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DUTCH DISEASE OR AGGLOMERATION? THE LOCAL ECONOMIC EFFECTS OF NATURAL RESOURCE BOOMS IN MODERN AMERICA

Hunt Allcott
Daniel Keniston

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Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America
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ABSTRACT

Does natural resource production benefit producer economies, or does it instead create a “Natural Resource Curse,” perhaps as Dutch Disease crowds out the manufacturing sector? We combine a new panel dataset of oil and gas production and reserves with county-level aggregate outcomes and restricted-access Census of Manufactures microdata to estimate how oil and gas booms have affected local economic growth in the U.S. since the 1960s. We find that a boom that doubles national oil and gas employment increases total employment by 2.9 percent in a county with one standard deviation larger oil and gas endowment. Despite substantial migration, wages also rise. Notwithstanding, manufacturing employment and output are actually pro-cyclical with oil and gas booms, because many manufacturers in resource-abundant counties supply inputs to the oil and gas sector, while many others sell locally-traded goods and benefit from increases in local demand. Manufacturers' revenue productivity also grows during booms, especially in linked and local industries, but there is no evidence that output prices rise. The results demonstrate how a meaningful share of manufacturers produce locally traded goods, and they highlight how linkages to natural resources can be a driver of manufacturing growth.

Hunt Allcott
Department of Economics
New York University
19 W. 4th Street, 6th Floor
New York, NY 10012
and NBER
hunt.allcott@nyu.edu

Daniel Keniston
Yale University
P. O. Box 208269
New Haven, CT 06520-8269
and NBER
daniel.keniston@yale.edu

1 Introduction

Over the past decade, high oil prices and improvements in drilling technology have made western North Dakota a dramatic case study of the local economic effects of natural resource booms. "It's hard to think of what oil hasn't done to life in the small communities of western North Dakota," writes the New York Times Magazine (Brown 2013). "It has minted millionaires, paid off mortgages, created businesses ... It has forced McDonald's to offer bonuses and brought job seekers from all over the country." Locals hope that unlike the previous boom of the 1970s and early 1980s, this boom "won't afflict the state with the so-called Dutch Disease in which natural-resource development and the sugar rush of fast cash paradoxically make other parts of the economy less competitive and more difficult to sustain."

Oil and gas production has affected producer economies worldwide, not just in North Dakota: the histories of Canada, Iraq, Nigeria, Qatar, Venezuela, and many other countries have been shaped both positively and negatively by the booms and busts of the past 40 years. A series of policy questions have arisen. Most broadly, should policymakers encourage oil and gas development through low royalties and other complementary policies? Or should they discourage development or even ban new drilling technologies, as some countries and local areas have done?[1]

If markets are efficient, then standard trade models predict that a resource-abundant region will benefit from an increase in the resource price. However, there is also substantial concern about the potential "Natural Resource Curse," in which resource extraction interacts with market failures to make producer regions worse off. This concern has been fueled by empirical studies such as Auty and Mikesell (1998), Gylfason, Herbertsson, and Zoega (1999), and Sachs and Warner (1995, 1999, 2001), which find that resource abundance is negatively associated with growth in cross-country data. If Sachs and Warner (2001) are correct that the Resource Curse is "a reasonably solid fact," then policymakers should either restrain resource booms or enact other policies to address mechanisms through which the Resource Curse might act.

One leading potential mechanism for a Natural Resource Curse is Dutch Disease, in which growth in the natural resource sector crowds out other sectors such as manufacturing by increasing factor prices. If manufacturers exert positive productivity spillovers that resource firms do not, natural resource production would reduce these spillovers and could reduce growth (Corden and Neary 1982, Krugman 1987, Matsuyama 1992, van Wijnbergen 1984). There is growing evidence for manufacturing productivity spillovers from Ellison, Glaeser, and Kerr (2010), Greenstone, Hornbeck, and Moretti (2010), Kline and Moretti (2013), and others. In contrast, it has long been argued that natural resource extraction is less likely to experience productivity growth or exert positive

[1] The state of New York, the cities of Dallas, Los Angeles, and Santa Cruz, the Delaware River Basin, Mora County New Mexico, Newfoundland, the countries Bulgaria, France, and Germany, and other areas have banned hydraulic fracturing; see http://keeptapwatersafe.org/global-bans-on-fracking/.

productivity spillovers on other industries.[2]

There are, however, arguments to the contrary. For example, Wright and Czelusta (2007) argue that "linkages and complementarities to the resource sector were vital in the broader story of American economic success." Furthermore, as van der Ploeg (2011) documents, the cross-country evidence on the Resource Curse is sensitive to the sample period and countries, the definition of explanatory variables, and other factors.[3] Thus, van der Ploeg (2011) concludes, "the road forward might be to exploit variation within a country where variables that might confound the relationship between resources and macroeconomic outcomes do not vary and the danger of spurious correlation is minimized." This is the road we follow.

In this paper, we ask: *how do oil and gas booms and busts differentially affect economic growth, and the manufacturing sector in particular, in resource-abundant U.S. counties?* We begin with a simple model that clarifies how "domestic Dutch Disease" could act in local economies within a common currency area with mobile labor. As long as labor supply is not fully elastic, an increase in labor demand from the natural resource sector drives up local wages. This causes the traded goods sector to contract, as it sells into national or international output markets with exogenous prices. This is analogous to the familiar cross-country Dutch Disease: in both cases, local wages rise relative to traded good output prices. Whether manufacturing contracts during and after a local natural resource boom thus depends on three factors: whether local manufacturing wages rise, whether manufacturing is traded or non-traded, and also whether there are local productivity spillovers from resources to manufacturing. The model also clarifies that because labor is mobile, the population and wage effects of resource booms spill over to non-producer areas. This is why our research question above refers to *differential* impacts across counties, and we are careful to address this issue as we interpret our empirical results.

To test this, we combine a newly-constructed dataset of oil and gas production and reserves with publicly-available data on county-level aggregate employment, earnings, and population. Crucially, we also use restricted-access establishment-level microdata from the U.S. Census of Manufactures, which allow us to examine a variety of outcomes and subsectors. Our empirical strategy is closely related to Bartik (1991) and the literature that follows, such as Blanchard and Katz (1992), Moretti (2010), and others. We correlate changes in local economic activity with an exogenous measure of an oil and gas boom: the interaction of time series variation in national oil and gas employment with cross-sectional variation in economically recoverable oil and gas endowment. Extending our study back to the 1960s allows us to exploit dramatic time series variation, as hundreds of thousands of oil and gas jobs are created and destroyed nationwide in the boom of the 1970s, the bust of the

[2] See the introductions to van Wijnbergen (1984) and Lederman and Maloney (2007a) for a history of this argument.

[3] Cross-country studies following on Sachs and Warner have arrived at different results when instrumenting for resource abundance (Brunnschweiler and Bulte 2009), including country fixed effects (Manzano and Rigobon 2001), using different measures of resource intensity (Lederman and Maloney 2007b) or conditioning on the quality of institutions (Collier and Goderis (2009), Mehlum, Moene, and Torvik (2006)).

1980s, and the second boom of the past decade. Exploiting multiple booms and busts not only allows us to compare the current shale boom to the 1970s, but it also provides assurance that our qualitative results are not driven by spurious secular trends.

There are two main results. First, oil and gas booms substantially increase local economic growth, although the employment gains are reversed just as quickly during a bust. A boom that doubles national oil and gas employment increases total employment by 2.9 percent in a county with one standard deviation larger oil and gas endowment. Although there is also substantial population migration, average wages rise: they are 1 to 2.5 percent higher than their pre-1970s level for an eleven-year period from 1975 to 1985 in counties with one standard deviation larger endowment. This relative wage increase confirms the possibility of Dutch Disease.

Second, however, there is in fact no evidence of Dutch Disease in manufacturing: total manufacturing employment in resource-abundant counties grows during resource booms and shrinks during busts. This result is highly robust: it is visible and statistically significant in multiple independent datasets and invariant to different controls and variable definitions. Other measures of manufacturing growth such as number of establishments, revenues, and capital investments are similarly procyclical with oil and gas.

We explore several hypotheses for why this is the case. First, there are clear agglomeration economies for manufacturers of locally-traded goods and those that are linked through upstream or downstream inputs to the oil and gas industry. Also consistent with an increase in local demand, employment, output, and investment in local and linked plants are all particularly procyclical with resource booms in producer counties, conditional on nationwide trends. More surprisingly, we also find that revenue-based total factor productivity (TFP-R) also increases substantially for these local and linked plants.

Finally, we examine the subset of plants that are most likely to be affected by Dutch Disease: those in industries that are not linked to oil and gas and have low transportation costs and thus are more likely to be selling outside of local markets. Consistent with the theory, we find these industries contract during booms, although estimates are somewhat imprecise. However, we find no effects on the productivity of tradable manufacturers. This suggests that the forces driving the long-term Dutch Disease–the loss of competitiveness in the tradable manufacturing sector–do not occur. And indeed, by 1997 we find few effects of the 1970s and 1980s boom and bust in resource-rich counties.

In the remainder of this first section, we discuss related literature. Section 2 provides background on the recent oil and gas booms. Section 3 presents the model. Section 4 details the data, Section 5 outlines the empirical strategy, and Section 6 presents results. Section 7 concludes.

1.1 Literature

We build upon a growing literature that uses within-country variation to identify the effects of resource booms. We follow on other studies in the United States (Carrington (1996), James and Aadland (2011), James and James (2012), Papyrakis and Gerlagh (2007), and others) and other countries (Aragon and Rud (2011), Asher and Novosad (2014), Caselli and Michaels (2013), Domenech (2008), Dube and Vargas (2013), Monteiro and Ferraz (2012), and others). Black, McKinnish, and Sanders (2005a) study the Appalachian coal boom and bust, finding increased incomes and employment spillovers to non-tradables but neither positive nor negative spillovers to manufacturing. An important paper by Michaels (2010) studies the long-term effects of resource abundance in the southern United States. He shows that resource discoveries cause oil abundant counties to specialize in oil production, but this did not reduce growth in other sectors: higher incomes increased population, which increased the provision of local public goods, which in turn increased output in agriculture and manufacturing.

On paper differs from this important existing work in several ways. First, our geographic scope is broad–the entire United States instead of a smaller region. This affords us a larger sample and thus more precise estimates, as well as parameter estimates that apply to a larger and thus potentially more policy-relevant population. Second, we benefit from substantially improved data on both oil and gas resources and manufacturing outcomes. The U.S. Census of Manufactures data allow us to test mechanisms suggested by Michaels (2010) and other previous work, such as whether agglomerative forces actually increase TFP and whether booms affect manufacturing through upstream and downstream linkages vs. other channels.

Our work is also connected to the broader empirical literature on agglomeration and productivity spillovers. As Ellison and Glaeser (1997) point out, agglomerative spillovers are difficult to identify because both heterogeneous local natural advantages and spillovers can cause firms to co-locate. To identify spillovers, several recent papers have exploited natural experiments, including the siting of large manufacturing plants (Greenstone, Hornbeck, and Moretti 2010), portage sites (Bleakley and Lin 2012), and the boundaries of the Tennessee Valley Authority development region (Kline and Moretti 2012). Our analysis identifies spillovers using the natural experiment of local resource booms and busts. More broadly, this project builds on previous analyses of local economic shocks from national-level sectoral trends (Bartik 1991, Blanchard and Katz 1992), military base closures (Hooker and Knetter 2001), place-based economic development policies (Busso, Gregory, and Kline 2012), and other factors.

2 Background: Evolution of the Oil and Gas Sector

Figure 1 presents oil and natural gas prices in the U.S. from 1960 to the present, using data from the U.S. Energy Information Administration (EIA). Like all prices in this paper, these are in real 2010 dollars. Real oil and gas prices were steady and slowly declining from the end of the Second World War through the early 1970s. Prices rose suddenly in October 1973 due to the Arab oil embargo and again in 1979-1980 due to the Iranian Revolution and the Iran-Iraq war. Natural gas prices closely follow oil prices over the entire study period, except for the most recent two years, when natural gas supply markedly increased.

Figure 2 shows that U.S. oil production peaked in 1970 and began to decline. The decline was monotonic for the first few years of the 1970s, until it was arrested by the supply response to the 1973 price shock. This supply response, coupled with the recession of the early 1980s, caused prices to drop steadily from March 1981 to the end of 1985, and then sharply in the first six months of 1986. In the past decade, global demand growth has spurred a second boom of high prices and increased drilling activity.

While oil production entails large capital costs, it also requires significant labor input. Figure 2 also shows total national employment in the oil and gas sector, as reported by the U.S. Bureau of Economic Analysis through the Regional Economic Information System (REIS). Closely mirroring the price trend, employment rose from under 400 thousand people in the early 1970s to over one million in the early 1980s, then dropped sharply in 1986 and continued to decline steadily until 2002. We switch from the SIC to the NAICS classification system in 2000 and plot both SIC and NAICS data points in that year.

Of course, these large fluctuations in oil and gas employment are concentrated in the more resource-abundant counties. Prior to the late 1990s, oil and gas were almost exclusively recovered from "conventional" reserves: oil and gas accumulations trapped beneath an impermeable rock layer where the resulting reservoir could be reached with a vertical well. Figure 3 shows each county's early endowment: that is, the value of oil and gas per square mile that was in the ground in 1960 and was economically recoverable using technologies available during the boom and bust of the 1970s and 1980s. (We detail the construction of this variable in Section 4.1.)

More recently, prospecting and extraction has focused on the large volumes of "unconventional" oil and gas trapped in tiny pores within impermeable rocks. These unconventional resources can be exploited by fracturing the rock with horizontal drilling and injecting gas, sand and chemicals, allowing the hydrocarbons from wide areas to migrate to wells. "Fracking" was pioneered for oil and gas wells in 1947 and was used in some areas during the 1970s boom. There were significant advances in horizontal drilling in the 1980s and 1990s, and commercially-viable shale gas extraction was pioneered in the Barnett Shale in northern Texas in 1997. Since then, large amounts of tight oil and shale gas have become economically recoverable. Figure 4 maps the additional endowment that became economically exploitable only after the end of the 1990s. This illustrates regions where large amounts of shale gas or tight oil are newly economically recoverable, such as the Bakken Shale in western North Dakota, the Niobara shale in eastern Colorado, the Marcellus and Utica Shales in Pennsylvania, Ohio, New York, and West Virginia, the Barnett Shale, Granite Wash, and Eagle Ford in Texas, the Woodford Shale in Texas and Oklahoma, and the Haynesville Shale on the border of Texas and Louisiana.

3 Theoretical Framework

3.1 Setup

To demonstrate how Dutch Disease might act within a country with mobile labor and a common currency, we outline a simple model of a small open economy that builds upon Matsuyama (1992). The economy consists of three sectors: natural resources, tradable goods, and non-tradable goods, indexed by $j = \{r, m, l\}$, respectively. Sector j has output X_j, productivity Ω_j, and employment n_j. Each sector j has aggregate production function $X_j = \Omega_j F_j(n_j)$, where $F_j(0) = 0$, $F_j'(\cdot) > 0$, and $F_j''(\cdot) < 0$. Producers of tradable goods and natural resources sell into global markets, so prices p_m and p_r are exogenous. The price of non-tradable goods p_l is endogenous.

Labor receives wage w and is perfectly substitutable across sectors. Total labor supply in the economy $N(w)$ is a function of wages, with $N(\cdot) \geq 0$ and $N'(\cdot) \geq 0$. For simplicity, our exposition of the model assumes that each consumer supplies one unit of labor, so there is no unemployment or elasticity of hours worked. Instead, labor supply elasticity arises from migration into and out of the region - for example, from other counties and states into a producer county.

Consumers have Cobb-Douglas preferences over consumption of tradable and non-tradable goods, denoted C_l and C_m. Their utility function is:

$$U = \alpha \ln C_l + (1 - \alpha) \ln C_m. \tag{1}$$

Consumers have aggregate budget constraint

$$(w + \pi) N(w) = p_l C_l + p_m C_m, \tag{2}$$

with π being the household's share of profits from local firms. For simplicity, we assume that household income from profits comes only from the resource sector[4]:

$$\pi N(w) = (p_r X_r - w n_r). \tag{3}$$

Including resource sector profits captures the role of royalty payments made by resource firms to landowners. With Cobb-Douglas demand, the $\pi > 0$ term also ensures that a resource boom increases consumption of non-tradables instead of increasing wages and non-tradable goods prices proportionally. This is the "spending effect" discussed by Corden and Neary (1982).

The region's aggregate demand functions for tradable and non-tradable goods are thus:

[4] Profits from tradable and non-tradable sectors should be excluded if, for example, firms in these sectors are owned by individuals outside the region. Including profits from only the non-tradables sector would further increase demand for non-tradables during a resource boom, which would drive up wages and increase the contraction of the traded sector. Additionally including profits from the tradables sector would act in the opposite direction, as tradables profits decrease during the boom.

$$
\begin{aligned}
p_l C_l &= N(w)\,\alpha\,(w+\pi) && (4)\\
p_m C_m &= N(w)\,(1-\alpha)\,(w+\pi)\,. && (5)
\end{aligned}
$$

In equilibrium, the price of local goods adjusts to equilibrate non-tradable supply and demand

$$
C_l = X_l = \Omega_l F_l(n_l)\,, \tag{6}
$$

the sum of employment in all three sectors must equal total regional labor supply,

$$
n_r + n_l + n_m = N(w)\,, \tag{7}
$$

and the marginal product of labor is equalized across sectors:

$$
w = p_r \Omega_r F_r'(n_r) = p_l \Omega_l F_l'(n_l) = p_m \Omega_m F_m'(n_m)\,. \tag{8}
$$

3.2 Effects of a Resource Boom

We define a resource boom as an increase in resource productivity Ω_r, as has occurred due to improvements in hydraulic fracturing and horizontal drilling. An increase in p_r, as in the oil price shocks of the 1970s and the 2000s would generate equivalent effects in the model. The model predicts several effects of resource booms.

Prediction 1: If labor supply is not fully elastic, a resource boom increases wages. Furthermore, if labor supply is not fully inelastic, a resource boom increases population.

Increases in resource price or productivity increase the marginal return to labor in the resource sector, with the first order effect that wages rise: $\partial w / \partial \Omega_r \geq 0$. This causes an increase in labor supply, which in turn mitigates the wage increase. The inequality is strict if $N'(\cdot) < \infty$. If labor supply is fully elastic, however, resource booms do not affect wages, and all adjustment occurs through migration. Appendix A contains additional details.

Prediction 2: Resource booms increase prices and production of non-tradable goods.

To see this, we can re-write total profits in the resource sector as:

$$
N(w)\,\pi = p_r \Omega_r n_r \left(\frac{F_r(n_r)}{n_r} - F_r'(n_r) \right) \tag{9}
$$

Differentiating shows that a resource boom increases resource sector profits[5]:

[5] In Equation (10), the first term $\frac{F(n_r)}{n_r} - F_r'(n_r)$ must be positive, since if it is not positive the resource sector makes

$$\frac{\partial\left(N\left(w\right)\pi\right)}{\partial\Omega_{r}}=n_{r}p_{r}\left(\left(\frac{F\left(n_{r}\right)}{n_{r}}-F_{r}'\left(n_{r}\right)\right)-\Omega_{r}F_{r}''\left(n_{r}\right)\frac{\partial n_{r}}{\partial\Omega_{r}}\right)>0. \tag{10}$$

Combined with the fact that wages and population both increase at any non-zero and finite labor supply elasticity, this implies that booms increase consumers' aggregate budget constraint $N\left(w\right)\left(w+\pi\right)$, which in turn implies an increase in demand for non-tradables. Appendix A contains additional details.

Prediction 3: If labor supply is not fully elastic, resource booms decrease contemporaneous local production of tradable goods.

Prediction 1 showed that if labor supply is not fully elastic, then resource booms will increase wages. The tradable goods sector thus contracts in response to its reduction in profitability. This is immediate from Equation (8), which shows that $w=p_{m}\Omega_{m}F_{m}'\left(n_{m}\right)$, given that contemporaneous tradables sector productivity and prices are exogenous and the production function is concave. Given that labor input n_{m} drops, output X_{m} must also drop. This mirrors Corden and Neary's "resource movement" effect.

This captures the fundamental mechanism behind how "Dutch Disease" could act on resource abundant regions *within* a country. In the cross-country setting, resource booms cause wages to rise relative to real traded goods prices because the currency appreciates. By contrast, in the within-country setting, nominal wages rise even if the exchange rate across regions is unaffected. In either case, resource booms reduce margins for tradable goods producers, causing that sector to contract.

3.2.1 A Resource Curse from Domestic Dutch Disease

The potential decline of the tradables sector due to a resource boom does not reduce welfare if there are no market failures (von Wijnbergen 1984). Indeed, welfare increases due to higher wages and resource profits. However, if there are uninternalized productivity spillovers in the tradables sector but not in the resource sector, then the loss of these spillovers would reduce long-run welfare. To illustrate this potential mechanism of a Resource Curse, we compare the resource producer region to another region that does not experience a resource boom. We label the producer region A, and the non-boom region B.

There is an initial condition, followed by two periods. For ease of comparison, we assume that regions A and B are ex-ante identical in sector productivities, population, and wages. In period 1, region A experiences a resource boom. By contrast, region B does not experience a resource boom, perhaps because it has a different geology such that resource sector productivity Ω_{r} is not enhanced

negative profits and goes out of business. The second term $\Omega_{r}F_{r}''\left(n_{r}\right)\frac{\partial n_{r}}{\partial\Omega_{r}}$ must be negative, since by assumption $F''\left(\cdot\right)<0$, and the other two terms are positive.

by the same technology that causes a boom in region A. In period 2, the boom ends, meaning that resource productivity (or the resource price) returns to its initial condition. For simplicity, we assume that the two regions are part of a large country, such that labor demand in region A does not affect region B.

We assume that tradables sector productivity evolves over time t:

$$\Omega_{mt} = \Omega_{m(t-1)} + \delta X_{m(t-1)} + \gamma X_{r(t-1)}. \tag{11}$$

A value of $\delta > 0$ would imply productivity spillovers or "learning by doing" in the tradables sector, as documented by Ellison, Glaeser, and Kerr (2010), Greenstone, Hornbeck, and Moretti (2010), Kline and Moretti (2013), and others. A value of $\gamma > 0$ would imply that the resource sector exerts positive productivity spillovers on the tradables sector.

Prediction 4: If labor supply is not fully elastic and there is learning-by-doing in tradables production, then a symmetric resource boom and bust will leave a region with lower tradables sector productivity and output than an otherwise-identical region that does not experience a boom. This also causes relatively lower wages and population.

Thus, foregone local productivity spillovers could cause a Resource Curse: the resource boom could reduce period 2 wages and population, in region A relative to region B. Again, Appendix A contains details.

Our model suggests that an alternative outcome is also possible. If spillovers from the resource sector are strong and/or the size of the boom is large enough, then $\gamma\left(X_{r1}^{A} - X_{r1}^{B}\right)$ could be greater than $\delta\left(X_{m1}^{B} - X_{m1}^{A}\right)$, and the opposite result could be obtained: period 2 tradables productivity and output, as well as population and wages, could be higher in region A. The literature on agglomeration and spillovers, such as Bleakley and Lin (2010), suggests that this could occur, although it is an empirical question whether the resource sector actually does exert positive productivity spillovers.

3.3 Geographic Spillovers

The model also suggests how a resource boom in one region could affect other regions: as labor supply increases in response to a resource boom, the population that migrates in must have come from somewhere else. Thus, as Busso, Gregory, and Kline (2012) point out in the related context of place-based local economic development policies, our estimates at least partially reflect re-allocation of economic activity from one area to another. Geographic spillovers could also occur through other channels. For example, producer states may redistribute tax revenues to their non-producer counties, and firms may expand in non-producer regions to serve higher demand in nearby producer regions.

Our "treatment effects" thus measure the average *difference* in potential outcomes for more vs. less resource-abundant counties, but they do not identify the absolute *levels* of potential outcomes that would have been experienced in the absence of a boom. For small counties that by themselves have small general equilibrium effects, these treatment effects also approximately equal the effects of restraining a resource boom. This is a relevant policy question: for example New York state and many local areas have banned fracking, while other states and counties are choosing how high to set royalty tax rates, how quickly to approve drilling permits, and how extensively to provide complementary public goods such as roads. Our estimates are the necessary parameters for policy makers evaluating the local costs and benefits of policies that determine the magnitude of a local boom.

3.4 Tests

The model suggests three main empirical questions, which organize our empirical strategy and results. First, how much do resource booms affect county-level aggregate outcomes: employment, earnings, population, and wages? These outcomes are of interest *per se* as measures of growth. The answer to this question also suggests the magnitude of effects on the manufacturing sector. Elastic migration of population to producer counties could limit wage increases, which reduces the possible magnitude of Dutch Disease.

Second, how do resource booms contemporaneously affect employment and output in the manufacturing sector? There is substantial variation across manufacturing establishments that could moderate the effects of natural resource booms: some establishments might produce locally non-traded goods, and local demand increases could be stronger for "linked" manufacturers that produce inputs to the resource sector.

Third, do resource booms affect manufacturing productivity? Contemporaneous productivity increases identify positive spillover effects (γ) from resource booms, which would also reduce the possible magnitude of Dutch Disease or even cause an opposite positive effect. Here again, heterogeneity within manufacturing could be important, as spillovers may depend on the degree of linkages to a local resource sector.

4 Data

Our analyses exploits panel data from the 1960s through today, using regressions with a measure of resource booms as the key independent variable and an economic outcome as the dependent variable. This section describes these resource and outcome data.

We study the entire population of counties in the continental United States. On rare occasions, counties will merge or split. In these cases, we define counties at the most disaggregated level at which data are observed for a consistent geographic area over the entire sample period. This gives a population of 3075 counties.

4.1 Resource Data

In theory, we would like to know each county's oil and gas supply curve under the technologies available in each year. This is not available. Instead, we proxy with the amount of oil and gas that is "economically recoverable" under two different major technologies.

A county's total oil and gas endowment is comprised of three categories of resource. The first, past production, is the total resource removed from the county. The second, proven reserves, are the underground resources known to exist with relative certainty by oil and gas producers. The third, undiscovered reserves, are the underground resources that have not been established with certainty but are likely to exist given the geological profile of the area.

Oil and gas production data are from a new county-by-year panel dataset from 1960 to 2011, which we constructed for this project. While production data are easily available by state, this is the first comprehensive county-level dataset. The original source of most of these data is a database of well-level oil and gas production from DrillingInfo, a market research company, which we collapse to the county-by-year level. The DrillingInfo data are incomplete, however: a number of producer states are either missing entirely or do not appear until after the boom of the 1970s. Therefore, we have acquired county-level oil and gas production data from oil and gas regulatory agencies or severance tax authorities in 13 additional states; see Appendix Table A1 for details. In a couple of states, it is not possible to acquire county-level production data for some early years, so we impute production by multiplying state-level production by the county's share of state production in the earliest year when it is observed.

Proven reserves data are from the EIA's survey 23L, which collects proven reserves and production by each firm in each oil field. The EIA granted us confidential access to county-by-year totals.[6] This allows a substantial improvement over publicly-available proven reserves data used in other previous work, which covers only the largest fields. We also use the 23L production data to supplement incomplete DrillingInfo data in a few cases.

Undiscovered resources are estimated by the US Geological Survey (USGS) on the basis of the expected oil, gas, and natural gas liquid yield using current technology, including estimated future discoveries over the next 30 years. Undiscovered reserves are defined as "undiscovered petroleum is that which is postulated from geologic knowledge and theory to exist *outside of known accumulations* [emphasis added]."[7] These resources are unaffected by existing or past extraction

[6] For figures estimated using Equation (16) below, we approximate early period reserves with data from the 1999 Oil and Gas Journal Data Book and total reserves using the EIA list of top 100 oil fields in 2009, which is available from www.eia.gov/naturalgas/crudeoilreserves/archive/2009/pdf/top100fields.pdf. The figures are substantively similar when made with the 23L data, but it was prohibitive to disclose so many data points for this draft.

[7] See http://energy.usgs.gov/OilGas/AssessmentsData/NationalOilGasAssessment/Methodology.aspx for more de-

except insofar as greater prospecting in an area might transfer resources from the "undiscovered" to the "proven" category. [8]

These three components of oil and gas endowments are combined to create our county-level measure of resource abundance: the value of economically recoverable oil and gas endowment per square mile as of 1960. The numerator is the sum of proven and undiscovered reserves as of some end year T plus total production between 1960 and T:

$$r_c = \frac{\sum_{t=1960}^{T} Production_{ct} + Proven\,Reserves_{cT} + Undiscovered\,Reserves_{cT}}{Area\,(Square\,Miles)_c} \tag{12}$$

As discussed in Section 2, technological changes made additional oil and gas economically recoverable before the oil and gas price spike of the recent decade. We thus construct two different measures of an area's resource endowment. r_c^{early} measures endowment in the first boom, with $T = 1995$, using the estimates of proven and undiscovered reserves from the late 1990s. r_c^{total} measures endowment over the entire period, with $T = 2011$, using the latest estimates of proven and undiscovered reserves. For our primary specifications, we define an endowment variable r_{ct}, which takes value r_c^{early} until 2000, and r_c^{total} beginning in 2001, although we also show that the conclusions are not sensitive to using either r_c^{early} or r_c^{total} for the entire period.

We scale this endowment measure in units of $10 million per square mile, which gives easily-readable regression coefficient magnitudes. Conveniently for interpretation, r_c^{total} also has standard deviation of approximately $10 million per square mile within the set of counties with non-zero resource. We translate physical units of oil and gas to dollar values using average prices over 1969-2011: $38.12 per barrel of oil and $3.65 per mmBtu of gas.

Table 1 presents descriptive statistics for the resource data, focusing on r_c^{total}. There are several basic facts to highlight. First, the primary constituent of oil endowment is the actual production over 1960-2011–proven and undiscovered reserves are relatively small. Second, however, reserves are a much larger share of natural gas endowment. Third, there are 730 more counties with undiscovered oil than counties that produce oil, and 1,166 more counties with undiscovered gas than counties that produce gas. This highlights the exogeneity of our measure of resource endowments: although endowments certainly predict production, r_c^{total} does not simply include counties that produce in equilibrium. Fourth, multiplying total endowments by average prices shows that oil and gas are roughly equal constituents in r_c^{total}. Fifth, there is substantial variation in r_c^{total} across counties: the standard deviation across all counties (not just non-zeros) is about 3 times the mean. This variation is also highlighted in Figures 3 and 4 , which show r_c^{early} and $r_c^{total} - r_c^{early}$, respectively.

tails on assessment methodology.

[8] The USGS reports undiscovered reserves at the field (post-1995) or play (1995) level. To map this data to counties we intersect the most detailed available USGS geological maps of these fields or plays with county outlines. Resources are then assigned to counties assuming a uniform distribution within field or play. We assume 50% of Utica Shale resources lie within the USGS-identified "sweet spot".

4.2 Regional Economic Information System

Our primary source of data on employment, earnings, and population is the Regional Economic Information System (REIS).[9] The U.S. Bureau of Economic Analysis prepares the REIS using Internal Revenue Service tax records, unemployment insurance and social security payments, Census data, and other information. Data are available annually for 1969-2011. We use the REIS for national-level oil and gas employment, as well as county-level population, total employment, total earnings, manufacturing employment, and manufacturing earnings.[10] Manufacturing earnings and employment are occasionally non-disclosed for small counties. In cases where earnings are bottom coded at $50,000, we assign a value of $25,000. Since the REIS data begins in 1969, we collected data on the equivalent wage and employment outcomes from the 1964 and 1968 County Data Books[11], and on population from the 1960 and 1966 US Census data to control for pre-trends. Data on county area, including both land and water area, also comes from the US Census.[12] The top panel of Table 2 describes the REIS data.

4.3 Current Population Survey

Because wage increases are a necessary condition for Dutch Disease, it is important to cleanly estimate how resource booms affect labor input costs. The REIS and Census microdata allow us to calculate earnings per worker by dividing total earnings by total employment, but there are two potential concerns with using earnings per worker as a proxy for labor input costs. First, labor quality could change endogenously, for example if a resource boom induces lower-education workers to enter the local workforce either by transitioning from unemployment or by migrating from elsewhere. Second, labor input quantity could change: if people work more hours during resource booms, earnings per worker would increase even if unit labor costs did not.

[9] The REIS data are available from http://www.bea.gov/regional/.

[10] The REIS gathers two measures of employment and earnings. Series 7 and 27 measure wage and salary earnings and employment, based primarily on unemployment insurance payment records. This corresponds closely to data from the Quarterly Census of Employment and Wages. Series 5 and 25 measures total earnings and employment, adding sole proprietors (who file a Schedule C on their tax returns) and general partners in partnerships (who file a Form 1065). Neither series includes limited partners, who are likely to be passive investors. Series 5 and 25 are intended to be a more comprehensive measure of total earnings and employment, so we use these series in all specifications, with one exception: for county-level average wages, we use series 7 and 27 to construct wage and salary earnings per wage and salary worker, which we shorten to "wage earnings/worker." This provides a closer proxy to wage rates. In robustness checks, we substitute national oil and gas wage and salary employment instead of total employment in constructing our resource boom measure; the results are unchanged.

These measures appear to correctly allocate economic activity to counties. Unemployment insurance payments are assigned to the county where the employing *establishment* is located, not the firm headquarters. Sole proprietor and partnership earnings and employment are assigned to the tax-filing address of the recipient, which is typically the person's residence. This will misallocate employment when the filer is not working in his or her county of residence. In (unreported) robustness checks, we find that using total county employment from REIS series 5 and 7 give similar results, suggesting that this is not an important source of bias.

[11] We downloaded the County Data Book datasets from ICPSR, series 25984.

[12] The land area data are available from http://quickfacts.census.gov/qfd/download_data.html.

Microdata from the Current Population Survey (CPS) helps to test these two potential concerns, as the CPS includes demographic information and a direct measure of hourly wages.[13] The CPS surveys 50 to 60 thousand households each month. Households are surveyed for four consecutive months, then after a period of eight months they are surveyed again for the next four months. From 1969-1987, hourly wage questions were asked on the May CPS. Beginning in 1979, hourly wage questions were also asked on each household's "outgoing rotation": the fourth and eighth interviews of the panel, which occur exactly 12 months apart. These data are available in the Merged Outgoing Rotation Group (MORG) database.[14]

We construct two datasets from the CPS. The first is a repeated cross section formed by combining all observations from the May CPS for 1977 and 1978 with all observations from the MORG beginning in 1979. Table 2 describes these data for hourly wage and hours worked. The second dataset is a panel based on the MORG, which includes each individual's change in hourly earnings in the 12 months between his or her two outgoing rotations.[15] We include only workers employed by the private sector or government and exclude self-employed and unemployed.

Except for large counties in recent years, the CPS does not include county identifiers. In regressions with CPS data, we thus use state-level treatment intensity, which is constructed analogously to the county-level measure described earlier.[16]

4.4 Manufacturing Census Microdata

While the REIS data provides annual frequency data over a uniquely long period (1969-2011), it is not informative about firm productivity, nor does it allow us to test the differential predictions of the model by sub-sector. For this we turn to the restricted-access establishment-level microdata from the Census of Manufactures (CM).

The Census of Manufactures includes microdata for all manufacturing establishments in the United States. The data include the county where the establishment is located, its four-digit SIC

[13]To measure wages for people who are paid by the hour, we use the answer to the question, "How much does [person] earn per hour?" For non-hourly employees, we divide weekly earnings ("How much does [person] usually earn per week at this job before deductions?") by weekly hours ("How many hours per week does [person] usually work at this job?").

[14]The May CPS data we use can be downloaded from http://www.nber.org/data/cps_may.html, and the MORG data are available from http://data.nber.org/morg/annual/.

[15]Since the CPS sampling frame is the household, not the individual, this panel includes only individuals who do not change residence between the two interviews. The CPS does not include unique individual identifying codes, so we use the approach of Madrian and Lefgren (1999) to match individuals between interviews.

[16]It is not possible to construct a panel over our entire study period using any consistently-defined geographical area less aggregated than the state. Before 1977, the May CPS data do not include a complete set of state identifiers. From 1977 to June 1985, there are geographic identifiers for state and approximately 45 Standard Metropolitan Statistical Areas (MSAs). From July-December 1985, only state identifiers are included. In 1986 and again in 1993, the CPS changes to different and more disaggregated MSA definitions, and beginning in late 2004 there are identifiers for large counties and for Core Based Statistical Areas (CBSAs). While these geographical areas comprise precisely-defined sets of counties in any particular year, counties are often moved between areas over time. To avoid potentially confounding effects of changes in geographic definitions, we use only state identifiers.

code, as well as number of employees, total wage bill, value of materials inputs, and total revenues.[17] The CM microdata are available for 1963 and quinquennially (every five years) beginning in 1967, i.e. 1972, 1977, ..., 2007. Because the CM includes all manufacturing establishments in the country in each year, it also allows us to infer each establishment's year of entry and exit within a 5-year period, except for establishments that entered before the data began in 1963. We convert all industry codes to four-digit year-1987 SIC codes using standard crosswalks.

For about 6000 relatively-homogeneous products defined at the 7-digit SIC level, the CM records both physical production quantities and sales revenues. [18] We divide revenues by physical output to arrive at an establishment-by-product-by-year dataset of manufacturing output prices. We drop imputed data, as well as any reported prices that differ from the 7-digit median by a factor of more than five.

We use revenue TFP (TFP-R) estimates made available within the census CM data by Foster, Grim, and Haltiwanger (2013) for years 1972-2007. These are standard Cobb-Douglas log-TFP-Rs estimated in OLS, with separate production function coefficients for each industry.

4.4.1 Industry Classifications

When using the CM, we also examine subsets of manufacturers that may be differentially affected by resource booms. We distinguish subsectors along two dimensions: tradability and linkage to oil and gas.

Using the Commodity Flow Survey, Holmes and Stevens (2014) calculate a measure of transportation costs for each four-digit SIC industry that is closely correlated with average product shipment distance. Ready-mixed concrete, ice, and newspapers have the highest η, while watches, x-ray equipment, space propulsion units, and aircraft parts have the lowest. We define a four-digit SIC industry as "highly tradable" if the Holmes and Stevens η^{loglog} is less than 0.8, which corresponds to an average shipment distance of approximately 500 miles. By this definition, 69 percent of four-digit manufacturing industries are highly tradable.

We classify four-digit SIC industries as upstream or downstream of the oil and gas sector using the Bureau of Economic Analysis (BEA) Input-Output tables for 1987. For each industry, we calculate the direct oil and gas output share (the share of output purchased by the oil and gas sector) and the indirect oil and gas output share (the share of output purchased by the oil and gas sector through an intermediate industry), and we define the "upstream linkage share" as the sum of these two quantities. We define an industry as "upstream" of oil and gas if this upstream

[17] Employment and earnings data for non-responders and small establishments with fewer than five employees is imputed and/or marked as an "administrative record." For these establishments, we use the employment and earnings data drawn in from tax records, but we do not use any imputed variables.

[18] These are the data used by Foster, Haltiwanger, and Syverson (2008) to study physical productivity and revenue productivity.

linkage share is larger than 0.1 percent. An industry is "downstream" if the oil and gas input cost share is larger than 0.1 percent. (We do not add the analogous "indirect input share" because this is primarily a measure of electricity intensity, given that substantial amounts of natural gas are used by the electricity generation sector.) We refer to an industry as "non-linked" if it is neither upstream nor downstream. Using such small cutoff values in defining upstream and downstream is conservative in the sense that "non-linked" industries have very limited linkage to oil and gas and thus should not be directly affected by that sector. 27 percent of industries are upstream, 2.5 percent are downstream, 73 percent are non-linked, and 2.1 percent (largely chemical plants) are both upstream and downstream. Appendix Table A2 presents the most-linked upstream industries (such as oil and gas field machinery and equipment, cement, lubricants, chemicals, and pipes) and downstream industries (such as petroleum refining, fertilizers, chemicals, and plastics).

5 Empirical Strategy

5.1 Basic Estimating Equations

Our estimation strategy is based on the idea that the level of an outcome Y is determined by the the intensity of resource production E_t, with an elasticity depending on the level of local resource endowment r_c, and some shock $\tilde{\psi}$:

$$Y_{ct} = E_t^{\tau r_c} \tilde{\psi}_{ct}. \tag{13}$$

This equation indexes geographic areas by c, referring to counties, although for CPS regressions we use states instead. Taking logs and denoting time differences by $\Delta Y_{ct} = Y_{ct} - Y_{c(t-1)}$, we have:

$$\Delta \ln Y_{ct} = \tau \Delta \ln E_t r_c + \psi_{ct}. \tag{14}$$

We implement $\Delta \ln E_t$ as the change in log national-level oil and gas employment and r_c as the county's economically recoverable endowment of oil and gas per square mile. As described above, we separately measure early endowment through the year 2000 and total endowment beginning in 2001; to signal this change we index the endowment variable by time, denoted r_{ct}. All endowments are scaled in units of \$10 million per square mile.

We substitute specific controls in place of the shock ψ_{ct}. First, we control for the main effect of local resources, κr_{ct}, to allow for the possibility of a differential growth trend with respect to endowment and to capture the direct effect of the switch from conventional to full resource endowment in 2000. Second, we include $\ln \mathbf{Y}_{0c}$, a vector of baseline values of the outcome variable from two different years at the beginning and end of the 1960s.[19] Finally, ϕ represents a vector of

[19] When using log population as the dependent variable, we control for log of the county's population in 1960

Census division-by-year indicator variables, where d indexes Census divisions.

These substitutions give our estimating equation:

$$\Delta \ln Y_{ct} = \tau \Delta \ln E_t r_{ct} + \kappa r_{ct} + \sum_t \gamma_t \ln \mathbf{Y}_{0c} + \phi_{dt} + \varepsilon_{ct}. \tag{15}$$

In this and all other specifications, we use robust standard errors and cluster by county, because treatment intensity varies primarily at the county level and errors may be serially correlated within county.

Because Y and E are logged, the estimated τ is like an elasticity, except that it is the differential elasticity for counties with \$10 million additional endowment per square mile r_{ct}. Furthermore, since $\Delta \ln Y_{ct} \approx \frac{Y_{ct} - Y_{c(t-1)}}{Y_{ct}}$ we can interpret effects in terms of changes to the growth rate of local outcomes. Combining this with the fact that \$10 million per square mile is one standard deviation within the set of counties with positive endowment, τ can be interpreted as "the differential percent increase in Y caused by a boom that increases national oil and gas employment by one percent, for a county with one standard deviation additional endowment."

The right-hand-side variable $\Delta \ln E_t r_{ct}$ is closely analogous to the Bartik (1991) instruments: it is the interaction of cross-sectional variation in the baseline share of an industry with the time trend in national-level employment. One difference is that we use initial resource endowment per capita instead of initial resource employment per capita. We prefer endowment for three reasons. First, it is a a function of economically exogenous geological features instead of economically endogenous equilibrium employment. (Ideally, we would use initial endowment before oil production began in 1859, but such data are not available for most states.) Second, because our measure of endowment does in practice exclude pre-1960 production, it is a more accurate measure of future activity than 1960s-era employment, which could reflect operations at existing wells in fields with no future drilling potential. This is especially important in some states such as Mississippi and Kansas where oil and gas resources had been almost fully exploited before 1973. Third, while we have good measures of oil and gas endowment at the county level, oil and gas employment is withheld from the REIS for all but the largest producer counties.

Unlike Blanchard and Katz (1992) and others who use the Bartik instruments, we directly use $\Delta \ln E_t r_{ct}$ on the right-hand-side instead of using it as an instrument for changes in employment. In this sense, we present the reduced form of an IV estimator. We do not report instrumental

and 1966. When examining natural log of employment or earnings per worker, we control for logs of the 1968 and 1964 values from the County Data Book. In regressions using the county-level Census of Manufactures dataset, we analogously control for logs of 1967 and 1963 value of the outcome. Including two logged baseline values and allowing their coefficients to vary by year means that we control for how baseline levels and trends in $\ln Y$ are associated with the outcome in any later year.

variables estimates because we do not intend to suggest that the exclusion restriction would be satisfied: resource booms affect local economies through royalties and other factors in addition to changes in oil and gas employment.

5.2 Additional Estimating Equations

5.2.1 Regressions for Graphical Results

Before presenting formal results, we also present visual evidence on how outcomes vary over time for more or less resource-intensive counties. The estimating equation is:

$$\ln Y_{ct} = \sum_t \tau_t r_{ct} + \kappa r_{ct} + \sum_t \gamma_t \ln \mathbf{Y}_{0c} + \phi_{dt} + \varepsilon_{ct}. \tag{16}$$

The equation excludes 1969, the first year of the sample, from the interaction coefficients in τ_t.

5.2.2 Current Population Survey Wage Regressions

As discussed above, we analyze two CPS datasets to estimate wage effects net of changes in worker characteristics or hours worked. We estimate two parallel specifications. For the CPS repeated cross section, we regress wages on the resource boom variable, using controls X_i for individual i's age, education, gender, race, and industry. We index states by s, months by m, and years by t, and include vectors of state indicators η_s, month indicators μ_m, and year indicators ν_t. We construct a resource endowment variable r_{st} for state s that parallels the county-level variable. The specification is:

$$\ln Y_{ismt} = \tau \ln E_t r_{st} + \kappa r_{st} + \beta X_i + \eta_s + \mu_m + \nu_t + \varepsilon_{ismt}. \tag{17}$$

To present visual evidence, we also plot the coefficients on τ_t when estimating Equation (17) after substituting $\sum_t \tau_t r_{st}$ for $\tau \ln E_t r_{st}$.

For the MORG panel, we regress individual i's change in wages in the 12 months between the interview on the change in the resource boom:

$$\Delta \ln Y_{ismt} = \tau \Delta \ln E_t r_{st} + \kappa r_{st} + \eta_s + \mu_m + \nu_t + \varepsilon_{ismt}. \tag{18}$$

In all CPS regressions, standard errors are robust and clustered by state.

5.2.3 Regressions Using Establishment-Level Census Microdata

We estimate two sets of regressions using establishment-level Census microdata. The first analyzes changes in outcomes for incumbent establishments first differenced across time, analogous to the CPS panel regression in Equation (18). In the estimating equation, f indexes establishments, and we also add λ_{nt}, the full interactions of four-digit SIC codes and years.

$$\Delta \ln Y_{fct} = \tau \Delta \ln E_t r_{ct} + \kappa r_{ct} + \phi_{dt} + \lambda_{nt} + \varepsilon_{fct}. \tag{19}$$

In these specifications, Δ denotes a 5-year difference between rounds of the Census of Manufactures.

Our second microdata specification looks at the establishments that enter and exit between rounds of the CM. In each round we identify establishments as entrants if they appeared in the dataset in the 5 years since the previous round, and exiters if they disappear prior to the next CM round 5 years later. Since we do not know the exact year of entry, we use the mean national oil and gas employment for the past (future) 5 year for entrants (exiters) as a measure of the resource boom or bust. Thus for entrants we define $\bar{E}_t^- = \sum_{t-4}^{t} E_t/5$, with $\bar{E}_t^+$ defined analogously for exiters in the next 5 years. We use a county-level fixed effect estimator for the entry and exit specifications:

$$\ln Y_{fct} = \tau \ln \bar{E}_t^{-/+} r_{ct} + \kappa r_{ct} + \phi_{dt} + \lambda_{nt} + \xi_c + \varepsilon_{fct}, \tag{20}$$

where ξ_c denotes county fixed effects.

In all Census microdata regressions, standard errors are robust and clustered by county.

6 Results

We present results in the following order. First, we examine "initial conditions" before the boom of the 1970s. Second, we use the REIS data to test for pre-trends and study county aggregate outcomes. Third, we present the CPS regressions, which document the effects of resource booms on wages and test whether earnings per worker is a good proxy for wages. Fourth, we use the REIS data to test for expansion or contraction of the manufacturing sector as a whole. Fifth, we use the county-level Census data to examine manufacturing subsectors and alternative outcomes other than employment. Sixth, we exploit the establishment-level Census data, testing for effects on productivity and prices. Finally, we examine long-run effects.

6.1 Initial Conditions

Table 3 presents initial conditions before the 1970s oil boom. Of course, these are "initial conditions" only in the sense that our datasets begin in the 1960s. Most counties and states that experienced the 1970s oil boom had already been producing oil for many years, and their economies had already been shaped by resource abundance. The first two rows present population and employment data from the 1969 REIS, while the remaining five rows show manufacturing employment from the 1967 Census of Manufactures. Column 1 shows the mean across all 3075 counties in the data. Manufacturing is about one-sixth of employment. Of that, 73 percent is "non-linked" by our conservative definition. Of non-linked employment, 73 percent is tradable by our definition, while the remainder is local.

Column 2 shows coefficient of regressions of late-1960s population or employment on oil and gas endowment per square mile r^{early}, controlling for division fixed effects. Resource abundance is positively correlated with population, employment, and manufacturing employment. Consistent with Michaels (2010), this suggests that resource-abundant counties had grown faster over the decades since they began producing oil and gas. Building on that result, the confidential Census microdata shows that much of this is due to upstream linkages: a \$10 million increase in oil and gas abundance is associated with a 11.3 percent increase in upstream manufacturing employment. By contrast, the relationships between resource endowment and other sub-sectors of the manufacturing industry are insignificant and point estimates are negative.[20]

6.2 Aggregate Effects Using REIS Data

6.2.1 Pre-Trends

As Figures 1 and 2 in Section 2 showed, oil and gas prices and employment were relatively steady in the years leading up to the 1973 oil shock. Table 4 tests whether changes in economic outcomes over this "pre-treatment" period are associated with resource abundance. The absence of pre-trends would provide additional support for our causal interpretation of the association of resource abundance with changes in outcomes during resource booms. Furthermore, even if there were monotonic trends associated with resource abundance, our identification would still be highly credible because it exploits non-monotonic changes in the resource sector: a boom, a bust, and a boom over a 43-year period. Notwithstanding, monotonic trends associated with resource abundance would bias tests of whether busts have larger effects than booms.

The outcome variables in all columns of Table 4 are the difference in a logged outcome between 1969 and 1972. Column 1 regresses this on endowment r_c^{early}, with no other controls. Column 2 includes controls for baseline levels $\ln \mathbf{Y}_{0c}$ and Census division-by-year fixed effects, the same controls as in Equation (15). With no controls, wages in resource rich areas appear to be decreasing faster than in other counties, although the results are small: a difference of -0.0044 over 3 years is consistent with an annual wage growth rate 0.15 percent lower. Controlling for baseline levels of $\ln \mathbf{Y}_{0c}$ in column 2 substantially reduces the size and significance of the coefficients, with no remaining significant estimates.

[20] Including division fixed effects does affect the magnitudes and even the signs of these correlations. This is partially because as the map in Figure 3 shows, a large amount of oil and gas is in sparsely-populated Rocky mountain states. The sensitivity of the cross sectional correlations to the inclusion of such controls emphasizes the importance of exploiting time series variation in oil and gas booms.

6.2.2 Main Results

Figure 5 presents the estimates of τ_t from Equation (16) for employment, population, and wage earnings per worker using the REIS data. Our key time-series variable E_t (national oil and gas employment) is plotted against the right axis, with annual percent changes from the NAICS data applied to extend the SIC series after 2000. Each of the outcomes is highly procyclical with the resource boom. The graph also illustrates the dynamic adjustment to a local economic shock highlighted by Blanchard and Katz (1992). As the resource sector expands, total employment and wages rise immediately. Population adjusts more slowly, meaning that the short-run effects of a resource boom are to increase wages and decrease unemployment. However, within one to three years, people migrate in search of higher wages, and this migration puts downward pressure on wages. Appendix Figure A1 shows each series individually and includes confidence intervals.

Table 5 presents the formal estimates of the effects of resource booms on county-level aggregates. The three panels examine three different outcome variables. Within each panel, column 2 presents the estimates of τ from Equation 15, while column 1 excludes Census division-by-year fixed effects ϕ_{dt}. Including ϕ_{dt} brings down the point estimates, but the qualitative signs and significance levels are the same. The table shows that resource booms substantially increase growth in resource-abundant counties. A boom that doubles national oil and gas employment increases population, employment, and earnings per worker by 1.29, 2.87, and 2.14 percent, respectively, for counties with \$10 million/square mile additional endowment. Recall that \$10 million/square mile can also be interpreted as approximately one standard deviation within the counties with positive endowment.

Connecting to Prediction 1 of the model, these results show that migration is neither fully elastic nor fully inelastic. While population increases in response to the resource boom, wages (more precisely, earnings per worker) rise also. This implies that the assumptions for Predictions 3 and 4 are satisfied: because wages rise in resource-abundant counties, Dutch Disease is possible. If manufacturers are selling into a national output market with exogenous prices, the sector should contract when faced with this increase in labor costs. The coefficients in Figure 5 show that earnings per worker are one to 2.5 percent higher than their 1969 levels in counties with one standard deviation additional endowment for the entire period from 1975-1985.

We can benchmark the magnitude of these earnings impacts in two ways. First, given that the average labor input revenue share in manufacturing is on the order of 0.25, total costs increased by 0.4 percent of revenues over the period 1975-1985. While this is small, it represents a much larger share of profits, and it may be exacerbated by increases in costs of any locally-sourced materials inputs. Second, for 2011, the coefficient of variation across counties in earnings per worker is 21.6 percent. Thus, an increase in earnings per worker of 2.14 percent (the coefficient in Table 5) represents almost exactly a tenth of a standard deviation. Again by this measure, the earnings per worker effects are meaningful but small.

Column 3 of Table 5 includes two interactions with $\tau \Delta \ln E_t r_{ct}$. The first tests whether busts, as measured by a decline in national oil and gas employment, have larger or smaller effects than booms. If busts have larger effects, this is consistent with a Resource Curse, as it implies that a symmetric boom and bust would have net negative effects. Agglomeration, sunk costs, or other factors could cause busts to have smaller effects. Column 3 shows that employment contracts equally quickly during a bust as it grew during the boom. Population, however, contracts more slowly: people tended to stay in the declining resource counties during the 1980s. Consistent with this excess labor supply, results in the bottom panel show that wages drop more quickly during busts.

The second interaction in Column 3 tests whether the unconventional boom of the 2000s has larger or smaller effects than the boom of the 1970s, again per log unit of national employment change. Consistent with the graphical evidence in Figure 5, the unconventional boom has had a smaller effect on total employment and population per log unit of national oil and gas employment change. The point estimate suggests that earnings per worker has grown more slowly during the most recent boom, although unlike in the CPS results below, this difference is not statistically significant.

Appendix Table A3 presents robustness checks. The results are highly robust to using r_c^{early} or r_c^{total} in place of r_{ct}, measuring resource boom intensity by oil and gas wage and salary employment or oil and gas prices instead of total employment, or using an analogous fixed effects estimator instead of a difference estimator. When using oil and gas prices to measure booms, coefficients have comparable t-statistics but are mechanically smaller, because the oil and gas booms have caused a larger percentage increase in prices than in national oil and gas employment (see Figure 1). In other alternative specifications available upon request, we construct coal abundance data analogous to our oil and gas data and control for the coal boom studied by Black, McKinnish, and Sanders (2005a, 2005b). Although the coal boom occurred in a similar period and in some of the same counties, it was small relative to the oil and gas boom and does not affect the results.

6.2.3 Geographic Spillovers

Section 3 discussed how resource booms create geographic spillovers. Table 6 studies spillovers to other counties within the same state. While wage spillovers should almost certainly be positive, because higher wages in one county should drive up wages more in nearby counties than in far-away counties, employment and population spillovers could go in either direction. On the one hand, a resource boom in a nearby county should draw migrants away from a non-producer county. On the other hand, nearby counties may also experience labor demand growth if firms there provide goods and services for the resource boom or if income from the boom is redistributed through state taxation.

Column 1 of Table 6 restates the base estimates of Equation 15 from column 2 of Table 5. Column 2 adds state-by-year fixed effects. This identifies the coefficients only off of within-state variation in endowment. Point estimates decrease in absolute value, although these differences are not statistically significant. This suggests that there are positive spillovers on each outcome from more to less resource abundant counties within a state. Column 3 examines this more explicitly by limiting only to the sample of counties with zero endowment. Here, the key independent variable is the average oil and gas intensity per square mile of the other counties in the state. The positive coefficients again demonstrate positive geographic spillovers: zero-endowment counties in more resource-abundant states grow more during resource booms and contract more during the resource bust.

Column 4 returns to the sample of all counties and tests the joint association with county endowment, state endowment, and the interaction thereof. As before, the county and state endowment variables are associated with growth during booms. The interaction is negative, implying that within-state geographic spillovers are focused in counties that are not experiencing a boom. This result is intuitive: a business will be more able to expand to serve a boom in a nearby county if it does not need to pay high wages due to a boom in a local county. Additional results available upon request show that the spillovers are not limited to counties with larger cities that might be providing financial and other professional services to the resource boom. In fact, geographic spillovers actually covary negatively with the population of the county's largest city.

6.3 Current Population Survey Wage Regressions

Table 7 presents the results of the Current Population Survey wage regressions. The top and bottom panels present estimates for all workers and manufacturing workers, respectively. Column 1 presents estimates of Equation (17). The coefficient of 0.0348 implies that an oil and gas boom that doubles national oil and gas employment increases wages by 3.48 percent more in states with an additional \$10 million per square mile oil and gas endowment. For context, Pennsylvania has an endowment of almost exactly \$10 million per square mile in the post-fracking era and is the fourth most densely-endowed state, while Maine, Rhode Island, and New Hampshire are the states with zero endowment. The standard deviation of state endowments per square mile is \$4.4 million.

Figure 6a illustrates these results, using an approach analogous to Equation (16): we plot the coefficients on the interaction of year indicators with r_{ct}, with an omitted interaction for the year 2001. States with \$10 million extra endowment per square mile saw relative wages remain at least five percent higher than their year-2001 equilibrium for the entire eleven-year period between 1977 and 1987. Figure 6b presents analogous results, limiting to manufacturing workers only. While the estimates for manufacturing workers are noisier, the basic trend is very similar to the estimates for all workers.

Both figures, especially Figure 6a, suggest that the more recent boom has had smaller wage effects than the 1970s-1980s boom. Column 2 of Table 7 adds the interaction of an indicator for years 2001 and later with the resource boom variable. Results confirm that the more recent boom has had statistically significantly smaller effects on the average worker's wages, although not the average manufacturing worker.

Column 3 of Table 7 presents estimates of Equation (17), except with natural log of hours worked as the left-hand-side variable. There are no statistically-significant effects on hours worked, and the standard errors rule out that a boom that doubles oil and gas employment increases hours worked by more than about about one percent in states with \$10 million additional endowment per square mile. Column 4 presents estimates of Equation (17), but excluding controls βX_i for age, education, race, and industry. The point estimates are very similar to and statistically indistinguishable from column 1. Because worker-level demographic controls do not affect the estimates and there are no significant effects on hours worked, this suggests that measures of earnings per worker available in the REIS provide unbiased estimates of the effects of oil and gas booms on "wages," i.e. quality-adjusted per-unit labor input costs.

Column 5 presents estimates of Equation (18) using the MORG panel data, with the log of each individual's 12-month wage change as the dependent variable. The sample size is much smaller because the MORG panel does not begin until 1979, because it includes only individuals who can be matched between their first and second outgoing rotations, and because each person is counted as one observation when calculating differences, while estimates of Equation (17) include both of an individual person's observations. The qualitative results are very similar.

When limiting the sample to manufacturing workers only, the standard errors widen, but the point estimates are similar and statistically indistinguishable from the effects on all workers. In Appendix Table A4, we confirm that these results are robust to the same set of robustness checks as the REIS data, as well as to dropping outlying hourly wages.

6.4 Manufacturing Sector Effects

So far, we have shown that population is not sufficiently mobile to fully offset local wage increases during oil and gas booms. Thus, a necessary condition for Dutch Disease is satisfied. Does the local manufacturing sector shrink during a boom, as predicted for the traded goods sector in Prediction 3?

Figure 7 presents estimates of Equation (16) with the log of county-level manufacturing sector output as the dependent variable. There is certainly no evidence of Dutch Disease. To the contrary, manufacturing in resource-abundant counties is clearly pro-cyclical with resource booms. Manufacturing growth is not associated with resource abundance between 1969 and the early 1970s, then grows during the boom of the 1970s, drops off during the bust, and begins to grow again during the boom of the 2000s. In counties with one standard deviation additional endowment, manufacturing sectors were approximately five percent larger at the peak of the 1970s boom compared to the early 1970s. This almost the same percent growth as for aggregate employment across all sectors displayed in Figure 5.

Table 8 presents the formal estimates of the effects of resource booms on manufacturing employment. The columns parallel the columns for county aggregate outcomes in Table 5. A boom that doubles national oil and gas employment increases manufacturing employment by 2.89 percent in counties with one standard deviation larger endowment.

One reason why manufacturing might not contract as county average wages rise is that manufacturing workers might not be substitutable with labor in oil and gas and other sectors. The bottom panel of Table 8 estimates effects on total manufacturing sector earnings per manufacturing sector worker. As in the CPS wage data, the coefficient is positive and not statistically different than the estimate for all workers.

To parallel the aggregate results tables, Appendix Tables A5 and A6 present robustness checks and geographic spillovers. Results are similarly robust, except that τ is not statistically different from the base τ estimate or from zero when measuring boom intensity with oil and gas price. Geographic spillovers are consistent with the results for other outcomes in Table 6, except that estimates for manufacturing earnings per worker are less precise.

6.5 County-Level Census Dataset: Subsectors and Alternative Outcomes

Table 9 presents estimates of Equation (15) using the county-level Census dataset. Each panel presents a different outcome, while each column presents estimates with outcomes collapsed from different subsets of establishments.

Column 1 presents estimates for all manufacturing establishments. The first panel examines employment, confirming the result from Table 8 that the sector is procyclical with oil and gas. The point estimates are slightly larger in the CM data but not statistically different, as would be expected from parallel datasets. The second and third panels use revenues ("total value of shipments") and investment as outcomes instead of employment. These confirm that the procyclicality of manufacturing is not a spurious result of studying employment. In fact, revenues grow much more in percent terms, suggesting that revenues per worker may be increasing. Investment is even more procyclical than revenues. While disclosing graphical results is more difficult for this draft, the graphs of results in column 1 look qualitatively similar to the up-down-up pattern illustrated by Figures 5 and 7.

Do firms adjust to resource booms on the "intensive margin," by hiring more workers within the same establishment, or on the "extensive margin," by opening and keeping open more establishments? Because opening physical establishments may involve larger sunk costs than hiring workers into existing establishments, this could affect the persistence of a resource boom's effects. The fifth panel shows that the count of manufacturing establishments is indeed procyclical with resource booms, although the coefficient is about two-thirds the size as the coefficient on employment. Thus, under the approximation that exiting establishments are about the same size as non-exiters, these point estimates would suggest that about 2/3 of the manufacturing sector's adjustments to resource booms is on the extensive margin. For the number of establishments to be pro-cyclical, births and/or deaths must also be procyclical. The next two panels show that entry rate is positively and significantly associated with resource booms, while overall establishment exit rates have no significant correlation with booms.

Column 2 presents analogous results for establishments that are upstream or downstream of oil and gas. Results are generally consistent (and not statistically differentiable) from the overall effects in column 1, with the exception of the exit rate. Perhaps not surprisingly, linked establishments are less likely to exit resource-rich counties during booms, and more likely to exit during busts.

Columns 3, 4 and 5 of Table 9 examine non-linked establishments, divided into subsamples that produce more vs. less tradable goods. Non-linked, local industries are generally procyclical. Perhaps surprisingly, local industries also have a pro-cyclical establishment exit rate, a point we discuss further below.

In stark contrast, the results for tradable industries in column 5 appear to be almost universally counter-cyclical, although these are often noisily estimated. Point estimates on employment, revenue, and number of establishments have the same magnitude but opposite sign as coefficients for local non-tradables, with p-values of 0.082, 0.210, and 0.107, respectively. These results suggest that, consistent with the model, resource booms cause the tradable manufacturing sector to contract due to increased input costs that are not offset by an increase in demand.

6.6 Productivity and Price Effects

A key parameter in the model in Section 3 represents productivity spillovers from the resource sector to manufacturing. Such productivity spillovers could help to explain why the manufacturing sector does not contract during resource booms. Table 10 tests this by estimating Equation (19) using plant-level data from the Census of Manufactures. Recall that this specification first-differences outcomes within plants across five year periods between each Census of Manufactures round. As in the previous table, each panel examines a different outcome, and the columns include analogous subsets of plants. For each outcome, we present two sets of estimates: the first has only census division-by-year fixed effects, while the second also includes four-digit industry-by-year effects. Sample sizes are rounded to the nearest 1,000.

The first and second panels analyze two different measures of revenue productivity: value added per worker and total factor productivity. Both tell qualitatively similar stories. First, revenue productivity is positively associated with oil and gas booms. These effects are smaller for TFP-R than value added per worker, although the VA effects are substantially attenuated by including industry-year controls. Second, effects appear to be stronger for local industries and those linked to the oil and gas sector. In contrast, plants in non-linked and tradable industries do not experience a statistically significant increase in value added per worker or TFP-R, with point estimates close to zero.

The bottom panel in Table 10 uses the price dataset for the smaller sample of plants that sell relatively homogeneous output. The first row of this panel shows that resource booms are associated with higher output prices when we do not condition on industry fixed effects. This is largely driven by higher prices in linked industries, with higher output prices in refining being an essentially mechanical effect. However, including 4-digit SIC by year fixed effects significantly reduces the magnitude of all coefficients, rendering them all statistically indistinguishable from zero. In contrast to the model predictions, local manufacturing does not experience a price increase. While surprising, this result may be related to the fact that we only observe prices for only relatively homogeneous goods, which may be more tradable and less subject to local price increases.

Nevertheless, these results suggest that much of the revenue productivity increase during resource booms may be driven by an increase in physical productivity, not higher prices, and the TFP-R estimates in columns 1 and 4 are statistically more positive than the price estimates. We examine this further in Appendix Table A7, which limits the sample used for TFP-R estimation to only those plants with both TFP-R and price data. The overall TFP-R point estimate is actually larger than in the full sample, but the 86 percent drop in sample size makes precise inference impossible.

The price and value-added results are especially interesting when combined with the logic of the "initial conditions" in Table 3. Establishments that are linked to the oil and gas sector agglomerate near oil and gas production. Some of these linkages are "observable" in the sense that the establishment is part of an industry that is linked through input-output channels to oil and gas, such as "oil and gas field machinery and equipment" (SIC 3533). Other linkages are "unobservable," in the sense that the establishment produces output for an oil and gas producer but is in a larger industry that typically does not. Resource booms increase value added and price for linked establishments nationwide, and without industry-by-year fixed effects, our estimates include selection effect of highly (but unobservably) linked establishments in less-linked industries having sorted into resource-abundant counties. As we include more disaggregated industry fixed effects, our estimates increasingly focus on local revenue productivity spillovers and less on selection. Using the coefficient movement logic from Altonji, Elder, and Taber (2005), the fact that the TFP-R estimates (and to a lesser extent, the price estimates) don't change between the top and bottom panels suggests that the TFP effects are spillovers from a local resource boom, not industry-wide effects in unobservably-selected industries.

The results in Table 10 allow us to draw some inference on the potential mechanisms of the productivity spillovers. While a complete investigation of these channels would require a separate paper, we examine a few channels that have previously been considered by the literature. A natural starting point is Marshall's (1890) three types of transport costs: goods, people, and ideas. Goods linkages might primarily affect the scale of the firm rather than TFP, but they could have productivity effects if downstream industries get access to higher quality inputs and upstream industries can deliver goods to customers more efficiently. This linkage does not see particularly important, at least for the oil and gas industry: linked establishments' TFP-R grows 0.37 percentage points more in booming counties, but non-linked local plants' TFP-R grows 0.45 percentage points faster in these counties. This difference between linked and non-linked plants is not significant, and there is no evidence that TFP spillovers are primarily through input-output linkages.

Worker flows seem to be less important than in Greenstone, Hornbeck, and Moretti (2010) or Serafinelli (2012). For the entire CPS-MORG panel, which includes 281,301 manufacturing workers, there are only 220 that transition from oil and gas to manufacturing. Of these, 130 go to refining, and in every other two-digit industry, around 0.001 percent of incoming workers come from oil and gas.

Of the 3 classical channels, the "ideas" channel seems least likely to apply in this setting. Much of the oil and gas sector's innovation does not occur at the drilling site, and even then might be unlikely to spill over to non-resource based industries.

Beyond the three classical linkages, several other channels might contribute to the productivity effects. Local government actions, from tax cuts to the infrastructure improvements studied by Michaels (2010), might contribute to improved productivity. However, this channel does not seem particularly important given the near-zero effects on the tradable-producing plants that would presumably also benefit from any government assistance. Productivity impacts might also work through access to finance, with increased wealth from the boom allowing liquidity-constrained investors to open businesses or invest to increase productivity in ways not previously possible. Testing for this channel is difficult since many of the correlates of lack of access to finance, for example firm size, would themselves be correlated with low-tradability of an establishment's output. However, Table 11 shows that entering non-linked plants are larger (in terms of employment) during booms, which is inconsistent with a simple story of resource booms allowing financially-constrained individuals to start up small businesses.

Another potential channel is the selection pressure induced by higher wage costs and greater competition drawn to the increased market density, as discussed in Behrens, Duranton, Robert-Nicoud (2013), Syverson (2004), and elsewhere. These selection effects, whatever their source, would cause a left truncation of the productivity distribution, with incumbents pressured to increase productivity, relatively low productivity plants exiting, and only relatively high productivity plants entering. We find mixed evidence in support of the selection mechanism. Table 11 presents estimates of Equation (20), regressing natural log TFP-R and employment of all entering and exiting establishments on the averaged measures of local oil and gas booms in the past (entrants) and future (exiters) 5 years. Exiting plants in booming areas have higher TFP-R in all but the linked industries, including in the tradable sector where we see no TFP-R increase among incumbent plants. The small and insignificant selection effects in linked industries are not surprising, since these plants may be the most affected by positive demand shocks. Entrants' productivity, however, is not differentially affected by booms and busts in any sector. Perhaps entering plants learn only slowly about their altered chances of success in local markets being rapidly reshaped by oil and gas booms and busts.

Comparing the TFP-R effects in Tables 11 vs. 10 is informative about mechanisms that affect different manufacturing sub-sectors. For non-linked and tradable sectors, there are no effects on continuing incumbent establishments in Table 10, nor is there a change in plant exit rates in Table 8, but there is an increase in TFP-R of exiters in Table 11. One potential explanation for this is that plants within our "non-linked and tradable" group that (unobservably) trade more widely both have higher TFP and are also more likely to exit as local input prices rise. For linked sectors, Table 10 shows a large TFP-R increase for continuers, but Table 11 shows no differences in average TFP-R of entrants or exiters. For these linked plants, the resource boom appears to increase TFP-R and also increase entry, without increasing the productivity cutoffs that determine entry and exit.

6.7 Long-Term Effects

So far, we have analyzed the contemporaneous effects of resource booms. While these illustrate how the resource sector interacts with the larger economy, the ultimate test of the Resource Curse or agglomerative effects lies in enduring impact of the boom on resource-endowed counties. Table 12 examines these long-term effects using both the REIS data and the TFP-R of plants in resource-rich areas. We compare outcomes in 1972, just prior to the initial boom, to 1997, the last round of the CM prior to the beginning of the second resource boom in the early 2000s.

Table 12, sub-table (a), examines the long-term effects of the boom and bust on log TFP-R. The first specification mirrors the county level results in Table 9, collapsing log TFP-R to county means then differencing between 1972 and 1997 to generate the long-term change outcome. The second specification maintains the data at the firm level and tests whether firms in resource-rich counties have differentially higher TFP-R in 1997 controlling for both county fixed effects and 4-digit SIC-by-year effects. Both specifications find no significant differences in productivity in any sector. Thus the conditions for Prediction 4, that regions experience Dutch Disease if their manufacturing productivity is relatively lowered by the boom, do not hold. Nor do we find evidence of long-term agglomerative effects that might result from positive productivity spillovers from the resource sector to other industries.

Table 12, sub-table (b), regresses changes in natural log of REIS outcomes from 1972 to 1997 on r_c^{early}, the early period oil and gas endowment, controlling for Census division dummies and pre-1969 levels and trends of the outcome variable. The bust canceled out the boom: changes in population, employment, and manufacturing employment were statistically insignificant and economically small. This is also consistent with the graphical results in Figure 5. Only manufacturing wage shows a small and marginally significant differential decrease in resource counties. Although the boom of the 1970s and the bust of the 1980s were not exactly symmetric, results in both sub-tables suggest that effects of the boom were almost offset by the effects of the bust.

7 Conclusion

The rise in oil and gas prices and drilling activity in the past decade has caused economists and policymakers to again consider whether natural resource production benefits producer economies or whether there is a "Natural Resource Curse." In industrialized economies like the United States with relatively well-developed political institutions, one of the most natural mechanisms for a Natural Resource Curse would be Dutch Disease. To test for "domestic Dutch Disease" within the U.S., we combine a new panel dataset of oil and gas production and reserves with public data and restricted-access microdata from the Census of Manufactures to estimate how oil and gas booms have affected growth in U.S. counties since the 1960s.

The dispersion in oil and gas endowment across U.S. counties, combined with the dramatic time-series variation provided by oil and gas booms of the past fifty years, provides a clean and well-defined local economic shock. We find that resource booms can significantly boost growth: a boom that doubles national oil and gas employment increases total employment by 2.9 percent in a county with one standard deviation larger oil and gas endowment. Despite substantial migration, wages also rise. Notwithstanding, manufacturing employment, output, and TFP are actually procyclical with resource booms. On most outcomes, the bust of the 1980s offset the boom of the 1970s, leaving no enduring effects.

There are several remarkable facets to the results. First, while Dutch Disease is theoretically possible and wages do rise, our statistical and even graphical results clearly reject the idea of Dutch Disease within the United States. Second, while manufacturers are often thought of as producing nationally- or internationally-traded goods, this paper echoes Holmes and Stevens (2014) in highlighting how a meaningful share of manufacturers benefit from local (county-level) demand growth. Third, our results counter the argument that natural resource extraction is unlikely to drive productivity growth. Instead, natural resource booms cause significant employment and TFP growth in linked and local manufacturing industries.

References

[1] Altonji, Joseph, Todd Elder, and Christopher Taber (2005). "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy*, Vol. 113, No. 1, pages 151-184.

[2] Aragon, Fernando, and Juan Pablo Rud (2011). "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine." Working Paper, Simon Fraser University (April).

[3] Asher, Sam, and Paul Novosad (2014). "Digging for Development: Mining Booms and Local Economic Development in India." Working Paper, Oxford University (April).

[4] Auty, Richard, and Raymond Mikesell (1998). Sustainable Development in Mineral Economies. Oxford, UK: Oxford University Press.

[5] Bartik, Timothy (1991). Who Benefits from State and Local Economic Development Policies? Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

[6] Black, Dan, Terra McKinnish, and Seth Sanders (2005a). "The Economic Impact of the Coal Boom and Bust." *The Economic Journal*, Vol. 115, No. 503 (April), pages 449-476.

[7] Black, Dan, Terra McKinnish, and Seth Sanders (2005b). "Tight Labor Markets and the Demand for Education: Evidence from the Coal Boom and Bust." *Industrial and Labor Relations Review*, Vol. 59, No. 1 (October), pages 3-16.

[8] Behrens, Kristian, Gilles Duranton, and Frederic Robert-Nicoud (2013). "Productive Cities: Sorting, Selection, and Agglomeration." *Journal of Political Economy*, forthcoming.

[9] Blanchard, Olivier, and Lawrence Katz (1992). "Regional Evolutions." *Brookings Papers on Economic Activity*, Vol. 1992, No. 1, pages 1-75.

[10] Bleakley, Hoyt, and Jeffrey Lin (2012). "Portage and Path Dependence." *Quarterly Journal of Economics*, Vol. 127, No. 2, pages 587-644.

[11] Brown, Chip (2013). "North Dakota Went Boom." *The New York Times Magazine*, January 31, 2013.

[12] Brunnschweiler, Christa, and Erwin Bulte (2008). "The Resource Curse Revisited and Revised: A Tale of Paradoxes and Red Herrings." *Journal of Environmental Economics and Management*, Vol. 55, No. 3, pages 248-264.

[13] Bureau of Economic Analysis (2013). "Gross-Domestic-Product-(GDP)-by-Industry Data." http://www.bea.gov/industry/gdpbyind_data.htm

[14] Busso, Matias, Jesse Gregory, and Patrick Kline (2012). "Assessing the Incidence and Efficiency of a Prominent Place-Based Policy." Forthcoming, *American Economic Review*.

[15] Carrington, William (1996). "The Alaskan Labor Market during the Pipeline Era." *Journal of Political Economy*, Vol. 104, No. 1 (February), pages 186-218.

[16] Caselli, Francesco, and Guy Michaels (2013). "Do Oil Windfalls Improve Living Standards? Evidence from Brazil." *American Economic Journal: Applied Economics*, Vol. 5, No. 1 (January), pages 208-238.

[17] Collier, Paul, and Benedikt Goderis (2009). "Commodity Prices, Growth, and the Natural Resource Curse: Reconciling a Conundrum." Working Paper, Oxford University (December).

[18] Corden, Max, and Peter Neary (1982). "Booming Sector and De-Industrialisation in a Small Open Economy." *The Economic Journal*, Vol. 92, No. 368 (December), pages 825-848.

[19] Domenech, Jordi (2008). "Mineral Resource Abundance and Regional Growth in Spain, 1860-2000. *Journal of International Development*, Vol. 20, pages 1122-1135.

[20] Dube, Oeindrila, and Juan Vargas (2013). "Commodity Price Shocks and Civil Conflict: Evidence from Colombia." *Review of Economic Studies*, Vol. 80, pages 1384-1421.

[21] Ellison, Glenn, and Edward Glaeser (1997). "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach." *Journal of Political Economy*, Vol. 105, No 5, pages 889-927.

[22] Ellison, Glenn, Edward Glaeser, and William Kerr (2010). "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns." *American Economic Review*, Vol. 100, No. 3 (June), pages 1195-1213.

[23] Foster, Lucia, Cheryl Grim, and John Haltiwanger (2013). "Reallocation in the Great Recession: Cleansing or Not?" Center for Economic Studies Discussion Paper CES-WP-13-42.

[24] Glaeser, Edward, and Joshua Gottlieb (2009). "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States." *Journal of Economic Literature*, Vol. 47, No. 4, pages 983-1028.

[25] Glaeser, Edward, Sari Pekkala Kerr, and William Kerr (2012). "Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines." Working Paper, Harvard University (July).

[26] Greenstone, Michael, Richard Hornbeck, and Enrico Moretti (2010). "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings." *Journal of Political Economy*, Vol. 118, No. 3, pages 536-598.

[27] Gylfason, Thorvaldur, Tryggvi Herbertsson, and Gylfi Zoega (1999). "A Mixed Blessing: Natural Resources and Economic Growth." *Macroeconomic Dynamics*, Vol. 3, pages 204-225.

[28] Harding, Torfinn, and Anthony Venables (2013). "The Implications of Natural Resource Exports for Non-Resource Trade." OxCarre Research Paper 103 (January).

[29] Holmes, Thomas, and John Stevens (2014). "An Alternative Theory of the Plant Size Distribution, with Geography and Intra- and International Trade." *Journal of Political Economy*, forthcoming.

[30] Hooker, Mark, and Michael Knetter (2001). "Measuring the Economic Effects of Military Base Closures." *Economic Inquiry*, Vol. 39, No. 4 (October) pages 583-598.

[31] Jacobsen, Grant, and Dominic Parker (2013). "The Economic Aftermath of Resource Booms: Evidence from Boomtowns in the American West." Working Paper, University of Oregon (December).

[32] James, Alexander, and David Aadland (2011). "The Curse of Natural Resources: An Empirical Investigation of U.S. Counties." *Resource and Energy Economics*, Vol. 33, pages 440-453.

[33] James, Alexander, and Robert James (2011). "Do Resource Dependent Regions Grow Slower than they Should?" *Economics Letters*, Vol. 111, pages 194-196.

[34] Kline, Patrick (2008). "Understanding Sectoral Labor Market Dynamics: An Equilibrium Analysis of the Oil and Gas Field Services Industry." Working Paper, UC Berkeley (November).

[35] Kline, Patrick, and Enrico Moretti (2012). "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority." *Quarterly Journal of Economics*, forthcoming.

[36] Krugman, Paul (1987). "The Narrow Moving Band, the Dutch Disease, and the Competitive Consequences of Mrs. Thatcher." *Journal of Development Economics*, Vol. 27, pages 41-55.

[37] Lederman, Daniel, and William Maloney, Eds. (2007a). Natural Resources: Neither Curse Nor Destiny. Stanford, CA: Stanford University Press.

[38] Lederman, Daniel, and William Maloney (2007b). "Trade Structure and Growth." In Lederman, Daniel, and William Maloney, Eds., Natural Resources: Neither Curse Nor Destiny. Stanford, CA: Stanford University Press.

[39] Madrian, Brigitte, and Lars Lefgren (1999). "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents." NBER Technical Working Paper 247 (November).

[40] Manzano, Osmel, and Roberto Rigobon (2001). "Resource Curse or Debt Overhang?" NBER Working Paper 8390 (July).

[41] Marshall, Alfred (1890). Principles of Economics. New York, NY: MacMillan.

[42] Matsuyama, Kiminori (1992). "Agricultural Productivity, Comparative Advantage, and Economic Growth." *Journal of Economic Theory*, Vol. 58, pages 317-334.

[43] Mehlum, Halvor, Karl Moene, and Ragnar Torvik (2006). "Cursed by Resources or Institutions?" *The World Economy*, pages 1117-1131.

[44] Michaels, Guy (2010). "The Long Term Consequences of Resource-Based Specialisation." *The Economic Journal*, Vol. 121 (March), pages 31-57.

[45] Monteiro, Joana, and Claudio Ferraz (2012). "Does Oil Make Leaders Unaccountable? Evidence from Brazil's Offshore Oil Boom." Working Paper, Pontificia Universidade Catolica do Rio de Janeiro (May).

[46] Moretti, Enrico (2004). "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions." *American Economic Review*, Vol. 94, No. 3 (June), pages 656-690.

[47] Moretti, Enrico (2010). "Local Multipliers." *American Economic Review*, Vol 100, No. 2 (May), pages 1-7.

[48] Papyrakis, Elissaios, and Reyer Gerlagh (2007). "Resource Abundance and Economic Growth in the United States." *European Economic Review*, Vol. 51, pages 1011-1039.

[49] Sachs, Jeffrey, and Andrew Warner (1995). "Natural Resource Abundance and Economic Growth." NBER Working Paper 5398 (December).

[50] Sachs, Jeffrey, and Andrew Warner (1999). "The Big Push, Natural Resource Booms, and Growth." *Journal of Development Economics*, Vol. 59, pages 43-76.

[51] Sachs, Jeffrey, and Andrew Warner (2001). "The Curse of Natural Resources." *European Economic Review*, Vol. 45, pages 827-838.

[52] Serafinelli, Michel (2012). "Good Firms, Worker Flows, and Productivity." Working Paper, UC Berkeley (November).

[53] Syverson, Chad (2004). "Market Structure and Productivity: A Concrete Example." *Journal of Political Economy*, Vol. 112, No. 6, pages 1181-1222.

[54] U.S. Energy Information Administration (2013). "Detailed Oil and Gas Field Maps." http://www.eia.gov/pub/oil_gas/natural_gas/analysis_publications/maps/maps.htm

[55] U.S. Energy Information Administration (2014). "EIA-23L Reserves Information Gathering System." http://www.eia.gov/survey/form/eia_23l/rigs.cfm

[56] U.S. Geological Survey (2013). "National Oil and Gas Assessment." http://energy.usgs.gov/OilGas/AssessmentsData/NationalOilGasAssessment.aspx.

[57] van der Ploeg, Frederick (2011). "Natural Resources: Curse or Blessing?" Journal of Economic Literature, Vol. 49, No. 2, pages 366-420.

[58] van Wijnbergen, Sweder (1984). "The 'Dutch Disease': A Disease After All?" *The Economic Journal*, Vol. 94, No. 373 (March), pages 41-55.

[59] Wright, Gavin, and Jesse Czelusta (2007). "Resource-Based Growth Past and Present." In Lederman, Daniel, and William Maloney, Eds., Natural Resources: Neither Curse Nor Destiny. Stanford, CA: Stanford University Press.

Tables

Table 1: **Resources: Descriptive Statistics**

	Mean	SD	Max	N>0
Oil (million barrels)				
Output 1960-2011	27.7	199.6	8261	1139
Current proven reserves	7.88	63.8	2000	698
Current undiscovered reserves	7.21	41.0	878	1869
1960-2011 average price ($/barrel)	34.9			
Natural Gas (billion cubic feet)				
Output 1960-2011	244	1102	20,033	1121
Current proven reserves	136	990	30,544	734
Current undiscovered reserves	284	1318	50,538	2287
1960-2011 average price ($/mcf)	3.20			
1960 oil and gas resource ($10 million/Sq. Mile)	0.44	1.75	46.9	2295

Notes: This table presents oil and natural gas resource data for the sample of 3075 counties. Prices are in real 2010 dollars.

Table 2: **Outcomes: Descriptive Statistics**

	N	Mean	SD	Min	Max
Regional Economic Information System					
Population (000s)	132,205	81.8	270	0.055	9889
Employment (000s)	132,205	43.7	161	0.06	5773
Wages per worker ($000s)	132,205	30.4	6.78	11.4	105
Manufacturing employment (000s)	108,082	7.12	25.2	0.01	950
Manufacturing earnings per worker ($000s)	108,082	45.9	15.4	3.11	211
Current Population Survey					
Hourly wage ($/hour)	5,511,041	18.4	13.8	0.0001	2827
Hours worked per week	5,541,458	38.3	10.8	0	99

Notes: REIS data are at the county-by-year level. CPS data are at the individual-by-interview level. Prices are in real 2010 dollars.

Table 3: **Baseline County Characteristics**

	(1)	(2)
	Mean (000s)	Association with Endowment
Population	63.1	0.093**
		(0.029)
Total Employment	16.8	0.165***
		(0.034)
Manufacturing employment	5.993	0.034
		(0.059)
Up/downstream manufacturing employment	1.645	0.113*
		(0.067)
Non-linked manufacturing employment	4.349	-0.027
		(0.063)
Non-linked local manufacturing employment	1.162	-0.023
		(0.057)
Non-linked tradable manufacturing employment	3.187	-0.045
		(0.080)

Notes: This table presents baseline county characteristics. Population is from the 1966 Census estimates and total employment is from the 1967 County Business Patterns. Manufacturing employment is from the 1967 Census of Manufactures. Column 2 presents the coefficient of a regression of natural log of baseline population or employment on oil and gas endowment per square mile, controlling for Census division fixed effects. Robust standard errors in parentheses.

Table 4: **Pre-Trends**

	(1)	(2)
1969-1972 Population		
Endowment$_{ct}$	-0.000214	-0.000387
	(0.00130)	(0.00138)
1969-1972 Employment		
Endowment$_{ct}$	-0.00171	-0.00196
	(0.00188)	(0.00206)
1969-1972 Wage Earnings/Worker		
Endowment$_{ct}$	-0.00442***	-0.000954
	(0.00127)	(0.00109)
1969-1972 Manufacturing Employment		
Endowment$_{ct}$	0.00850	-0.0100
	(0.00912)	(0.00945)
1969-1972 Mfg. Earnings/Mfg. Worker		
Endowment$_{ct}$	-0.00487*	-0.00375
	(0.00274)	(0.00289)
Controls for baseline levels	No	Yes
Census division fixed effects	No	Yes

Notes: Dependent variable is natural log of the change in the variable listed above each set of results. Sample size for population, employment, and wage earnings per worker is 3,075. Sample size for manufacturing outcomes is 2,514. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses.

Table 5: **Aggregate Effects**

	(1)	(2)	(3)
Population			
$\Delta\ln(\text{National oil\&gas employment}_{t-1})\times\text{endowment}_{ct}$	0.0168***	0.0129***	0.0251***
	(0.0024)	(0.0022)	(0.0050)
$\Delta\ln(\text{National oil\&gas employment}_{t-1})\ \times\text{endowment}_{ct}$			-0.0116***
$\times 1(\Delta\text{National oil\&gas employment}_{t-1}<0)$			(0.0032)
$\Delta\ln(\text{National oil\&gas employment}_{t-1})\ \times\text{endowment}_{ct}$			-0.0179***
$\times 1(\text{year}>2000)$			(0.0039)
Employment			
$\Delta\ln(\text{National oil\&gas employment}_{t})\times\text{endowment}_{ct}$	0.0379***	0.0287***	0.0412***
	(0.0055)	(0.0049)	(0.0090)
$\Delta\ln(\text{National oil\&gas employment}_{t})\ \times\text{endowment}_{ct}$			0.00242
$\times 1(\Delta\text{National oil\&gas employment}_{t}<0)$			(0.0045)
$\Delta\ln(\text{National oil\&gas employment}_{t})\ \times\text{endowment}_{ct}$			-0.0321***
$\times 1(\text{year}>2000)$			(0.0079)
Wage Earnings/Worker			
$\Delta\ln(\text{National oil\&gas employment}_{t})\times\text{endowment}_{ct}$	0.0334***	0.0214***	0.0152***
	(0.0050)	(0.0041)	(0.0049)
$\Delta\ln(\text{National oil\&gas employment}_{t})\ \times\text{endowment}_{ct}$			0.0141**
$\times 1(\Delta\text{National oil\&gas employment}_{t}<0)$			(0.0065)
$\Delta\ln(\text{National oil\&gas employment}_{t})\ \times\text{endowment}_{ct}$			-0.0015
$\times 1(\text{year}>2000)$			(0.0037)
Census division-by-year fixed effects	No	Yes	Yes

Notes: This table presents estimates of Equation (15). Sample size for the mining employment regressions is 91,409. Sample size for all other regressions is 129,130. All regressions include controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 6: **Aggregate Spillovers**

	(1)	(2)	(3)	(4)
	All counties	All counties	Zero endowment counties	All counties
	Population			
Δln(National oil&gas employment$_{t-1}$)	0.0129***	0.0117***		0.0254***
$\times$endowment$_{ct}$	(0.0022)	(0.0021)		(0.0035)
Δln(National oil&gas employment$_{t-1}$)			0.0280**	0.0200***
$\times$endowment$_{st}$			(0.0112)	(0.0029)
Δln(National oil&gas employment$_{t-1}$)				-0.0104***
$\times$endowment$_{ct}$$\times$endowment$_{st}$				(0.0016)
	Employment			
Δln(National oil&gas employment$_{t}$)	0.0287***	0.0246***		0.0487***
$\times$endowment$_{ct}$	(0.0049)	(0.0047)		(0.0066)
Δln(National oil&gas employment$_{t}$)			0.0747	0.0460***
$\times$endowment$_{st}$			(0.0532)	(0.00621)
Δln(National oil&gas employment$_{t}$)				-0.0176***
$\times$endowment$_{ct}$ $\times$endowment$_{st}$				(0.0023)
	Wage Earnings/Worker			
Δln(National oil&gas employment$_{t}$)	0.0214***	0.0173***		0.0362***
$\times$endowment$_{ct}$	(0.0041)	(0.0037)		(0.0060)
Δln(National oil&gas employment$_{t}$)			0.0597**	0.0455***
$\times$endowment$_{st}$			(0.0235)	(0.0048)
Δln(National oil&gas employment$_{t}$)				-0.0135***
$\times$endowment$_{ct}$ $\times$endowment$_{st}$				(0.0023)
N	129,130	129,130	34,536	129,130
State-by-year fixed effects	No	Yes	No	No

Notes: This table presents estimates of Equation (15), plus additional interaction terms to measure spillovers. All regressions include controls for year interacted with natural log of the outcome variable in two baseline years, as well as Census division-by-year fixed effects. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 7: **Current Population Survey Regressions**

	(1)	(2)	(3)	(4)	(5)
Outcome Variable:	ln(wage)	ln(wage)	ln(hours)	ln(wage)	Δln(wage)
		All Workers			
ln(National oil&gas employment$_t$)	0.0348***	0.0810***	-0.00455	0.0333***	0.0345***
$\times$endowment$_{ct}$	(0.0092)	(0.0162)	(0.0075)	(0.0098)	(0.0072)
ln(National oil&gas employment$_t$)		-0.0557***			
$\times$endowment$_{ct}\times$1(year>2000)		(0.0194)			
N	5,511,041	5,511,041	5,537,883	5,511,041	1,527,184
		Manufacturing Workers			
ln(National oil&gas employment$_t$)	0.0516***	0.0677***	-0.00780	0.0384**	0.0492**
$\times$endowment$_{ct}$	(0.0187)	(0.0221)	(0.0137)	(0.0188)	(0.0204)
ln(National oil&gas employment$_t$)		-0.0315			
$\times$endowment$_{ct}\times$1(year>2000)		(0.0268)			
N	959,266	959,266	964,098	959,266	281,301
Age, Education, Gender, Race, Industry	Yes	Yes	Yes	No	No

Notes: Columns 1-4 present estimates of variants of Equation (17), while column 5 presents estimates of Equation (18). All regressions include year, month, and state indicator variables. *, **, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively. Robust standard errors in parentheses, clustered by state.

Table 8: **Effects on Manufacturing**

	(1)	(2)	(3)
	Manufacturing Employment		
$\Delta\ln(\text{National oil\&gas employment}_t)\times\text{endowment}_{ct}$	0.0435***	0.0289***	0.0463**
	(0.0085)	(0.0082)	(0.0187)
$\Delta\ln(\text{National oil\&gas employment}_t)\times\text{endowment}_{ct}$			0.0002
$\times 1(\Delta\text{National oil\&gas employment}_t<0)$			(0.0228)
$\Delta\ln(\text{National oil\&gas employment}_t)\ \times\text{endowment}_{ct}$			-0.0478***
$\times 1(\text{year}>2000)$			(0.0173)
	Mfg. Earnings/Mfg. Worker		
$\Delta\ln(\text{National oil\&gas employment}_t)\times\text{endowment}_{ct}$	0.0278***	0.0190***	-0.0035
	(0.0060)	(0.0056)	(0.0075)
$\Delta\ln(\text{National oil\&gas employment}_t)\times\text{endowment}_{ct}$			0.0421**
$\times 1(\Delta\text{National oil\&gas employment}_t<0)$			(0.0193)
$\Delta\ln(\text{National oil\&gas employment}_t)\times\text{endowment}_{ct}$			0.0124
$\times 1(\text{year}>2000)$			(0.0089)
N	105,568	105,568	105,568
Census division-by-year fixed effects	No	Yes	Yes

Notes: This table presents estimates of Equation (15). All regressions include controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 9: **County-level Manufacturing Subsector Outcomes**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			Employment		
Δln(National oil&gas employment$_t$)	0.0368**	0.0538**	0.0169	0.0557**	-0.0503*
$\times$endowment$_{ct}$	(0.0171)	(0.0255)	(0.0171)	(0.0227)	(0.0290)
			Revenue		
Δln(National oil&gas employment$_t$)	0.0657*	0.0429	0.0474	0.0733	-0.0756
$\times$endowment$_{ct}$	(0.0339)	(0.0542)	(0.0641)	(0.0720)	(0.0604)
			Investment		
Δln(National oil&gas employment$_t$)	0.126***	0.126**	0.0611	0.116**	-0.0129
$\times$endowment$_{ct}$	(0.0446)	(0.0500)	(0.0568)	(0.0497)	(0.0547)
			Establishments		
Δln(National oil&gas employment$_t$)	0.0229***	0.0374***	0.0057	0.0126	-0.0145
$\times$endowment$_{ct}$	(0.0067)	(0.0092)	(0.0067)	(0.0095)	(0.0090)
			Establishment Births		
Δln(National oil&gas employment$_t$)	0.0455***	0.0562***	0.0274**	0.0311**	0.0103
$\times$endowment$_{ct}$	(0.0129)	(0.0138)	(0.0122)	(0.0129)	(0.0107)
			Establishment Death Rate		
Δln(National oil&gas employment$_t$)	0.00246	-0.0110**	0.00685	0.00981*	-0.0033
$\times$endowment$_{ct}$	(0.0036)	(0.0047)	(0.00479)	(0.00566)	(0.0062)
N	24,596	24,596	24,596	24,596	24,596

Notes: This table presents estimates of Equation (15) for different outcomes (in rows) and manufacturing subsectors (in columns). All specifications use county-level differenced outcomes; the time between each Census is 5 years. All regressions include controls for year interacted with natural log of the outcome variable in two baseline years, as well as Census division-by-year fixed effects. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 10: **Plant-Level Results**

(a) **No Industry Controls**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			Value Added per Worker		
$\Delta\ln$(National oil&gas employment$_t$)	0.0158***	0.0122*	0.0157***	0.0227***	0.0029
$\times$endowment$_{ct}$	(0.0048)	(0.0062)	(0.0046)	(0.0062)	(0.0046)
N	1,140,000	388,000	752,000	379,000	372,000
			TFP-R		
$\Delta\ln$(National oil&gas employment$_t$)	0.00355***	0.0034**	0.0044**	0.00464*	0.0015
$\times$endowment$_{ct}$	(0.0013)	(0.00162)	(0.0020)	(0.00242)	(0.0031)
N	756,000	280,000	476,000	251,000	225,000
			Price		
$\Delta\ln$(National oil&gas employment$_t$)	0.0162***	0.0278**	0.0038	0.0021	0.0090
$\times$endowment$_{ct}$	(0.0052)	(0.0132)	(0.0030)	(0.00385)	(0.0110)
N	420,000	87,000	333,000	248,000	86,000

(b) **With 4-digit Industry-by-Year Controls**

			Value Added per Worker		
$\Delta\ln$(National oil&gas employment$_t$)	0.0066**	0.0066	0.00574*	0.0094**	0.0011
$\times$endowment$_{ct}$	(0.0031)	(0.0048)	(0.00337)	(0.0048)	(0.0042)
N	1,140,000	388,000	752,000	379,000	372,000
			TFP-R		
$\Delta\ln$(National oil&gas employment$_t$)	0.0038***	0.0037**	0.0031	0.0045*	0.0014
$\times$endowment$_{ct}$	(0.0013)	(0.0017)	(0.0021)	(0.0026)	(0.0029)
N	756,000	280,000	476,000	251,000	225,000
			Price		
$\Delta\ln$(National oil&gas employment$_t$)	-0.0043	-0.0097	-0.0014	-0.0026	0.0034
$\times$endowment$_{ct}$	(0.0038)	(0.0087)	(0.0026)	(0.0027)	(0.0081)
N	420,000	87,000	333,000	248,000	86,000

Notes: This table presents estimates of Equation (19). All specifications use plant-level differenced outcomes; the time between each Census is 5 years. All regressions include Census division-by-year fixed effects. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 11: **Plant-Level Results: Entrants and Exiters**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			TFP - Entrants		
ln(National oil&gas employment$_t$)	.0017	0.00004	.00288	0.0019	.0032
$\times$endowment$_{ct}$	(0.0017)	(0.0029)	(0.0019)	(0.0026)	(0.0030)
N	359,000	108,000	251,000	120,000	132,000
			TFP - Exiters		
ln(National oil&gas employment$_t$)	.0076**	0.0028	.00920**	.00859	0.0098***
$\times$endowment$_{ct}$	(0.0031)	(0.0039)	(0.0395)	(0.0064)	(0.0049)
N	303,000	87,000	218,000	99,000	118,000
			Employment - Entrants		
ln(National oil&gas employment$_t$)	.0133**	0.0049	.0145	0.0047	0.0089
$\times$endowment$_{ct}$	(0.0061)	(0.0053)	(0.0074)	(0.0078)	(0.0066)
N	1,005,000	277,000	727,000	349,000	378,000
			Employment - Exiters		
ln(National oil&gas employment$_t$)	.0202***	0.00048	.0230***	0.0113	.0182
$\times$endowment$_{ct}$	(0.0067)	(0.0089)	(0.0081)	(0.0128)	(0.0113)
N	977,000	242,000	735,000	361,000	374,000

Notes: This table presents estimates of Equation (20). All regressions include 4-digit industry-by-year controls, county fixed effects, and Census division-by-year fixed effects. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table 12: **1972-1997 Changes**

(a) **TFP-R**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
1997-1972 County-level means					
Endowment_{ct}	0.00214	0.00876	-0.0128	-0.0061	-0.0093
	(0.0102)	(0.0122)	(0.0132)	(0.0109)	(0.0184)
N	2,769	2,033	2,710	2,525	2,260
Firm level with 4-digit SIC-by-year controls					
$\mathbb{I}\,(t = 1997) \times \text{endowment}_{ct}$	0.0017	0.0014	0.0041	0.0010	0.0030
	(0.0023)	(0.0019)	(0.0030)	(0.0026)	(0.0034)
N	338,000	116,000	222,000	110,000	112,000

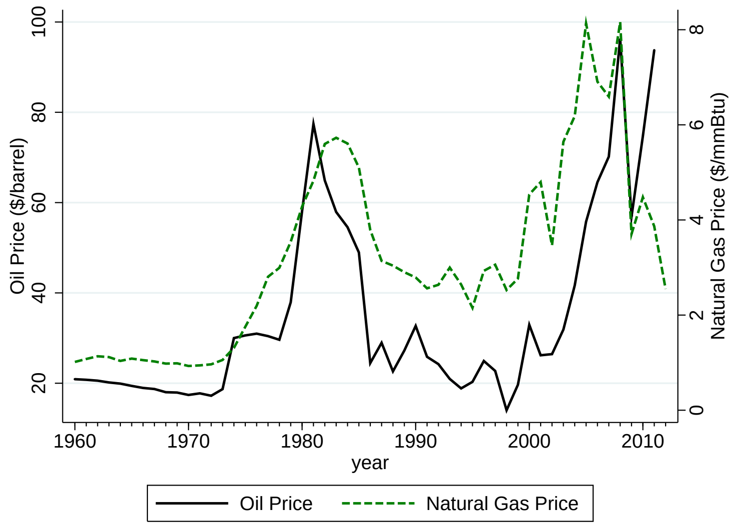
(b) **REIS Outcomes**

	(1)	(2)	(3)	(4)	(5)
Outcome Variable:	Population	Employment	Wage Earnings/ Worker	Mfg. Employment	Mfg. Earn-ings/Mfg. Workers
r_c^{early}: Early period oil & gas endowment	0.0015	0.0095	0.0006	0.0170	-0.0149*
	(0.0060)	(0.0062)	(0.0023)	(0.0195)	(0.0090)
N	3075	3075	3075	2514	2514

Notes: The first specification of sub-table (a) regresses changes in county-average log TFP on early period oil and gas endowment. The second specification regresses log TFP at the firm level, using data from 1972 and 1997, on interactions of year and endowment as well as 4-digit industry-by-year interactions. All regressions control for Census division dummies. Sub-table (b) regresses changes in natural logs of county aggregate outcomes on early period oil and gas endowment. All regressions control for Census division dummies, and county-level regressions control for pre-1969 levels and trends of the outcome variable. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, with plant-level estimates clustered by county.

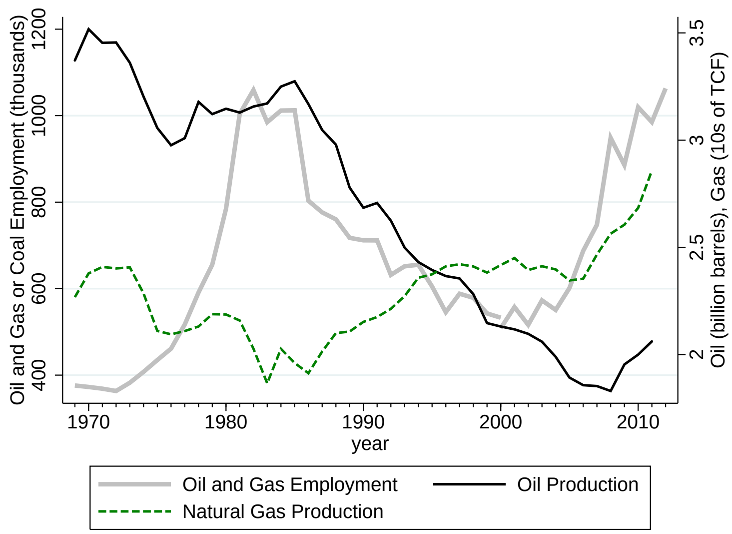
Figures

Figure 1: **Real Oil and Gas Prices**



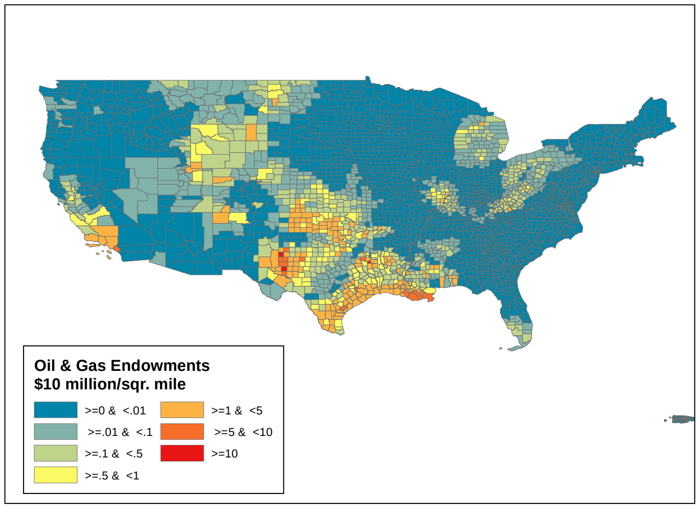
Notes: Prices are in real 2010 dollars.

Figure 2: **Oil and Gas Production and Rig Counts**



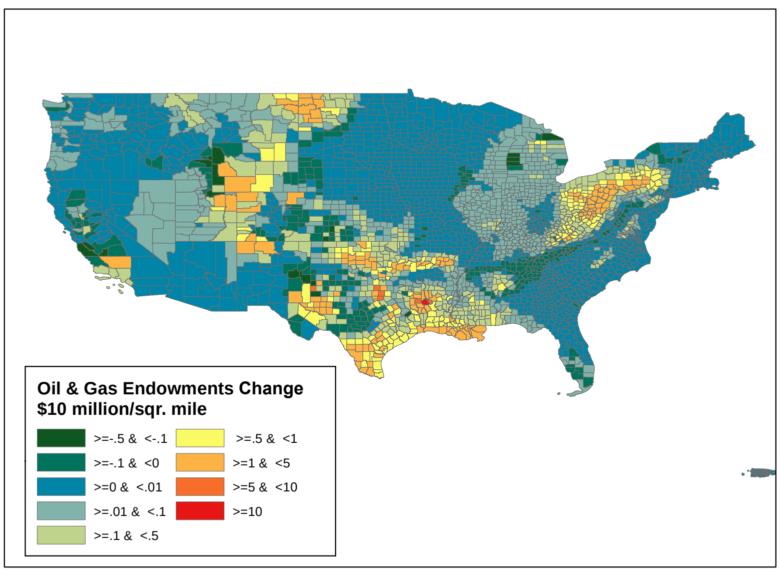
Notes: Oil and gas production data are from the Energy Information Administration. Oil and gas employment data are from the Regional Economic Information System. We switch from the SIC to the NAICS classification system in 2000 and plot both data points in that year.

Figure 3: **Early Endowment per Square Mile**



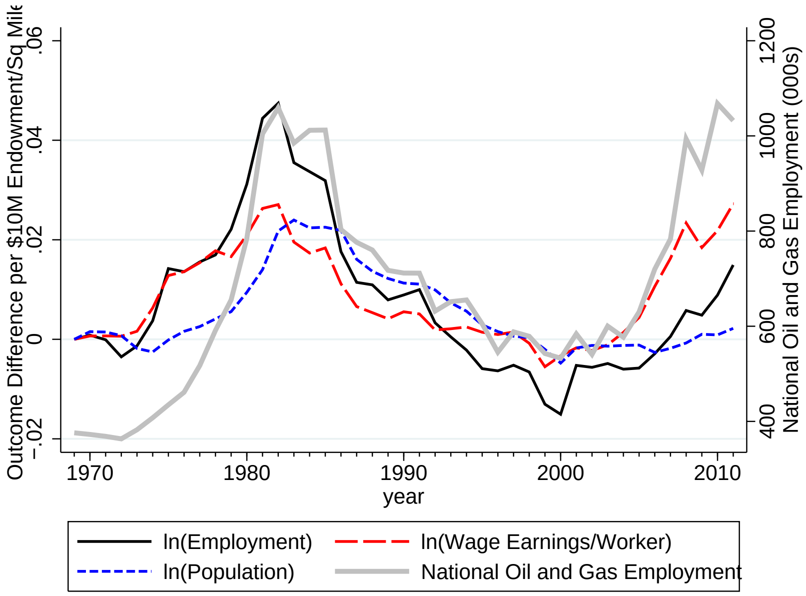
Notes: This figure maps the oil and gas endowment as of 1960 that is economically recoverable during the oil and gas boom of the 1970s and 1980s. See Section 4.1 for details of variable construction.

Figure 4: **Change in Endowment After Early Period**



Notes: This figure maps the change between the early period oil and gas endowment in Figure 3 and the total endowment. See Section 4.1 for details of variable construction.

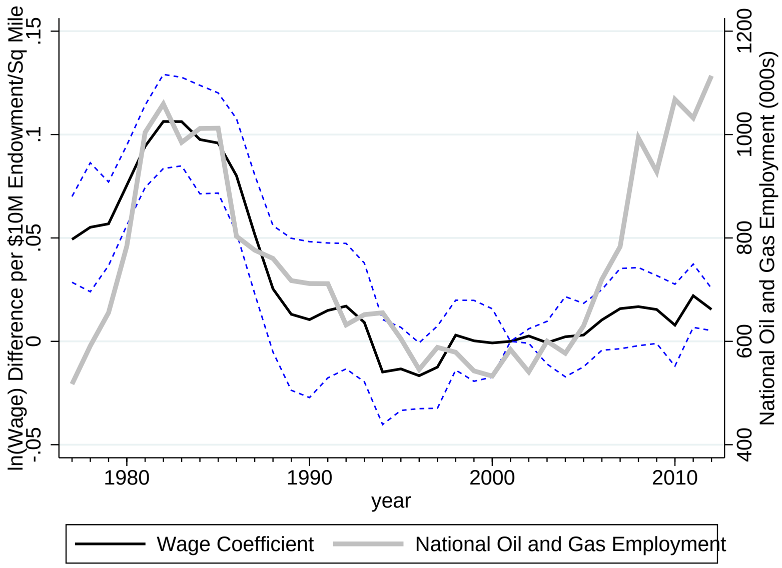
Figure 5: **Aggregate Effects**



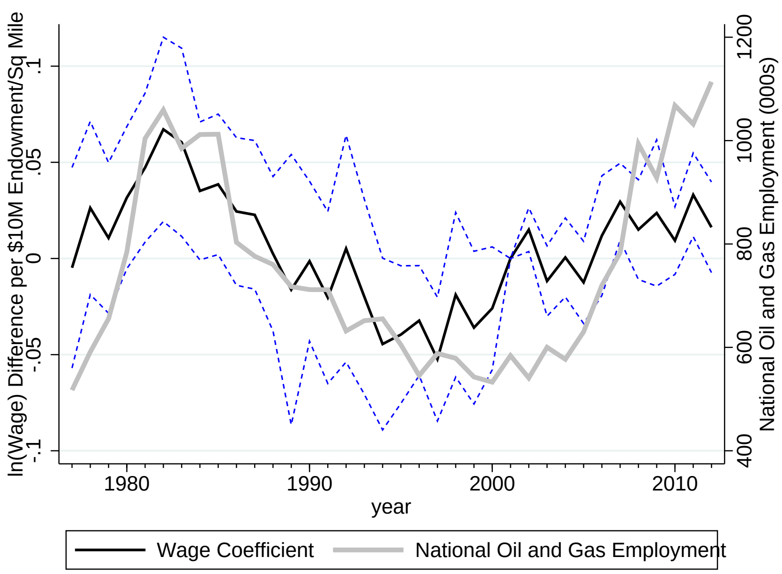
Notes: This shows the regression coefficients from Equation (16) with natural log of county aggregate employment, population, and wage earnings per worker as dependent variables.

Figure 6: **Effects on Wages in the Current Population Survey**

(a) **All Sectors**

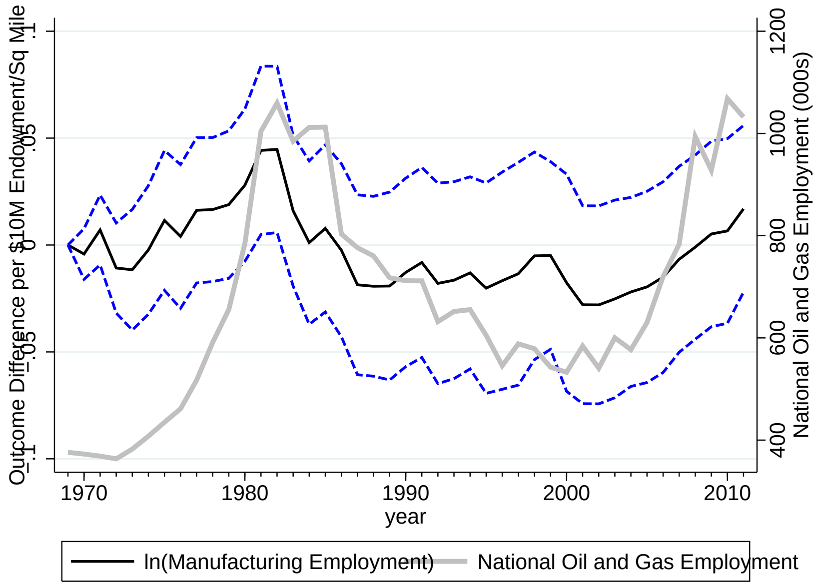


(b) **Manufacturing Wages**



Notes: These figures present the coefficients and 90 percent confidence intervals on τ_t when estimating Equation (17) after substituting $\sum_t \tau_t r_{st}$ for $\tau \ln E_t r_{st}$, using samples of all workers and manufacturing workers, respectively.

Figure 7: **Manufacturing Employment Effects**



Notes: This figure shows the coefficients and 90 percent confidence intervals from estimating Equation (16) with natural log of manufacturing employment as the dependent variable.

Appendix: For Online Publication

Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America

Hunt Allcott and Daniel Keniston

A Appendix to Theoretical Framework

A.1 Details of Prediction 1

To see Prediction 1 more formally, note that the labor used in tradable and non-tradable sectors can be expressed as a function of resource labor:

$$\begin{aligned} n_l &= F_l'^{-1}\left(\frac{p_r\Omega_r}{p_l\Omega_l}F_r'(n_r)\right) \\ n_m &= F_m'^{-1}\left(\frac{p_r\Omega_r}{p_m\Omega_m}F_r'(n_r)\right) \end{aligned}$$

Since $F_j'(\cdot)$ is positive and decreasing, both types of non-resource labor are increasing in n_r and decreasing in Ω_r. The labor market clearance equation and the relationship between the wage and the marginal product of the resource sector define the wage-labor supply equilibrium:

$$w = p_r\Omega_r F_r'(n_r)$$

$$n_r + F_l'^{-1}\left(\frac{p_r\Omega_r}{p_l\Omega_l}F_r'(n_r)\right) + F_m'^{-1}\left(\frac{p_r\Omega_r}{p_m\Omega_m}F_r'(n_r)\right) = N(w) \tag{21}$$

We now show that an increase in Ω_r must both increase wages and labor supply. Consider the case in which this is not true, that is that an increase in Ω_r only reallocates labor to n_r but does not lead to a change in wages or total population. However, equation 21 now cannot hold, since the first term is increasing and the second two are constant, but by assumption the right hand side is constant. Thus it must be that Ω_r increases total labor supply, and as long as the labor supply curve is upward sloping, wages too must increase.

A.2 Details of Prediction 2

Two equations pin down the price of non-tradables. First, substituting the production function into the demand function from Equation (4) gives

$$\Omega_l F_l(n_l) = \frac{N(w)\,\alpha\,(w+\pi)}{p_l}.$$

Second, Equation (8) gives that the marginal product of labor equals the wage: $w = p_l\Omega_l F_l'(n_l)$. Combining these two equations and simplifying generates the condition determining production of the non-tradable goods sector,

$$\frac{F_l(n_l)}{F_l'(n_l)} = N(w)\left(\alpha + \alpha\frac{\pi}{w}\right) = N(w)\,\alpha + \alpha\left(\frac{F_r(n_r)}{F_r'(n_r)} - n_r\right) \tag{22}$$

It is straightforward to show that since $\partial n_r/\partial\Omega_r > 0$, $\partial N(w)/\partial w \geq 0$, and $F_l(n_l)$ is concave, non-tradable labor input, output, and prices must be increasing in resource sector productivity Ω_r.

A.3 Details of Prediction 3

During a boom in period 1, if labor supply is not fully elastic, Prediction 1 shows that wages will increase, and Prediction 3 shows that the tradables sector will contract. Mathematically, $X_{m1}^A < X_{m1}^B$: tradables sector output is lower in region A.

Due to learning-by-doing in tradables, region A's period 2 tradable productivity will be lower than in region B,

$$\Omega_{m2}^{A} = \Omega_{m1}^{A} + \delta X_{m1}^{A} + \gamma X_{r1}^{A} < \Omega_{2m}^{B}$$

if $\delta\left(X_{m1}^{B} - X_{m1}^{A}\right) > \gamma\left(X_{r1}^{A} - X_{r1}^{B}\right)$. This inequality holds if learning by doing spillovers within the tradables sector are stronger than the possible spillovers from the resource sector to the tradables sector.

In period 2, the resource boom ends, so $\Omega_{r2}^{A} = \Omega_{r2}^{B}$. Taking the ratio of wages gives

$$\frac{F_r'\left(n_{r2}^{A}\right)}{F_m'\left(n_{m2}^{A}\right)} \cdot \frac{\Omega_{m2}^{B}}{\Omega_{r2}^{B}} \frac{\Omega_{r2}^{A}}{\Omega_{m2}^{A}} = \frac{F_r'\left(n_{r2}^{B}\right)}{F_m'\left(n_{m2}^{B}\right)}.$$

Since $\frac{\Omega_{m2}^{B}}{\Omega_{r2}^{B}} \frac{\Omega_{r2}^{A}}{\Omega_{m2}^{A}} > 1$, $\frac{F_r'\left(n_{r2}^{A}\right)}{F_m'\left(n_{m2}^{A}\right)} < \frac{F_r'\left(n_{r2}^{B}\right)}{F_m'\left(n_{m2}^{B}\right)}$, implying that after the resource boom is over in period 2, region A has relatively less labor in the tradables sector. Since tradables sector productivity is now lower than in region B, tradables output is unambiguously lower. Furthermore, the higher period 2 productivity in region B will cause higher wages relative to region A, similarly to the logic of Prediction 1, and population will be larger as well. Thus, the period 1 migration into region A is more than fully reversed in period 2. In sum, the lack of a natural resource boom has led to an advantage for region B. As Matsuyama (1992) argues, even short-term differences in resource sector productivity may lead to long term divergence.

B Appendix Tables and Figures

Table A1: **State-Level Sources of Oil and Gas Production Data**

State	Resource	Title	Source	Years
CA	Oil, Gas	Summary of Operations: California Oil Fields	ftp://ftp.consrv.ca.gov/pub/oil/Summary_of_Operations/	1960-1977
IL	Gas	Natural Gas Production in Illinois	Bryan Huff, Illinois State Geological Survey	1973-1992
IL	Oil	Historic County Production in Illinois	Bryan Huff, Illinois State Geological Survey	1932-2011
IN	Gas	Petroleum Data Management System	http://igs.indiana.edu/PDMS/WellSearch.cfm	1863-2011
IN	Oil	Petroleum Data Management System	http://igs.indiana.edu/PDMS/Fields.cfm	1965-2011
KS	Oil, Gas	County Production	http://www.kgs.ku.edu/PRS/petro/interactive.html	1960-2011
KY	Oil	Oil and Gas Production	http://kgs.uky.edu/kgsmap/OGProdPlot/OGProduction.asp	1883-2011
KY	Gas	Oil and Gas Production	http://kgs.uky.edu/kgsmap/OGProdPlot/OGProduction.asp	1986-2011
LA	Oil, Gas	Crude and Natural Gas Production by Parish	Sharron Allement, Louisiana Office of Conservation	1965-1977
MI	Oil, Gas	Michigan's Oil and Gas Fields, 1965-1982	http://www.michigan.gov/deq	1965-1982
MT	Oil, Gas	Annual Reviews for the Years 1965-1985	http://bogc.dnrc.mt.gov/annualreview/	1965-1985
NV	Oil, Gas	Historical Production	Lowell Taylor, Nevada Division of Minerals	1954-2011
NY	Oil, Gas	New York Natural Gas and Oil Production	http://www.dec.ny.gov/energy/1601.html	1967-2011
OK	Oil	Report on Oil and Natural Gas Activity	Jason Lawter, Oklahoma Corporation Commission	1963-2011
PA	Oil	Oil and Gas Developments in Pennsylvania	http://www.libraries.psu.edu/	1960-1991
UT	Oil, Gas	Pre-1984 Production Download File	http://oilgas.ogm.utah.gov/	1965-1983

Notes: This details additional state-level sources of oil and gas production data that are used to augment the DrillingInfo database.

Table A2: **Linked Manufacturing Industries**

Top Ten Upstream Industries		
SIC Codes	Industry	Upstream Linkage Share
3533	Oil and gas field machinery and equipment	0.23
324	Hydraulic cement	0.12
3295	Ground or treated minerals	0.086
2899	Chemicals and chemical preparations, n.e.c.	0.066
3491, 3492, 3494, 3498	Pipe, valves, and pipe fittings	0.037
3441	Fabricated structural metal	0.034
3312	Blast furnaces and steel mills	0.033
2892	Explosives	0.031
2992	Lubricating oils and greases	0.031
3313	Electrometallurgical products, except steel	0.028
All Downstream Industries		
SIC Codes	Industry	Input Cost Share
291	Petroleum refining	0.69
2999	Products of petroleum and coal, n.e.c.	0.31
2873, 2874	Nitrogenous and phosphatic fertilizers	0.081
2895	Carbon black	0.062
281, 2865, 2869	Industrial inorganic and organic chemicals	0.021
308	Miscellaneous plastics products, n.e.c.	0.001
285	Paints and allied products	0.001

Notes: Linkages are calculated using data from the 1987 Bureau of Economic Analysis input-output tables. Upstream linkage share is the sum of oil and gas output share and the share of output purchased by the oil and gas sector through an intermediate industry. "n.e.c." stands for "not elsewhere classified."

Table A3: **Aggregate Effects: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endow-ment r^{early}	Use total endowment r^{total}	Measure intensity by wage emp. only	Measure intensity by oil and gas price	Fixed effects
			Population		
Δln(National intensity$_{t-1}$)$\times$endowment$_{ct}$	0.0253***	0.0188***	0.0247***	0.00269***	0.0132***
	(0.0051)	(0.0028)	(0.0048)	(0.0004)	(0.0043)
Δln(National intensity$_{t-1}$)$\times$endowment$_{ct}$	-0.0119***	-0.0085***	-0.0118***		
$\times$1(ΔNational intensity$_{t-1}$ <0)	(0.0034)	(0.0022)	(0.0028)		
Δln(National intensity$_{t-1}$)$\times$endowment$_{ct}$	-0.0170***	-0.0124***	-0.0161***		
$\times$1(year >2000)	(0.0035)	(0.0019)	(0.0035)		
			Employment		
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	0.0414***	0.0326***	0.0434***	0.00647***	0.0224***
	(0.0090)	(0.0051)	(0.0093)	(0.0011)	(0.0052)
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	0.0019	-0.0024	-0.0014		
$\times$1(ΔNational intensity$_{t}$<0)	(0.0047)	(0.0045)	(0.0037)		
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	-0.0273***	-0.0222***	-0.0258***		
$\times$1(year >2000)	(0.0063)	(0.0038)	(0.0076)		
			Wage Earnings/Worker		
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	0.0151***	0.0166***	0.0190***	0.00677***	0.0205***
	(0.0049)	(0.00375)	(0.0057)	(0.0013)	(0.0047)
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	0.0141**	0.0036	0.0077		
$\times$1(ΔNational intensity$_{t}$<0)	(0.0067)	(0.0051)	(0.0053)		
Δln(National intensity$_{t}$)$\times$endowment$_{ct}$	0.0032	-0.0002	0.0086**		
$\times$1(year >2000)	(0.0024)	(0.0024)	(0.0041)		
N	129,130	129,130	129,130	129,130	132,205

Notes: This table presents alternative estimates of Equation (15). Columns 1, 2, and 5 measure "National intensity" with "National oil&gas employment," as in the main estimates. All regressions include Census division-by-year fixed effects and controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table A4: **Current Population Survey Regressions: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endow-ment r^{early}	Use total endowment r^{total}	Measure intensity by wage emp. only	Measure intensity by oil and gas price	Drop outlying wages
			All Workers		
ln(National intensity$_t$)	0.0810***	0.0447***	0.120***	0.0812***	0.0793***
$\times$endowment$_{ct}$	(0.0162)	(0.0113)	(0.0142)	(0.0108)	(0.0148)
ln(National intensity$_t$)	-0.0557***	-0.0263*	-0.0860***	-0.0624***	-0.0524***
$\times$endowment$_{ct}\times$1(year>2000)	(0.0194)	(0.0138)	(0.0186)	(0.0230)	(0.0189)
N	5,511,041	5,511,041	5,511,041	5,362,618	5,493,297
			Manufacturing Workers		
ln(National intensity$_t$)	0.0677***	0.0277*	0.0968***	0.0621***	0.0704***
$\times$endowment$_{ct}$	(0.0221)	(0.0149)	(0.0217)	(0.0142)	(0.0200)
ln(National intensity$_t$)	-0.0315	-0.00181	-0.0474	-0.0474**	-0.0319*
$\times$endowment$_{ct}\times$1(year>2000)	(0.0268)	(0.0208)	(0.0298)	(0.0227)	(0.0187)
N	959,266	959,266	959,266	942,290	957,698

Notes: This table presents alternative estimates of Equation (17). Columns 1, 2, and 5 measure "National intensity" with "National oil&gas employment," as in the main estimates. All regressions include year, month, and state indicator variables, plus age, education, gender, race, and industry controls. *, **, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively. Standard errors are robust and clustered by state.

Table A5: **Effects on Manufacturing: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endow- ment r^{early}	Use total endowment r^{total}	Measure intensity by wage emp. only	Measure intensity by oil and gas price	Fixed effects
	Manufacturing Employment				
Δln(National intensity$_t$)$\times$endowment$_{ct}$	0.0478**	0.0235**	0.0528***	0.0026	0.0248**
	(0.0192)	(0.0098)	(0.0195)	(0.0024)	(0.0110)
Δln(National intensity$_t$)$\times$endowment$_{ct}$	-0.0033	-0.0015	-0.0080		
$\times$1(ΔNational intensity$_t$ <0)	(0.0237)	(0.0147)	(0.0202)		
Δln(National intensity$_t$)$\times$endowment$_{ct}$	-0.0432**	-0.0246**	-0.0371*		
$\times$1(year >2000)	(0.0174)	(0.00998)	(0.0202)		
	Mfg. Earnings/Mfg. Worker				
Δln(National intensity$_t$)$\times$endowment$_{ct}$	-0.0045	0.0023	-0.0021	0.0047**	0.00837*
	(0.0075)	(0.0045)	(0.0074)	(0.0021)	(0.00479)
Δln(National intensity$_t$)$\times$endowment$_{ct}$	0.0445**	0.0229**	0.0313**		
$\times$1(ΔNational intensity$_t$ <0)	(0.0196)	(0.0108)	(0.0139)		
Δln(National intensity$_t$)$\times$endowment$_{ct}$	0.0220*	0.0116	0.0193**		
$\times$1(year >2000)	(0.0126)	(0.0081)	(0.0096)		
N	105,568	105,568	105,568	105,568	108,082

Notes: This table presents alternative estimates of Equation (15) for manufacturing outcomes. Columns 1, 2, and 5 measure "National intensity" with "National oil&gas employment," as in the main estimates. All regressions include Census division-by-year fixed effects and controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Table A6: **Manufacturing Spillovers**

	(1)	(2)	(3)	(4)
	All counties	All counties	Zero endowment counties	All counties
Manufacturing Employment				
Δln(National oil&gas employment$_t$)	0.0289***	0.0239***		0.0480***
$\times$endowment$_{ct}$	(0.00819)	(0.00842)		(0.0133)
Δln(National oil&gas employment$_t$)			0.222**	0.0475***
$\times$endowment$_{st}$			(0.112)	(0.017)
Δln(National oil&gas employment$_t$)				-0.0169**
$\times$endowment$_{ct}$ $\times$endowment$_{st}$				(0.00718)
Mfg. Earnings/Mfg. Worker				
Δln(National oil&gas employment$_t$)	0.0190***	0.0133**		0.0210**
$\times$endowment$_{ct}$	(0.00565)	(0.00539)		(0.00847)
Δln(National oil&gas employment$_t$)			-0.023	0.0518***
$\times$endowment$_{st}$			(0.071)	(0.0124)
Δln(National oil&gas employment$_t$)				-0.00457
$\times$endowment$_{ct}$ $\times$endowment$_{st}$				(0.005)
N	105,568	105,568	29,196	105,568
State-by-year fixed effects	No	Yes	No	No

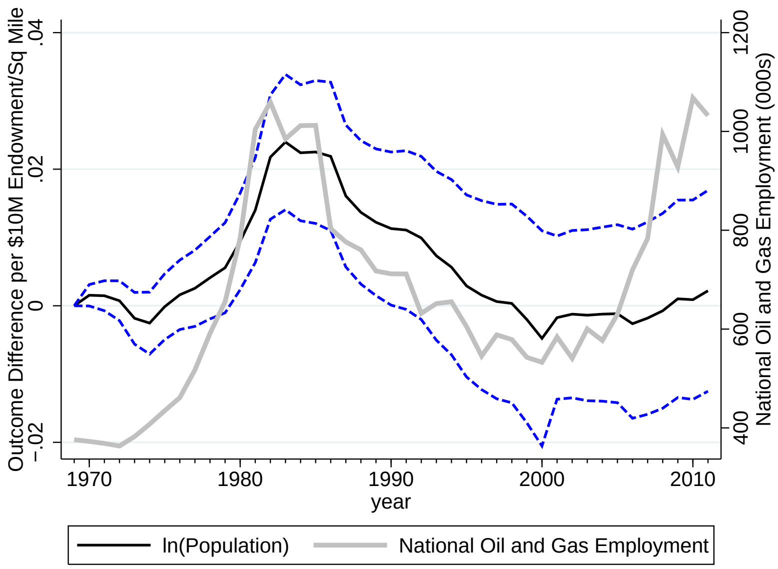
Notes: This table presents alternative estimates of Equation (15), plus additional interaction terms to measure spillovers. It parallels Table 6 but focuses on manufacturing outcomes. All regressions include controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors, clustered by county.

Table A7: **TFP-R Estimates for Firms with Price Data**

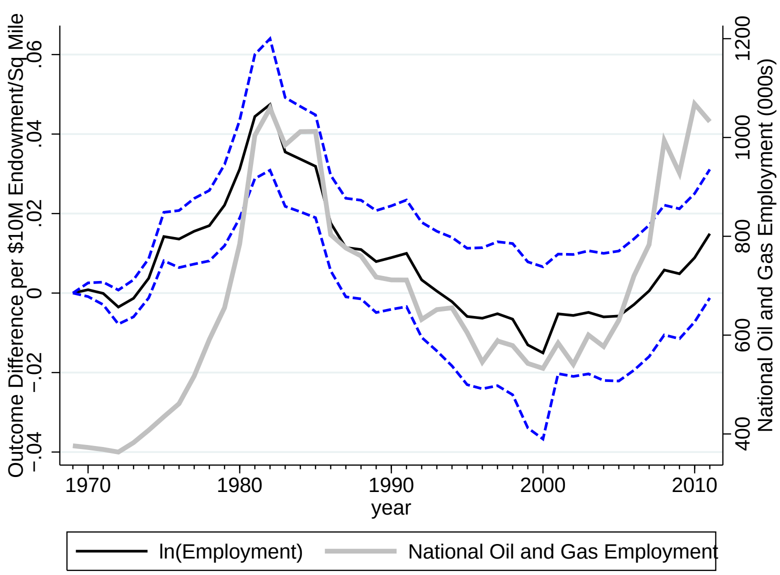
	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
		TFP-R			
Δln(National oil&gas employment$_t$)	0.0042	0.0004	0.00465	0.00753	0.00003
$\times$endowment$_{ct}$	(0.0036)	(0.0048)	(0.00376)	(0.00487)	(0.0108)
N	108,000	27,000	81,000	55,000	26,000

Notes: This table presents estimates of Equation (19), with the sample limited to plants that report physical output and are thus included in the price regressions. All specifications use plant-level differenced outcomes; the time between each Census is 5 years. All regressions include Census division-by-year fixed effects. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors in parentheses, clustered by county.

Figure A1: **Effects on County Aggregates and Mfg. Earnings/Mfg. Worker**



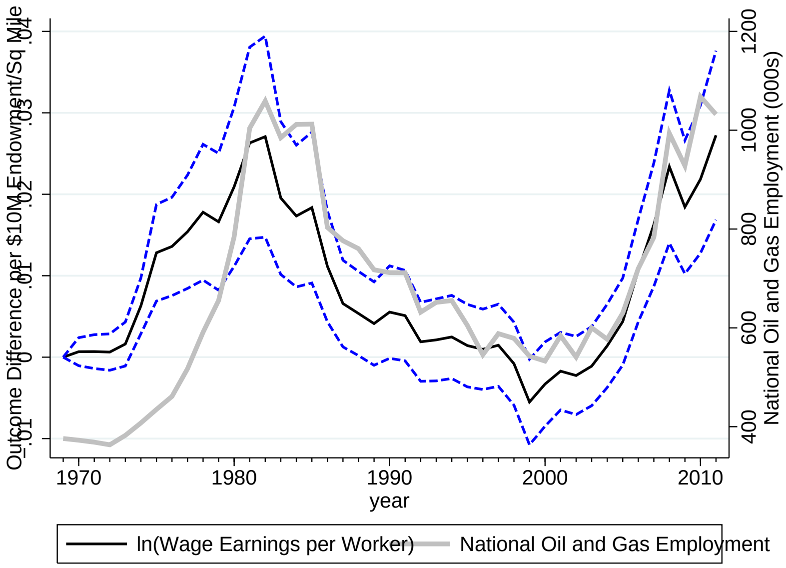
(a) **Population**



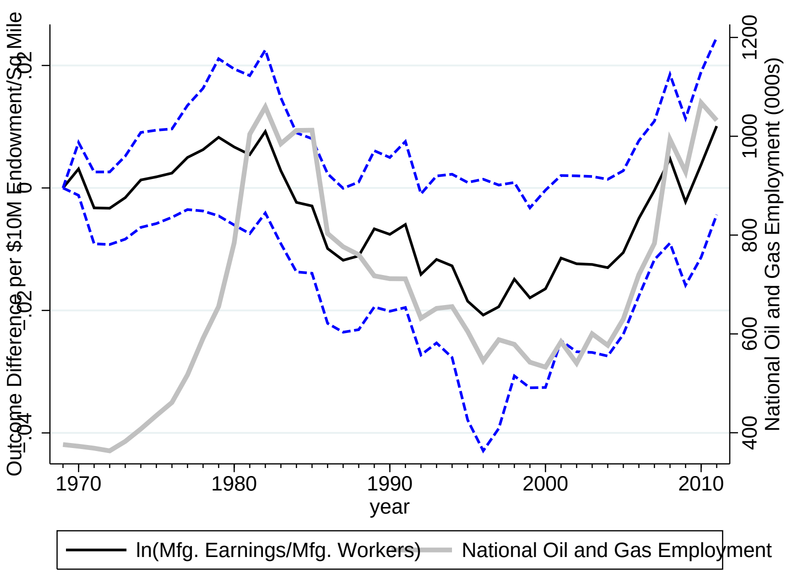
(b) **Employment**

Figure A1

(c) **Earnings per Worker**



(d) **Mfg. Earnings/Mfg. Worker**



Notes: These figures present the coefficients and 90 percent confidence intervals from estimating Equation (16), with different outcome variables. The point estimates for the population, employment, and earnings per worker graphs are the same as in Figure 5.