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Capital-Skill Complementarity in Manufacturing: Lessons from the US Shale Boom

Victor Hernandez Martinez†

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Abstract

This paper tests the existence of capital-skill complementarity in the manufacturing sector using quasi-experimental increases in the relative price of low-skill labor induced by the US shale boom. I find that in response to the shale boom, local manufacturing firms decreased their relative usage of low-skill labor while increasing their capital expenditures. These endogenous changes in the input mix allowed manufacturers to maintain the value added despite the increase in the price of low-skill labor, avoiding the potential short-term crowding-out effects of the natural resource boom. Combined with the findings of previous work, my results indicate that the degree of skill substitutable with capital in manufacturing has increased over the last several decades.

Keywords: Capital-Skill Complementarity, Manufacturing, Fracking, Natural Resources, Labor Markets

JEL Codes: E22, E24, O13, J24

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1 Introduction

The degree of substitutability or complementarity among production inputs has long been a major focus of economic research (Griliches (1969); Katz and Murphy (1992)). In recent years, the literature has focused on the degree of substitutability between low- and high-skill labor and capital, motivated by an increased earnings dispersion among college- and non-college-educated workers since 1980 (Stokey (1996); Krusell et al. (2000)). However, despite the perennial interest, there is limited causal evidence analyzing this topic because of the difficulty in finding exogenous variation in input prices without changes in product demand.

This paper gives causal evidence for capital-skill complementarity in the manufacturing sector using exogenous changes in the relative price of low-skill labor in local labor markets impacted by the US shale boom. In response to fracking, local manufacturers replace low-skill labor with capital. This allows them to maintain their value added and avoid the crowding-out effects generated by the US shale boom.

The US shale boom refers to the discovery of horizontal fracking (the combination of hydraulic fracturing with horizontal drilling), which created a major economic revolution across certain areas of the United States (Feyrer et al. (2017); Bartik et al. (2019)). Using an IV approach that exploits exogenous variation in local geological conditions, I document novel evidence that the shale boom increased local product demand in low-skill-intensive sectors such as mining, construction, trade and transportation, and real estate. This shifted the relative local labor demand toward low-skill labor and increased its relative price. Specifically, I find that a 94 percent increase in total horizontal wells (the average 4-year growth rate in fracking counties) raised the low- to high-skill employment ratio outside of manufacturing by 2.8 percent and reduced the high- to low-skill labor income gap by over 2 percent.

To understand whether the response of the local manufacturing sector to this shock is consistent with the existence of capital-skill complementarity, I introduce a model with an "oil-related" (or non-manufacturing) sector and a manufacturing sector. In the model, production in the oil-related sector uses only low-skill labor, while the manufacturing sector utilizes low-skill labor, high-skill labor, and capital. I model manufacturing production as in Stokey (1996) and Lewis (2011), imposing a CES nesting that allows for capital-skill complementarity.[1] I assume that output prices are exogenous in both sectors, labor supply is fully inelastic, capital is supplied perfectly elastically, and there are no cross-sector productivity spillovers.

Using the model, I derive predictions on how the manufacturing sector would respond to a positive shock to the productivity of the oil-related sector –the US shale boom. Since the manufacturing sector is not directly affected by the shock, manufacturers will only see its effects through the upward pressure it puts on low-skill wages. This will change the relative price of low-skill labor, reducing manufacturing's relative utilization of low-skill labor. The key insight of the model arises in the responses of manufacturing capital and output. If and only if manufacturing operates under capital-skill complementarity, then the response of capital in manufacturing to the shock should be strictly positive. On the other hand, if capital and low-skill labor were complementary, manufacturers would instead reduce their capital utilization. Moreover, because the shock does not affect manufacturing product demand, the response of output should be weakly negative, following that of high-skill wages.

Testing the validity of the model's assumptions empirically reveals one shortcoming: the model assumes an inelastic labor supply, while the data indicate that the local labor supply responds to the shock. I find evidence that the fracking boom increased total local employment, labor force participation, and population. To circumvent this issue, the estimated manufacturing responses I use to test the predictions of the model will control for aggregate changes in low- and high-skill employment at the county level. This allows me to compare manufacturers in fracked and non-fracked counties where the aggregate labor supply grew similarly, and thus, from the perspective of the model, hold the labor supply constant.[2]

Using the exogenous variation of the US shale boom, I document four novel facts about the manufacturing sector's response to a change in the relative price of local low-skill labor. First,

[1] This setup was chosen to be consistent with basic facts of how labor is used in manufacturing and has proved to be effective in previous work. Nevertheless, I also consider a model using the approach in Krusell et al. (2000)) and find similar conclusions.

[2] After holding aggregate employment growth constant, the estimated responses of manufacturing to the shock will still be causal and informative of manufacturing's degree of capital-skill complementarity under two assumptions. First, manufacturing is small enough not to determine the aggregate change in a county's employment growth. Second, manufacturing product demand is uncorrelated with fracking conditional on aggregate employment growth.

compared to areas where the aggregate labor supply was growing similarly, manufacturers in fracked areas saw total employment decline. Second, this decline was driven by a significant reduction in the demand for low-skill labor, which significantly reduced manufacturers' low- to high-skill labor ratio. Third, despite the reduction in manufacturing employment, local manufacturing firms impacted by fracking significantly increased their capital expenditures. Fourth, manufacturing value added declined insignificantly in response to fracking. My results indicate that a 94 percent increase in total horizontal wells reduced manufacturing employment by almost 8 percent, reduced the low- to high-skill employment ratio in manufacturing by 4.5 percent, increased manufacturers' capital expenditures by approximately 25 percent, and decreased manufacturing value added by an insignificant 4 percent.

These responses perfectly match the predictions of the model for a manufacturing sector operating under capital-skill complementarity. A manufacturing sector in which there is no capital-skill complementarity would have required a negative estimated response of capital to the shock. Given the large economic magnitude of my estimates and their significance, this seems highly unlikely.

This paper contributes to a large literature studying the degree of substitutability between different types of labor and capital.[3] This is one of the very few papers using exogenous variation in input quantities or prices to assess the substitutability between low-skill labor and capital. My approach is similar to that in Lewis (2011). Using exogenous variation in low-skill immigration based on historical migration patterns, he shows that manufacturers in areas where low-skill immigrants are more likely to locate adopted technology more slowly during the 1980s. Similarly, Acemoglu and Finkelstein (2008) use exogenous changes in the price of capital driven by a modification to the Medicare reimbursement formula to show that impacted hospitals increased their high-skill labor. In related work, Akerman et al. (2015) use

[3] The literature studying capital-skill complementarity dates at least as far back as Griliches (1969). At the turn of the 21st century, the widening gap in the earnings of college-educated and non-college-educated workers over the preceding 20 years reignited interest in this topic. Some examples of this work are Stokey (1996), Krusell et al. (2000), Duffy et al. (2004), Lindquist (2004), Papageorgiou and Chmelarova (2005), and Polgreen and Silos (2008). In recent years, the literature has revisited this topic to assess whether the patterns present in the late 1900s still exist today and propose alternative approaches to look at this question. Some examples of the former are Maliar et al. (2022), Castex et al. (2022), and Ohanian et al. (2023)., while the latter can be found in Lise and Postel-Vinay (2020) and Acemoglu and Restrepo (2021), among others.

exogenous variation in broadband adoption in Norway to show that this type of investment substitutes low-skill labor while complementing the work of high-skill workers. Compared to this previous work, my results are more general than those in Acemoglu and Finkelstein (2008) in that I analyze a significantly wider and more varied industry. Since I analyze a change in relative labor prices, my results provide a more complete understanding of the substitutability of low-skill labor with capital than those in Akerman et al. (2015), whose analysis is focused on a very specific type of capital access. Further, I analyze a period of time much more recent than that in Lewis (2011). Thus, I show that capital-skill complementarity was still an important force affecting large parts of the economy well into the 21st century.

Moreover, when combined with the results of the previous literature, my findings suggest that the degree of skill that is substitutable with capital in manufacturing has increased over the last 30 to 50 years. Lewis (2011) shows that only workers with less than a high school diploma are easily substitutable with capital in manufacturing. I, on the other hand, document that all workers with less than a college degree appear to be similarly easily substitutable with capital. This suggests that, within manufacturing, the types of tasks capital can substitute for have expanded or that the types of tasks that workers with less than a college education perform have become more similar across different education groups.

This paper also adds to the literature studying cross-industry spillovers from economic shocks, primarily natural resource booms. More specifically, it speaks to the literature analyzing the starting premise for the so-called "Dutch disease": natural resource booms that raise the local price of labor, crowding out manufacturing in the short run by reducing its employment and output. Previous work in Michaels (2011) and Allcott and Keniston (2018) shows that natural resource booms in the 20th century did not satisfy the starting premise of the Dutch disease because they directly increased local manufacturing product demand.[4] Similar to them, I find no evidence of the US shale boom crowding out local manufacturing employment or output. However, the novelty of this paper is to show that, during the US

[4] Allcott and Keniston (2018) document that some manufacturing subsectors unrelated to natural resource extraction see some crowding out, but the negative effects on these subsectors are not enough to overcome the positive demand effect on the subsectors related to natural resource extraction. Branstetter and Laverde-Cubillos (2024) analyze the effects of a commodity boom in Colombia and show evidence of manufacturing crowd-out driven by the appreciation of the Colombian peso.

shale boom, this was not driven by increased manufacturing product demand but instead by endogenous changes to the manufacturing input mix. By substituting low-skill labor, whose price had risen, with capital, manufacturers circumvented the local pressures of the US shale boom that otherwise could have resulted in the beginning of the Dutch disease.

This paper also contributes to the literature studying the effects of natural resource booms, specifically horizontal fracking (see Weber (2014); Maniloff and Mastromonaco (2017); Feyrer et al. (2017); and Bartik et al. (2019), among others). I show that the economic boom created by fracking especially impacted the labor market outcomes of low-skill workers, reducing the labor earnings inequality across educational groups. Previous work has mostly focused on documenting the aggregate local impacts of fracking. Compared to the previous literature, my findings allow for a more complete understanding of the labor market winners and losers from fracking, the mechanisms that generated these groups, and how those not directly affected by fracking responded to its indirect effects.[5]

The rest of the paper is organized as follows: Section 2 describes the US fracking boom. Section 3 introduces the model and derives predictions of the responses of different manufacturing inputs to a productivity shock in the oil-related sector. Section 4 presents the empirical strategy to estimate the effects of fracking and describes the data. Section 5 presents the main empirical results and validity exercises. Section 6 uses the empirical results to test the model predictions and considers alternative model specifications. Section 7 discusses the empirical results in the context of the Dutch disease. Finally, Section 8 concludes.

2 US Shale Boom

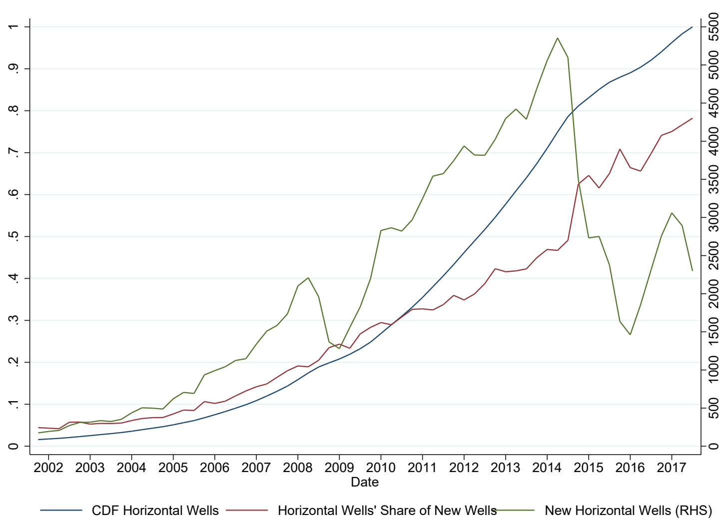
The US shale boom, or fracking boom, refers to the significant increase in oil and natural gas production in the United States that started in the mid-2000s. As explained in Brown (2014) and Wang and Krupnick (2015), this "boom" resulted from two different technological advances in the extraction sector: hydraulic fracturing and horizontal drilling. The combination

[5] Beyond its effects on the labor market, there is a vast literature analyzing the negative effects of fracking on air pollution, water pollution, and, more generally, health outcomes (see the review of the previous literature in Black et al. (2021)). Similarly, previous work also suggests that fracking could have increased crime (James and Smith (2017), Komarek (2018), and reduced educational attainment (Zuo et al. (2019); Cascio and Narayan (2022)).

of both technologies made possible the extraction of fossil fuels trapped in shale formations, whose existence had been known for decades (Feyrer et al. (2017)). The deregulation of the oil and gas sector (see Joskow (2013)) and the high cost of natural gas in the early 2000s made these technological advances viable from an economic perspective.

The quick expansion of horizontal fracking can be seen in Figure 1. The figure uses proprietary data from Drillinginfo, a private energy information service that provides detailed information for the vast majority of wells spudded in the United States.

Figure 1: Horizontal Fracking in the 21st Century: The Evolution



Note: Figure 1 shows in blue the cumulative distribution function of total horizontal wells spudded until the end of 2017 by quarter. The series in red shows the share of new wells spudded by quarter that are horizontal. The series in green shows the total number of new horizontal wells spudded each quarter (right y-axis). The graph uses data from Drillinginfo.

Figure 1 shows that, before 2003, horizontal fracking was in its infancy. Less than 5 percent of newly spudded wells were horizontal, and less than 2 percent of all horizontal wells spudded until the end of 2017 had been built, with most of these wells representing experimental wells.[6] This is consistent with the findings in Bartik et al. (2019), who, using investor calls and production announcements, determined that most shale plays started production post-2003.[7] Over the next decade, however, horizontally drilled wells would become the predominant type. By 2014, the number of new horizontal wells spudded per quarter had risen to over 5000

[6]The primary objective of experimental wells is to evaluate the production performance, capabilities, and limitations of either new or existing technologies across various scenarios.

[7]Only the Barnett shale play in Texas had production announcements before 2005.

and represented around 50 percent of all newly spudded wells each quarter. In late 2014, the decline in oil and gas prices slowed the development of new production capacity, significantly reducing the number of new horizontal wells spudded per quarter. However, this only made horizontal drilling even more pervasive. By the end of 2017, 80 percent of newly spudded wells were horizontal.

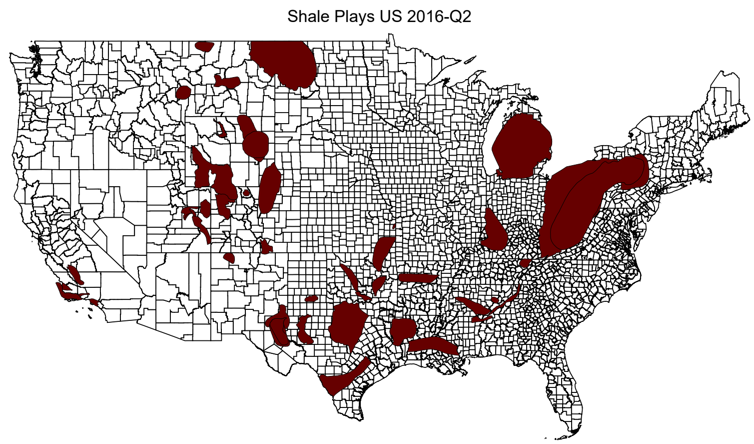
Horizontal drilling is a localized phenomenon made possible by the existence of shale plays in the area. Figure 2 (a) shows the existing shale plays in the US, based on 2016 data from the US Energy Information Administration (EIA). The uneven spatial distribution of shale plays made the relevance of horizontal fracking highly heterogeneous across space. Therefore, by the end of 2017, only 19.1 percent of all US counties had spudded any horizontal wells. Nevertheless, the rollout of horizontal fracking was fairly homogeneous over time for the areas that decided to pursue it. As shown in Figures 2 (b) and (c), most counties where horizontal fracking was possible had fewer than 50 horizontal wells in early 2003. However, as of late 2017, this number increased in most of these counties by at least one order of magnitude.

Beyond its localized nature, an important implication of horizontal fracking for the model in the next section is that its development heavily relies on the use of low-skill labor. This is discussed and analyzed in detail in Section 5. Fracking relies upon the use of low-skill labor not only driven by the mining sector but also because most economic activity supporting fracking development is low-skill labor intensive. As Section 5.1 details, fracking significantly pushes economic activity in construction, transportation, real estate, and warehousing, all low-skill intensive sectors.

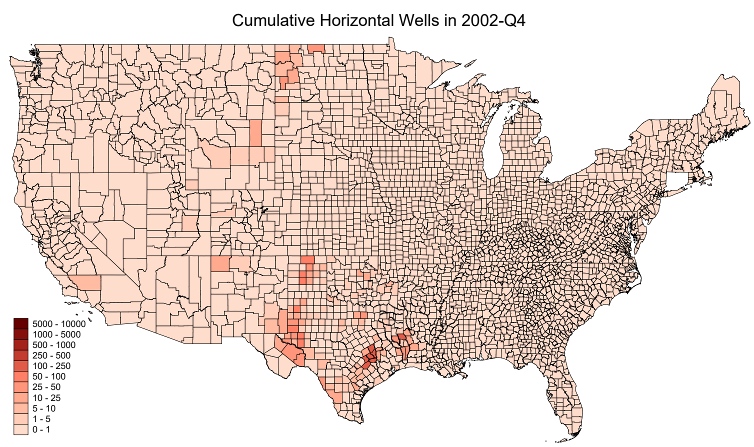
3 Model

This section introduces a two-sector model with the objective of understanding how the effects of fracking can propagate to sectors of the local economy not directly affected by it. In the model, the economy is divided between the "oil-related" sector (or non-manufacturing sector), o, and the manufacturing sector m. In each sector, there is one representative firm that is a

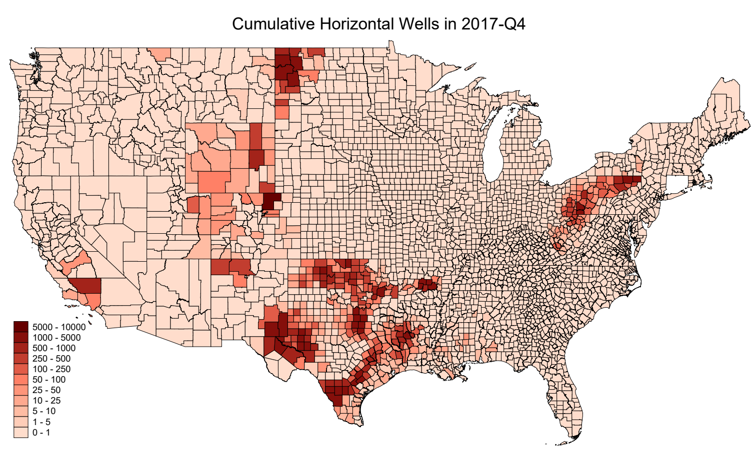
Figure 2: Horizontal Fracking in the 21st Century: The Geographic Component



(a) Shale Plays 2016-Q2



(b) Cumulative Horizontal Wells as of 2002-Q4



(c) Cumulative Horizontal Wells as of 2017-Q4

Note: Figure 2 (a) displays data from the EIA on the location of tight oil and shale gas plays in the continental US in 2016. Figure 2 (b) displays the total number of horizontal wells spudded by county as of the end of the last quarter of 2002. Figure 2 (c) displays the total number of horizontal wells spudded by county as of the end of the last quarter of 2017. Panels (b) and (c) use data from Drillinginfo.

price taker. The production function in the oil-related sector is:

$$Y_o = A_o L_o^{\beta}, \quad \beta < 1 \tag{1}$$

where L_o represents low-skill labor, and A_o is neutral technological change in the oil-related sector.

To model production in manufacturing while allowing for capital-skill complementarity, I follow Stokey (1996) and Lewis (2011). This setup was chosen to be consistent with the basic facts of how labor is used in manufacturing during my period of interest while still highlighting the main mechanisms of interest and remaining tractable enough.[8]

$$Y_m = A_m (K_m^{\theta} + L_m^{\theta})^{\frac{\alpha}{\theta}} H_m^{1-\alpha} \tag{2}$$

where L_M and H_M represent manufacturing's low- and high-skill labor, respectively, and $\alpha \in (0, 1)$.[9] I assume that all labor is supplied locally and inelastically and, as in Autor et al. (2003), capital is supplied perfectly elastically at a price r. The latter assumption is consistent with the idea that counties affected by fracking are small and there is free mobility of capital. Finally, output prices in both sectors are assumed to be exogenous because both sectors' output consists of tradeable goods whose product market extends beyond the county.

The manufacturing sector production function is consistent with capital-skill complementarity if $\theta > \alpha$, where $\theta \leq 1$ governs the elasticity of substitution between low-skill labor and capital in the manufacturing sector. Describing equation (2) as allowing for capital-skill complementarity is a slight abuse of the terminology that I maintain to remain consistent with the previous literature. In this model, investing in capital does not necessarily increase the productivity of high-skill labor, raising the wages of high-skill workers. Instead, capital-skill complementarity in this model allows the manufacturing sector to more easily substitute away

[8] Section 6.2 considers manufacturing production functions that allow for alternative forms of capital-skill complementarity and discusses the implications of the empirical results based on them.

[9] Compared to the work of Lewis (2011), the production function in equation (2) completely omits manufacturing non-production output. The reasons behind this choice are discussed in further detail in Section 6.1 and Appendix C. Equation (2) is also closely related to the production function in Stokey (1996). The main difference is that I assume that the relative efficiency of unskilled labor in supplying high-skill labor inputs is zero. I do not include this relative efficiency because its analysis is beyond the focus of this paper.

from low-skill labor using capital, with a smaller impact on output.

In the economy presented in equations (1) and (2), an equilibrium is defined as prices (w_L, w_H) and quantities $(L_o,\ L_m, H_m)$ such that, given prices, firms maximize profits and both labor markets clear. From the perspective of the model, the fracking boom represents an exogenous increase in the productivity of the oil-related sector, A_o. Using this setup, I aim to understand how exogenous changes in productivity in the oil-related sector affect the skill mix and the capital utilization in the manufacturing sector and how those changes differ from a model in which capital behaves as skill-neutral.

Under the previous assumptions, in equilibrium, a positive shock in the productivity of the oil-related sector increases the price of low-skill labor. Therefore, if $\theta > \alpha$, the amount of capital in the manufacturing sector responds positively to a productivity increase in the other sector:

$$\frac{\mathrm{d}ln(K_m)}{\mathrm{d}A_o} = \frac{\theta - \alpha}{(1-\alpha)(1-\theta)} C \frac{\mathrm{d}w_L}{\mathrm{d}A_o} > 0 \tag{3}$$

where C is:

$$C = \frac{(\frac{w_L}{r})^{\frac{1}{\theta-1}} \frac{1}{r}}{1 + (\frac{w_L}{r})^{\frac{\theta}{\theta-1}}} \tag{4}$$

The capital-skill complementarity condition ($\theta > \alpha$) is critical for this result. In a case in which capital is skill-neutral, an increase in productivity in the oil-related sector would imply a negative response of capital in the manufacturing sector. On the other hand, the response of output must not follow that of capital under capital-skill complementarity, and instead, it will weakly decrease, following the response of high-skill wages.

$$\frac{\mathrm{d}ln(Y_m)}{\mathrm{d}A_o} = \frac{\mathrm{d}ln(w^H)}{\mathrm{d}A_o} = -\frac{\alpha}{1-\alpha} C \frac{\mathrm{d}w_L}{\mathrm{d}A_o} \leq 0 \tag{5}$$

Finally, note that the use of low-skill labor in manufacturing (and, by extension, the low- to high-skill labor ratio) will also decrease following an increase in productivity in the oil-related sector:

$$\frac{\mathrm{d}ln(\frac{L_m}{H_m})}{\mathrm{d}A_o} = \frac{\mathrm{d}ln(L_m)}{\mathrm{d}A_o} = -\frac{1}{1-\alpha}\left(\frac{\mathrm{d}ln(w_L)}{\mathrm{d}A_o} + \frac{\theta-\alpha}{1-\theta}D\frac{\mathrm{d}w_L}{\mathrm{d}A_o}\right) < 0 \tag{6}$$

where D is:

$$D = \frac{(\frac{r}{w_L})^{\frac{1}{\theta-1}}\frac{r}{w_L^2}}{1+(\frac{r}{w_L})^{\frac{\theta}{\theta-1}}} \tag{7}$$

The reduction in low-skill manufacturing employment in response to the shock will increase with the degree of capital-skill complementarity. When $\theta > \alpha$, both terms on the right-hand side of equation (6) will put downward pressure on low-skill manufacturing employment. The more substitutable low-skill labor is with capital (i.e., the larger θ is for a given α), the more low-skill manufacturing labor will decrease in response to an exogenous increase in its own price.

In combination, the above expressions and assumptions also determine the responses of manufacturing employment and relative wages across skill groups:

$$\frac{\mathrm{d}(L_m + H_m)}{\mathrm{d}A_o} < 0 \qquad \text{and} \qquad \frac{\mathrm{d}(\frac{w_H}{w_L})}{\mathrm{d}A_o} < 0 \tag{8}$$

The empirical exercises that follow serve as an examination of whether the estimated moments in the data are consistent with the different predictions of the model.

4 Empirical Strategy

My empirical strategy uses the US shale boom as a change in productivity in the oil-related sector. The predictions of the model connect *changes* in different outcomes to *changes* in productivity in the oil-related sector. Therefore, my baseline empirical strategy is directly a reduced-form equation connecting the changes in outcomes to changes in the number of horizontal wells:

$$\Delta_{4Q}Y_{it} = \beta_1\Delta_{4Q}lnTotWells_{it} + \boldsymbol{\beta X} + \kappa_t + \theta_i + S_i \times t + \epsilon_{it} \tag{9}$$

$\Delta_{4Q} Y_{it} = \Delta Y_{i,\{t,t-4\}}$ refers to the *annual* change in the outcome of interest in quarter t and county i. The measure of the change in productivity in the oil-related sector is given by $\Delta_{4Q} lnTotWells_{it} = \Delta lnTotWells_{i,\{t,t-4\}}$. It measures the *annual* change in the *ln* of the total number of horizontal wells in county i in quarter t. $\boldsymbol{X}$ represents different control variables (which are specified when included), κ_t captures time fixed effects, and θ_i represents county fixed effects. Finally, S_i is a dummy variable taking the value of 1 if the county is located fully or partially over a shale play and zero otherwise. Its interaction with t allows for differential linear trends in growth rates for on- and off-shale counties.

The coefficient of interest is β_1, associated with the change in the total number of horizontal wells. The change in the number of horizontal wells will depend on the availability of oil and natural gas in the county and the decisions taken to extract it. While the former is potentially exogenous (more on this below), the latter is probably not. Counties may increase or cease horizontal fracking based on their economic conditions, creating an omitted variable bias problem. Similarly, the decision to allow for fracking in a county could be affected by the availability of different types of labor, which would generate a reverse causality problem.

To avoid these issues, I instrument the change in the total number of new horizontal wells using a two-step procedure. First, I estimate the predicted cumulative number of horizontal wells in period t and county i using the area's geological characteristics combined with the evolution of horizontal fracking at the national level on different types of CBSAs:

$$lnTotWells_{it} = a_i + \sum_{c \in CT} \sum_{t \in T} b_t^c \mathbb{1}(CT = c) \mathbb{1}(T = t) OS_i + u_{it} \tag{10}$$

In equation (10), α_i is a dummy variable for each county i, $c \in CT$ is the type of CBSA the county is part of (metropolitan, micropolitan, or non-metropolitan and non-micropolitan), and OS_i is the percentage of the county's total area on a shale play. In the second step, I use the annual difference in the predicted values ($\widehat{lnTotWells}_{it} = \widehat{a_i} + \widehat{b_t^c} OS_i$) between period t and $t-4$ to generate an estimate of $\Delta \widehat{lnTotWells}_{i,\{t,t-4\}}$.

This IV strategy uses the evolution of fracking productivity at the national level to predict the county-level number of new horizontal wells. The predicted values for total horizontal wells are based on the development of fracking at the national level across different types of CBSAs and the share of the county with the resource potential for hydraulic fracturing. Because each individual county represents a small part of the national development of fracking (even within CBSA type), the instrument is exogenous with respect to the idiosyncratic rollout of fracking within individual counties.

This instrumental variable approach is common in the literature studying the effects of natural resource booms. For instance, Weber (2014), Brown (2014), and Maniloff and Mastromonaco (2017) use the percentage or area of a county located on shale to instrument for the local development of horizontal fracking. The previous literature has also used the national evolution of natural resource extraction to construct instruments of the county-level evolution. Feyrer et al. (2017) use the total new oil and gas production in a complete shale play during a year as an instrument to estimate the annual new production of all counties located on that shale play. Similarly, Allcott and Keniston (2018) use the interaction between the change in national employment in the oil and gas sectors and the county's original oil and gas resources to instrument for the county's time-varying resource extraction.

Allcott and Keniston (2018) and Bartik et al. (2019) argue that off-shale counties do not represent a good counterfactual to study the effects of horizontal fracking on the local communities. Their findings indicate that on-shale vs. off-shale counties differ along many dimensions in both levels and trends since at least the 1970s. This is not a major concern in this paper, even if the instrument is partially constructed using variation in shale resources across counties. The empirical strategy above allows me to identify the causal effects of horizontal fracking even if on- and off-shale counties present different trends. The estimation using *differences* in outcomes and including county fixed effects allows for on- and off-shale counties to differ in both levels and trends. Furthermore, the inclusion of a different linear trend in growth rates across on- and off-shale counties guarantees that fracking and non-fracking counties can vary not only in their growth rate levels but also in their growth rate trends. Section 5.4 explores in detail the validity of this empirical strategy. I use data from the period before the shale boom (1995 to 2003) to assess whether the instrument correlates with different outcomes before the shale boom.

The data on manufacturing capital expenditures and value added (described below) are only available every 5 years, requiring a different empirical specification compared to that used above. I use a long-differences approach while maintaining the same basic structure as before. The estimation equation will be:

$$\Delta Y_{it} = \beta_1 \Delta lnTotWells_{it} + \boldsymbol{\beta X} + \kappa_t + \theta_i + S_i \times t + \epsilon_{it} \tag{11}$$

In equation (11), ΔY_{it} represents the 5-year change (between years t and $t-5$) in the outcome of interest in county i. Similarly, $\Delta lnTotWells_{it}$ measures the 5-year change in the total number of horizontal wells in that same county. As before, I construct the instrument in two steps, maintaining an identical first step but adapting the second to the new data structure. In the new second step, I calculate $\Delta lnTotWells_{it}$ as the 5-year difference in the predicted values of $lnTotWells_{it}$. While the procedure for constructing the instrument varies slightly, the identification assumptions remain unchanged and still allow for on- and off-shale counties to differ in both levels and prior trends.

4.1 Data

In addition to the data from Drillinginfo and the US EIA described above, I use several different data sources. The data for employment and earnings at the aggregate level and by industry and education come from the Quarterly Workforce Indicators (QWI). The QWI provides local labor market statistics by industry, worker demographics, employer age, and size. The source data for the QWI is the Longitudinal Employer-Household Dynamics microdata. A variety of record sources also contribute to the construction of the QWI, including unemployment insurance earnings records, the Quarterly Census of Employment and Wages, and the Business Dynamics Statistics. Demographic information going into the QWI indicators comes from the 2000 and 2010 Census, the American Community Survey, Social Security records, and tax returns. The data on capital expenditures and value added for manufacturing firms come from the Economic Census (EC). The EC is the official five-year measure of businesses in the United States. It provides comprehensive statistics at the national, state, and local levels, serving as the benchmark for current economic activity. I use EC census data on value added and capital expenditures in manufacturing at the county level for the years 2002, 2007, 2012, and 2017.[10] Finally, I use data from the BLS' LAUS to measure employment, unemployment, and participation rates at the county level. My analysis focuses on the period between the first quarter of 2003 and the last quarter of 2017 using only counties whose minimum population in any of these years is more than 2000 individuals.

5 Local Labor Market Effects of Horizontal Fracking

I begin by confirming earlier findings of the aggregate local labor market effects of fracking. From there, I move to document two novel effects the US shale boom created in local labor markets: it increased the relative demand for low-skill labor and raised its relative price.

5.1 Aggregate Local Labor Market Effects of Horizontal Fracking

My estimates of the aggregate local labor market effects of fracking are very similar to those found in the previous literature. I briefly discuss them here and provide further details in Appendix B. I find that, over the average 4-year period, fracking increased total employment and earnings by roughly 11.4 and 4.4 percent, respectively, and population by 1.7 percent. Similarly, it increased the employment-to-population ratio by 2.3 percentage points while reducing the local unemployment rate by 0.5 percentage points. The magnitude of these estimated effects is very similar to that from previous work (Bartik et al. (2019); Feyrer et al. (2017); Maniloff and Mastromonaco (2017)).[11]

Across industries, the largest employment effects of fracking are seen primarily in mining, construction, real estate, and trade and transportation. On the other hand, the effects on manufacturing, agriculture, and health and education employment are insignificantly different from zero. This findings perfectly match previous results in Weber (2014), Maniloff and Mastromonaco (2017), Feyrer et al. (2017), and Bartik et al. (2019).

[10] I additionally use county-level data from EC for 1992 and 1997 to test the validity of my empirical strategy in Section 5.4.

[11] The results on earnings use nominal earnings as the outcome. Appendix B replicates these results (for the period 2007 to 2017) using real earnings. I find evidence of local price increases eroding part of the wage gains from fracking. Over the average 4-year period, fracking increased all average wage measures by approximately 1 percentage point less in real terms than in nominal terms.

5.2 Relative Local Labor Market Effects of Horizontal Fracking

This section documents two novel facts about the US shale boom: it increased the relative demand for low-skill labor in the impacted local labor markets and raised its relative price. These two facts connect with the model in Section 3 by providing exogenous variation in relative input prices in the manufacturing sector.

I define high-skill labor as workers with a college education or above and low-skill labor as workers with some college, high school diplomas, or less than a high school education. The choice of the education categories forming the high- and low-skill labor groups and alternative classifications are further discussed in detail in Appendix C. In short, the classification I impose is not arbitrary and instead is based on how manufacturers use different types of labor in the data. I find evidence that, among workers with less than a college degree, workers across different education levels are similarly substitutable with capital. Moreover, this classification allows me to relate the findings here to those of Katz and Murphy (1992), Krusell et al. (2000), Card and Lemieux (2001), and Autor and Dorn (2013), who also define high-skill labor using college-educated workers.

Table 1 shows the responses of high- and low-skill employment and earnings to the US shale boom, using the specification in equation (9). Looking first at columns (1) to (3) in Panel (b), the effect of fracking on employment in non-manufacturing sectors varied significantly across skill groups. While both high- and low-skill workers' employment increases, the increase is larger for low-skill workers (0.109 vs 0.080). As a result, a 10 percent increase in horizontal wells significantly increased the low- to high-skill employment ratio outside of manufacturing by a significant 0.30 percent.[12]

Columns (4) to (6) highlight how these differential effects on different types of labor demand translated into relative changes in labor input prices. Columns (4) and (5) show that the average earnings of low-skill workers increased more than those of high-skill workers in response to fracking. As a consequence, the earnings gap between low- and high-skill workers

[12] The differential effects on employment and earnings in the non-manufacturing sector are driven by a larger increase in labor demand from low-skill-intensive industries (construction, transportation, etc.) with higher wages rather than a change in relative demand or prices within each of these industries. This is shown in Table A.1. Within industries, there is no change in the relative demand and little change in the relative price for low- and high-skill labor.

Table 1: The Impact of Fracking on Relative Employment, Earnings

Panel a: All Sectors						
	$\Delta lnEmp_L$	$\Delta lnEmp_H$	$\Delta ln\frac{Emp_L}{Emp_H}$	$\Delta lnEarn_L$	$\Delta lnEarn_H$	$\Delta ln\frac{Earn_H}{Earn_L}$
$\Delta lnTotWells$	0.112***	0.086***	0.025***	0.059***	0.038***	-0.022**
	[0.019]	[0.018]	[0.008]	[0.010]	[0.011]	[0.008]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	170,541	170,541	170,541	170,541	170,541	170,541
KP F-Stat	103.19	103.19	103.19	103.19	103.19	103.19
Counties	3,005	3,005	3,005	3,005	3,005	3,005
Panel b: Non-Manufacturing						
	$\Delta lnEmp_L^{NM}$	$\Delta lnEmp_H^{NM}$	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$
$\Delta lnTotWells$	0.109***	0.080***	0.030***	0.074***	0.046***	-0.027***
	[0.018]	[0.016]	[0.008]	[0.010]	[0.011]	[0.008]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	158,442	159,169	156,324	158,178	157,400	156,195
KP F-Stat	102.12	100.62	100.67	102.18	101.52	100.73
Counties	2,922	2,966	2,890	2,897	2,892	2,873

Note: Table 1 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (9). Panel (a) includes data from all sectors in the estimation. Panel (b) uses data from all sectors except manufacturing. The outcomes (in logs) are low-skill employment, high-skill employment, relative low-to-high-skill employment, low-skill earnings, high-skill earnings, and relative high-to-low-skill earnings, respectively."KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

significantly declined. As shown in column (6), a 10 percent increase in horizontal wells reduced the low- to high-skill average earnings gap outside of manufacturing by 0.27 percent.

For additional robustness, in Table A.2, I show the estimated effects of fracking on relative employment and earnings using the long-differences empirical strategy in equation (11). I do this to remain consistent with the results below on manufacturing capital expenditures and value added, whose data structure only permits the use of long differences. The use of long differences does not affect the conclusions derived from Table 1. The point estimates remain unchanged and maintain similar significance levels. Panel (b) of Table 1 restricts the sample to counties with information on manufacturing value added and capital expenditures in the EC. The results in Panel (b) still provide identical conclusions, even if the point estimates for the *absolute* changes (not the relative changes) are somewhat smaller.[13]

In summary, Tables 1 and A.2 strongly indicate that fracking increased the relative

[13] Counties with available data on capital expenditures and value added in manufacturing tend to be larger. Therefore, they are less likely to have their local labor markets disrupted by the shale boom because it represents a potentially smaller shock relative to the county's economy. This could explain why the results in Panel (b) are slightly more muted in absolute terms.

demand for low-skill labor in fracked counties, raising its relative price. This allows me to use the US shale boom as a source of exogenous variation in input prices for the manufacturing sector and test for capital-skill complementarity.

However, the results in Section 5.1 also highlight that one of the assumptions of the model is not satisfied in the data. The model assumes that, in response to the shock, the labor supply does not change. On the other hand, the estimates in the data indicate that fracked counties saw increases in employment, labor force participation, and population.

To address this issue, I expand the empirical model in equation (9) when analyzing the responses of the manufacturing sector to fracking. Specifically, I include controls for the overall change in low- and high-skill employment at the county level in the specification. This allows me to compare manufacturers in fracked and non-fracked counties where the aggregate labor supply grew similarly and, thus, from the perspective of the model, hold the labor supply constant.[14]

Two assumptions underpin this updated empirical strategy so that I can still interpret the results as the causal effect of fracking on manufacturing and use them to assess its degree of capital-skill complementarity. First, I am assuming that aggregate changes in employment at the county level are not driven by the manufacturing sector. A different way to read this assumption is that the local manufacturing sector was small enough that its evolution did not determine the evolution of local aggregated employment in any local area (fracked or not). A comparison of Panels (a) and (b) of Table 1 shows that this assumption is consistent with the data. Including or excluding the manufacturing sector from the estimation of the relative/absolute effects of fracking on the local labor market leaves the conclusions unchanged.

Second, I am assuming that changes in local manufacturing product demand were identical in areas where the supply of low- and high-skill labor was growing similarly, regardless of whether the area was exposed to fracking. Note that it is not possible to directly test this assumption by analyzing the effects of fracking on local manufacturing value added. The

[14]While it is possible to extend the model to incorporate this feature, I do not take this route. The reason is that, from the perspective of the model, it is irrelevant whether the lack of changes in labor supply arises because I am comparing fracked counties against counties with similar changes in labor supply or because the shock simply had no effects on labor supply.

reason is that, in the model, manufacturing product demand is held constant, and output weakly declines in response to the shock. Therefore, an estimate of the effects of fracking on manufacturing value added will be a combination of the effects of fracking on manufacturing product demand and output. Without having a direct measure of manufacturing product demand, it is not positive to separate one effect from the other.

In summary, the results in Tables 1 and A.2 indicate that the US shale boom represented an exogenous change in manufacturing relative input prices. By comparing manufacturers in fracked and non-fracked areas with similar labor supply growth, I can assess whether the responses of manufacturing firms to fracking are consistent with capital-skill complementarity in a way that remains consistent with the modeling assumptions.

5.3 Manufacturing's Response to Horizontal Fracking in the Local Labor Market

Table 2 shows the estimated effects of fracking on relative employment and earnings in manufacturing. Panel (a) shows the results without including any additional controls (discussed in Section 7), while Panel (b) adds controls for aggregated growth in low- and high-skill employment in the local labor market. I focus here on the results in Panel (b) because, as discussed above, they more closely align with the assumptions of the model.

Column (1) of Table 2 shows that, compared to areas where employment was growing similarly, fracked areas saw manufacturing employment decline. In other words, while fracking significantly increased employment in general, the growth it created in the manufacturing sector was significantly smaller than what would have been expected, given the strong total employment growth of the local labor market. Furthermore, all the negative effects on employment arose through a decline in low-skill labor employment. As shown in columns (2) and (3), compared to areas growing similarly, manufacturers in fracked areas saw a significant decline in low-skill labor employment while seeing no changes in their usage of high-skill labor. As a consequence, relative to areas with similar employment growth, fracking significantly reduced local manufacturing's relative low-skill employment. A 10 percent increase in the number of total horizontal wells decreased employment in manufacturing by 0.73 percent, low-skill manufacturing employment by 0.77 percent, and the low- to high-skill employment ratio in manufacturing by 0.48 percent. Finally, the effects of fracking on relative wages in manufacturing (column (6)) follow those estimated for the local labor market (column (6) of Table 1), even if the larger standard errors render the point estimate insignificant.

Table 2 allows me to estimate the short-run elasticity of substitution between low- and high-skill labor under perfect competition. My preferred estimate, using the moments in Panel (b), is 2.4. Compared to the previous literature, my estimate is slightly larger, even if it remains within a reasonable range. In a meta-study analyzing work produced between 1970 and 2015, Havranek et al. (2020) find a mean elasticity of substitution between low- and high-skill labor of 2.2. For manufacturing, their mean estimate is lower, at 1.2.[15]

The results in Table 2 are robust to alternative specifications and different sample restrictions. Table A.3 shows equivalent estimates using the long-differences empirical strategy. The estimated responses of relative employment and earnings in manufacturing remain unchanged compared to those in Table 2. Panel (b) of Table A.3 restricts the sample to counties with data on manufacturing value added and capital expenditures in the Economic Census. Within this sample of counties, the results still remain very similar to the estimates reported in Table 2.

Next, I move to estimate the effects of fracking on manufacturing capital utilization and value added. Unfortunately, the EC only provides data on manufacturers' capital expenditures but not on capital stocks at the county level. Therefore, this section analyzes the responses of capital expenditures to the US shale boom. Since I am only interested in the signs and statistical significance of these responses, I will treat the responses of capital expenditures as equivalent to those of capital. An additional issue is that the data on capital expenditures at this level of disaggregation are not available for 2017. To circumvent this limitation, I use the data from 2002 to 2012 at the county level to estimate the association between capital expenditures and other covariates in the EC. I restrict my estimation sample to counties with at least two observations on capital expenditures between 2002 and 2012 to include county fixed effects in the estimation. The results of this exercise are shown in Table A.4, whose main takeaway is an R^2 of 0.91. Using the estimated coefficients from Table A.4 and the

[15] It is not uncommon to find estimates larger than 2.5 or smaller than 1. For instance, Bils et al. (forthcoming) estimate a lower bound of 4 for the long-run elasticity of substitution.

Table 2: The Impact of Fracking on Relative Employment, Earnings: Manufacturing

Panel a: Manufacturing							
	$\Delta lnEmp^M$	$\Delta lnEmp_L^M$	$\Delta lnEmp_H^M$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta lnEarn_L^M$	$\Delta lnEarn_H^M$	$\Delta ln\frac{Earn_H^M}{Earn_L^M}$
$\Delta lnTotWells$	0.053	0.044	0.091***	-0.034**	0.025**	0.006	-0.018
	[0.033]	[0.031]	[0.034]	[0.015]	[0.012]	[0.018]	[0.014]
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	162,161	158,268	157,400	156,207	158,178	157,400	156,195
KP F-Stat	102.38	102.11	101.52	100.73	102.18	101.52	100.73
Counties	2,938	2,906	2,892	2,874	2,897	2,892	2,873
Panel b: Manufacturing. Controls for Changes in Agg. High- and Low-Education Employment							
	$\Delta lnEmp^M$	$\Delta lnEmp_L^M$	$\Delta lnEmp_H^M$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta lnEarn_L^M$	$\Delta lnEarn_H^M$	$\Delta ln\frac{Earn_H^M}{Earn_L^M}$
$\Delta lnTotWells$	-0.073**	-0.077**	-0.013	-0.048***	0.025**	0.005	-0.020
	[0.033]	[0.031]	[0.033]	[0.015]	[0.012]	[0.018]	[0.014]
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	162,161	158,268	157,400	156,207	158,178	157,400	156,195
KP F-Stat	101.15	101.02	100.58	99.79	101.09	100.58	99.79
Counties	2,938	2,906	2,892	2,874	2,897	2,892	2,873

Note: Table 2 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (9). Panel (a) does not include controls for aggregate low- and high-skill employment growth at the county level, while Panel (b) does. The outcomes (in logs) are total manufacturing employment, low-skill manufacturing employment, high-skill manufacturing employment, relative low-to-high-skill manufacturing employment, low-skill manufacturing earnings, high-skill manufacturing earnings, and relative high-to-low-skill manufacturing earnings, respectively."KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

county fixed effects (not shown), I predict the 2017 capital expenditures only for the counties with at least two prior observations on capital expenditures. Nevertheless, I also restrict the estimation to just the observed data between 2002 and 2012 for additional robustness (see Table A.11).

Table 3 presents the estimated responses of capital expenditures and value added in the manufacturing sector to the shale boom. Column (1) uses all the available data on manufacturers in the EC. Column (2) restricts the sample to counties with information not only on capital expenditures but also on value added. Column (3) uses the same sample as column (2) but adds controls for the change in aggregate high- and low-skill employment in the county. The specification in column (3) allows me to remain consistent with the assumptions of the model.

The results in column (3) of Panel (a) indicate that horizontal fracking significantly increased manufacturers' capital expenditures. Relative to areas with similar aggregate high- and low-skill employment growth, a 10 percent increase in the number of horizontal wells

Table 3: The Impact of Fracking on Manufacturers' Capital Expenditures, Revenues, and Capital to Output Ratios: Long Differences

Panel a: Capital Expenditures			
	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$
$\Delta lnTotWells$	0.206**	0.315**	0.275**
	[0.100]	[0.127]	[0.130]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	3,983	3,211	3,146
KP F-Stat	44.15	34.19	31.29
Counties	1,407	1,128	1,116
Sample	All	Restricted	Restricted
Panel b: Value Added			
	$\Delta lnValAdd$	$\Delta lnValAdd$	$\Delta lnValAdd$
$\Delta lnTotWells$	0.023	0.022	-0.041
	[0.067]	[0.063]	[0.067]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	3,868	3,211	3,146
KP F-Stat	33.77	34.19	31.29
Counties	1,338	1,128	1,116
Sample	All	Restricted	Restricted
Panel c: Capital Expenditures to Value Added Ratio			
		$\Delta ln\frac{CapEx}{Rev}$	$\Delta ln\frac{CapEx}{Rev}$
$\Delta lnTotWells$		0.293**	0.326**
		[0.132]	[0.142]
Ctrls. $\Delta lnEmp_{L,H}$		No	Yes
County FE		Yes	Yes
Time FE		Yes	Yes
On Shale LT		Yes	Yes
N		3,211	3,146
KP F-Stat		34.19	31.29
Counties		1,128	1,116
Sample		Restricted	Restricted

Note: Table 3 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (11). In Panel (a), the outcome is the log of manufacturing capital expenditures. In Panel (b), the outcome is the log of manufacturing value added. In Panel (c), the outcome is the log of the ratio between manufacturing capital expenditures and value added. "Ctrls. $\Delta lnEmp_{L,H}$": Whether the estimation includes controls for aggregate low- and high-skill employment growth at the county level. "KP F-Stat": F-statistic of the first-stage IV regression. "Counties": Number of unique counties included in the estimation. "Sample = All": The estimation sample includes all counties with information on the outcome. "Sample = Restricted": The estimation sample only includes counties with information on the opposite (i.e., capital expenditures or value-added) outcome. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

increased capital expenditures by 2.8 percent. Put differently, the average 5-year growth rate in the total number of horizontal wells in fracking counties with information on the change in capital expenditures was 94 percent.[16] This translates into fracking increasing manufacturers' capital expenditures by roughly 26 percent over an average 5-year period.

[16]The average growth rate across counties with at least 1 horizontal well spudded by 2017 for the period 2002 to 2007, 2007 to 2012, and 2012 to 2017.

Panel (b) presents the estimated responses of manufacturing value added. The results in column (3) indicate that a 10 percent increase in horizontal wells decreased manufacturing value added by an insignificant 0.4 percent. Thus, over the average 5-year period, manufacturers in fracking areas saw an insignificant decline in value added of approximately 4 percent relative to manufacturers in counties with similar aggregate low- and high-skill employment growth.

Panel (c) combines the above results and shows the response of the capital expenditures to value added ratios. In column (3), I estimate that a 10 percent increase in horizontal wells increased the capital expenditures to output ratio by 3.3 percent. Using the average 5-year growth in horizontal wells, fracking is estimated to have increased the capital to output ratio of local manufacturing firms by roughly 31 percent.[17]

5.4 IV Validity

To test the validity of the IV empirical strategy, I use data from the period between 1995 and 2003, before the horizontal fracking boom. The idea is to assess whether the instrument correlates with different outcome changes before the shale boom. If that were the case, then the IV empirical strategy presented above would be compromised.

Following the ideas in Mitaritonna et al. (2017), I start by estimating whether changes in outcomes during the period before the fracking boom are correlated with future changes in the value of the instrument. To do this, for each county quarter observation, I assign a value of the change in the instrument from a series of years after. Complete coverage of the pre-period with the instrument allows me to shift back the instrument any number of years between 9 and 14.[18] Because there is no clear reason to choose a specific number of years to shift back the instrument, I use all possible combinations and stack them together for the estimation, following the specification in equation (12).[19] For additional robustness, in Table

[17]Table A.11 re-estimates these results using only data for 2002, 2007, and 2012. Removing the predicted data for 2017 reduces the number of observations per county to two, which renders the instrument weak. Therefore, the results in Table A.11 are estimated after removing the differential growth trends for on- and off-shale counties. The point estimates remain very similar regardless of whether I include or exclude the data from 2017, even if the standard errors increase when 2017 is removed.

[18]If the instrument is shifted back 9 years, changes in the outcomes in 1995 (2003) would be mapped to changes in the instrument in 2004 (2012).On the other hand, shifting the instrument back 14 years would connect changes in the outcomes in 1995 (2003) to changes in the instrument in 2009 (2017).

[19]I cluster the standard errors at the county level so that the introduction of duplicate observations does not

A.5, I estimate these same results for each possible shift backward of the instrument (from 9 years to 14 years) separately.

$$\Delta_{4Q} \widehat{lnTotWells_{i,t+Lag}} = \boldsymbol{\alpha \Delta_{4Q}} Y_t + \kappa_t + \theta_i + S_i \times t + \epsilon_{it} \tag{12}$$

In equation (12), t ranges from the first quarter of 1995 to the last quarter of 2003. $Lag \in \{36, 40, 44, 48, 52, 56\}$ represents the number of quarters the instrument is shifted backward (from 9 to 14 years). $\boldsymbol{Y_t}$ is a vector of county outcomes that contains all outcomes analyzed above in the results. Therefore, it includes the change in the employment and earnings in the aggregate, as well as the changes in employment and earnings of low-skill labor (in manufacturing and in all other sectors). Similarly, it also contains the change in the low- to high-education employment ratio and earnings gap in manufacturing and in all other sectors. Changes in high-skill employment and earnings (in manufacturing and outside of manufacturing) are not included because, by construction, they are collinear with the variables already included.

The results of this exercise are shown in Panel (a) of Table 4. I find no relationship between pre-shale outcome changes and future changes in the instrument. Thus, the F-statistic of this specification is 1.43, insignificantly different from zero at all confidence levels.[20] An equivalent test using the data on manufacturing capital expenditures and value added for the pre-period is shown in Panel (b). It uses data from the EC for 1992, 1997, and 2002 and follows the specification described above using 5-year differences in outcomes and covariates. All point estimates are insignificant and very close to zero, indicating no correlation between pre-shale manufacturing outcome changes and future changes in the instrument. The F-statistic is 0.09, insignificantly different from zero.[21]

Tables A.7 and A.8 explore whether a less demanding empirical specification than the

bias the estimates of the standard errors.

[20]Replicating this same estimation for each possible shift backward of the instrument (from 9 years to 14 years) separately shows that 5 of the 6 possible shifts to the instrument have an F-statistic insignificantly different from zero at the 95 percent confidence level. These results are shown in Table A.5.

[21]Table A.6 replicates these same results for each possible shift backward of the instrument separately. The results show no positive associations between the future values of the instrument and manufacturing value-added and capital expenditures in the pre-period.

Table 4: Test of Pre-Trends:
Correlation between Future Changes in the Instrument and Pre-Shale Changes in Outcomes

Panel a: Employment and Earnings		Panel b: Manufacturers' Capital Expenditures and Value Added	
	$\Delta_{4Q}\widehat{lnTotWells}$		$\Delta_{5Y}\widehat{lnTotWells}$
$\Delta_{4Q}lnEmp_L^M$	-0.0005	$\Delta_{5Y}lnCapEx$	-0.0003
	[0.0006]		[0.0010]
$\Delta_{4Q}ln(Emp_L^M/Emp_H^M)$	0.0003	$\Delta_{5Y}lnValAdd$	-0.0004
	[0.0006]		[0.0019]
$\Delta_{4Q}lnEarn_L^M$	-0.0004		
	[0.0007]		
$\Delta_{4Q}ln(Earn_L^M/Earn_H^M)$	-0.0001		
	[0.0003]		
$\Delta_{4Q}lnEmp_L^{NM}$	-0.0002		
	[0.0020]		
$\Delta_{4Q}ln(Emp_L^{NM}/Emp_H^{NM})$	-0.0021*		
	[0.0012]		
$\Delta_{4Q}lnEarn_L^{NM}$	0.0019		
	[0.0016]		
$\Delta_{4Q}ln(Earn_L^{NM}/Earn_H^{NM})$	0.0002		
	[0.0006]		
$\Delta_{4Q}ln$Emp	-0.0013		
	[0.0024]		
$\Delta_{4Q}ln$Earnings	-0.0006		
	[0.0017]		
County FE	Yes	County FE	Yes
Time FE	Yes	Time FE	Yes
On Shale LT	Yes	On Shale LT	Yes
N	338,886	N	15,695
F-Stat	1.43	F-Stat	0.09
Counties	2,713	Counties	1,672

Note: Table 4 tests the validity of the IV empirical strategy in the data pre-fracking boom using equation (12). In both panels, the outcome is the future change in the value of the instrument (see text for details). In Panel (a) all the included covariates are outcomes related to employment and earnings in the pre-shale boom period. In Panel (b) the included covariates are manufacturer's capital expenditures and value-added in the pre-shale boom period. "F-Stat": F-statistic of joint significance of all the covariates included in the regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

one proposed in this paper could also satisfy the exclusion restriction. The main takeaway is that the exclusion restriction is only satisfied using a specification in changes that includes county fixed effects and differential trends for on- and off-shale counties.

An alternative approach to test the validity of the instrument is to re-estimate the main specification of the paper, in equation (9), changing the outcome to that same variable in the period pre-shale boom. This results in the following estimation equation:

$$\Delta_{4Q}Y_{i,t} = \beta_1 \Delta_{4Q}\widehat{lnTotWells}_{i,t+Lag} + \boldsymbol{\beta X_t} + \kappa_t + \theta_i + S_i \times t + \epsilon_{i,t} \tag{13}$$

where t ranges from the first quarter of 1995 to the last quarter of 2003, and Lag represents the number of quarters the instrument is shifted backward. As before, I stack together all potential lags of the instrument (i.e., the instrument lagged by 9, 10, 11, 12, 13, and 14 years) for the estimation.

The results are shown in Table A.9 for all variables related to employment and earnings and in Table A.10 for the variables related to manufacturers' capital expenditures and value added. I find that future changes in the instrument have very little predictive power in explaining changes in my outcomes of interest in the period before the fracking boom. Of the 26 estimates in Table A.9, only 4 are significantly different from zero at the 90 percent confidence level and only 1 at the 95. The only minor difference appears to be related to the evolution of low-skill employment in the non-manufacturing sectors. The IV variation in fracking intensity is slightly correlated with a county having a slightly lower trend growth in low-skill employment outside of the manufacturing sector pre-shale boom. In the case of the results regarding manufacturers' capital expenditures and value added, in Table A.10, all point estimates are insignificant and very close to zero.

In summary, the results in this section confirm the validity of the IV variable strategy used above. I find that after using annual differences and controlling for county fixed effects and differential trends on and off shale, future changes in the instrument are uncorrelated with pre-shale changes in my outcomes of interest.

6 Testing for Capital-Skill Complementarity

To assess whether the predictions of the model are satisfied in the data, I use the results controlling for the county's aggregate change in low- and high-skill employment. This allows me to remain consistent with the assumptions of the model. According to the model, two responses are key to determining the existence of capital-skill complementarity. First, the response of capital in manufacturing to a change in productivity in the oil-related sector must be positive. Second, the response of output must be weakly negative. Column (3) in Panels (a) and (b) of Table 3 shows that this is exactly the case in the data. The response of capital expenditures in manufacturing to the shale boom is large, positive, and significant, while the response of output is slightly negative and insignificant.

Furthermore, the predictions on absolute and relative employment and wages that we observe in the data are also consistent with the predictions of the model. The model predicts a decline in manufacturing employment, which is shown in column (1) of Panel (b) of Table 2. This decline should be driven primarily by a large decline in low-skill employment, which should lower relative low-skill employment in manufacturing. These predictions are consistent with the results in columns (2) to (4) of Panel (b) of Table 2. Finally, the model predicts the relative wage of low-skill labor should increase. This is consistent with the findings in column (7) of Panel (b) of Table 2.

In summary, all the predictions of the model appear to be satisfied by the estimated moments in the data. In combination, these results suggest that the manufacturing sector in the 21st century still shows an important degree of capital-skill complementarity.

6.1 Alternative Low- and High-Skill Classifications

A key aspect of accurately assessing the degree of capital-skill complementarity in manufacturing is correctly determining what constitutes low- and high-skill labor. This paper defines workers with at least a college degree as high-skill and all other workers as low-skill. However, this is not the only possible choice. Previous work (Ciccone and Peri (2005); Lewis (2011)) has used alternative classifications, where high-skill labor included workers with less than a college degree.

The results of this paper suggest that only workers with a college degree or more should be included as high-skill labor. To see this, note that equation (3) indicates that manufacturing capital utilization should increase in response to a change in productivity in the oil-related sector if and only if $\theta > \alpha$. The previous empirical results show that capital expenditures in manufacturing increase significantly in response to the shale boom, indicating that $\theta > \alpha$.

If $\theta > \alpha$, equation (6) states that manufacturing's low- to high-skill employment ratio must decline in response to a productivity shock in the oil-related sector. However, as discussed in Appendix C, this is not satisfied in the data when high-skill labor also includes workers with some college or associate degrees. Table C.1 estimates the effects of the US shale boom on relative labor prices and relative employment in manufacturing using an alternative classification of low- and high-skill labor. In Table C.1, I classify workers with a high school education or less as low-skill and all other workers as high-skill. Using this classification system, columns (1) and (4) show that the shale boom still raised the relative demand for low-skill labor outside of manufacturing, increasing its relative price. However, as shown in column (6), manufacturers did not substitute away from low-skill labor.

Therefore, classifying workers with some college or associate degrees as high-skill labor leads to a contradiction from the perspective of the model. The positive response of capital expenditures in manufacturing to the shock implies that $\theta > \alpha$, while the lack of response of relative employment in manufacturing indicates that $\theta < \alpha$.

When combined with the findings of the previous literature, these results have implications for the understanding of the evolution of capital-skill complementarity over the last few decades. Lewis (2011) shows that during the 1980s, the type of labor that was more easily substitutable with capital in manufacturing was that of workers with less than a college degree. On the other hand, this paper argues that any workers with less than a college degree are similarly easily substitutable with capital. In combination, this suggests that the degree of skill that is substitutable with capital has increased over the last 40 years.

6.2 Testing for Capital-Skill Complementarity Using Alternative Manufacturing Production Functions

The approach used in Section 3 to model production in manufacturing so that it allows for capital-skill complementarity is not unique. For instance, an alternative is that proposed in Krusell et al. (2000):

$$Y_m = A_m K_{s,m}^{\alpha} (\mu L_m^{\sigma} + (1-\mu)[\lambda K_{e,m}^{\rho} + (1-\lambda) H_m^{\rho}]^{\frac{\sigma}{\rho}})^{\frac{1-\alpha}{\sigma}}, \tag{14}$$

where K_s represents capital in structures, and K_e is capital equipment. μ and λ govern the income shares, and σ and ρ (both smaller than one) determine the elasticity of substitution between unskilled labor and capital equipment and skilled labor and capital equipment (for additional details, see Krusell et al. (2000)). Capital-skill complementarity using this model requires $\sigma > \rho$.

There are two main differences between my main model and this alternative one (beyond the introduction of two separate types of capital here). First, each model imposes a different CES nesting of capital (in equipment), low-skill labor, and high-skill labor. While the main model's manufacturing production function forces the elasticity of substitution between low-skill labor and high-skill labor to be identical to that between capital and high-skill labor, Krusell et al.'s (2000) does the opposite. It forces the elasticity of substitution between capital equipment and low-skill labor to be identical to that between high-skill labor and low-skill labor. Second, the differences in the CES nesting translate into differences in the interpretation of each model. In the alternative model, capital is truly complementary to high-skill labor. This means that an increase in capital equipment utilization increases the productivity of high-skill workers, raising their wages. This is not the case in the main model, where capital does not complement high-skill labor but instead allows manufacturers to more easily substitute low-skill labor with capital. Therefore, an increase in capital utilization in manufacturing in the main model will not increase the productivity of high-skill workers and should not translate into higher high-skill wages.

Using this alternative model, it is possible to directly test for capital-skill complementarity using the responses of relative wages, manufacturing relative employment, and manufacturing capital equipment to a change in productivity in the oil-related sector:

$$\frac{\frac{\mathrm{d}ln\frac{w_H}{w_L}}{\mathrm{d}A_o} - (1-\sigma)\frac{\mathrm{d}ln\frac{L_m}{H_m}}{\mathrm{d}A_o}}{E\frac{\mathrm{d}K_{e,m}}{\mathrm{d}A_o}} = (\sigma - \rho) > 0 \tag{15}$$

where E is: $(K_{e,m}/H_m)^{\rho-1}/H_m[(1-\lambda)+\lambda(K_{e,m}/H_m)^{\rho}] > 0$.[22] Equation (15) links the existence of capital-skill complementarity to the signs of three moments directly estimable in the data. However, it does so by imposing certain restrictions on the value of σ. In other words, it answers the question of whether there is capital-skill complementarity in the manufacturing sector for a given elasticity of substitution between low-skill labor and capital.[23]

[22] Under the assumptions in Section 3, equation (15) can further be reduced to: $\mathrm{d}ln(w_H/w_L)/\mathrm{d}A_o - (1-\sigma)\mathrm{d}lnL_m/\mathrm{d}A_o = (\sigma-\rho)E\mathrm{d}K_{e,m}/\mathrm{d}A_o$. I proceed with the expression in the main text because, when taken to the data, it imposes less restrictive assumptions about selection in and out of manufacturing.

[23] It is possible to point estimate σ and ρ directly by combining equation (15) with the following expression: $\rho = 1 - \mathrm{d}lnw_H/\mathrm{d}lnK_{e,m}$. However, point identification of these parameters requires data on capital equipment

Since the estimated response of capital expenditures to fracking is positive and significant, the existence of capital-skill complementarity simply requires the numerator of equation (15) to be positive.[24] My preferred estimates of $\mathrm{d}ln(w_H/w_L)/\mathrm{d}A_o$ and $\mathrm{d}ln(L_m/H_m)/\mathrm{d}A_o$ are -0.020 and -0.048, from columns (7) and (4) of Panel (b) of Table 2. Using these two values, equation (15) indicates that any value of σ smaller than 0.58 satisfies the inequality and would be consistent with capital-skill complementarity in the data.[25] Since capital-skill complementarity in this model implies $\sigma > \rho$, then ρ must also be smaller than 0.58. Values of σ and ρ smaller than 0.58 are consistent with the findings of Krusell et al. (2000), who estimate $\sigma = 0.4$ and $\rho = -0.5$. Similarly, these values are also consistent with subsequent estimations of these same parameters in more recent years (see Maliar et al. (2022), Castex et al. (2022) and Ohanian et al. (2023)).

However, the fact that the data appear consistent with the existence of capital-skill complementarity using this production function does not imply that the data are consistent with the structure of the model in other dimensions. To see this, note that it is possible to express the response of manufacturing capital equipment to a change in productivity in the oil-related sector as: $\mathrm{d}ln(K_{e,m})/\mathrm{d}A_o = 1/(1-\rho)\mathrm{d}ln(w_H)/\mathrm{d}A_o$. Because capital and high-skill labor are true complements in this model, high-skill wages and capital must move in the same direction in response to a productivity shock in the oil-related sector. However, the estimated responses in the data are not consistent with this prediction. I find a positive and significant response of capital expenditures in manufacturing to the fracking boom, but I also estimate a small, insignificant decline in high-skill wages in manufacturing.

While this result could indicate that the nesting used in Krusell et al. (2000) is not

(not capital expenditures) and assumptions about selection that do not seem to be satisfied in the data. For these reasons, I do not pursue it and instead restrict myself to testing for the existence of capital-skill complementarity using only equation (15).

[24] I am assuming that the sign of the response in capital expenditures and capital equipment is identical. According to the FRB Estimates of Manufacturing Investment, Capital Stock, and Capital Services, over my period of interest, real investment in capital equipment (equipment plus software) represented 87 percent of all manufacturing real investment. Further, it did not vary much across different four-digit manufacturing subsectors (FRB Estimates of Manufacturing Investment, Capital Stock, and Capital Services) or US states (Annual Surveys of Manufactures). Given the large share of investment that capital equipment investment represents and the homogeneity of this estimate over sub-industries and space, it seems very unlikely that the sign of the former response is different from the sign of the latter.

[25] A value of σ smaller than 0.58 implies that the elasticity of substitution between low-skill labor and capital must be smaller than 2.4.

consistent with manufacturing production, it is also possible that this prediction is not satisfied because of selection in and out of manufacturing within high-skill workers. The response of high-skill wages to fracking is only interpretable from the lens of the model under the assumption that fracking does not affect the selection into manufacturing within high-skill workers. If, in response to fracking, the best high-skill workers leave manufacturing, my estimates of the effect of fracking on high-skill wages in manufacturing will be biased.

The issues related to selection are not exclusive to the responses used for this specific prediction. They could also be present when taking to the data any other predictions of this model or the main model. However, all other predictions outlined above use the responses of relative wages as inputs, whose interpretation under the lens of the model requires less stringent assumptions about selection. When using relative earnings as inputs, the required assumption is that within-group selection in and out of manufacturing is identical in both high- and low-skill groups. This assumption is significantly less restrictive than the assumption required when using the change in earnings of one of these groups as the input, which requires no within-group selection in and out of manufacturing in response to the shock. Further, the estimated responses of wages in manufacturing and outside of manufacturing suggest that the former assumption may be reasonable and the latter may be unrealistic. I find that relative wages in manufacturing and outside manufacturing respond equivalently to the fracking boom. This would be consistent with selection into (or out of) manufacturing being identical in high- and low-skill groups in response to the shock. On the other hand, the estimated responses to the fracking boom of high- and low-skill wages in manufacturing do not follow those of the rest of the local labor market. This suggests that assuming no-within-group selection into manufacturing in response to the shock could be inappropriate.

Beyond selection, it is possible that the predictions from the alternative model are not satisfied because, in response to fracking, manufacturing firms are also changing additional aspects of their production that both models assume remain constant. One example arises if the manufacturing production function itself responds to fracking. This would translate into fracking affecting the parameters θ, α, λ, μ, σ, or ρ, whose response to fracking is assumed to be zero throughout this paper.

7 Interpreting the Empirical Results through the Lens of the Dutch Disease

The "Dutch disease" refers to the possibility of a natural resource boom crowding out manufacturing in the short run, reducing its employment and output. This short-term crowding-out could ultimately affect the local manufacturing sector's long-run productivity and output due to the potential learning-by-doing spillovers. The premise under which the Dutch disease starts is that a natural resource boom increases the price of labor in the local labor market. Because manufacturing produces tradeable goods, manufacturers located in impacted areas cannot raise prices. This results in a local manufacturing sector whose employment and output decline in response to the local boom. Previous work refers to this as a short-run crowding-out of the local manufacturing sector.

The empirical results of this paper allow me to test whether the conditions that could start the Dutch disease were present during the US shale boom. Here, I focus on the empirical results without controls for aggregate low- and high-skill employment growth. The reason is that the starting point of the Dutch disease is the crowding out of local manufacturing relative to areas not exposed to the natural resource boom and not relative to unexposed areas with similar employment growth during the boom.

First, I find no evidence of manufacturing losing employment as a consequence of the US shale boom. This is shown in column (1) of Panel (a) of Table 2. Local manufacturing employment was unaffected by fracking. Second, I find no evidence of local manufacturing output declining in response to fracking. As shown in columns (1) and (2) of Panel (b) of Table 3, local manufacturing value added saw no changes in response to fracking. Therefore, I find no evidence of the US shale boom generating any effects on local manufacturing that satisfy the hypothesis under which the Dutch disease could unravel.

While the previous literature also finds that natural resource booms during the 20th century did not satisfy the premise to start a local Dutch disease, the reasons differ between this paper and previous work. In Michaels (2011) and Allcott and Keniston (2018)), who study natural resource booms during the 1900s, local resource booms directly increase local manufacturing product demand. This is not the case in this paper, where I find no evidence of the shale boom changing the product demand of local manufacturing firms. On the other hand, my results indicate that local manufacturers avoided the increase in input prices fracking created by substituting away from inputs whose price had increased (low-skill labor) toward capital. Thus, it was the ability of manufacturers to endogenously change their input mix that avoided the possible starting point of the Dutch disease during the US shale boom.

8 Conclusion

This paper confirms the existence of capital-skill complementarity in the US manufacturing sector during the 21st century. I use exogenous variation in the relative price of labor inputs created by the US shale boom and find that manufacturers respond to these changes by substituting low-skill labor with capital. This allows them to maintain value added and circumvent the starting premise of the Dutch disease. In combination with the findings of the previous literature, my results indicate that the degree of skill substitutable with capital in manufacturing has increased over the last few decades.

This paper still leaves open several questions about the substitutability of low-skill labor with capital in manufacturing. What types of tasks does it replace? What types of occupations? Does it create new, previously non-existent jobs? What are the long-run implications of these endogenous changes in the input mix? Most of these questions could be further advanced using employer-employee data and information on the types of technologies used by manufacturers.

Finally, this paper highlights that despite the intense scrutiny the US shale boom has received in the literature, some of its potential effects may still remain undiscovered. The shock's almost quasi-natural experimental nature may make these unknown effects useful in the study of more general questions in economics.

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Appendix

A Additional Tables

Table A.1: The Impact of Fracking on Relative Employment, Earnings: Non-Manufacturing within Industry Changes

	$\Delta lnEmp_L$	$\Delta lnEmp_H$	$\Delta ln\frac{Emp_L}{Emp_H}$	$\Delta lnEarn_L$	$\Delta lnEarn_H$	$\Delta ln\frac{Earn_L}{Earn_H}$
$\Delta lnTotWells$	0.111***	0.099***	0.000	0.050***	0.044***	-0.005
	[0.016]	[0.015]	[0.005]	[0.006]	[0.008]	[0.005]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	2,222,418	2,397,330	2,170,945	2,210,554	2,397,323	2,162,324
KP F-Stat	98.84	100.27	98.30	98.54	100.27	98.09
Counties	3,005	3,005	3,005	3,005	3,005	3,005

Note: Table A.1 shows the effects of fracking on the outcomes displayed at the top of the columns, using industry-level data by county and quarter. These effects are estimated using a variation of equation (9) that additionally includes industry fixed effects. The outcomes (in logs) are low-skill employment, high-skill employment, relative low-to-high-skill employment, low-skill earnings, high-skill earnings, and relative high-to-low-skill earnings, respectively."KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.2: The Impact of Fracking on Employment, Relative Employment, Earnings: Non-Manufacturing Long Differences

Panel a: All Counties						
	$\Delta lnEmp_L^{NM}$	$\Delta lnEmp_H^{NM}$	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$
$\Delta lnTotWells$	0.126***	0.095***	0.035***	0.082***	0.053***	-0.026**
	[0.024]	[0.022]	[0.010]	[0.015]	[0.017]	[0.013]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	8,088	8,096	7,969	8,085	8,027	7,968
KP F-Stat	69.92	69.03	70.06	70.10	69.90	70.18
Counties	2,744	2,750	2,705	2,743	2,724	2,705
Panel b: Only Counties with Data on Capital Expenditure Changes in EC						
	$\Delta lnEmp_L^{NM}$	$\Delta lnEmp_H^{NM}$	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$
$\Delta lnTotWells$	0.073***	0.049***	0.024**	0.053***	0.025	-0.028**
	[0.016]	[0.018]	[0.010]	[0.012]	[0.018]	[0.014]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	3,910	3,910	3,910	3,910	3,910	3,910
KP F-Stat	43.94	43.94	43.94	43.94	43.94	43.94
Counties	1,395	1,395	1,395	1,395	1,395	1,395

Note: Table A.2 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (11). Panel (a) includes all counties with available data, while Panel (b) restricts the sample to counties with available information on capital expenditure changes. The outcomes (in logs) are non-manufacturing low-skill employment, non-manufacturing high-skill employment, relative low-to-high-skill non-manufacturing employment, non-manufacturing low-skill earnings, non-manufacturing high-skill earnings, and relative high-to-low-skill non-manufacturing earnings, respectively. "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.3: The Impact of Fracking on Employment, Relative Employment, Earnings: Manufacturing Long Differences

Panel a: All Counties					
	$\Delta lnEmp^M$	$\Delta lnEmp^M$	$\Delta ln\frac{Emp_L^M}{Emp_H^{NM}}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta ln\frac{Earn_L^M}{Earn_H^M}$
$\Delta lnTotWells$	0.072*	-0.079*	-0.025	-0.043**	-0.015
	[0.040]	[0.042]	[0.021]	[0.021]	[0.022]
Ctrls. $\Delta lnEmp_{L,H}$	No	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes
N	8,307	8,307	7,968	7,968	7,968
KP F-Stat	69.87	65.69	70.18	65.80	70.18
Counties	2,813	2,813	2,705	2,705	2,705
Panel b: Only Counties with Data on Capital Expenditure Changes in EC					
	$\Delta lnEmp^M$	$\Delta lnEmp^M$	$\Delta ln\frac{Emp_L^M}{Emp_H^{NM}}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta ln\frac{Earn_L^M}{Earn_H^M}$
$\Delta lnTotWells$	0.035	-0.054**	-0.025	-0.031**	-0.021
	[0.028]	[0.027]	[0.018]	[0.016]	[0.022]
Ctrls. $\Delta lnEmp_{L,H}$	No	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes
N	3,910	3,910	3,910	3,910	3,910
KP F-Stat	43.94	41.27	43.94	41.27	43.94
Counties	1,395	1,395	1,395	1,395	1,395

Note: Table A.3 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (11). Panel (a) includes all counties with available data, while Panel (b) restricts the sample to counties with available information on capital expenditure changes. The outcomes (in logs) are total manufacturing employment (x2), relative low-to-high-skill manufacturing employment (x2), and relative high-to-low-skill manufacturing earnings, respectively."Ctrls. $\Delta lnEmp_{L,H}$": Whether the estimation includes controls for aggregate low- and high-skill employment growth at the county level. "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.4: The Association Between Different Covariates and Capital Expenditures

	lnCapEx
lnRev	0.306***
	[0.099]
lnCosts	0.063
	[0.076]
lnPayroll_PW	-0.443**
	[0.195]
lnHours_PW	0.206
	[0.203]
lnEmp_PW	0.145
	[0.312]
lnPayroll	0.644***
	[0.225]
lnEmp	-0.048
	[0.312]
lnEstablishments	0.136
	[0.115]
County FE	Yes
Time FE	Yes
N	3,798
Adj R^2	0.91
Counties	1,452

Note: Table A.4 presents the coefficients of the association between capital expenditures and other covariates in the manufacturing sector. It uses Economic Census data from 2002 to 2012 at the county level. I restrict the estimation sample to counties with at least two observations on capital expenditures between the years 2002 and 2012 to include county fixed effects in the estimation. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.5: Test of Pre-Trends

Correlation between Future Changes in the Instrument and Changes in Outcomes in the Pre-period: Employment and Earnings

	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$
$\Delta_{4Q}lnEmp_L^M$	0.0002	-0.0001	-0.0020**	-0.0004	-0.0002	-0.0004
	[0.0011]	[0.0011]	[0.0010]	[0.0009]	[0.0011]	[0.0012]
$\Delta_{4Q}ln(Emp_L^M/Emp_H^M)$	0.0009	0.0003	0.0002	0.0000	0.0001	-0.0000
	[0.0009]	[0.0010]	[0.0008]	[0.0008]	[0.0009]	[0.0009]
$\Delta_{4Q}lnEarn_L^M$	0.0011	-0.0018	-0.0001	0.0002	-0.0011	-0.0004
	[0.0012]	[0.0016]	[0.0012]	[0.0010]	[0.0015]	[0.0010]
$\Delta_{4Q}ln(Earn_L^M/Earn_H^M)$	0.0014**	-0.0001	-0.0011*	0.0007	-0.0004	-0.0009
	[0.0006]	[0.0005]	[0.0007]	[0.0005]	[0.0006]	[0.0006]
$\Delta_{4Q}lnEmp_L^{NM}$	-0.0039	-0.0037	-0.0009	0.0036	0.0020	0.0016
	[0.0033]	[0.0033]	[0.0030]	[0.0026]	[0.0035]	[0.0034]
$\Delta_{4Q}ln(Emp_L^{NM}/Emp_H^{NM})$	0.0012	-0.0002	-0.0014	-0.0041**	-0.0021	-0.0063***
	[0.0022]	[0.0020]	[0.0020]	[0.0020]	[0.0027]	[0.0023]
$\Delta_{4Q}lnEarn_L^{NM}$	0.0018	0.0013	0.0040	0.0029	0.0017	-0.0004
	[0.0030]	[0.0028]	[0.0025]	[0.0028]	[0.0030]	[0.0027]
$\Delta_{4Q}ln(Earn_L^{NM}/Earn_H^{NM})$	0.0007	0.0018	-0.0006	0.0000	-0.0001	-0.0004
	[0.0012]	[0.0011]	[0.0011]	[0.0011]	[0.0012]	[0.0011]
$\Delta_{4Q}ln$Emp	-0.0006	0.0033	0.0033	-0.0039	-0.0040	-0.0063
	[0.0043]	[0.0041]	[0.0037]	[0.0033]	[0.0044]	[0.0045]
$\Delta_{4Q}ln$Earnings	0.0013	-0.0020	-0.0021	0.0006	-0.0009	-0.0007
	[0.0033]	[0.0029]	[0.0029]	[0.0027]	[0.0031]	[0.0030]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
Lag	9 Years	10 Years	11 Years	12 Years	13 Years	14 Years
N	56,394	56,394	56,394	56,394	56,394	56,394
F-Stat	2.45***	0.91	1.49	1.81*	0.70	1.69*
Counties	2,626	2,626	2,626	2,626	2,626	2,626

Note: Table A.5 tests the validity of the IV empirical strategy in the data pre-fracking boom using equation (12). The outcome is the future change in the value of the instrument (see text for details). Each column shifts the instrument backward by a certain number of years specified by "Lag." In all columns all the included covariates are outcomes related to employment and earnings in the pre-shale boom period. "F-Stat": F-statistic of joint significance of all the covariates included in the regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.6: Test of Pre-Trends

Correlation between Future Changes in the Instrument and Changes in Outcomes in the Pre-period: Manufacturing Capital Expenditures and Value Added

	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$	$\Delta_{4Q}\widehat{lnTotWells}$
$\Delta lnCapEx$		-0.0005	-0.0006	-0.0005	-0.0002	0.0003
		[0.0029]	[0.0020]	[0.0017]	[0.0019]	[0.0028]
$\Delta lnValAdd$		0.0010	0.0004	-0.0012	-0.0020	-0.0007
		[0.0061]	[0.0040]	[0.0031]	[0.0036]	[0.0057]
County FE		Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes
On Shale LT		Yes	Yes	Yes	Yes	Yes
Lag	9 Years	10 Years	11 Years	12 Years	13 Years	14 Years
N		2,408	2,408	2,408	2,408	2,408
F-Stat		0.02	0.04	0.15	0.20	0.01
Counties		1,204	1,204	1,204	1,204	1,204

Note: Table A.6 tests the validity of the IV empirical strategy in the data pre-fracking boom using equation (12). The outcome is the future change in the value of the instrument (see text for details). Each column shifts the instrument backward by a certain number of years specified by "Lag." In all columns, the included covariates are manufacturing capital expenditures and value added in the pre-shale boom period. "F-Stat": F-statistic of joint significance of all the covariates included in the regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.7: Test of Pre-Trends

Correlation between Future Changes in the Instrument and Changes in Outcomes in the Pre-period: Employment and Earnings

	$lnTotWells$	$\Delta lnTotWells$	$\Delta lnTotWells$	$\Delta_{4Q} lnTotWells$
$lnEmp_L^M$	-0.0177	-0.0003	-0.0005	-0.0005
	[0.0147]	[0.0002]	[0.0008]	[0.0006]
$ln(Emp_L^M/Emp_H^M)$	0.0449***	0.0000	0.0005	0.0003
	[0.0142]	[0.0002]	[0.0007]	[0.0006]
$lnEarn_L^M$	0.0410**	-0.0003**	-0.0001	-0.0004
	[0.0185]	[0.0001]	[0.0009]	[0.0007]
$ln(Earn_L^M/Earn_H^M)$	0.0009	-0.0001	0.0002	-0.0001
	[0.0097]	[0.0001]	[0.0004]	[0.0003]
$lnEmp_L^{NM}$	-0.1189***	-0.0009**	0.0002	-0.0002
	[0.0431]	[0.0005]	[0.0025]	[0.0020]
$ln(Emp_L^{NM}/Emp_H^{NM})$	0.0008	-0.0011***	-0.0045***	-0.0021*
	[0.0381]	[0.0003]	[0.0015]	[0.0012]
$lnEarn_L^{NM}$	0.0920**	-0.0002	0.0010	0.0019
	[0.0430]	[0.0003]	[0.0019]	[0.0016]
$ln(Earn_L^{NM}/Earn_H^{NM})$	0.0235	-0.0001	0.0014*	0.0002
	[0.0165]	[0.0001]	[0.0007]	[0.0006]
lnEmp	0.1461***	0.0004	-0.0008	-0.0013
	[0.0454]	[0.0005]	[0.0030]	[0.0024]
lnEarnings	-0.1292***	0.0000	-0.0023	-0.0006
	[0.0482]	[0.0004]	[0.0020]	[0.0017]
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
On Shale LT	No	No	No	Yes
Outcome and Covariates	Levels	Quarterly Differences	Quarterly Annual Differences	Quarterly Annual Differences
N	406,656	388,296	338,886	338,886
F-Stat	3.20***	4.79***	1.59*	1.43
Counties	2,845	2,750	2,713	2,713

Note: Table A.7 tests the validity of the IV empirical strategy in the data pre-fracking boom using different empirical specifications in each column. Column (1) uses a specification in levels (instead of changes) in the outcome and explanatory variables without differential trends for on- and off-shale counties. Column (2) uses a specification with quarterly differences in outcomes and does not allow for differential trends for on- and off-shale counties. Column (3) maintains the specification of column (2) but uses quarterly data on annual differences for both the outcome and covariates. Column (4) uses the specification in equation (12), which includes differential trends on- and off-shale. The results of column (4) are identical to those in Panel (a) of Table 4. In all columns all the included covariates are outcomes related to employment and earnings in the pre-shale boom period. "F-Stat": F-statistic of joint significance of all the covariates included in the regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.8: Test of Pre-Trends

Correlation between Future Changes in the Instrument and Changes in Outcomes in the Pre-period: Manufacturers' Capital Expenditures and Value Added

	$lnTotWells$	$\Delta lnTotWells$	$\Delta lnTotWells$
$lnCapEx$	0.0179*	0.0007	-0.0003
	[0.0102]	[0.0010]	[0.0010]
$lnValAdd$	-0.0233	-0.0040**	-0.0004
	[0.0177]	[0.0020]	[0.0019]
County FE	Yes	No	Yes
Time FE	Yes	No	Yes
On Shale LT	No	No	Yes
Outcome and Covariates	Levels	5-Year Differences	5-Year Differences
N	28,196	15,695	15,695
F-Stat	1.89	1.97	0.09
Counties	2,030	1,672	1,672

Note: Table A.8 tests the validity of the IV empirical strategy in the data pre-fracking boom using different empirical specifications in each column. Column (1) uses a specification in levels (instead of changes) in the outcome and explanatory variables without differential trends for on and off-shale counties. Column (2) uses a specification with 5-year differences in outcomes and does not allow for differential trends for on and off-shale counties. Column (3) uses the same specification as column (2) but also includes differential trends on and off-shale. The results of column (3) are identical to those in Panel (b) of Table 4. In all columns, the included covariates are manufacturing capital expenditures and value added in the pre-shale boom period. "F-Stat": F-statistic of joint significance of all the covariates included in the regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.9: Correlation between Future Changes in the Instrument and Changes in Outcomes in the Pre-period: Employment and Earnings

Panel a: Aggregates						
	ΔlnEmp	ΔlnEarnings				
$\Delta lnTotWells$	-0.014*	0.005				
	[0.007]	[0.005]				
County FE	Yes	Yes				
Time FE	Yes	Yes				
On Shale LT	Yes	Yes				
N	374,304	374,304				
KP F-Stat	84.27	84.27				
Counties	2,884	2,884				
Panel b: All Sectors						
	$\Delta lnEmp_L$	$\Delta lnEmp_H$	$\Delta ln\frac{Emp_L}{Emp_H}$	$\Delta lnEarn_L$	$\Delta lnEarn_H$	$\Delta ln\frac{Earn_L}{Earn_H}$
$\Delta lnTotWells$	-0.015**	-0.006	-0.009	0.004	0.005	0.000
	[0.007]	[0.009]	[0.006]	[0.005]	[0.007]	[0.005]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	374,304	374,304	374,304	374,304	374,304	374,304
KP F-Stat	84.27	84.27	84.27	84.27	84.27	84.27
Counties	2,884	2,884	2,884	2,884	2,884	2,884
Panel c: Non-Manufacturing						
	$\Delta lnEmp_L^{NM}$	$\Delta lnEmp_H^{NM}$	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_L^{NM}}{Earn_H^{NM}}$
$\Delta lnTotWells$	-0.008	0.005	-0.012*	0.009*	0.011	0.002
	[0.006]	[0.008]	[0.006]	[0.004]	[0.007]	[0.005]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	344,472	346,644	339,336	343,926	341,022	338,886
KP F-Stat	79.13	81.52	79.59	79.81	80.85	80.28
Counties	2,763	2,814	2,733	2,740	2,733	2,713
Panel d: Manufacturing						
	$\Delta lnEmp_L^M$	$\Delta lnEmp_H^M$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta lnEarn_L$	$\Delta lnEarn_H^M$	$\Delta ln\frac{Earn_L^M}{Earn_H^M}$
$\Delta lnTotWells$	-0.033	-0.050*	0.009	-0.011	-0.013	-0.003
	[0.024]	[0.028]	[0.013]	[0.010]	[0.012]	[0.009]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	344,094	341,022	338,892	343,926	341,022	338,886
KP F-Stat	79.79	80.85	80.28	79.81	80.85	80.28
Counties	2,748	2,733	2,714	2,740	2,733	2,713
Panel e: Manufacturing. Controls for Changes in Aggregate High- and Low-Education Employment						
	$\Delta lnEmp_L^M$	$\Delta lnEmp_H^M$	$\Delta ln\frac{Emp_L^M}{Emp_H}$	$\Delta lnEarn_L^M$	$\Delta lnEarn_H^M$	$\Delta ln\frac{Earnv_L}{Earn_H^M}$
$\Delta lnTotWells$	-0.007	-0.032	0.015	-0.012	-0.016	-0.003
	[0.021]	[0.024]	[0.012]	[0.010]	[0.012]	[0.009]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	344,094	341,022	338,892	343,926	341,022	338,886
KP F-Stat	79.80	80.85	80.28	79.82	80.85	80.28
Counties	2,748	2,733	2,714	2,740	2,733	2,713

Note: Table A.9 tests the validity of the IV empirical strategy in the data pre-fracking boom using equation (13). In each panel, the outcome is displayed at the top. The covariate of interest, $\Delta lnTotWells$, is the predicted value of the instrument in the future (see text for details). "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.10: Correlation Between Future Changes in the Instrument and Changes in Outcomes in the Pre-Period: Manufacturers' Capital Expenditures and Value Added

Panel a: Value Added			
	$\Delta lnValAdd$	$\Delta lnValAdd$	$\Delta lnValAdd$
$\Delta lnTotWells$	-0.026	-0.006	0.002
	[0.023]	[0.017]	[0.002]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	18,578	15,695	4,932
KP F-Stat	38.77	40.95	46.45
Counties	1,886	1,672	662
Sample	All	Restricted	Restricted
Panel b: Capital Expenditures			
	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$
$\Delta lnTotWells$	-0.007	-0.012	0.002
	[0.031]	[0.032]	[0.001]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	Yes
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	16,574	15,695	4,932
KP F-Stat	44.28	40.95	46.45
Counties	1,736	1,672	662
Sample	All	Restricted	Restricted
Panel c: Capital Expenditures to Value Added Ratio			
		$\Delta ln\frac{CapEx}{Rev}$	$\Delta ln\frac{CapEx}{Rev}$
$\Delta lnTotWells$		-0.006	-0.000
		[0.030]	[0.001]
County FE		Yes	Yes
Time FE		Yes	Yes
On Shale LT		Yes	Yes
N		15,695	4,932
KP F-Stat		40.95	46.45
Counties		1,672	662
Sample		Restricted	Restricted

Note: Table A.10 tests the validity of the IV empirical strategy in the data pre-fracking boom using equation (13). In each panel, the outcome is displayed at the top. The covariate of interest, $\Delta lnTotWells$, is the predicted value of the instrument in the future (see text for details). "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. "Sample = All": The estimation sample includes all counties with information on the outcome. "Sample = Restricted": The estimation sample only includes counties with information on the opposite (i.e., capital expenditures or value added) outcome. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table A.11: The Impact of Fracking on Manufacturers' Capital Expenditures, Revenues, and Capital to Output Ratios: Long Differences Using Only 2002, 2007, and 2012 Data

Panel a: Capital Expenditures						
	Data: 2002, 2007, 2012, and 2017			Data: 2002, 2007, and 2012		
	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$	$\Delta lnCapEx$
$\Delta lnTotWells$	0.198*	0.313***	0.264**	0.195	0.247*	0.209
	[0.103]	[0.118]	[0.121]	[0.123]	[0.145]	[0.145]
Ctrls. $\Delta Emp_{L,H}$	No	No	Yes	No	No	Yes
County FE	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes	Yes
N	3,983	3,211	3,146	2,398	1,938	1,856
KP F-Stat	51.09	40.85	37.39	28.06	20.46	19.28
Counties	1,407	1,128	1,116	1,199	969	928
Sample	All	Restricted	Restricted	All	Restricted	Restricted

Panel c: Capital to Value Added Ratio						
	Data: 2002, 2007, 2012, and 2017			Data: 2002, 2007, and 2012		
		$\Delta ln\frac{CapEx}{ValAdd}$	$\Delta ln\frac{CapEx}{ValAdd}$		$\Delta ln\frac{CapEx}{ValAdd}$	$\Delta ln\frac{CapEx}{ValAdd}$
$\Delta lnTotWells$		0.268**	0.297**		0.242*	0.263*
		[0.123]	[0.132]		[0.145]	[0.152]
Ctrls. $\Delta Emp_{L,H}$		No	Yes		No	Yes
County FE		No	No		Yes	Yes
Time FE		No	No		Yes	Yes
N		3,211	3,146		1,938	1,856
KP F-Stat		40.85	37.39		20.46	19.28
Counties		1,128	1,116		969	928
Sample	All	Restricted	Restricted	All	Restricted	Restricted

Note: Table A.11 shows the effects of fracking on the outcomes displayed at the top of the columns. The effects are estimated using a variation of equation (11) in which I do not include differential linear trends on- and off-shale. The first three columns in each panel use data on capital expenditures at the county level for the years 2002, 2007, and 2012, and the predicted values for 2017 (see text). The last three columns in each panel use data on capital expenditures at the county level only for the years 2002, 2007, and 2012, without including the predicted values for capital expenditures in 2017. In Panel (a), the outcome is the log of manufacturing capital expenditures, while in Panel (b), the outcome is the log of the ratio between capital expenditures and value added. "Ctrls. $\Delta lnEmp_{L,H}$": Whether the estimation includes controls for aggregate low and high-skill employment growth at the county level. "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. "Sample = All": The estimation sample includes all counties with information on the outcome. "Sample = Restricted": The estimation sample only includes counties with information on the opposite (i.e., capital expenditures or value-added) outcome. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

B Local Labor Market Effects of Horizontal Fracking

Table B.1 presents the estimated effects of horizontal fracking on different aggregate labor market outcomes. The results indicate that a 10 percent increase in horizontal wells increases employment by 1.2 percent and labor earnings by 0.47 percent. The development of shale also affected the county's labor supply. I estimate that a 10 percent increase in horizontal wells increased the county's population by 0.18 percent, increased the labor force participation rate by 0.2 percentage points, and decreased the unemployment rate by 0.05 percentage points. Using the average 4-year growth rate in total horizontal wells (94 percent), I estimate that, over a 4-year period, fracking increased total employment and earnings by roughly 11.4 and 4.4 percent, respectively, and population by 1.7 percent. Similarly, it increased the employment-to-population ratio by 2.3 percentage points while reducing the local unemployment rate by 0.5 percentage points.

These results are similar to the findings of the previous literature, including those studies using different methodologies. For instance, Bartik et al. (2019), using the same data, estimate that 4 years after the initiation of fracking in a shale play, employment in high prospectivity counties increases by an average of 11 percent relative to counties in the same play with lower prospectivity. Using different data, they also estimate that wage and salary income rises by 8 percent, population by 2.7 percent, and employment-to-population by 2.6 percentage points, and the unemployment rate declines by 0.6 percentage points. Similarly, Maniloff and Mastromonaco (2017) estimate that an increase of 100 horizontal wells in a county increased local employment and earnings by 16 and 12 percent, respectively. Allcott and Keniston (2018) use a sample of natural resource booms and busts starting in the 1970s and also find that natural resource booms increase employment, earnings, and population in the affected local areas. The same findings are also present in Feyrer et al. (2017), who show that increased oil and gas production during the US shale boom increased employment and income at the county level.

The results on earnings in Table B.1 use nominal earnings as the outcome. However, prices could have varied differently based on fracking exposure, making the previous results uninformative of the real wage gains of fracking. To assess this, Table B.2 replicates the main empirical results using real earnings. To convert nominal to real earnings, I use the BEA's MSA-level implicit price deflators for the years in which they are available, 2007 to 2017, discarding the data from the years before 2007. For counties not assigned to an MSA, I use the implicit price deflators for the non-MSA areas of the state in which they are located. I find evidence of price increases eroding a small part of the earnings gains estimated as a result of horizontal fracking. Over the average 4-year period, fracking increases all average earnings measures by approximately 0.9 percentage points less in real terms than in nominal terms (i.e., a 94 percent increase in horizontal wells is estimated to have increased wages of low-skill workers by 3.8 percent in nominal terms and by 2.9 percent in real terms (column (2) of Table B.2).

Finally, Figure B.1 shows the estimated effects of fracking on employment for different sectors. The mining and construction sectors show the largest positive employment effects, followed by financial services (via real estate) and trade and transportation. On the other hand, the effects on manufacturing, agriculture, and health and education are insignificantly different from zero. These results are identical to the findings in Weber (2014), Maniloff and Mastromonaco (2017), Feyrer et al. (2017), and Bartik et al. (2019). The null effects in manufacturing employment may seem at odds with the findings in Allcott and Keniston (2018), who estimate that resource booms positively affect manufacturing employment. However, the sample in Allcott and Keniston (2018) starts in the 1970s and has multiple boom and bust cycles. Their estimated effects post-2001 (during the shale boom) indicate the opposite result: natural resource booms do not affect manufacturing employment.

Table B.1: The Impact of Fracking on Employment, Earnings and Population

	QCEW		SEER-Census	LAUS		
	ΔlnEmp	ΔlnEarnings	ΔlnPop	ΔLF/Pop	ΔEmp/Pop	ΔUR
$\Delta lnTotWells$	0.121***	0.047***	0.018***	0.020***	0.024***	-0.005**
	[0.019]	[0.010]	[0.003]	[0.005]	[0.006]	[0.002]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	170,541	170,541	171,171	168,126	168,126	168,238
KP F-Stat	103.19	103.19	103.75	101.90	101.90	101.91
Counties	3,005	3,005	3,003	3,003	3,003	3,005

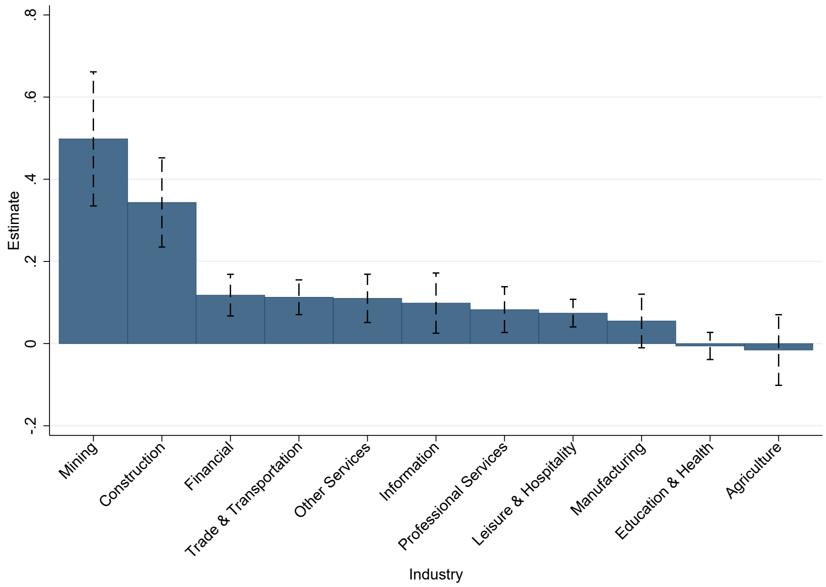
Note: Table B.1 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (9). The data source used for the outcome data in each column is shown at the top. The outcomes are log total employment, log earnings, log population, labor force participation, employment to population, and unemployment rate, respectively."KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table B.2: The Impact of Fracking on Earnings: Nominal vs. Real Dollars, 2007 to 2017

Panel a: Nominal Dollars			
	$\Delta lnEarn$	$\Delta lnEarn_L$	$\Delta lnEarn_H$
$\Delta lnTotWells$	0.023*	0.040***	0.003
	[0.014]	[0.014]	[0.016]
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	119,872	119,872	119,872
KP F-Stat	63.01	63.01	63.01
Counties	3,005	3,005	3,005
Panel b: Real Dollars (Deflated Using MSA-level Implicit Price Deflators)			
	$\Delta lnEarn$	$\Delta lnEarn_L$	$\Delta lnEarn_H$
$\Delta lnTotWells$	0.014	0.031**	-0.006
	[0.014]	[0.014]	[0.016]
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes
N	119,872	119,872	119,872
KP F-Stat	63.01	63.01	63.01
Counties	3,005	3,005	3,005

Note: Table B.2 shows the effects of fracking on earnings estimated using equation (9). The table uses data from 2007 to 2017. Panel (a) shows the results using nominal earnings, while Panel (b) uses real earnings. I convert nominal to real earnings using MSA implicit price deflators from the BEA (only available starting in 2007). The outcomes (in logs) are earnings, low-skill earnings, and high-skill earnings."KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Figure B.1: The Impact of Fracking on Different Industries' Employment



Note: Figure B.1 shows the effects of fracking on different industries' employment, estimated using equation (9). Dashed bars represent the 95 percent confidence intervals calculated using clustered standard errors at the county level.

C Alternative Classifications of Low- and High-Skill Labor

This appendix discusses alternative classifications of low- and high-skill labor. Specifically, I focus on a classification that includes workers with some college and workers with associate degrees as part of the high-skill group instead of the low-skill group.

Table C.1 shows the estimated responses of relative employment (in and outside manufacturing) and earnings to fracking using this alternative classification of high- and low-skill labor. Classifying workers with some college and associate degrees as high-skill still shows that the relative demand for low-skill labor in the non-manufacturing sector increased, and the earnings gap between high- and low-skill labor decreased. However, I see very limited evidence suggesting that these effects in other sectors of the local labor market translated into changes in the manufacturing sector. Looking at the change in relative employment in manufacturing in columns (5) and (6), I see no evidence suggesting an opposite response to that of the rest of the labor market.

The reason the effects on relative employment in manufacturing in Table C.1 mostly disappear is that, in manufacturing, the relative demand for workers with a high school education or less and workers with some college education or associate degrees does not seem responsive to changes in their relative price. To make this clear, Table C.2 presents estimates of the responses of relative employment and earnings to fracking, ignoring college-educated workers. Specifically, in Table C.2, low-educated workers include workers with a high school education or less, and high-educated workers are workers with associate degrees or some college. Columns (1) to (3) indicate that even when defining low- and high-skill labor in this way, the fracking boom generated an increase in labor demand for low-skill workers. Column (4) shows that these changes in relative demand translated into changes in relative prices in the local labor market. However, the estimated response of the relative employment in manufacturing simply remains unchanged despite the change in relative prices (columns (5) and (6)). Thus, from the perspective of the model (see Section 6.1), it would be inconsistent to include workers with associate degrees or some college as part of the high-skill group.

While the data drive the division between low- and high-skill labor in this paper, using only college-educated workers as high-skill labor is not uncommon in the previous literature (Katz and Murphy (1992); Krusell et al. (2000); Card and Lemieux (2001); Autor and Dorn (2013), among others). On the other hand, this categorization is not ubiquitous. For instance, the work of Ciccone and Peri (2005) or Lewis (2011) uses different classifications. In general, previous work studying more developed countries and more recent time periods imposes a higher threshold to define high-skill labor, while work focused on cross-country comparisons, developing nations, or periods in the 1900s sets the bar lower. Of special relevance is the work of Lewis (2011), who also studies the manufacturing sector and considers the degree of substitutability between low-skill labor and capital. Lewis (2011) defines low-skill labor as workers with less than a high school education. This is reasonable in his set-up centered around the late 1980s and exploiting exogenous variation arising from drastic increases in immigration for very low-skill workers. This is another commonality of most of the previous empirical literature on this topic, where the definitions of low- and high-skill labor are determined based on the type of exogenous variation observed.

Table C.1: The Impact of Fracking on Employment, Relative Employment, Earnings: Long Differences Using Alternative Definitions of Low- and High-Education Labor

	Panel a: All Counties					
	Non-Manufacturing				Manufacturing	
	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$	$\Delta ln\frac{Emp_L^{M}}{Emp_H^{M}}$	$\Delta ln\frac{Emp_L^{M}}{Emp_H^{M}}$
$\Delta lnTotWells$	0.027***	0.086***	0.066***	-0.020**	-0.001	-0.018
	[0.008]	[0.015]	[0.015]	[0.010]	[0.012]	[0.013]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	No	No	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	8,866	8,090	8,026	7,968	7,969	7,969
KP F-Stat	72.19	70.08	70.61	70.18	70.06	65.14
Counties	2,991	2,745	2,724	2,705	2,705	2,705

	Panel b: Only Counties with Data on Capital Expenditure Changes					
	Non-Manufacturing				Manufacturing	
	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$	$\Delta ln\frac{Emp_L^{M}}{Emp_H^{M}}$	$\Delta ln\frac{Emp_L^{M}}{Emp_H^{M}}$
$\Delta lnTotWells$	0.018***	0.061***	0.036**	-0.025**	0.012	-0.000
	[0.007]	[0.012]	[0.014]	[0.011]	[0.011]	[0.011]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	No	No	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	3,910	3,910	3,910	3,910	3,910	3,910
KP F-Stat	43.94	43.94	43.94	43.94	43.94	40.55
Counties	1,395	1,395	1,395	1,395	1,395	1,395

Note: Table C.1 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (11). This table classifies low- and high-skill labor differently than the main text. Low-skill labor here includes workers with, at most, a high school diploma. High-skill labor includes all other workers (workers with associate degrees, some college, and college degrees or more). Panel (a) includes all counties with available data, while Panel (b) restricts the sample to counties with available information on capital expenditure changes. The outcomes (in logs) are relative low-to-high-skill non-manufacturing employment, non-manufacturing low-skill employment, non-manufacturing high-skill employment, relative high-to-low-skill non-manufacturing earnings, and relative low-to-high-skill manufacturing employment (x2), respectively."Ctrls. $\Delta lnEmp_{L,H}$": Whether the estimation includes controls for aggregate low- and high-skill employment growth at the county level. "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

Table C.2: The Impact of Fracking on Employment, Relative Employment, Earnings: Long Differences. High-Education: Only Workers with Some College or Associate Degrees

Panel a: All Counties						
	Non-Manufacturing				Manufacturing	
	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$
$\Delta lnTotWells$	0.023***	0.086***	0.066***	-0.020**	0.005	-0.009
	[0.007]	[0.015]	[0.015]	[0.010]	[0.012]	[0.013]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	No	No	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	8,866	8,090	8,026	7,968	8,088	8,088
KP F-Stat	72.19	70.08	70.61	70.18	69.92	65.25
Counties	2,991	2,745	2,724	2,705	2,744	2,744

Panel b: Only Counties with Data on Capital Expenditure Changes						
	Non-Manufacturing				Manufacturing	
	$\Delta ln\frac{Emp_L^{NM}}{Emp_H^{NM}}$	$\Delta lnEarn_L^{NM}$	$\Delta lnEarn_H^{NM}$	$\Delta ln\frac{Earn_H^{NM}}{Earn_L^{NM}}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$	$\Delta ln\frac{Emp_L^M}{Emp_H^M}$
$\Delta lnTotWells$	0.018***	0.061***	0.036**	-0.025**	0.023**	0.010
	[0.006]	[0.012]	[0.014]	[0.011]	[0.010]	[0.010]
Ctrls. $\Delta lnEmp_{L,H}$	No	No	Yes	No	No	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
On Shale LT	Yes	Yes	Yes	Yes	Yes	Yes
N	3,910	3,910	3,910	3,910	3,910	3,910
KP F-Stat	43.94	43.94	43.94	43.94	43.94	40.43
Counties	1,395	1,395	1,395	1,395	1,395	1,395

Note: Table C.2 shows the effects of fracking on the outcomes displayed at the top of the columns, estimated using equation (11). This table classifies low- and high-skill labor differently than the main text. Low-skill labor here includes workers with, at most, a high school diploma. High-skill labor includes only workers with associate degrees and some college (I exclude workers with college degrees or more from this estimation). Panel (a) includes all counties with available data, while Panel (b) restricts the sample to counties with available information on capital expenditure changes. The outcomes (in logs) are relative low-to-high-skill non-manufacturing employment, non-manufacturing low-skill employment, non-manufacturing high-skill employment, relative high-to-low-skill non-manufacturing earnings, and relative low-to-high-skill manufacturing employment (x2), respectively."Ctrls. $\Delta lnEmp_{L,H}$": Whether the estimation includes controls for aggregate low- and high-skill employment growth at the county level. "KP F-Stat": F-statistic of the first stage IV regression. "Counties": Number of unique counties included in the estimation. Standard errors clustered at the county level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01. 0.05, *** 0.01.