similar between Panels A and B, but there are some apparent differences.[18] First, the coefficient estimate increases substantially for black males to 2.03 in Panel B. The coefficient estimates increase for some other groups as well including Hispanic males (1.35), Hispanic females (0.50), and white females (0.37). Asian males and Asian females have especially large coefficient estimate increases from Panel A to B, but their estimates are very noisy and not statistically significant. The coefficient estimates decrease from Panel A to B for white males (0.49) and black females (-0.34), and the black female coefficient estimate is now negative but not statistically different from zero. Overall, black males and Hispanic males continue to be the most responsive to local oil and gas employment in terms of gaining jobs in the industry. The coefficient of 2.03 for black males indicates that a one standard deviation (0.025) increase in the local oil and gas share would increase the probability of oil and gas employment for black males by roughly five percentage points on average. Black males are indeed quite responsive to local oil and gas employment booms in their local areas.

Results in Panel C using IV2014 are generally similar to results in Panel B using IV2000. Some of the coefficient estimates are larger, while others are smaller, but none of the coefficient estimates in Panel C is statistically different at the ten percent level from its corresponding estimate in Panel B. Hispanic males (1.61) and black males (1.38) still have the two largest coefficients that are statistically significant, but the Hispanic male coefficient is larger in Panel C than in Panel B, while the black male coefficient

[18] The bottom of Panel B reports the p-values for tests that the OLS results are endogenous, which amount to testing the statistical significance of the difference between OLS and 2SLS coefficients. None of the OLS endogeneity tests in Panel B are significant at the five percent level for any group; the test for black males is significant at the ten percent level.

decreases from Panel B to C. Some variation in coefficient estimates is to be expected with different instruments, but the qualitative pattern of results is largely similar.

Overall, the results in Table 1 suggest that both men and women gain jobs in the oil and gas industry when oil and gas employment grows in their local area. Thus, both genders appear to benefit. However, the gains are not evenly distributed across genders or racial/ethnic groups. Men are more likely than women to gain employment in the oil and gas industry due to increased local oil and gas employment. Hispanic males and black males are especially likely to gain oil and gas employment, while black females appear to gain the least and may not gain at all.

4.2 Income Effects

While we expect that gaining oil and gas employment provides direct benefits to the workers who get those oil and gas jobs, additional benefits may spillover to local workers outside the oil and gas industry via local income multipliers. Specifically, a boom in the local oil and gas industry may increase local demand for restaurants, retail stores, personal services, and other places where oil and gas workers spend money in the local economy. This increased demand for local labor will drive up wages and incomes in the local areas, even for workers not working in the oil and gas industry. In any given year of our data period, less than three percent of all workers in Texas are employed in the oil and gas industry. However, the other 97 percent or more may still benefit from local oil and gas development through these local spillover effects.

Table 2 reports the estimated effects of the local oil and gas employment share on the log earnings of workers employed outside the oil and gas industry. Table 2 is structured similarly to

Table 1 with three panels and eight columns.[19] The OLS results in Panel A indicate significant positive effects for only five of the eight groups, with estimates for black males, Asian males, and black females not statistically significant at the ten percent level or higher. As discussed before, there are some limitations with OLS estimates.

Panel B of Table 2 presents our preferred income results from 2SLS estimation using IV2000. The weak identification statistics are above the relevant critical value for all groups except for Asian males and Asian females. Only five of the eight groups have statistically significant 2SLS coefficient estimates, but now black males, black females and Asian females are the ones not statistically significant at conventional levels. However, it is important to note that all of the coefficient estimates in Panel B are relatively large and most are comparable in magnitude. Thus, it is likely incorrect to conclude that there is zero effect for black males, black females, and Asian females. Their estimates are too noisy to draw strong inferences, but their estimated coefficients are comparable in magnitude to other groups. The largest coefficient estimate in Panel B is for Asian males (8.42), which is noisily estimated and only statistically significant at the 10 percent level.

OLS endogeneity tests in Panel B of Table 2 are significant at the five percent level for five of the eight groups and significant at the ten percent level for a sixth group. In all six of these cases, the OLS coefficient estimates are smaller than the corresponding 2SLS estimate in Panel B. This indicates that these OLS coefficient estimates in Table 2

[19] The sample sizes in Table 2 are slightly smaller than in Table 1 because Table 2 excludes workers employed in the oil and gas industry and excludes workers with non-positive earnings in the prior 12 months. A few workers have non-positive earnings because they are new entrants to the labor market, work unpaid for a family business, or are self-employed without making a positive income.

are biased downward due to endogeneity.[20] In all instances, our preferred estimates are from 2SLS using IV 2000.

Interpreting the magnitude of the income spillover effects in Table 2 requires consideration of the size and dispersion of the $OilGasShare_{ct}$ explanatory variable. As noted above, $OilGasShare_{ct}$ has a mean of 0.020 and a standard deviation of 0.025. The dependent variable is the natural log of earned income. Thus, a hypothetical coefficient of 2.0 would imply that a one standard deviation increase in the local oil and gas share of employment would increase average wages for workers outside the oil and gas industry by about five percent. All coefficients in Panel B exceed 2.0 except for Asian females (1.92), which is very close to 2.0, so these are meaningfully large effects. Workers outside the oil and gas industry appear to benefit in a very real way from increased oil and gas employment in their area. It is also worth noting that the income spillover estimates are not very different between genders or racial/ethnic groups except for Asian males.

2SLS results in Panel C using IV2014 are largely similar to those in Panel B using IV2000. However, the coefficient estimates in Panel C are statistically significant for seven of the eight groups, with only the estimate for Asian females not significant. The coefficient magnitudes are generally similar to corresponding estimates in Panel B, and none of the coefficient estimates in Panel C is statistically different at the ten percent level from its corresponding estimate in Panel B. In terms of estimated magnitude, the most notable increase from Panels B to C is for black females (4.70) and the most notable decrease is for Asian females (0.31).

[20] Endogeneity is a much more severe problem for OLS in Table 2 than in Table 1. While we can only speculate, this may suggest that OLS results in Table 1 have competing negative and positive biases that partially offset, while OLS in Table 2 is much more strongly affected by negative bias.

While Table 2 estimates spillover effects on income, one might also be interested in the direct effects on income for workers receiving high-paying jobs in the oil and gas industry during a boom. Unfortunately, we are not able to estimate this effectively with our data, in part because we only observe individuals at a single point in time, i.e., we do not have individual-level panel data. Essentially, we do not have enough information to construct a valid counterfactual about how much individual workers who gained employment in the oil and gas industry would have earned had the industry not boomed and they not gained oil and gas employment. Table 3 extends Table 2 and provides estimated effects of the local oil and gas employment share on average log incomes of all workers, including both workers employed in the oil and gas sector and workers employed outside of oil and gas. The results are overall quite similar to Table 2, which should be expected since the oil and gas workers added in Table 3 account for less than three percent of the total workforce. Focusing on 2SLS results using IV2000 in Panel B of Table 3, we see that the largest increase in coefficient is for Hispanic males and black females are the only group with a (slightly) smaller coefficient estimate in Table 3 than in Table 2.

The takeaway from Table 3 is that incorporating direct effects from income in oil and gas employment increases the income benefits from local oil and gas employment. This is consistent with expectations that oil and gas jobs are typically high-paying and that more workers getting these jobs during oil and gas booms will increase average wages in an area.

4.3 Additional Robustness Checks

We also conducted additional sensitivity analysis with results in Table 4. First, we estimated OLS regressions for Tables 1 and 2 excluding year 2000 to ensure that including year

2000 was not driving differences with the preferred 2SLS results; this did not significantly change the OLS results. Second, we simultaneously used IV2000 and IV2014 as instruments in the same 2SLS regressions; results were not significantly different from our preferred estimates in Tables 1 and 2 that just use IV2000. Third, we excluded the five largest geographic area consistent PUMAs, which may have noisily estimated oil and gas shares; most of the main results were qualitatively similar, except the oil and gas employment dummy outcome for white males using IV2000 was no longer significant at the ten percent level, though the coefficient estimate is not statistically different from the preferred estimate in Panel B of Table 1.

We also experimented with altering the set of control variables. Excluding the education dummy control variables did not significantly alter the results relative to our preferred 2SLS specifications in Panel B of Tables 1 and 2. Similarly, adding dummy controls for marital status and presence of children in the household did not significantly alter the results. We also experimented with adding a Bartik (1991) style shift-share control variable to our preferred specification; the Bartik control predicts local employment outside the oil and gas sector in year *t* by multiplying industry employment shares in year 2000 by the national growth (excluding local growth) factor in employment by industry between year 2000 and year *t* and then sums across industries. Results with the Bartik control were qualitatively similar to our preferred estimates. Finally, we also experimented with replacing our local oil and gas employment share variable calculated from the IPUMS data with the local mining employment share computed from the Quarterly Workforce Indicators (QWI) dataset; the results were again qualitatively similar.

5. Conclusion

Oil and gas employment boomed in the U.S. from 2005-2014, due to new technology that made shale resources profitable to develop. Oil and gas booms have the potential to benefit many workers, both directly though employment in the high-paying oil and gas industry and indirectly via spillover effects to other industries. However, the incidence of these benefits may vary by worker gender, race, and ethnicity. For example, it is widely known that oil and gas industry employment is disproportionately male, and the benefits from oil and gas booms may be expected to be concentrated among males as well. Expectations are less clear for differences across race and ethnicity, but there is some concern that African Americans may suffer from racial discrimination, spatial mismatch, and thin networks that limit their access to employment in the oil and gas industry.

We use data from the 2000 decennial census and 2001-2016 American Community Survey to examine how effects of increased oil and gas employment in Texas vary by gender, race, and ethnicity. We first present descriptive trends for the state as a whole and find that men had a stronger oil and gas employment response than women as expected. Descriptive evidence also suggests that African Americans lag the other major racial/ethnic groups in gaining oil and gas employment in Texas. We additionally conduct regression analysis of the effects of local oil and gas employment on two individual labor outcomes: gaining employment in the oil and gas industry and the natural log of annual income for workers employed outside the oil and gas industry. In order to address concerns regarding endogeneity in OLS estimates, two-stage least squares regressions were run. We estimate these regressions separately for eight demographic groups that include gender-specific categories for white, black, Hispanic, and Asian workers.

Our preferred estimates indicate that most groups that we examine experience an increased likelihood of employment in the oil and gas industry in Texas due to the oil and gas boom. However, the effects vary across groups. In particular, men were generally more likely to gain oil and gas employment than women during the boom, with the largest gains found for Hispanic males and black males. Black females appear to gain oil and gas employment very little or possibly not at all.

Less than three percent of all workers in Texas are employed in the oil and gas industry, so most workers are not directly affected by employment gains in the oil and gas industry. However, we find that income spillovers are economically important and generally similar in magnitude across demographic groups. A one standard deviation increase in the local oil and gas employment share increases incomes by more than five percent for most groups that we examine. Additional analysis indicates that the positive income effects from local oil and gas employment are even larger if we incorporate the direct effects from workers gaining high-paying jobs in the oil and gas industry.

Public policy decisions regarding the oil and gas industry have important consequences for various stakeholders, with benefits for some and costs for others. Our study cannot resolve any particular policy dispute, and there are certainly considerations beyond labor market impacts. We hope this research contributes to energy policy discussions by providing useful evidence on the distribution of labor market benefits from local oil and gas employment growth. Our results suggest that the labor market benefits are quite widespread and economically meaningful. Most workers appear to benefit from increased oil and gas employment in their local area via higher average incomes. The labor market benefits do not just accrue to workers in the oil and gas industry; we find strong evidence of income spillovers accruing to workers outside the oil and gas industry. The benefits do not just accrue to men; they accrue to women too, especially via income spillovers. The benefits do not just accrue to one or two racial/ethnic groups; they appear to benefit all of the major demographic groups considered. Thus, not only are there positive labor market impacts from oil and gas employment in an area, they appear to be widespread across different groups of workers.

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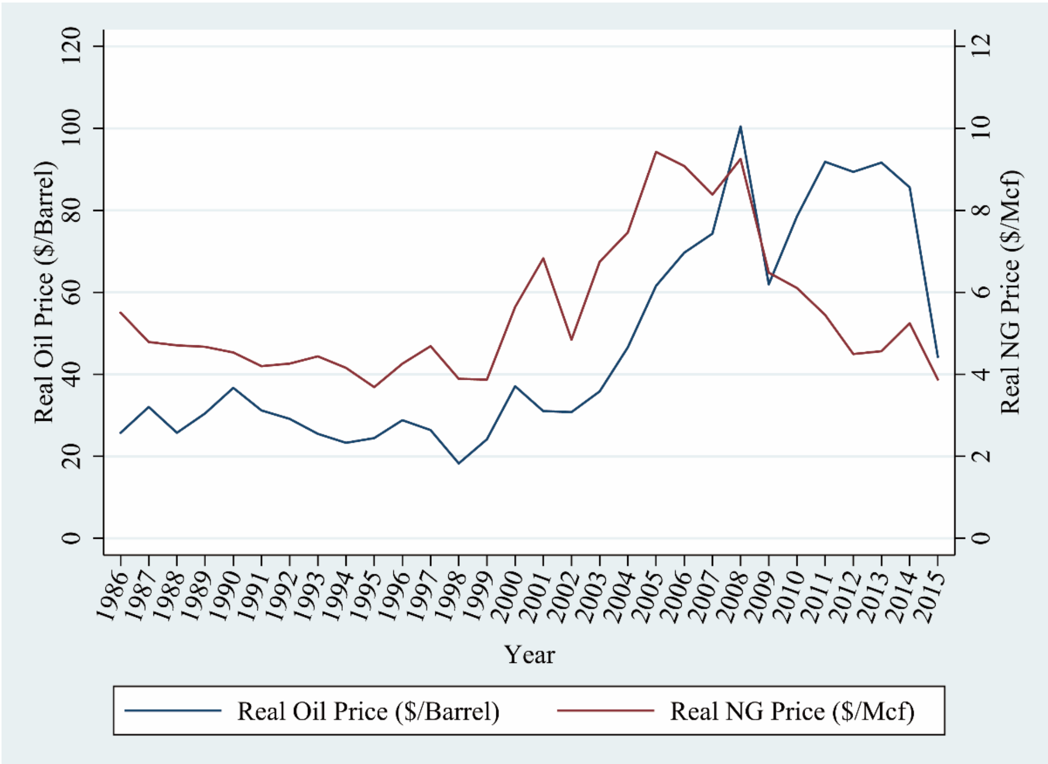
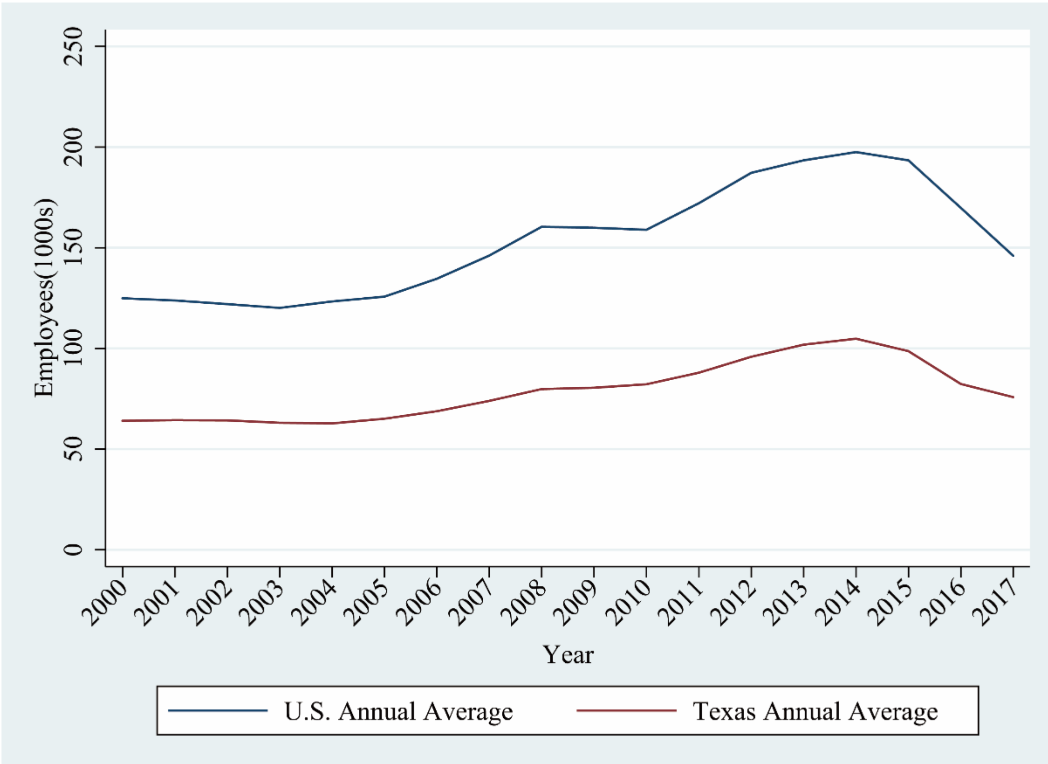
Figure 1: U.S. Real Oil and Natural Gas Prices: 1986-2015



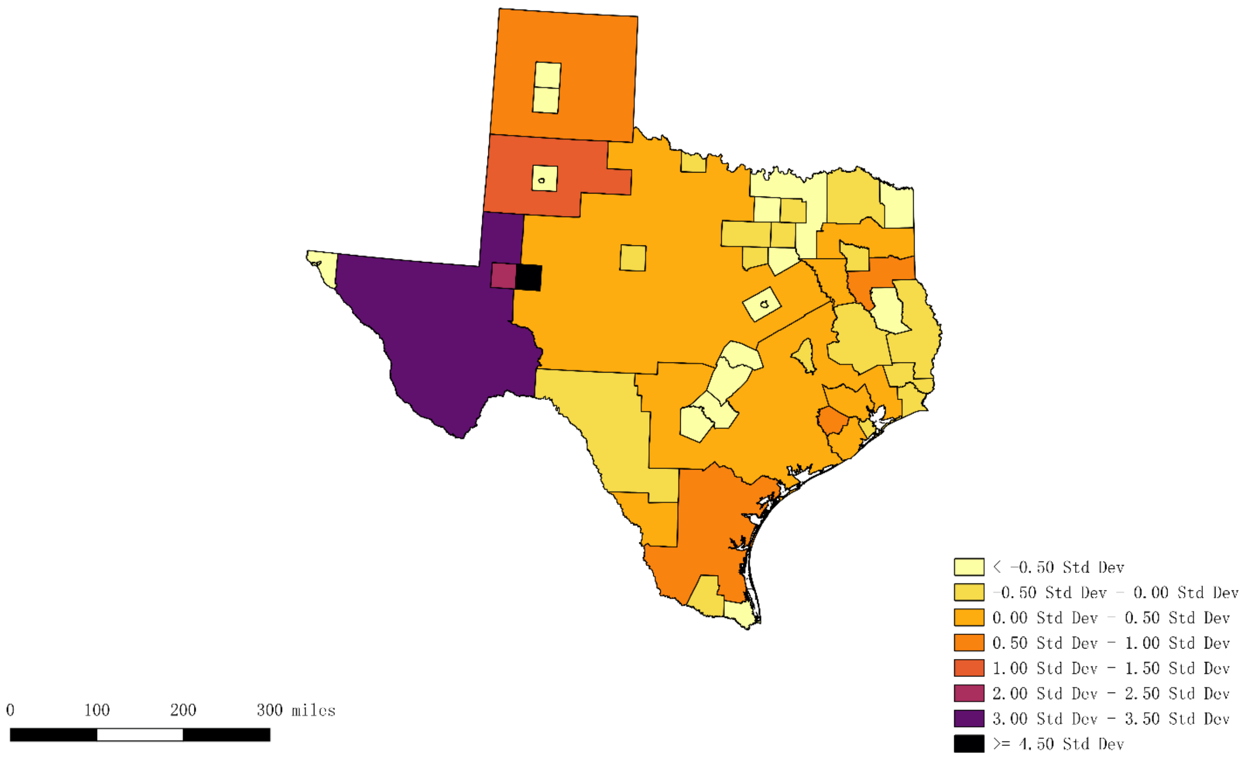
Source: EIA: U.S. Natural Gas citygate price ($/Mcf); EIA: Cushing, OK WTI Spot Price FOB ($/Barrel) 2016
Note: Prices are converted to real prices using the Federal Reserve Economic Data (FRED) Gross Domestic product chained index.

Figure 2: Average Number of Oil and Gas Extraction Employees (Thousands/Seasonally Adjusted)



Source: BLS - Employment, Hours, and Earnings from the Current Employment Statistics Survey. NAICS 211.

Figure 3: Map of Year 2000 Energy Employment in the 49 Consistent PUMAs of Texas



Source: Constructed by authors based on IPUMS data. The boundaries are for the 49 consistent PUMAs of Texas, some of which comprise a single urban area while others are aggregates of several contiguous counties. The energy employment share is measured as the share of oil and gas employment relative to total employment in all industries. The energy employment share in 2000 has unweighted mean of 0.016 and unweighted standard deviation of 0.026. The map categorizes consistent PUMAs based on the standard deviations their energy employment is above or below the mean.

Figure 4: Texas Oil and Gas Employment Rates over Time for Men and Women in IPUMS

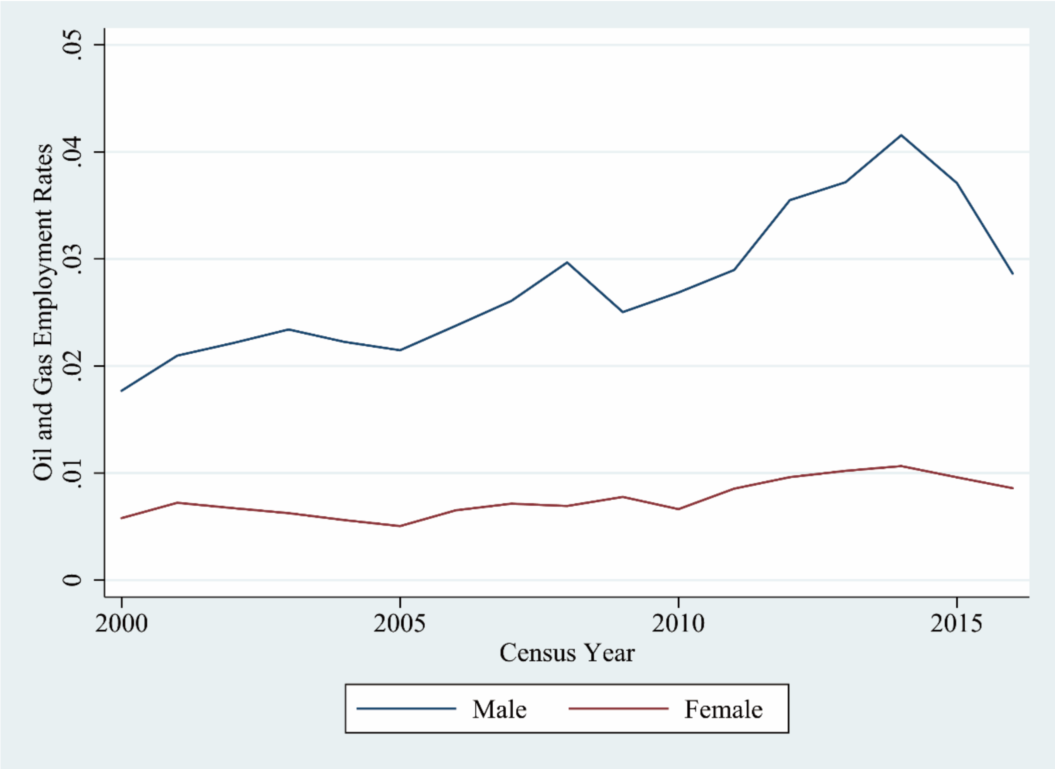


Figure 5: Texas Oil and Gas Employment Rates over Time by Race/Ethnicity in IPUMS

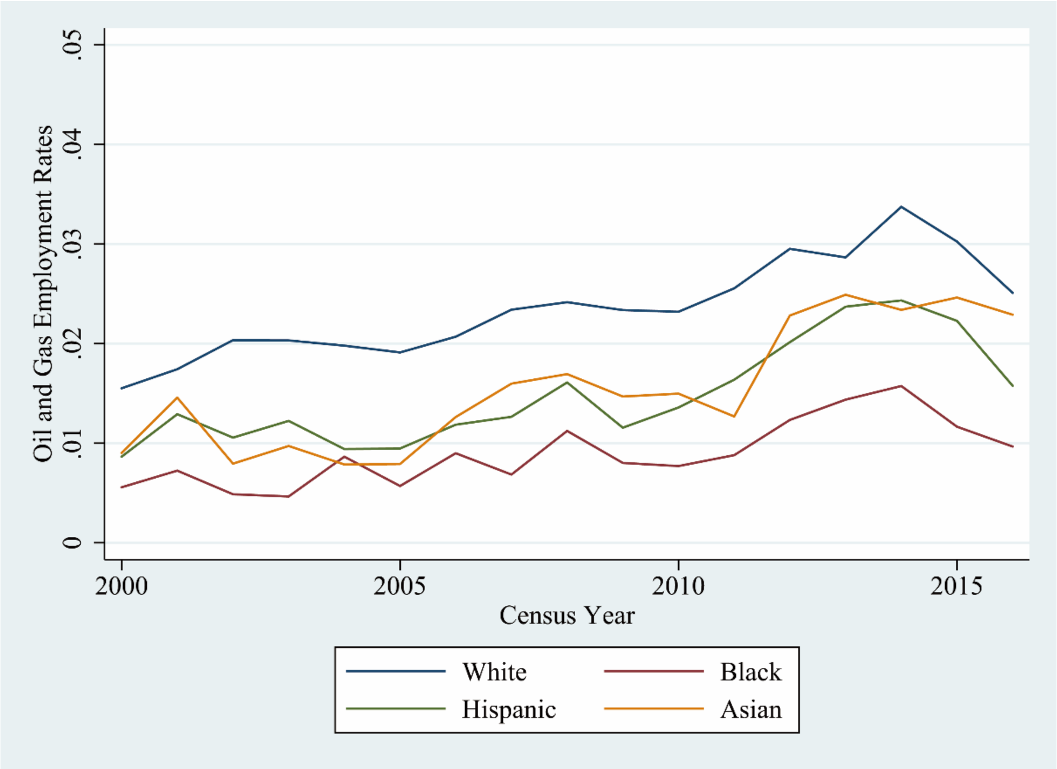


Table 1: Effects of Local Oil and Gas Employment Shares on Individual Oil and Gas Employment by Demographic Group

	(1) White Males	(2) Black Males	(3) Hispanic Males	(4) Asian Males	(5) White Females	(6) Black Females	(7) Hispanic Females	(8) Asian Females
A. OLS								
Local Oil and Gas Share	0.648***	0.953***	1.186***	0.391	0.254***	0.091***	0.234***	0.270
	(0.108)	(0.223)	(0.084)	(0.382)	(0.028)	(0.030)	(0.084)	(0.273)
Number of observations	484,927	66,173	268,172	32,886	413,622	80,201	204,410	28,368
B. 2SLS Using IV2000								
Local Oil and Gas Share	0.485*	2.027***	1.350***	1.146	0.375***	-0.343	0.502**	1.495
	(0.247)	(0.569)	(0.172)	(1.367)	(0.067)	(0.336)	(0.209)	(1.316)
Number of observations	343,875	48,150	204,076	26,839	296,301	59,077	159,416	23,458
Weak identification statistic	55.844	18.784	67.971	5.542	52.689	18.820	55.363	8.193
OLS endogeneity test p-value	0.580	0.097	0.293	0.481	0.105	0.346	0.173	0.323
C. 2SLS Using IV2014								
Local Oil and Gas Share	0.667***	1.378***	1.611***	1.407	0.404***	-0.005	0.359**	1.685
	(0.248)	(0.369)	(0.144)	(1.567)	(0.056)	(0.233)	(0.149)	(1.404)
Number of observations	456,445	61,786	249,629	30,335	389,139	74,935	189,791	26,188
Weak identification statistic	85.896	44.576	98.328	9.144	87.778	40.229	80.018	10.413
OLS endogeneity test p-value	0.722	0.269	0.024	0.377	0.069	0.646	0.223	0.275

Notes: The dependent variable is an oil and gas industry employment dummy. All samples are restricted to persons who at the time of their survey were ages 18-61, employed, and resided in the state of Texas. Samples in Panel A cover years 2000 and 2005 - 2016; Panel B excludes 2000; Panel C excludes 2014. A large number of age, birth place, educational attainment, consistent PUMA (local area), and year dummies are absorbed by the REGHDFE command in Stata and not reported. All regressions use Census/ACS survey weights. Standard errors are shown in parentheses and are clustered by consistent PUMA.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Spillover Effects of Oil and Gas Employment on Log Incomes of Workers Outside the Oil and Gas Industry

	(1) White Males	(2) Black Males	(3) Hispanic Males	(4) Asian Males	(5) White Females	(6) Black Females	(7) Hispanic Females	(8) Asian Females
A. OLS								
Local Oil and Gas Share	0.915***	0.149	0.782**	-0.255	0.690***	1.107	1.064***	2.113**
	(0.196)	(0.567)	(0.302)	(0.926)	(0.223)	(0.684)	(0.365)	(0.798)
Number of observations	465,228	64,542	258,569	32,004	405,577	78,973	200,768	27,844
B. 2SLS Using IV2000								
Local Oil and Gas Share	2.656***	2.327	2.191***	8.423*	2.418***	2.521	2.513***	1.919
	(0.641)	(1.565)	(0.532)	(4.233)	(0.567)	(1.827)	(0.362)	(2.469)
Number of observations	330,102	47,364	198,187	26,207	292,618	58,730	158,665	23,164
Weak identification statistic	45.864	17.145	56.408	5.640	49.847	18.605	53.357	8.364
OLS endogeneity test p-value	0.033	0.066	0.021	0.014	0.000	0.435	0.001	0.952
C. 2SLS Using IV2014								
Local Oil and Gas Share	2.546***	3.130**	2.221***	7.169*	2.361***	4.699***	1.975***	0.307
	(0.496)	(1.458)	(0.644)	(3.628)	(0.618)	(1.485)	(0.353)	(3.787)
Number of observations	438,183	60,262	240,759	29,534	381,476	73,740	186,237	25,693
Weak identification statistic	85.207	40.438	95.130	9.354	89.919	38.453	79.043	10.740
OLS endogeneity test p-value	0.011	0.046	0.009	0.004	0.000	0.034	0.004	0.775

Notes: The dependent variable is log total earned income. All samples are restricted to persons who at the time of their survey were ages 18-61, employed outside the oil and gas industry, and resided in the state of Texas. Samples in Panel A cover year 2000 and 2005 - 2016; Panel B excludes 2000; Panel C excludes 2014. Log usual hours worked per week and a large number of weeks worked, age, birth place, educational attainment, consistent PUMA (local area), and year dummies are absorbed by the REGHDFE command in Stata and not reported. All regressions use Census/ACS survey weights. Standard errors are shown in parentheses and are clustered by consistent PUMA. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3: Effects of Local Oil and Gas Employment on Log Incomes Including Oil and Gas Workers

	(1) White Males	(2) Black Males	(3) Hispanic Males	(4) Asian Males	(5) White Females	(6) Black Females	(7) Hispanic Females	(8) Asian Females
A. OLS								
Local Oil and Gas Share	1.232***	0.275	1.453***	-0.113	0.830***	1.155*	1.148***	2.276***
	(0.198)	(0.546)	(0.308)	(0.882)	(0.223)	(0.666)	(0.392)	(0.809)
Number of observations	481,757	65,437	265,348	32,670	409,642	79,362	201,533	28,149
B. 2SLS Using IV2000								
Local Oil and Gas Share	2.924***	2.601*	3.003***	8.584**	2.567***	2.491	2.683***	3.596
	(0.604)	(1.518)	(0.482)	(4.217)	(0.550)	(1.688)	(0.378)	(2.916)
Number of observations	343,362	48,123	203,954	26,810	295,870	59,047	159,331	23,435
Weak identification statistic	55.707	18.761	67.951	5.599	52.693	18.868	55.416	8.249
OLS endogeneity test p-value	0.019	0.055	0.013	0.016	0.000	0.424	0.002	0.642
C. 2SLS Using IV2014								
Local Oil and Gas Share	3.001***	3.177**	3.231***	7.371*	2.553***	4.687***	2.128***	2.209
	(0.461)	(1.453)	(0.545)	(3.861)	(0.611)	(1.471)	(0.364)	(4.250)
Number of observations	453,301	61,050	246,810	30,122	385,188	74,097	186,919	25,972
Weak identification statistic	85.353	43.065	97.661	9.175	87.081	39.411	79.261	10.347
OLS endogeneity test p-value	0.004	0.051	0.002	0.006	0.000	0.032	0.002	0.877

Notes: The dependent variable is log total earned income. All samples are restricted to persons who at the time of their survey were ages 18-61, employed, and resided in the state of Texas. Samples in Panel A cover year 2000 and 2005 - 2016; Panel B excludes 2000; Panel C excludes 2014. Log usual hours worked per week and a large number of weeks worked, age, birth place, educational attainment, consistent PUMA (local area), and year dummies are absorbed by the REGHDFE command in Stata and not reported. All regressions use Census/ACS survey weights. Standard errors are shown in parentheses and are clustered by consistent PUMA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Sensitivity Analysis

	(1) White Males	(2) Black Males	(3) Hispanic Males	(4) Asian Males	(5) White Females	(6) Black Females	(7) Hispanic Females	(8) Asian Females
A. Table 1: OLS excluding year 2000								
Local Oil and Gas Share	0.585***	0.967***	1.163***	0.381	0.252***	0.088***	0.234***	0.241
	(0.111)	(0.249)	(0.085)	(0.400)	(0.034)	(0.030)	(0.087)	(0.289)
Number of observations	343,875	48,150	204,076	26,839	296,301	59,077	159,416	23,458
B. Table 2: OLS excluding year 2000								
Local Oil and Gas Share	0.815***	0.068	0.628**	-0.317	0.702***	1.284*	1.009**	2.086**
	(0.223)	(0.695)	(0.308)	(0.977)	(0.220)	(0.729)	(0.386)	(0.895)
Number of observations	330,102	47,364	198,187	26,207	29,2618	58,730	158,665	23,164
C. Table 1: 2SLS using IV2000 and IV2014								
Local Oil and Gas Share	0.730***	1.347**	1.429***	0.874	0.393***	-0.128	0.297**	0.705
	(0.231)	(0.556)	(0.125)	(0.782)	(0.077)	(0.277)	(0.134)	(0.515)
Number of observations	343,875	48,150	204,076	26,839	296,301	59,077	159,416	23,458
Weak identification statistic	91.400	31.152	160.643	26.758	87.730	34.952	159.646	46.944
OLS endogeneity test p-value	0.574	0.624	0.010	0.360	0.037	0.953	0.802	0.546
Overidentification p-value	0.007	0.035	0.577	0.707	0.697	0.224	0.150	0.392
D. Table 2: 2SLS using IV2000 and IV2014								
Local Oil and Gas Share	2.252***	2.637*	2.034***	5.059**	2.360***	4.192***	2.024***	1.729
	(0.384)	(1.511)	(0.434)	(2.002)	(0.589)	(1.351)	(0.421)	(2.108)
Number of observations	330,102	47,364	198,187	26,207	292,618	58,730	158,665	23,164
Weak identification statistic	76.692	31.942	153.935	25.820	81.007	34.555	151.411	46.334
OLS endogeneity test p-value	0.014	0.061	0.005	0.003	0.000	0.036	0.001	0.878
Overidentification p-value	0.366	0.737	0.551	0.224	0.857	0.071	0.210	0.905
E. Table 1: 2SLS using IV2000 excluding five largest consistent PUMA								
Local Oil and Gas Share	0.354	2.316***	1.303***	1.250	0.475***	-0.464	0.683**	1.672
	(0.376)	(0.678)	(0.301)	(1.709)	(0.105)	(0.354)	(0.276)	(1.652)
Number of observations	277436	43677	174136	25658	240526	54551	136072	22302
Weak identification statistic	67.153	15.545	130.709	5.076	65.949	16.408	128.758	7.741
OLS endogeneity test p-value	0.635	0.103	0.523	0.484	0.071	0.332	0.201	0.282

F. Table 2: 2SLS using IV2000 excluding five largest consistent PUMA								
Local Oil and Gas Share	3.367***	2.451	2.180***	11.061**	2.773***	2.427	2.388***	1.510
	(1.081)	(1.943)	(0.738)	(5.438)	(0.979)	(2.170)	(0.496)	(2.925)
Number of observations	268453	43014	170711	25052	237734	54216	135498	22018
Weak identification statistic	56.641	14.533	109.691	5.133	61.326	16.237	125.687	7.824
OLS endogeneity test p-value	0.056	0.133	0.110	0.022	0.002	0.494	0.007	0.811
G. Table 1: 2SLS using IV2000 excluding education dummies								
Local Oil and Gas Share	0.487*	2.019***	1.343***	1.097	0.375***	-0.344	0.502**	1.486
	(0.247)	(0.569)	(0.169)	(1.406)	(0.067)	(0.339)	(0.210)	(1.347)
Number of observations	343875	48150	204076	26839	296301	59077	159416	23458
Weak identification statistic	55.830	18.771	67.938	5.544	52.686	18.813	55.296	8.175
OLS endogeneity test p-value	0.588	0.099	0.295	0.495	0.101	0.348	0.173	0.331
H. Table 2: 2SLS using IV2000 excluding education dummies								
Local Oil and Gas Share	2.577***	1.462	2.428***	6.720	2.282***	2.089	2.475***	1.712
	(0.690)	(1.613)	(0.538)	(5.260)	(0.629)	(1.891)	(0.464)	(3.964)
Number of observations	330102	47364	198187	26207	292618	58730	158665	23164
Weak identification statistic	45.851	17.134	56.393	5.648	49.843	18.597	53.294	8.344
OLS endogeneity test p-value	0.039	0.340	0.010	0.030	0.001	0.601	0.002	0.920
I. Table 1: 2SLS using IV2000 including marital status and presence of children								
Local Oil and Gas Share	0.491*	2.023***	1.351***	1.146	0.370***	-0.340	0.502**	1.501
	(0.248)	(0.562)	(0.172)	(1.354)	(0.066)	(0.336)	(0.209)	(1.319)
Number of observations	343875	48150	204076	26839	296301	59077	159416	23458
Weak identification statistic	55.824	18.804	67.959	5.542	52.710	18.843	55.381	8.205
OLS endogeneity test p-value	0.609	0.096	0.296	0.481	0.109	0.348	0.173	0.322
J. Table 2: 2SLS using IV2000 including marital status and presence of children								
Local Oil and Gas Share	2.862***	2.396	2.324***	8.587**	2.375***	2.431	2.491***	1.928
	(0.652)	(1.535)	(0.527)	(4.165)	(0.564)	(1.820)	(0.359)	(2.429)
Number of observations	330102	47364	198187	26207	292618	58730	158665	23164
Weak identification statistic	45.847	17.160	56.398	5.637	49.868	18.628	53.377	8.379
OLS endogeneity test p-value	0.022	0.063	0.020	0.013	0.000	0.443	0.001	0.976

K. Table 1: 2SLS using IV2000 with Bartik controls								
Local Oil and Gas Share	0.474*	2.043***	1.341***	1.078	0.361***	-0.342	0.507**	1.479
	(0.247)	(0.572)	(0.166)	(1.312)	(0.070)	(0.336)	(0.211)	(1.283)
Number of observations	343875	48150	204076	26839	296301	59077	159416	23458
Weak identification statistic	51.133	18.846	66.893	5.761	48.494	18.691	54.759	8.540
OLS endogeneity test p-value	0.547	0.098	0.280	0.497	0.130	0.344	0.173	0.321
L. Table 2: 2SLS Using IV2000 with Bartik controls								
Local Oil and Gas Share	2.594***	2.294	2.149***	8.633*	2.356***	2.276	2.465***	1.878
	(0.649)	(1.547)	(0.541)	(4.374)	(0.580)	(1.460)	(0.366)	(2.453)
Number of observations	330102	47364	198187	26207	292618	58730	158665	23164
Weak identification statistic	42.435	17.229	56.514	5.853	45.968	18.471	52.878	8.700
OLS endogeneity test p-value	0.037	0.052	0.018	0.015	0.001	0.381	0.001	0.937
M. Table 1: 2SLS using IV2000 with QWI data								
QWI Local Mining Share	0.534*	2.337***	1.563***	1.490	0.415***	-0.372	0.560**	1.577
	(0.294)	(0.573)	(0.235)	(1.644)	(0.083)	(0.354)	(0.214)	(1.312)
Number of observations	343875	48150	204076	26839	296301	59077	159416	23458
Weak identification statistic	69.845	18.416	51.555	10.899	65.240	18.091	48.591	12.951
OLS endogeneity test p-value	0.398	0.050	0.358	0.741	0.079	0.314	0.168	0.317
N. Table 2: 2SLS using IV2000 with QWI data								
QWI Local Mining Share	2.945***	2.678	2.532***	10.569**	2.687***	2.715	2.804***	2.017
	(0.722)	(1.791)	(0.702)	(4.497)	(0.760)	(1.814)	(0.562)	(2.717)
Number of observations	330102	47364	198187	26207	292618	58730	158665	23164
Weak identification statistic	55.828	16.810	41.341	9.522	60.202	17.586	46.768	12.428
OLS endogeneity test p-value	0.059	0.147	0.286	0.049	0.013	0.627	0.078	0.946

Notes: The large number of dummy controls are the same as in the corresponding regressions in Tables 1 and 2 and not reported. All regressions use Census/ACS survey weights. Standard errors are shown in parentheses and are clustered by consistent PUMA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.