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Labor demand shocks and earnings and employment differentials: Evidence from the U.S. shale oil & gas boom☆

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ABSTRACT

In this paper, we show that labor market shocks that overwhelmingly directly impacted specific workers (male workers and workers with a high school education) in a specific industry (oil and gas sector) can have meaningful effects on employment and earnings differentials *within* sectors not directly impacted by the productivity shock. Empirical estimates suggest that college/high school earnings differentials *decreased* by 3.0% in the non-mining sectors, while male/female earnings differentials *increased* by 2.6% in the non-mining sectors. Results highlight the importance of considering differential effects of technology shocks by education and gender in studying earnings inequality.

1. Introduction

Technological developments have made the extraction of previously economically inaccessible energy resources feasible at prevailing market prices. Specifically, the advent of horizontal drilling and hydraulic fracturing techniques have created historic increases in the production of oil and natural gas. This created an economic boom in specific geographic areas with oil and gas-rich "shale" geological formations thousands of feet below the surface.

This research focuses on how these natural resource booms impacted employment and earnings differentials between groups of workers including (1) college/high school education levels and (2) males/females.[1] We examine seven geographic areas that were plausibly exogenously located above shale geological formations.[2]

For decades, earnings inequality has been a focus of the labor economics literature, both focusing on differentials across the income spectrum (Mincer, 1970; Maddison, 1987; Levy and Murnane, 1992; Katz, 1999) and male/female differentials (Blau and Kahn, 2017; Goldin, 2014; O'Neill, 2003; Gunderson, 1989). These dimensions of income inequality have experienced different trends and have been impacted by different factors over the past century in the United States.

Levy and Murnane (1992) describe distinct periods of changes in income inequality throughout modern history. Since the 1980s, the U.S. economy has experienced increases in income inequality that has persisted to the present day (Attanasio et al., 2012). In contrast, men and women have experienced convergence in earnings, and this has been called the "Grand Gender Convergence" (Goldin, 2014). While differences in pay for men and women persist, typically at least two-thirds of this differential can be explained by factors such as occupation differences (Blau and Kahn, 2017), career interruptions and hours worked per week (Bertrand et al., 2010), inter-firm mobility (Bono and Vuri, 2011), among others.[3]

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[1] Hereafter we refer to college-educated workers as all workers with a college degree or more. We refer to high school educated workers as workers with a high school degree or less.

[2] Namely, *Appalachia, Anadarko, Bakken, Eagle Ford, Haynesville, Niobrara*, and *Permian*. Appendix Figure A.1 shows the location of these "shale plays".

[3] Residuals in earnings differentials that cannot be explained by these factors are typically then attributed to psychological attributes, unobservable non-cognitive skills and/or discrimination (Blau and Kahn, 2017; Manning and Swaffield, 2008; Wood et al., 1993).

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Using a specific labor market shock that overwhelmingly directly impacted a male and blue-collar dominated industry, we provide estimates of the impact of a technology-induced labor market shock on employment and earnings differentials between workers with college/high school educations and males/females. We argue that the oil and gas shale boom of the past decade creates a unique opportunity to study this for at least three reasons.

First, the shale boom originated from a technology-induced labor market shock. Second, this shock overwhelmingly directly impacted two demographics of workers, male workers, and workers with a high school education or less.[4] Third, the shock is conveniently concentrated in very specific geographic areas that happened to have specific geological formations thousands of feet below the earth's surface. And the timing of these shocks all coincided with technological advancements alongside high oil and natural gas prices that allowed for extraction from these formations. This allows us to identify areas that received the treatment and still have access to plausible control areas with similar pre-treatment characteristics.

We then decompose the observed changes in earnings differentials into three channels. First, we observe earnings differentials change within the mining sector. Second, we observe earnings differentials change within non-mining sectors. Third, the residual of the first two effects which we interpret as associated with a change in the labor market composition due to factors such as labor substitution across sectors (Aragon et al., 2018), labor market entry and exit (Cascio and Narayan, 2020; Kearney and Wilson, 2018), and labor migration (Wilson, 2020). Interestingly, we show that the overwhelming majority of the change in earnings differentials comes from the second channel; changes in earnings differentials within non-mining sectors.

Economic impact of natural resource booms. Over the last two decades, the oil and natural gas landscape has changed both suddenly and dramatically. By the mid to late 2000s, after decades of declining production, technological breakthroughs alongside high oil and natural gas prices allowed oil and gas to be extracted from shale geological formations; the shale boom was underway.[5] Through a combination of horizontal drilling and hydraulic fracturing (informally referred to as "fracking") the U.S. is now experiencing production at levels not seen since "peak oil" of the 1970s. There has been a growing body of work that quantifies the effects of localized natural resource-based booms.[6] While this literature began before the specific shale boom of this past decade (Black et al., 2005), this new *Era of Shale* has created a significant resurgence in this literature.

Feyrer et al. (2017) estimate that every million dollars of oil and gas extracted generated $243,000 in wages, $117,000 in royalty payments, and 2.49 jobs within a 100-mile radius. In total, the authors estimate that the shale boom was associated with 725,000 jobs in aggregate and a 0.4 percent decrease in the unemployment rate during the Great Recession. Marchand (2012) similarly finds both direct and indirect impacts of production from shale on employment; for every 10 jobs created in the energy sector, 3 construction, 4.5 retail, and 2 service jobs are created. Agerton et al. (2017) find that one additional rig results in the creation of 31 jobs immediately and 315 jobs in the long-run. Other studies corroborated the positive impact of the shale boom on local labor markets.[7]

Several recent analyses have exploited natural resource booms as productivity shocks to male and/or high school educated workers in order to study earnings and educational inequality. Cascio and Narayan (2020) exploit the labor market shock associated with the shale boom to less-educated male labor and finds that this narrowed the male–female gap in teen high school dropout rates by nearly 40%. Marchand and Weber (2020) finds that attendance at local schools was reduced, likely due to the shale induced opportunities. Related, Aragon et al. (2018) exploit the closing of coal mines in the UK to study employment substitutions across sectors. They provide evidence that men and women are imperfect substitutes for labor in non-primary sectors and therefore a shock to the mining sector can impact employment and earnings in non-mining industries. Similarly, Kotsadam and Tolonen (2016) utilize data from Africa to test the effect of mining on local economies and find that female employment decreases in response to mining booms that increase male employment.

Contribution. We aim to contribute to the literature in two main ways.

First, ours is the first analysis to estimate the effect of the shale boom on earnings and employment differentials within sectors. We estimate differentials within both mining and non-mining sectors. More broadly, we show that a labor demand shock that overwhelmingly impacted male workers with a high school education (or less) in a specific industry has economically meaningful impacts on earnings differentials within industries that are seemingly unrelated to the industry that received the initial shock. Specifically, empirical estimates suggest that college/high school earnings differentials *decreased* by 3.0% in the non-mining sectors, while male/female earnings differentials *increased* by 2.6% in the non-mining sectors. We also show effects on earnings differentials within the construction, transportation, manufacturing, and services sectors.

Second, novel to this research, we present a decomposition of the observed changes in earnings differentials into three channels. Results of this decomposition show that the overwhelming share of the change in earnings differentials observed in these local areas (between both college/high school educated and male/female workers) are explained by earnings differentials changes *within* sectors that are not directly associated with the mining sector. This highlights the importance of considering productivity shocks to subsets of workers in explaining broadly earnings differentials.

2. Data

Data on employment and earnings are from the United States Census' Quarterly Workforce Indicators (QWI). QWI contains information on county-level average employment and earnings. We utilize a yearly panel of U.S. counties from 2001 until 2018. For our main difference-in-differences (DiD) estimations, we will utilize data to 2014 to focus on the boom time period.[8] Parameters from this main specification will then be utilized to decompose effects into three channels that are discussed in Section 3.2. Event studies and robustness checks considering the timing and intensity of the shale shock will utilize the full sample time period (i.e. 2001 to 2018).

For all difference-in-differences estimates, we consider 2007 the beginning of the treatment time period consistent with when EIA's

[4] Of course, many female workers and workers with college degrees are employed by the upstream oil and gas sector, but these jobs are primarily office positions in larger cities such as Houston where these companies' headquarters are located. The areas of interest in this study are where the hydrocarbons themselves are actually extracted. Also, landowners received royalty payments that also spurred economic activity through a different channel.

[5] The official start date of the shale boom can be debated. For our baseline specifications, we consider the official start date of the shale boom as 2007, consistent with the beginning of EIA's drilling productivity reports. We will also present event studies and a specification that incorporates the timing and intensity of the shock within and across plays.

[6] This literature is interested in short-term boom and busts induced by resource extraction, in contrast to the (very different) large literature on resource endowments and long run economic growth (van der Ploeg, 2011; Venables, 2016; Alexeev and Conrad, 2009; Michaels, 2010; Oliver and Upton, 2022).

[7] An non-exhaustive list includes Weber (2012), Cosgrove et al. (2015), Paredes et al. (2015), Marchand and Weber (2018), Komarek (2016), McCollum and Upton (2018), Decker et al. (2018), Allcott and Keniston (2018) and Bartik et al. (2019).

[8] The oil price dropped precipitously in 2015.

Drilling Productivity reports began tracking production and rig counts in shale regions, although robustness checks will consider the sensitivity of results to this choice.[9] A propensity score matching approach is implemented to choose plausible control counties (see Section 3.1.1 for more details).

As an additional robustness check, we consider the timing and intensity of the shock both within and across shale boom areas by estimating the value of oil and gas produced by county. To do so, county-level data on new wells drilled and the value of new production from new wells are sourced from *Enverus*.[10] The prices of crude oil and natural gas used for calculating the value of total production are WTI crude oil spot price and Henry Hub natural gas spot price from EIA.

2.1. Summary statistics

Table 1 show the labor market characteristics in counties with shale oil and/or gas activity compared to the propensity score matched control group (see Section 3.1.1 for choosing control counties). More specifically, Table 1 shows the change in employment and earnings for the treated (shale) counties and the propensity score matched control counties. We present average employment and earnings in the pre-shale (2001 to 2006) and post shale (2007 to 2014) time periods.

Total employment increased by approximately 3 percent in treated areas, but was essentially unchanged in control areas. Earnings, in contrast, increased in the control areas by about 20.3% in nominal dollars between the pre-and-post 2007 time periods, while earnings in shale areas increased by an even larger 31.6%. Thus, earnings growth in shale areas outpaced non-shale area earnings growth by about 11 percentage points.

Table 1 also breaks down these relative changes by demographic of workers. We point out three notable items. First, the relative earnings growth is largest for workers with a high school diploma or lower and male workers. More specifically, workers with a high school diploma or less and male workers experienced a 14.3 and 12.2-percentage point faster increase in earnings relative to control groups. Second, while earnings increases were largest for these prior-mentioned groups, we observe increases in earnings across all demographics of workers in shale areas, relative to controls. In fact, even female workers and workers with college degrees, the groups least directly affected by the shale boom, experienced a 7.7 and 7.0-percentage point increase in earnings relative to control areas. Third, and unsurprisingly given the nature of the shock, significant employment growth was experienced in the mining, construction, and transportation sectors. Specifically, we estimate that mining sector employment increased by around 56 percentage points in shale counties relative to non-shale control counties, while non-mining sector employment experienced relatively flat employment relative to non-shale sectors. The construction and transportation sectors in these shale areas experienced a 16.5% and 8.3% increase in employment relative to controls.

All three of these observations lead to a simple conclusion. While the initial labor demand shock directly impacted male workers and workers with a high school diploma in the mining sector (and likely through indirect effects construction and transportation sectors), earnings increased across all subsets of workers.

[9] Other papers in the literature have employed different stating dates for their DiD estimations. For instance, Cascio and Narayan (2020) use 2006, while McCollum and Upton (2018) use 2007.

[10] Formerly *DrillingInfo*.

3. Empirical specification

3.1. Difference-in-differences

For our main specification, we estimate the causal impact of shale oil and gas booms on employment and earnings differentials in local labor markets using a difference-in-differences (DiD) approach. Specifically, we consider the following specification:

$$Y_{c,t} = \beta_0 + \beta_1(Shale_C * Shale_T) + \lambda_c + \alpha_t + \epsilon_{i,t} \tag{1}$$

where $Y_{c,t}$ is the outcomes of interest, employment and earnings differentials, in county c and year t. $Shale_C$ is an indicator equal to 1 if county i is a county located within one of the seven key shale regions; otherwise, $Shale_C$ equals to 0. Similarly, $Shale_T$ is a dummy variable indicating the shale boom time period. λ_c and α_t stand for county fixed effects and year fixed effects, respectively. β_1 is the parameter of interest that shows the estimated average treatment effect. We will consider the shale boom (i.e. treatment period) from 2007 to 2014, although a number of robustness checks will address this choice. Our main specification will focus on the boom time period (through 2014), although robustness checks including an event study will utilize data through 2018.

3.1.1. Choosing control counties

When using the DiD approach, it is important to find an appropriate counterfactual county for each boom county. We utilize propensity score matching to identify a control group of counties from across the U.S. that are not in proximity to shale counties and whose demographic characteristics are similar to the boom counties in the pre-boom time period. Specifically, we conduct the propensity score matching as follows.

For each county, we calculate the mean of the following variables in the pre-boom time period: employment counts, aggregate earnings, the percent of workers with a college degree, the percent of workers in the mining sector, the total value of oil and natural gas from wells that are less than one year old (see further description below), and the change in employment and earnings differentials for college/high school and male/female workers. Next, we randomly sort all the counties in the sample and then conduct a propensity score match with a logit model using one-to-one matching without replacement.[11] As a result, each shale (treated) county is matched to one control county.

Identification will rest on the assumption that these treated counties would have similar trends in earnings and employment differentials absent the plausibly exogenous shock associated with having very specific geological formations thousands of feet below ground alongside a technological advancement that spurred the extraction of these resources.

Not including nearby counties is important due to potential spatial spillovers. Specifically, counties that are in states with shale activity but that themselves do not overlap with the seven major shale plays are removed from the sample before conducting the matching exercise. In addition, states that directly border counties with shale activity were removed.[12]

Using a relatively conservative approach in choosing a control group to mitigate potential spatial spillovers is important because of the significant midstream and downstream investments that have occurred in response to the shale boom. For instance, Dismukes and Upton (2020)

[11] The specific Stata code is: psmatch2 $shale_c$ $psmatchfactors, logit noreplacement, where 'psmatchfactors' are the means (calculated based on pre-boom values) of the variables listed above.

[12] After applying these criteria, the following non-shale boom states are included: AK, AZ, CA, CT, DE, FL, GA, HI, ID, IL, IA, ME, MI, MN, MS, MO, NV, NH, NJ, NC, OR, RI, SC, TN, VT, WA, and WI. For a more detailed description see McCollum and Upton (2018) and Decker et al. (2018).

Table 1
Summary Statistics: Baseline sample.

	Treatment group			Control group			%ΔTreatment - %ΔControl
	Pre 2007	Post 2007	Percent Change	Pre 2007	Post 2007	Percent Change	
Employment (Thousands of Workers)							
All	25.33	26.08	2.96%	25.80	25.82	0.08%	2.88%
College +	5.54	5.72	3.25%	5.73	5.84	1.92%	1.33%
Highschool (-)	9.05	9.54	5.41%	8.76	9.05	3.31%	2.10%
Male	12.90	13.29	3.02%	12.81	12.59	−1.72%	4.74%
Female	12.43	12.79	2.90%	12.99	13.23	1.85%	1.05%
Mining Sector	0.67	1.11	65.67%	0.30	0.33	10.00%	55.67%
Construction sector	1.55	1.57	1.29%	1.77	1.50	−15.25%	16.54%
Transportation sector	1.06	1.16	9.43%	1.77	1.79	1.13%	8.30%
Manufacturing sector	3.76	3.08	−18.09%	5.66	4.63	−18.20%	0.11%
Service sector	9.38	10.54	12.37%	13.71	15.39	12.25%	0.11%
Non-Mining sector (Mining Sample)	33.41	34.11	2.10%	116.40	118.70	1.98%	0.12%
Earnings ($)							
All	$2,478	$3,261	31.60%	$2,375	$2,857	20.29%	11.30%
College +	$3,742	$4,658	24.48%	$3,559	$4,183	17.53%	6.95%
Highschool	$2,177	$2,941	35.09%	$2,095	$2,530	20.76%	14.33%
Male	$3,075	$4,046	31.58%	$2,898	$3,459	19.36%	12.22%
Female	$1,847	$2,363	27.94%	$1,868	$2,247	20.29%	7.65%
Mining sector	$4,062	$5,705	40.45%	$3,814	$4,658	22.13%	18.32%
Construction sector	$2,665	$3,598	35.01%	$2,744	$3,177	15.78%	19.23%
Transportation sector	$2,929	$3,833	30.86%	$2,604	$3,058	17.43%	13.43%
Manufacturing sector	$3,086	$3,904	26.51%	$2,964	$3,607	21.69%	4.81%
Service sector	$2,083	$2,723	30.72%	$2,093	$2,571	22.84%	7.89%
Non-Mining sector (Mining Sample)	$2,431	$3,134	28.92%	$2,732	$3,240	18.59%	10.32%
Other Variables							
Value of Production $ /Worker	$53,460	$136,589	155.50%	$61	$31	−49.18%	204.68%
IV: Value of Production $/Worker of 2001	$33,480	$81,228	142.62%	$27	$32	18.52%	124.10%
College Share	18.0%	17.9%	−0.56%	18.4%	19.0%	3.26%	−3.82%

Averages of annual data for treatment and control groups. Pre-2007 period is 2001–2006. Post-2007 period is 2007–2014. Total employment in counts (a thousands people). Earnings are average monthly earnings of full time stable workers. The value of production per worker is the one-year value of production from new wells in a county divided by the total number of workers in that county. When generating the instrumental value of production per worker, the total number of workers in the starting year of the sample is used, following Feyrer et al. (2017).

estimates that over $110 billion in refining and chemical manufacturing investment occurred in Texas and Louisiana during the shale boom, but is mostly located near the Gulf of Mexico, not in the areas where the shale production actually occurred. Further, connecting this upstream production with refineries and chemical plants spurred significant investment in transportation infrastructure (Agerton and Upton, 2019; Agerton et al., 2020). Because these spatial spillovers created similar "boom town" effects in areas without shale production, the inclusion of these areas introduces the potential to bias empirical estimates.[13]

Throughout the analysis, we will also refer to a "full sample" and "small sample". The full sample includes all counties for which a balanced panel of earnings and employment differentials are available from Q1 2001 to Q4 2018. But central to our contribution, we will also be interested in how earnings and employment differentials responded within specific sectors. Thus, the small sample includes only U.S. counties for which a balanced panel was available for the mining sector. Because the mining sector makes up a relatively small share of U.S. employment, sectoral level data is censored when Census disclosure rules are not met.[14] Appendix Figure A.2 shows maps of the treated and control counties.

A number of additional robustness checks to further delve into the choice of the control group will be addressed below.

3.2. Decomposition

Next, we utilize results of the baseline specification to address the plausible channel through which the productivity shock impacted earnings differentials. To motivate these channels, consider earnings differentials within a region broken out into two representative sectors as follows:

$$\frac{e_H}{e_L} = \frac{N_m}{N}\frac{e_{H,m}}{e_{L,m}} + \frac{N_o}{N}\frac{e_{H,o}}{e_{L,o}} \tag{2}$$

where $N_{m|o}$ is employment counts in the mining and non-mining (other) sectors, and N is total employment. Eq. (2) states that the earnings differential in a region is an employment weighted average of earnings differentials within the two representative sectors. Any change in $\frac{e_H}{e_L}$ can therefore be decomposed into three channels.

Channel 1: Earnings differentials within mining sector. The first channel is a change in $\frac{e_{H,m}}{e_{L,m}}$. In words, this is the change the earnings differential within the mining sector, holding constant the earnings differential in the non-mining sectors ($\frac{e_{H,o}}{e_{L,o}}$), and the relative employment shares in the respective sectors ($\frac{N_m}{N}$, $\frac{N_o}{N}$).

Channel 2: Earnings differentials within non-mining sector. The second channel is a change in the earnings differential within the non-mining sector ($\frac{e_{H,o}}{e_{L,o}}$), again, holding constant the earnings differential in the mining sectors ($\frac{e_{H,m}}{e_{L,m}}$), and the relative employment shares in the respective sectors ($\frac{N_m}{N}$, $\frac{N_o}{N}$).

[13] For example, Lake Charles Louisiana was the fastest employment growth MSA in the country from 2013–2018 and had no shale activity. But, the MSA underwent billions of dollars of capital expenditure, in chemical manufacturing and the export of natural gas in the form of liquified natural gas (LNG) that was made possible by oil and gas extraction growth in shale regions (Scott and Upton, 2019).

[14] If we include counties with missing mining employment and earnings data in early years, and then begin to endogenously observe data in these counties when the shale boom induced employment to increase above thresholds for reporting in QWI, this would bias empirical results.

Channel 3: Labor market composition (residual). The third channel through which a change in $\frac{e_H}{e_L}$ can occur is through the relative share of the mining and non-mining employment relative to total employment. This channel can be influenced by a number of factors.

First, labor can substitute across sectors (e.g. a worker in the restaurant industry taking an oil and gas job) (Aragon et al., 2018). Second, the workers can substitute away from education towards the labor market due to the higher wages (Cascio and Narayan, 2020) or out of the labor market due to higher wages of a partner and fertility decisions (Kearney and Wilson, 2018). Third, labor migration can occur from outside of the county in response to either the oil and gas boom directly or the increased earnings associated with the boom town. These migrants have been shown to be more likely to be male, unmarried, young, and less educated than movers more generally (Wilson, 2020).

This third channel can more broadly be interpreted as the residual of channels 1 and 2. We are unable to disentangle this residual into its plausible components.

By construction, $\frac{N_m}{N} + \frac{N_o}{N} = 1$, i.e. 100% of the employment comes from these representative two sectors. Therefore, holding constant both $\frac{e_{H,m}}{e_{L,m}}$ and $\frac{e_{H,o}}{e_{L,o}}$, a change in $(1 - \frac{N_m}{N})$ (or similarly $(1 - \frac{N_o}{N})$) can create a change in the earnings differentials if earnings differentials are different in the two representative sectors.

We will utilize estimated changes in earnings differentials from the baseline specification, alongside summary statistics of the labor market composition *ex-ante* to the shock to empirically estimate the relative size of these three channels.

3.3. Robustness checks

We next conduct robustness checks.

3.3.1. Event study

To check the validity of our DiD approach, we conduct a series of event studies. While the DiD approach is convenient to estimate and coefficient estimates can easily be used for the prior-mentioned decomposition, it is also subject to some inherent limitations. First, it requires the establishment of treatment date. In this context, we choose 2007 as the treatment date consistent with when EIA begins its Drilling Productivity Reports that track shale production. But in reality, the timing and intensity of activity varied significantly across areas. To illustrate the importance in this context, consider that natural gas wellhead prices fell from a peak of more than $10 per thousand cubic feet in July of 2008 to less than $3 in September of 2009.[15] This natural gas price drop occurred about mid-way through our sample and impacted plays in different ways. A "dry gas" play like the Haynesville experienced a quick subsequent drop in drilling activity, while producers substituted towards oil plays such as the Bakken and Permian. The evolution of the value of production by shale play is illustrated in Appendix Figure A.3.

Therefore, we next expand the sample time period to 2018 and present an event-study:

$$Y_{c,t} = \beta_0 + \sum_{y=2001}^{2018} \beta_y (Shale_C \times y) + \lambda_c + \alpha_t + \epsilon_{i,t} \tag{3}$$

where β_y are the parameters of interest.

The event study will show the difference in outcomes in the treated (i.e. shale) and control areas in each year after controlling for county and year fixed effects. We expect to see approximately parallel trends in earnings and employment differentials in the pre-boom time period. And once the boom begins, we expect the changes in differentials to approximately mirror changes in the value of oil and natural gas produced in shale boom areas, that will be discussed in Section 3.3.3.

[15] Based on U.S. Monthly Natural Gas Wellhead Price from EIA.

While our main specification (Section 3.1) does not include data after 2014 due to the drop of oil price, we will utilize data until 2018 in the event studies to graphically show the relationship between changes in earnings differentials and the intensity of the value of oil and natural gas production in shale plays.

3.3.2. Spatial spillovers

Also a challenge to the baseline difference-in-differences estimation strategy, as highlighted in James and Smith (2020), spatial spillovers are possible due to labor migration across counties within shale regions, with employment effects occurring in urban areas in geographic proximity to rural areas where drilling activity and production occurs. In our main specification, we addressed this issue by choosing areas that are not in proximity to shale boom areas.

As a robustness test, we re-run the same specification, but not excluding counties within treated states from the potential control group. A comparison of the treated and control counties in the baseline specification and this new specification that includes all counties in the U.S. as potential controls are shown in Appendix Figure A.2. As can be seen from visual inspection, and unsurprisingly, in many instances the counties in close proximity to shale areas are chosen by the propensity score match that does not include the geographic restriction.

3.3.3. Value of production

Next, we will show that results are generally robust to regressing dependent variables of interest on the value of oil and gas produced from wells that are less than one year old. Specifically, we utilize well-level production estimates for more than one million wells in the United States as compiled by *Enverus* (formerly *DrillingInfo*).

Enverus collects data from state agencies such as the Railroad Commission of Texas, the Department of Natural Resources in Louisiana, and North Dakota Industrial Commission. In different states, oil and gas production is reported at different levels of aggregation, which typically include leases, units, or wells.[16] *Enverus* compiles the data across states and calculates well-level monthly production estimates of oil and natural gas.

We then aggregate oil and natural gas production by month from all wells that began production within the past 12 months across county-equivalents in the United States. We multiply oil and natural gas production by West Texas Intermediate oil price and Henry Hub natural gas price sourced from the U.S. Energy Information Administration (EIA) to calculate the estimated total value of oil and gas production from new wells in each county.[17] Data on the value of oil and gas production from new wells extends from 2001 to 2018.

As a related robustness examination, and following Feyrer et al. (2017), we will utilize an instrumental variables version of this value of production to account for possible endogenous decisions to drill in a county. Utilizing computer code published alongside Feyrer et al. (2017) and the most recent *Enverus* data from 2001 to 2018, we are able to reconstruct their instrument over the sample time period in this analysis. All values are expressed in 2015 millions of dollars using the CPI.[18]

[16] Unitization is when several tracts of land with different ownership are pooled together for purposes of sharing royalties. For instance, a company cannot typically drill on a one-acre plot of land and associate all of the production to the surface landowner, as the oil and natural gas is being pulled from adjacent land with different owners. Individual states have different processes for addressing this common issue. A detailed description of the laws surrounding oil and gas drilling with a focused comparison between Louisiana and Texas can be found in Martin and Yeates (1992).

[17] Agerton and Upton (2019) show that oil prices vary significantly across locations, especially during the peak of the shale boom. During the time of this writing, similar large wellhead price discounts are observed in natural gas markets. In this way, the value of production is likely over-stated, and therefore point estimates are likely understated.

[18] CPI retrieved from FRED, Federal Reserve Bank of St. Louis.

The value of production robustness checks will utilize all counties in the United States (with a balanced panel of data for relevant variables), and will not utilize propensity score matching utilized in prior specifications.

4. Results

4.1. Difference-in-differences

Table 2 presents our main result, namely the estimated effect on employment and earnings differentials.[19] All dependent variables are presented in log differences of employment and earnings for each respective group and therefore can be interpreted as the percent change in the differential of employment and earnings associated with the shale boom.

We find that college/high school employment differentials decreased by about 1.5% in both the full and small sample (See Section 3.1.1 for description of full and small sample). Employment differential decreases are also observed in the mining (1.1%) and non-mining (1.3%) sectors. For earnings differentials, we estimate a 2.9% decrease between workers with college/high school educations in the full sample and a 3.3% decrease in the small sample, with a larger effect in the non-mining sector (−3.0%) than that in the mining sector (−1.6%).

For male/female workers, we find that employment differentials increased by around 3.2% in the full sample and about 3.8% in the small sample. Point estimates suggest an imprecisely estimated 1.1% decrease in employment differentials within the mining sector, but a 2.2% increase in the non-mining sectors. Earnings differentials increased by around 2.8% in the full sample and 3.3% in the small sample. Similar to employment differentials, point estimates for the mining sector are not statistically different from zero, but earnings differentials increased by an estimated 2.6% in the non-mining sector.

We note a few broad observations to put these results into context.

First, we observe a *decrease* in earnings differentials between workers with college and high school educations, while we observe an *increase* in earnings differentials between male and female workers. Second, we observe a change in earnings differentials even within the non-mining sectors. In particular, college/high school earnings differentials decreased by 3.0% in the non-mining sectors. Similarly, the male/female earnings differentials increased by 2.6% in the non-mining sectors. Thus, not only did earnings differentials overall change because of a change in the industry composition of the labor force, but also because of changes within sectors not directly related to mining. Third, we observe a *decrease* in employment differentials between workers with college and high school educations and an *increase* in employment differentials between male and female workers within non-mining sectors.

4.2. Decomposition

Next, utilizing results from Table 2 alongside summary statistics from Table 1, we decompose these observed changes in earnings differentials into three channels; (1) changes in earnings differentials within the mining sector, (2) changes in earnings differentials within non-mining sectors and (3) changes in the labor market composition. More details on these three channels were discussed earlier in Section 3.2 and the specific algebra and calculations are shown in Online Appendix A.2. Results are summarized in Table 3.

The first rows in Panels A and B list point estimates from the difference-in-differences specification from Table 2. Results are broken out for college/high school and male/female in Panel A and B, respectively. In the second row of each panel, point estimates for the mining and non-mining sectors are scaled by the share of employment in the mining and non-mining sectors in treated areas in the pre-boom time period. For college/high school earnings differentials, we estimate that of the 3.3 percentage points decrease, only 0.031 percentage points are associated with the change in earnings differential within the mining industry, while 2.94 percentage points are associated with a change in the non-mining industries. This is due to two factors. First, the estimated change in the earnings differential in the non-mining industry is approximately twice the magnitude of the change in the mining industry. But second, only about 2% of the employment was in the mining sector before the boom. The residual, 0.33% is associated with the change in labor market composition, i.e. workers substituting across sectors, local workers entering into the labor market, and/or labor migrating from outside the county.

For male/female earnings differentials, of the 3.3% increase, 0% is associated with a change in the earnings differential within the mining-sector, while 2.55% is associated with a change in the non-mining sectors. The residual, 0.75%, is again associated with the change in the labor market composition.

The fourth row divides each of these three effects into the relative contribution such that the sum of all three effects is equal to 100%. Interestingly, the vast majority of the change in earnings differentials in these areas (relative to controls) for both college/high school and male/female come from changes within the non-mining industries. Specifically, 89% and 77% of the change in earnings differentials for college/high school and male/female respectively come from *within* the non-mining sectors. Very little of the change comes from within the mining sector itself. For college/high school and male/female, 9.9% and 22.8% respectively, of the change is associated with labor migration and substitution between sectors.[20]

This decomposition highlights how a labor market shock to a subset of workers in a specific sector (that is a relatively small share of total employment) can have a meaningful impact on earnings differentials in sectors that are not directly impacted by the shock. Further, while the shale boom did impact the industry composition of the labor force, the majority of the estimated change in earnings differentials comes from *within* sectors that are not directly associated with the mining sector. This highlights the importance of considering productivity shocks to subsets of workers in explaining broadly earnings differentials.

4.3. Robustness and extensions

4.3.1. Event study

Event study results are depicted in Fig. 1. Four event studies are shown for the four outcomes of interest, male/female, and college/high school employment and earnings differentials. Also shown on each of these figures is the value of oil and natural gas produced from wells that are less than one year old in treated counties (See Section 3.3.3).

A number of observations are worth emphasizing. First, and most obviously, the event study coefficients visually move with the value of production indicating that the sizes of the effects are driven by the intensity of the shale boom. Because the effects on college/high school employment and earnings are negative, we can see that the coefficients and the value of production move in the opposite direction.

Second, these event studies show approximately parallel trends in the early time period between 2001 and 2004 when the value of production within these shale plays was relatively small. The estimates, however, start to show signs of deviation from this parallel trend in 2005, mirroring the ramp-up in the value of production, when these shale plays started experiencing significant production. Note that our baseline specification utilizes 2007 as the treatment date,

[19] For completeness, we also show the effect of the shale boom on employment and earnings across education, gender, and in the mining and non-mining sectors. See Table A.1. For brevity, results are not discussed here.

[20] Results of the decomposition are not sensitive to the treatment year chosen. See Appendix Tables A.3 to A.5 for results using different treatment years.

Table 2
Impact of Shale Boom on employment and earnings differentials by sector.

	Employment differentials				Earnings differentials			
	(1) Full Sample	(2) Small Sample	(3) Mining Sector	(4) Non-Mining Sector	(5) Full Sample	(6) Small Sample	(7) Mining Sector	(8) Non-Mining Sector
Panel A: College (+) / High School (-)								
Treated	−0.015***	−0.015***	−0.011***	−0.013***	−0.029***	−0.033***	−0.016***	−0.030***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.005)	(0.002)
Panel B: Male / Female								
Treated	0.032***	0.038***	−0.011	0.022***	0.028***	0.033***	0.000	0.026***
	(0.002)	(0.002)	(0.012)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
N	8,176	5,432	5,432	5,432	8,176	5,432	5,432	5,432

Dependent variables are the natural log differentials in employment and monthly average earnings in columns (1)-(4) and (5)-(8), respectively. Standard errors are clustered at county and year level and are reported in parentheses.***p≤0.01, **p≤0.05, *p≤0.1.

Table 3
Decomposing changes in earnings differentials.

	(1) Mining Sector	(2) Non-Mining Sectors	(3) Employment Migration & Substitution	(4) Total
Panel A: College (+) / High School (-)				
Point Estimates Table 2	−1.6%	−3.0%	–	−3.3%
Share of Pre-Boom Employment (Table 1)	1.97%	98.03%		100%
Percent Change in Earnings Differential	−0.031%	−2.94%	−0.33%	−3.3%
Relative Contribution	0.95%	89.12%	9.92%	100%
Panel B: Male / Female				
Point Estimates (Table 2)	0.0%	2.6%	–	3.3%
Share of Pre-Boom Employment (Table 1)	1.97%	98.03%		100%
Percent Change in Earnings Differential	0.00%	2.55%	0.75%	3.3%
Relative Contribution	0.0%	77.24%	22.76%	100%

Detailed calculations can be found in Appendix A.2.

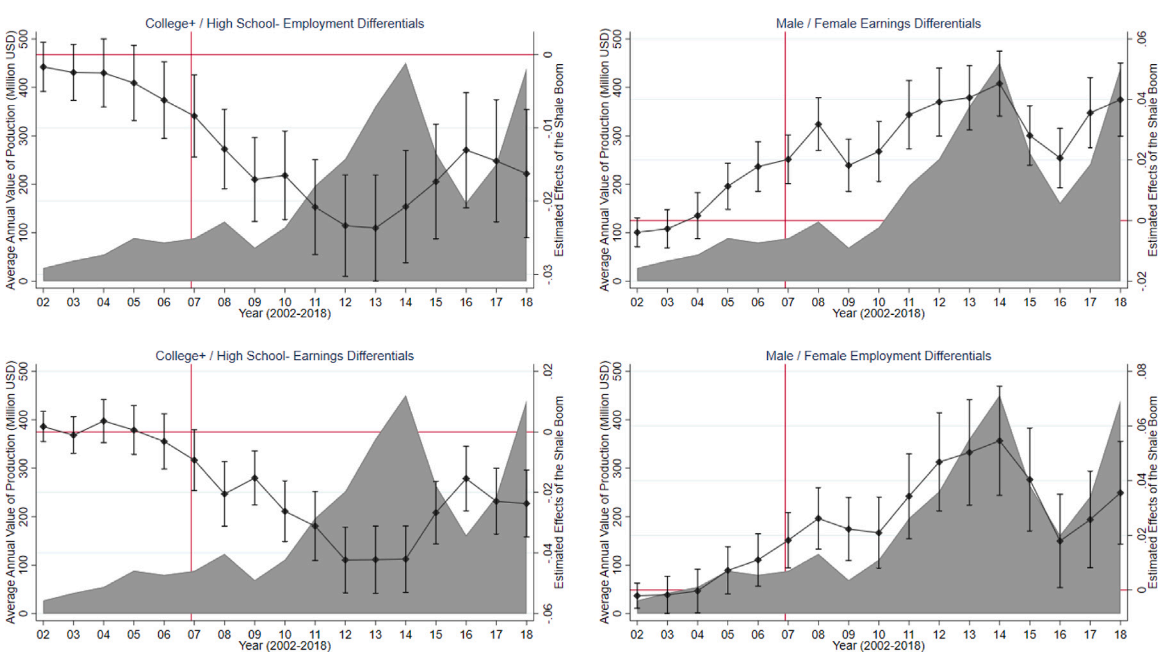

Fig. 1. Event Study and New Oil & Gas Production.

consistent with EIA's Drilling Productivity reports. If treatment began a little earlier, as is indicated here, point estimates are likely biased downward.[21]

Third, although the time period after 2014 is not included in the main analysis (which focuses on the "boom" time period), we include data to 2018 in the event studies to show a more complete picture of the effect of the shale boom and bust. The estimates clearly show strong links between the intensity of the shale boom and bust shocks on employment and earnings differentials.

[21] See Appendix Tables A.3–A.5 showing results of the decomposition with different treatment years.

4.3.2. Results by sector

One potential reason for the observed change in employment differentials within non-mining sectors might be due to the composition of the industries indirectly affected by the shale boom. As shown in Table 1, the construction and transportation sectors experienced relatively large employment growth relative to controls. This is consistent with prior research testing effects across sectors finding that the construction and transportation sectors were the most impacted, less that of course the oil and gas industry. And, like the oil and gas sector, the construction and transportation sectors are heavily employed by male workers and workers with high school educations.[22]

Thus, potentially, the estimated change in employment differentials within the non-oil and gas industries is due to the simple fact that the two most indirectly impacted industries also have a similar composition (predominantly male and high school educated workers).

To provide insight into this hypothesis, we report the results by sector in Table 4. The effects are estimated separately for the construction, transportation, manufacturing, and service sectors, as well as all other non-mining sectors. Of the ten coefficient estimates in Panels A and B, focusing on college/high school employment and earnings differentials, nine are negative and statistically significant.

For male/female differentials, results are more nuanced. For instance, male–female employment differential actually decreased in the construction and manufacturing sectors but increased in the transportation sector. We find no effect on employment differentials in the service sector or other non-mining sectors. For male/female earnings differentials, though, we find a positive and statistically significant effect across all industries.

More specifically, and focusing on earnings differentials, for college/high school, we find no effect in construction, a 2.9% decrease in transportation, 2.6% decrease in manufacturing, 1.7% decrease in service sectors and 1.7% decrease in other non-mining sectors. For male/female earnings differentials, we find increases of 1.3%, 1.6%, 1.2%, 1.2% and 1.8% increase across these sectors respectively. Thus, while the oil and gas industry only accounted for about 2% of employment in the pre-boom period in treated areas (as shown in Table 1), a productivity shock to this one (relatively small) sector had implications for earnings differentials in sectors not only outside of the oil and gas sector itself, but also outside of the two other most affected sectors, namely construction and transportation. This further speaks to the importance of labor market shocks to a small subset of workers in seemingly unrelated sectors of the economy.

To further consider the implications of related industries (i.e. construction and transportation), we next conduct the decomposition shown in Table 3, considering the mining, construction and transportation sectors relative to all other sectors of the economy. Results are presented in Table 5. Interestingly, very little of the change in earnings differentials comes from within the mining, construction, and transportation sectors. About 54 percent and 57 percent of the change in college/high school and male/female earnings differentials, respectively, come from within all other sectors. The residual approximately 43 percent (for both college/high school and male/female) or so comes from employment migration & substitution. Thus, this again speaks to the important impact a sector specific labor demand shock can impact earnings differentials within non-related sectors.

[22] More specifically, 83% and 71% of employment in the construction and transportation sectors nationally are male (as compared to 52% of the labor force is male). Similarly, 47% and 45% of these workers have a high school degree or less, compared to 37% of the U.S. labor force. Source: Quarterly Workforce Indicators, U.S. Census Bureau. Beginning of Quarter Employment counts. Q1 2017 to Q4 2017. The transportation sector includes transportation and warehousing.

4.3.3. Employment and earnings differentials by region

In Table 6 we disaggregate our main result (Table 2) by shale play. We do this for two reasons. First, we want to ensure that results are robust across different plays, to mitigate the concern that one area is driving all results. Second, this provides point estimates that might be useful for policymakers interested in geographic-specific regions. We conduct analyses on the *Anadarko, Appalachia, Bakken, Eagle Ford, Haynesville, Niobrara,* and *Permian* regions per the geographic definitions of EIA's Drilling Productivity Reports.

For college/high school earnings differentials, we find statistically significant and negative treatment effects in all seven regions. Of these seven regions, the magnitude of the effect ranges from around 1.0% (Niobrara) to 8.0% (Bakken). We estimate a positive and significant treatment effect for male/female earnings differentials in six out of the seven regions. Point estimates range from ≈0% (Niobrara) to 8.8% (Bakken).

These point estimates show the effect of the shale boom on earnings differentials, but do not take into account the varying intensity of the boom relative to the labor market size. For instance, the Bakken shale is in very rural areas and experienced large amounts of oil production. Further, oil prices remained high throughout the treatment time period. Thus, perhaps unsurprisingly the point estimate for Bakken is the largest in magnitude. The Haynesville shale, on the other hand, encompasses a metropolitan statistical area (Shreveport, LA) and experienced a "bust" due to the drop in the natural gas price around 2009, midway through the sample. This might explain the small and insignificant estimates for Haynesville.

4.3.4. Alternative control groups

We next test the sensitivity to alternative control groups. In all prior analyses, we utilize control counties identified by a propensity score matching approach as having demographic characteristics similar to boom counties in the pre-boom time period. In order to test the sensitivity of results to a different choice of control groups, Table 7 shows the results for employment and earnings differentials using 20 random control groups.[23] For this robustness test, we simply select a random control county for each treatment county in lieu of those control counties obtained through the propensity score match process. This process of generating a random control group is then performed 20 times, and for each of these iterations, we estimate a treatment effect. In total, the 80 treatment effects estimated are presented.

We highlight two observations. First, all of the estimated treatment effects for college/high school employment and earnings differentials are negative, and all estimated treatment effects for male/female employment and earnings differentials are positive, consistent with estimates using the propensity score match control group. Second, notice that in two of the categories, the baseline point estimates (from Table 2) fall in the range of the random control groups. But for male/female employment differentials and college/high school earnings differentials, the baseline specification utilizing the propensity score matched control group produces point estimates that are larger in absolute value than the range presented from these robustness checks. These results show the robustness of the result generally to considering alternative control groups, but also the importance of choosing a proper control group in estimating the precise point estimate.

[23] Again, we pull from the following states with no shale activity: AL, AZ, CA, CT, DE, FL, GA, HI, ID, IL, IN, IA, ME, MI, MN, MS, MO, NV, NH, NJ, NC, OR, RI, SC, TN, VT, WA, and WI.

Table 4
Impact of Shale Boom on employment and earnings differentials by sub-sector.

	(1) Construction Sector	(2) Transportation Sector	(3) Manufacturing Sectors	(4) Service Sector	(5) Other Non-Mining Sectors
Panel A: College (+) / High School (-) Employment Differentials					
Treated	−0.002***	−0.018***	−0.004***	−0.006***	−0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Panel B: College (+) / High School (-) Earnings Differentials					
Treated	0.001	−0.029***	−0.026***	−0.017***	−0.017***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.002)
Panel C: Male / Female Employment Differentials					
Treated	−0.017***	0.025***	−0.049***	0.002	−0.003
	(0.006)	(0.010)	(0.007)	(0.002)	(0.002)
Panel B: Male / Female Earnings Differentials					
Treated	0.013***	0.016***	0.012***	0.012***	0.018***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
N	7,224	6,468	6,496	4,060	3,248

The service sector includes the professional service, financial service, retail, and other service sectors. Other non-mining sectors are all sectors excluding the mining, construction, transportation, manufacturing, and service sectors. Standard errors are clustered at county and year level and are reported in parentheses. ***p≤0.01, **p≤0.05, *p≤0.1.

Table 5
Decomposing changes in earnings differentials — mining, construction & transportation.

	(1) Mining, Construction & Transportation	(2) All other Sectors	(3) Employment Migration & Substitution	(4) Total
Panel A: College (+) / High School (-)				
Point Estimates	−0.97%	−1.98%	–	−3.27%
Share of Pre-Boom Employment	10.79%	89.21%		100%
Percent Change in Earnings Differential	−0.105%	−1.77%	−1.40%	−3.27%
Relative Contribution	3.2%	54.0%	42.8%	100%
Panel B: Male / Female				
Point Estimates	0.25%	2.13%	–	3.36%
Share of Pre-Boom Employment	10.79%	89.21%		100%
Percent Change in Earnings Differential	0.03%	1.90%	1.43%	3.36%
Relative Contribution	0.8%	56.55%	42.64%	100%

Table 6
Impact of Shale Booms on earnings differentials by region.

	Shale play						
	Anadarko (1)	Appalachia (2)	Bakken (3)	Eagle Ford (4)	Haynesville (5)	Niobrara (6)	Permian (7)
Panel A: College (+) / High School (-) Earnings differential							
Treated	−0.043***	−0.018***	−0.080***	−0.058***	−0.017***	−0.010***	−0.033***
	(0.006)	(0.002)	(0.008)	(0.005)	(0.004)	(0.004)	(0.006)
Panel B: Male / Female earnings differential							
Treated	0.031***	0.021***	0.088***	0.054***	0.022***	−0.002	0.031***
	(0.005)	(0.002)	(0.008)	(0.006)	(0.004)	(0.004)	(0.005)
N	812	3,388	476	644	616	896	1,344

Dependent variable is logged differentials in earnings (USD). Earnings are average monthly earnings of full time stable workers. County and year fixed effects are controlled in all regressions. Standard errors are clustered at county and year level and are reported in parentheses. ***p≤0.01, **p≤0.05, *p≤0.1.

4.3.5. Spatial spillovers

Next, we examine the potential for spatial spillovers and consider how they might impact the main results of the paper. As discussed in Section 3.1.1, the counties used as controls are, by design, not in close proximity to treated areas. We choose to take this relatively conservative approach to choose control areas to mitigate concerns of spatial spillovers. But this conservative approach has both pros and cons. The benefit is that it allows us to rule out, for all intents and purposes, the possibility of spillovers into non-shale counties that are in close proximity. On the other hand, though, counties closer to shale counties are perhaps more similar and perhaps would be impacted the same by other external shocks that could threaten identification.

We, therefore, conduct an additional robustness check where we include all counties in the U.S. as potential candidates for selection as control counties identified by the propensity score match. A comparison of these control counties to the baseline specification is shown in Appendix Figure A.2. Visual inspection shows that when the full sample of counties is included in the potential control group, the propensity score match chooses many counties in close proximity to the shale boom areas.[24]

[24] Appendix Figure A.4 shows the overlap in the range of propensity scores across treatment and comparison groups for the full sample used in the baseline specification (see Appendix figure A.2a) compared to the alternative

Table 7
Impact of Shale Boom on employment and earnings differentials — Random control groups.

Iteration	Employment differentials		Earnings differentials	
	College/ High School (1)	Male/ Female (2)	College/ High School (3)	Male/ Female (4)
1	−0.015***	0.025***	−0.020***	0.026***
2	−0.015***	0.027***	−0.025***	0.025***
3	−0.013***	0.026***	−0.023***	0.027***
4	−0.015***	0.026***	−0.026***	0.026***
5	−0.013***	0.030***	−0.026***	0.028***
6	−0.013***	0.025***	−0.024***	0.027***
7	−0.014***	0.023***	−0.024***	0.023***
8	−0.013***	0.025***	−0.026***	0.028***
9	−0.014***	0.023***	−0.024***	0.024***
10	−0.011***	0.024***	−0.024***	0.025***
11	−0.016***	0.026***	−0.025***	0.026***
12	−0.015***	0.026***	−0.025***	0.024***
13	−0.012***	0.025***	−0.027***	0.028***
14	−0.016***	0.026***	−0.023***	0.027***
15	−0.015***	0.023***	−0.025***	0.024***
16	−0.013***	0.024***	−0.025***	0.028***
17	−0.009***	0.021***	−0.019***	0.026***
18	−0.014***	0.025***	−0.026***	0.029***
19	−0.017***	0.023***	−0.022***	0.026***
20	−0.014***	0.027***	−0.025***	0.027***
High	−0.017	0.030	−0.027	0.029
Average	−0.014	0.025	−0.024	0.026
Low	−0.009	0.021	−0.019	0.023
Baseline Results (Table 2)	−0.015***	0.032***	−0.029***	0.028***

Dependent variables are natural log of employment and earnings differentials, respectively. Standard errors are clustered at county and year level and are omitted for brevity. ***p≤0.01, **p≤0.05, *p≤0.1.

Table 8
Impact of Shale Boom on employment and earnings differentials by sector — Spatial proximity robustness check.

	Employment differentials				Earnings differentials			
	(1) Full Sample	(2) Small Sample	(3) Mining Sector	(4) Non-Mining Sector	(5) Full Sample	(6) Small Sample	(7) Mining Sector	(8) Non-Mining Sector
Panel A: College (+) / High School (-)								
Treated	−0.008***	−0.004***	0.007***	−0.003***	−0.014***	−0.007***	−0.008	−0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.005)	(0.002)
Panel B: Male / Female								
Treated	0.017***	0.012***	−0.012	0.004*	0.013***	0.017***	−0.004	0.015***
	(0.002)	(0.003)	(0.012)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
N	8,176	5,432	5,432	5,432	8,176	5,432	5,432	5,432

Compare point estimate to Table 2. Treated counties are identical to Table 2, but propensity score matched counties can come from anywhere in the United States, and therefore are often counties in close proximity to treated counties. A map of control and treated counties are in Appendix Table A.2. Dependent variables are the natural log differentials in employment and monthly average earnings in columns (1)-(4) and (5)-(8), respectively. Standard errors are clustered at county and year level and are reported in parentheses.***p≤0.01, **p≤0.05, *p≤0.1.

Results are shown in Table 8. Comparing to the baseline result in Table 2 yields a few observations.

First, the main result showing *decreases* in employment and earnings differentials between college/high school workers and *increases* between male/female workers is confirmed. But importantly, the magnitude of these estimated effects are smaller in absolute value. For example, the baseline specification estimates a 2.9% decrease in college/high school earnings differentials in the full sample, while a 1.4% reduction is estimated in this specification. This result is logical; because control counties are in many instances in close proximity, spatial spillovers are downward biasing estimates.

But second, results are quite different when examining differentials within the mining sector. For instance, we find an *increase* in the college/high school employment differential within the mining sector, and a *decrease* in the male/female employment differential in the mining sector. For earnings differentials within the mining sector, we find no statistically significant effect on college/high school or male/female earnings differentials.

specification presented in this section (see Appendix Figure A.2c). As expected, there is more overlap (i.e. better "common support") in the specification where nearby counties are not removed from the potential control group. This highlights the tradeoff between finding a control group that is similar to treated counties while mitigating the concern of spatial spillovers.

4.3.6. Value of production results

We next utilize the value of production approach discussed in Section 3.3.3. This approach has two benefits relative to our baseline results. First, it takes into account the variation in the intensity of the shale boom both across time and between shale play areas. Second, it allows us to expand the sample time period, including the years

Table 9
Value of production from New Wells and employment and earnings differentials.

	(1) Employment Differentials	(2) Earnings Differentials
Panel A: OLS		
College (+) / High School (-)		
County Value of Production/Capita	−0.004***	−0.004***
	(0.001)	(0.002)
Male / Female		
County Value of Production/Capita	0.010**	0.003
	(0.004)	(0.002)
Panel B: IV		
College (+) / High School (-)		
County Value of Production/Capita	−0.006**	−0.004
	(0.003)	(0.008)
Male / Female		
County Value of Production/Capita	0.024*	0.009**
	(0.013)	(0.004)
N	10,512	10,512

Dependent variables are natural log differentials in employment and monthly average earnings in columns (1) and (2), respectively. First stage F-value is 285 for IV regressions. County fixed effects and year fixed effects are controlled in all regressions. Standard errors are clustered at county and year level and are reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2001 to 2018. Third, and more practically speaking, it allows parameter estimates to be scaled such that they can be used more generally in other contexts. For comparison, we show results using both OLS and IV.

Results in Table 9 show that one million dollars of oil and gas production per person from wells with first production within the past 12 months are associated with about an 0.4% decrease in the college/high school employment differential, and about a 0.4% decrease in the earnings differential. Similarly, one million dollars of oil and gas production per person is associated with about a 1.0% increase in the male/female employment differential and a statistically imprecise 0.3% increase in the male/female earnings differential.

Results are generally robust to the IV, although point estimate and statistical significance vary. Importantly, all coefficients are in the direction consistent with prior results.

5. Discussion

It is important to consider the extent to which parameters estimated in this research can be generally applied to labor markets more broadly. We point out a number of factors that should be considered when applying the results of this research in other contexts.[25] Some of these factors can be considered when interpreting the literature estimating the economic implication of the U.S. shale oil and gas boom more broadly.

Great recession. The shale boom occurred around the time of the Great Recession; a time of historic slackness in the labor market. For instance, the national unemployment rate peaked at 10 percent during 2009, coinciding almost exactly with when U.S. oil production began to increase from its almost 40-year trough in 2008. Following a recession, the aggregate labor market is slack (Hall, 2005), and therefore had this shock occurred at a time with a tighter labor market, empirical point estimates might be very different. For instance, a demand shock during a tight labor market might experience more earnings gains relative to employment gains, while under slack conditions, the opposite is true.[26]

Barriers to entry. The oil and gas sector has relatively low barriers to entry. A male can plausibly get a job working as a "roustabout" on a rig out of high school, especially during a boom time. Similarly, unskilled workers in the construction and transportation sectors likely also have low barriers to entry. A productivity shock in an industry with higher barriers to entry would be expected to have higher earnings effects in the short-run, and less employment response.

Occupation. We consider earnings and employment by industry, but occupation is not considered due to the data being utilized (QWI). Although earnings effects have been shown across occupations (Jacobsen, 2019), in this analysis we cannot opine on whether occupational differences within sectors can explain some share of these changes in earnings differentials.

Also important to consider, is that within a sector men and women and/or workers with different education levels likely have different occupations on average. For instance, a male construction worker with a high school education might have a different job than a female worker in the construction industry with a college degree. Some of the observed changes in earning and employment differentials within sectors could be driven by occupational choice that differs across gender and education. While we cannot observe it here, perhaps the occupational makeup within these industries changed as well. Plausibly, heterogeneous treatment effects can exist within sectors based on the occupation of the worker and how that interacts with education level and gender. Any such effects are beyond the scope of this analysis due to this inherent data limitation.

Hours worked and self employment. Another inherent limitation of this analysis is that we focus on earnings, which can change through the mechanisms of both hours worked and wage rates. Further, self-employed individuals that do not receive a W-2 are not included in the Longitudinal Employer-Household Dynamics (LEHD), the micro data for which publicly available QWI is derived. We, therefore, cannot test the extent to which workers substitute into or out of self-employment due to the shale boom (Bellon et al., 2020; Tsvetkova and Partridge, 2017; Unel and Upton, 2020).

Representative areas. Some of the areas impacted by the shale oil and gas booms are relatively rural, and the response of a rural labor market to a productivity shock might not be representative of the U.S. economy as a whole. Notably, Denver CO and Pittsburgh PA are included in the treated areas. Differential effects across rural and urban areas are not considered explicitly in this analysis.

Direct channels. There are two direct channels through which an oil and gas boom can stimulate a local economy. First, there is employment associated with the initial drilling and completion of wells. As has been shown in this and prior research, these employment effects have been observed overwhelmingly by male workers with high school education in the mining sector (see Table 1 and A.1). Large effects are also observed in the construction and transportation sectors, that also have high concentrations of male and high school educated workers.

But also, local landowners receive bonus and royalty checks for oil and gas production that occurs beneath their land. A bonus check is given to the landowner at the time that a lease is signed as a lump sum payment. Once production begins landowners receive royalty payments that is some share of the value of the oil and gas produced (typically

[25] While these factors have been pointed out by various colleagues, this is by no means intended to be an exhaustive list.

[26] As an additional robustness check, we interact the shale boom treatment effect with the recession and recovery years. Table A.2 shows results. Comparing to Table 2 show that results are generally robust to the inclusion of differential effects during the recession and recovery. Coefficient estimates interacting treatment with recession are in fact the opposite sign of the main treatment effect, indicating that if anything the recession coinciding with the initial shale boom is downward biasing results.

20%–25%).[27] For perspective, Brown et al. (2016) estimate that six major shale plays generated $39 billion in private royalties in 2014.[28]

We are unable to distinguish between these (and perhaps other) channels, and channels could impact earnings and employment across sectors. This is a general limitation of the broader literature focusing on the economic implications of localized oil and gas activity.

6. Conclusions

In this paper, we exploit a plausibly exogenous labor market shock that overwhelmingly impacts a specific subset of workers (male workers with high school education) in a specific industry (oil and gas) on earnings and employment differentials within sectors not directly impacted by the shock. We find that earnings differentials between men and women increase while earnings differentials between workers with college and high school education decrease. These effects are also observed within sectors not directly impacted by the shock. Specifically, empirical estimates suggest that college/high school earnings differentials *decreased* by 3.0% in the non-mining sectors, while male/female earnings differentials *increased* by 2.6% in the non-mining sectors.

We decompose these effects into three channels. The first channel is that the shock might impact the earnings differentials *within* the affected sector, namely the mining sector in this context. The second channel is that the shock might impact the earnings differentials in the *non-mining* sectors. The third channel is the residual of channels 1 and 2 which can be described as the change in the composition of employment.

For college/high school and male/female earnings differentials, 89% and 77% respectively of the observed change in earnings differentials can be explained by changes *within the non-mining sectors*. Approximately 10% and 23% respectively can be explained through the residual, (i.e. labor market composition channel). Very little of the change in earnings differentials can be explained by changes within the mining sector.

Results of this research might also have significant policy implications. We show that labor market shocks to specific subsets of workers can have significant impacts on earnings differentials within seemingly unrelated sectors. No prior research of which we are aware has tested for effects labor market shocks stemming from a specific technological advancement in a specific industry on earnings differentials within unrelated sectors. Policies aimed at reducing income inequality across the income spectrum and/or at reducing income inequality between men and women should be aware of the sensitivity of labor market shocks on earnings differentials within seemingly unrelated sectors.

CRediT authorship contribution statement

Gregory B. Upton Jr: Conceptualization, Statistical analysis, Data curation, Writing – review & editing. **Han Yu:** Conceptualization, Statistical analysis, Data curation, Writing – review & editing.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105462.

[27] The surface owner of the land where the actual well is drilled typically receives a "rental" payment that is the value of renting the surface area needed to drill and produce. Most landowners, though, receive a bonus and royalty payments even though no actual drilling activity occurred on their land.

[28] There are other potential channels. For instance, many states collect severance taxes that can generate government spending in shale boom states (Upton and Richardson, 2020; Marchand and Weber, 2020).

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