NBER WORKING PAPER SERIES

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

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Working Paper 20508
http://www.nber.org/papers/w20508

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2014

We thank Yunmi Kong and Wendy Wei for superb research assistance and Julia Garlick for help in data preparation. We are grateful for feedback from Costas Arkolakis, Nathaniel Baum- Snow, Dan Black, Rick Hornbeck, Ryan Kellogg, Pat Kline, Erin Mansur, Enrico Moretti, Reed Walker, and seminar participants at the ASSA Annual Meetings, Bates White, Berkeley, the Census Center for Economic Studies, Cornell, LSE and UCL, Michigan State, NYU, Oxford, Sussex, Wharton, the World Bank, and Yale. Thanks also to Randy Becker, Allan Collard- Wexler, Jonathan Fischer, Todd Gardner, Cheryl Grim, Javier Miranda, Justin Pierce, and Kirk White for their advice and help in using U.S. Census of Manufactures data, and to Jean Roth for advice on the Current Population Survey. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. All results have been reviewed to ensure that no confidential information is disclosed.

Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America
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NBER Working Paper No. 20508
September 2014, Revised April 2015
JEL No. J2,L6,O4,Q43,R1

ABSTRACT

Do natural resources benefit producer economies, or is there a "Natural Resource Curse," perhaps as Dutch Disease crowds out manufacturing? We combine new data on oil and gas abundance with Census of Manufactures microdata to estimate how oil and gas booms have affected local economies in the United States. Migration does not fully offset labor demand growth, so local wages rise. Notwithstanding, manufacturing is actually pro-cyclical with resource booms, driven by growth in upstream and locally-traded sectors. The results highlight the importance of highly local demand for many manufacturers and underscore how natural resource linkages can drive manufacturing growth.

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I Introduction

Over the past decade, high oil prices and improvements in drilling technology 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." Yet hardly two years after this article appeared, oil prices had dropped by over 60 percent, and the number of drilling rigs was falling at the fastest rate since the last bust in 1986. In Williston, North Dakota, banks and developers were slowing investment as oil companies began cutbacks (Brown 2015), raising fears that the boom had ended and the next oil bust was beginning.

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 manufacturing firms generate positive local 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

[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/.

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 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 model of heterogeneous sectors and firms à la Melitz (2003), to illustrate how "domestic Dutch Disease" could act in local economies within a common currency area with mobile labor. As long as local labor supply is not fully elastic, an increase in labor demand from the natural resource sector drives up local wages. This causes firms producing traded goods to contract, as they compete against establishments in non-resource counties that have not suffered the same input cost increase. This is analogous to the familiar cross-country Dutch Disease caused by currency appreciation: 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.

We test the predictions of this model using 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 plant-level microdata from the U.S. Census of Manufactures, which allow us to examine the model's differential predictions across subsectors and outcomes. 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

[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)).

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 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 increases national oil and gas employment by 10 percent increases total employment by 0.29 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 overall 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 plants, 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: employment, output, and investment in locally-traded and linked sectors 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, consistent with decreases in transport costs in input and output markets. (We also explore whether this could be driven by higher prices instead of physical productivity, although unit prices are available only for a subset of plants.) These results support Wright and Czelusta's (2007) argument that natural resource exploitation can be a driver of manufacturing growth.

We also examine the subset of plants that are most likely to be affected by Dutch Disease: those selling highly-tradable goods that are not inputs to oil and gas. Consistent with the theory, we find these industries contract during booms, although estimates are somewhat imprecise. However, we find no contemporaneous effects on revenue productivity in tradable sectors.

In the long run, the employment, population, wage, and productivity effects of the boom and bust cycle of the 1970s and 1980s all appear to cancel out by 1997. This suggests that forces driving

Dutch Disease or other versions of a Resource Curse do not arise in the average US county. On the other hand, the positive agglomerative effects on productivity also do not persist. Overall, the predictions of static trade models such as Melitz (2003) capture many of the most important impacts of natural resource booms.

In the remainder of this first section, we discuss related literature. Section II provides background on the recent oil and gas booms. Section III presents the model. Section IV details the data, Section V outlines the empirical strategy, and Section VI presents results. Section VII concludes.

I.A 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). Recent work such as Bartik, Currie, Deutch, and Greenstone (2014) and Muehlenbachs, Spiller and Timmins (2014) studies the impacts of hydraulic fracturing on housing values and environmental quality. Black, McKinnish, and Sanders (2005a) study the Appalachian coal boom and bust, finding positive employment spillovers to construction, retail, and services sectors but no effect on manufacturing employment. An important paper by Michaels (2010) studies the long-term effects of oil abundance in the southern United States, using cross-sectional estimators to compare counties that have major oil fields to other nearby counties that do not. He finds 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 employment in agriculture and manufacturing.

Our paper differs from existing work in many ways. First and most importantly, the U.S. Census of Manufactures microdata allow us to test mechanisms that are implied by trade theory but that previous research could not test in sector-level aggregates. Do hypothesized agglomerative forces actually increase plant productivity? Do resource booms affect manufacturing through upstream and downstream linkages or through other channels? Unlike Michaels (2010) and Black, McKinnish, and Sanders (2005a), we do find some evidence that resource booms cause some manufacturers to contract, but this finding is only possible because our microdata allow us to look at the subset of manufacturers producing more highly-traded goods.

Second, for the bulk of our analysis, we look within-county or within-firm and estimate the contemporaneous effects of multiple booms or busts. Relative to a cross-sectional approach, this is useful from an identification perspective because our estimators sweep out time-invariant confounders that could be correlated with resource abundance. However, we also measure the longer-term effects across the boom and bust cycle of the 1970s and 1980s. A purely cross-sectional analysis cannot distinguish the contemporaneous effects of resource abundance through input demand and consumer wealth increases vs. the long-term agglomerative effects that may persist after a boom ends. By contrast, our combination of contemporaneous and long-term estimates allows us to separate these two mechanisms, showing that while there are meaningful contemporaneous effects, they summed to zero over the boom and bust of the 1970s and 1980s.

Third, we have gathered very detailed data on resource abundance. Black, McKinnish, and Sanders (2005a) proxy for resource abundance with binary variables based on initial coal sector employment, Michaels (2010) proxies with a binary variable for whether a county lies over a large existing oilfield, and Sachs and Warner and other cross-country studies use rough proxies such as the share of natural resource exports in GDP. By contrast, we have complete measures of each county's production since 1960, as well as proven and unproven reserves. While such data improvements may appear subtle, it can be important to include unproven reserves because resource sector employment and existing production may be endogenous to a county's other economic outcomes. For example, New York might be less likely to have banned hydrofracking if local economic conditions were worse.

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, our work connects to the literature on local economic growth, including studies of local effects of 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 2013), Chinese import competition (Autor, Dorn, and Hanson 2013), and other factors. Against this literature, our paper is novel in that it studies oil and gas booms, which have helped lead the recovery from the Great Recession (Moretti 2013). Our paper is also novel in that it studies cross-industry spillovers, while much of the local labor market literature studies how exogenous shocks affect county aggregates. Using the tech industry as an analogy, much of this literature essentially studies how the tech boom affects wages, unemployment, and other aggregates in places like Silicon Valley. But while a tech boom clearly benefits local land owners and labor suppliers, it hurts other industries that draw on the same pool of land or labor but are not experiencing positive productivity or demand shocks. Policy implications then depend on whether externalities from the booming industry are more positive than from the industries being crowded out. While the tech industry may have low pollution externalities and high productivity spillovers, oil and gas are often thought to have higher pollution externalities and low productivity spillovers.

II 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).[4] 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 spurred a second boom of high prices and increased production.

Oil and gas production requires significant labor input. Figure 2 shows total national employment in the oil and gas sector, as reported in the Regional Economic Information System (REIS). Closely mirroring the price trend, employment rose from under 400,000 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.[5] Over the past decade employment has surged again, almost doubling from 2002 until our data end in 2012.

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 IV.A.)

More recently, prospecting and extraction has focused on extracting "unconventional" oil and gas trapped in tiny pores within impermeable rocks. "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

[4] Like all prices in this paper, these are in real 2010 dollars.

[5] We switch from the SIC to the NAICS classification system in 2000 and plot both SIC and NAICS data points in that year.

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.

III Theoretical Framework

This section presents a theoretical framework to guide our empirical work. Drawing on Chaney (2008), Melitz (2003), and others, we develop a model with heterogeneous sectors and firms and generate seven predictions about the effects of resource booms.

III.A Setup

We consider counties indexed by i, j, or k that are part of a large economy with many counties. Within each county, there is a natural resource sector, denoted r, producing an undifferentiated product for export. There are also $H+1$ monopolistically competitive sectors indexed by h. The first H sectors produce final consumption goods, while sector number $H+1$, also denoted by u, is an "upstream" sector that produces intermediate goods for the resource sector. Within each monopolistically competitive sector, each firm produces a differentiated variety ω.

Due to migration and movement in and out of the labor force, total employment L_i is endogenous to wage w_i, with $L_i'(w_i) > 0$. The county-level labor market clearing condition is that total employment is the sum of labor demand across all sectors:

$$L_i(w_i) = L_i^r + \sum_{h=1}^{H+1} L_i^h. \tag{1}$$

III.A.1 Consumers

Consumers in county j have Cobb-Douglas preferences over constant elasticity of substitution (CES) aggregates of varieties within each sector of consumption goods:

$$U = \prod_{h=1}^{H} \left(Q_j^h\right)^{\mu_h}, \quad \sum_{h=1}^{H} \mu_h = 1, \tag{2}$$

where $Q_j^h = \left(\int_{\Omega_j^h} q_j(\omega)^\rho d\omega\right)^{1/\rho}$ is the CES aggregate good for sector h, with price index $P_j^h = \left(\int_{\Omega_j^h} p_j(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$. Ω_j^h is the (endogenously-determined) set of varieties in sector h that are sold in county j, $p_j(\omega)$ and $q_j(\omega)$ are price and consumption of variety ω, $\sigma > 1$ is the elasticity of substitution, and $\rho = (\sigma - 1)/\sigma$.

Consumers receive a share η of the profits from the resource sector $\left(\pi_j^r\right)$ county j, for example due to royalty payments to local landowners or part ownership of resource sector firms.[6] These profits enter the aggregate budget constraint:

$$\sum_{h=1}^{H} P_j^h Q_j^h = w_j L_j + \eta \pi_j^r \tag{3}$$

Cobb-Douglas preferences imply that the expenditure share on sector h is μ_h. Total expenditures on sector h in county j are thus:

$$R_j^h = P_j^h Q_j^h = \mu^h \left(w_j L_j + \eta \pi_j^r\right) \tag{4}$$

Maximizing utility also gives expenditures $r_j^h(\omega)$ for each variety sold in county j:

$$r_j^h(\omega) \quad = \quad R_j^h \left[\frac{p_j(\omega)}{P_j^h}\right]^{1-\sigma}. \tag{5}$$

III.A.2 The Natural Resource Sector

We model the natural resource sector as a representative firm with a Cobb-Douglas production function. The sector has two inputs: labor L_i^r and Q_i^u, a CES aggregate good of upstream varieties with aggregate price P_i^u. Resource output is sold outside the county at exogenous price p^r. Denoting resource productivity as A_i^r, the composite resource sector in county i maximizes the following profit function:

$$\pi_i^r = p^r A_i^r \left(Q_i^u\right)^{\alpha} \left(L_i^r\right)^{\beta} - P_i^u Q_i^u - w_i L_i^r. \tag{6}$$

Because the natural resource available within county i is finite, we assume decreasing returns to scale, i.e. $\alpha + \beta < 1$.

III.A.3 Monopolistically Competitive Sectors

The upstream sector and all consumption good sectors are monopolistically competitive. There is free entry. Potential entrants pay a fixed cost $w_i f_e$ to receive a productivity draw φ. After receiving

[6] The monopolistically competitive sectors earn zero profits in our model because of the free entry condition and fixed cost $w_i f_e$ discussed below.

a productivity draw, each potential entrant can then decide whether to produce or withdraw. There is one period of production, after which the game ends. In keeping with much of the theoretical literature and with empirical findings on the firm size distribution, we assume that potential entrants' productivities take the Pareto distribution, so $\Pr(\varphi < x) = G_i(x) = 1 - \left(\frac{b_i}{x}\right)^{\theta}$ for all $0 < b_i \leq x$.[7]

Actual entrant firms in county i can choose to sell into any county j, including their home county. Selling from county i into county j incurs fixed cost f_{ij} and iceberg trade cost $\tau_{ij}^h \geq 1$, with $\tau_{ii}^h = 1$. For a firm in county i, the total cost to produce and sell $q_j(\omega)$ units in county j is thus:

$$c_{ij}^h(q_j(\omega)) = \frac{w_i \tau_{ij}^h}{\varphi} q_j(\omega) + w_i f_{ij} \tag{7}$$

Profits for goods sold to county j are the revenues from Equation (5) minus these costs.

III.A.4 Labor Demand in Monopolistically Competitive Sectors

In Appendix A, we solve for equilibrium entry and labor demand in county i. We assume that the D counties other than county i are identical to each other, i.e. they have the same potential productivity distribution b_j and same trade costs τ_{ij} and f_{ij}. We focus on two special cases of trade costs: "local" sectors with infinite trade costs and (perfectly) "tradable" sectors with $\tau^h = 1$ and $f_{ij} = f_{ii}$. Actual entrants' labor demand to produce sector h varieties in county i for sale in all counties can be written as follows.

$$\text{Local: } L_i^h = \frac{R_i}{w_i} \tag{8}$$

$$\text{Tradable: } L_i^h = \frac{1}{w_i}(R_i + DR_j) - DL_j^h \left(\frac{b_j}{b_i}\right)^{\theta} \left(\frac{w_i}{w_j}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}} \tag{9}$$

In local sectors, labor demand is increasing in output market expenditures R_i and decreasing in local wages w_i. Notice that due to the free entry condition, $R_i = w_i L_i^h$ implies zero profits. (Although firms earn revenues to cover fixed costs f_e and f_{ij}, these fixed costs are paid through local wages.) In tradable sectors, labor demand is analogously increasing in "global" output market expenditures $(R_i + DR_j)$ and decreasing in local wages. The second term in Equation (9) reflects competition from suppliers in other counties: if competing counties have higher productivity distribution b_j or lower wages w_j, this decreases labor demand in county i.

[7] To ensure that the size distribution of firms has finite mean, we assume $\theta > \sigma - 1$. b can vary across sectors h, but we drop the superscript for simplicity.

III.B Effects of a Resource Boom

We consider the effects of a "resource boom" on workers and firms in county i. We define a resource boom as an increase in resource sector productivity A_i^r in county i, as has occurred due to improvements in hydraulic fracturing and horizontal drilling. An increase in resource price p^r, as in the oil price shocks of the 1970s and the 2000s, would generate analogous effects in counties with relatively high A_i^r. To keep the theoretical results simple, we assume that county i is "small" in the sense that there are many other counties and that wages and labor supply in all other counties are unaffected by the resource boom. See Appendix A for formal details on the predictions.

III.B.1 Predictions for Wages and Employment

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

Increases in A_i^r increase the marginal return to labor in the resource sector, pulling labor into resource production and driving up wages: $dw_i/dA_i^r \geq 0$. This causes an increase in labor supply, which mitigates the wage increase. The inequality $dw_i/dA_i^r \geq 0$ is strict if $L_i'(w_i) < \infty$. If labor supply is fully elastic, however, resource booms do not affect wages, and all adjustment occurs through migration and/or movement into the labor force.

Prediction 2: A resource boom increases local sector employment.

In Appendix A.D, we show that barring parameters that are empirically unrealistic, a resource boom increases the ratio of expenditures to wages $\frac{R_i^h}{w_i}$, i.e. $\frac{d(R_i/w_i)}{dA_i^r} > 0$. This can be driven either by an increase in labor supply L_i, which increases total demand even holding constant per-worker expenditures, or by a sufficiently large increase in resource sector profits $\eta\pi_j^r$. Prediction 2 is immediate from applying this result to local sector labor demand in Equation (8).

Prediction 3: If labor supply is not fully elastic, a resource boom decreases tradable sector employment.

This follows from taking the total derivative of tradable sector labor demand in Equation (9) with respect to A_i^r. Of course, the prediction requires that county i is "small" compared to the total market, just as a US county is small compared to the entire country or even its state. If not, a "tradable" good looks more like a local good, and county i's demand increase outweighs the wage increase.

Prediction 4: With sufficiently high trade costs τ_{ij}^u or upstream factor share α, a resource boom increases upstream sector employment.

The upstream sector is similar to the other monopolistically-competitive sectors, except that it benefits directly from the resource boom due to a direct increase in expenditures R_i^u. Thus, the upstream sector is more likely to expand during a resource boom, but this still depends on tradability. If upstream goods are purely local, then total upstream employment is proportional to resource industry employment and so must grow with a resource boom: $L_i^u = \frac{\alpha}{\beta} L_i^r$. If upstream industries are tradable, Appendix A shows the intuitive result that the boom will be more likely to increase upstream sector employment if the upstream factor share α is large.

III.B.2 Predictions for Firm Selection

Aside from affecting sectoral labor input, a resource boom could also affect the set of potential entrants that decide to produce instead of withdrawing from the market.

Prediction 5: A resource boom does not affect the minimum productivity threshold to produce tradable goods.

In Appendix A, we show that the productivity threshold to produce in local sectors is

$$\text{Local: } (\varphi_{ii}^*)^\theta = \lambda_1 f_{ij} b_i^\theta \frac{\sigma - 1}{f_e \theta}. \tag{10}$$

The lack of a selection effect results from two offsetting forces. First, increased demand increases revenues for local firms, allowing less-productive establishments to operate. Second, however, increased entry raises the number of local product varieties, lowering the price index and increasing competition. With CES demand and constant returns production, these forces perfectly offset each other.

Prediction 6: A resource boom increases the minimum productivity threshold to export tradable goods.

In Appendix A, we show that the productivity threshold to sell tradable goods into county j is

$$\text{Tradable: } \left(\varphi_{ij}^*\right)^\theta = \lambda_1 f_{ij} b_i^\theta \frac{1}{R_j^h} \left(\frac{\sigma - 1}{f_e \theta} \left(R_i^h + D R_k^h \right) \right), \tag{11}$$

where $\lambda_1 = \theta / (\theta + 1 - \sigma)$ is a constant and k refers to counties other than i. A resource boom increases R_i^h, which increases the productivity threshold φ_{ij}^*. If D is large, however, this effect will be small, because the change in R_i^h from a boom is still small relative to the $R_i^h + DR_k^h$. As we discuss in Appendix A, the productivity threshold to sell tradable goods in the home county (county i) actually decreases during booms due to home market demand growth, so this prediction applies only to the decision to export outside county i.

III.B.3 Endogenous Productivity and the Resource Curse

The potential decline of the tradables sector from Prediction 3 does not indicate a welfare loss if there are no market failures (van Wijnbergen 1984). Indeed, resource booms increase welfare due to higher wages and resource profits. However, if there are uninternalized productivity spillovers in tradable sectors 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 study the effects of a symmetric resource boom and bust relative to a counterfactual without the boom or bust.

We index periods by t and denote the tradable sector by x. In period t, county i experiences a resource boom (an increase in A_i^r). In period $t+1$, the boom ends, meaning that A_i^r returns to its initial condition. We compare county i to a "counterfactual" county j that has no resource boom and is unaffected by the boom in county i, but is otherwise identical.

We assume that the productivity parameter for tradables sectors b_{it}^x evolves as a function of previous period labor input in the tradable and resource sectors:

$$b_{i(t+1)}^x = b_{it}^x + \iota L_{it}^x + \zeta L_{it}^r. \tag{12}$$

A value of $\iota > 0$ would imply productivity spillovers or "learning by doing" in the tradable sector, as documented by Ellison, Glaeser, and Kerr (2010), Greenstone, Hornbeck, and Moretti (2010), Kline and Moretti (2013), and others. A value of $\zeta > 0$ would imply that the resource sector exerts positive productivity spillovers on the tradables sector.[8]

Relative to "counterfactual" county j, the post-boom tradable sector productivity parameter is

$$\Delta b_{i(t+1)}^x = b_{i(t+1)}^x - b_{j(t+1)}^x = \iota \left(L_{it}^x - L_{jt}^x \right) + \zeta \left(L_{it}^r - L_{jt}^r \right). \tag{13}$$

Prediction 7: If labor supply is not fully elastic and $\Delta b_{i(t+1)}^x < 0$, *then a 1-period resource boom in* t *causes lower county-level employment and wages in* $t+1$.

During the boom in period t, if labor supply is not fully elastic, Prediction 1 shows that wages will increase, and Prediction 3 shows that employment will decline in the tradables sector. If ι is sufficiently greater than ζ, then $\Delta b_{i(t+1)}^x$ will be negative. If $\Delta b_{i(t+1)}^x < 0$, Equation (9) shows that $L_{i(t+1)}^x$ would decrease, as more productive producers in other counties crowd out production from county i. This decrease in labor demand reduces county-level wages w_i.

Of course, the opposite outcome is possible: if spillovers from the resource sector are sufficiently strong for $\Delta b_{i(t+1)}^x > 0$, then productivity, employment, and wages could all increase. The agglomeration literature, 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.

[8]The Dutch Disease literature (e.g. van Wijnbergen 1984) has tended to focus on learning-by-doing in tradables, but there could also be productivity spillovers to or from the non-tradables or upstream sectors, or other forms of externalities imposed by any sector. Most broadly, impacts are determined by the relative uninternalized externality imposed by the sectors that grow vs. contract during a boom.

III.C Geographic Spillovers

Although we do not study this explicitly in the model, our assumption of elastic labor supply suggests how a resource boom in one county could affect other counties: the population that migrates into a county must have come from somewhere else. Thus, as Busso, Gregory, and Kline (2013) 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. Our estimates are thus the necessary parameters for policy makers evaluating the local costs and benefits of policies that determine the magnitude of a local boom. 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. Even in the case of a local fracking ban, these areas would still experience economic spillovers from areas with resource extraction. Our estimates are not informative about whether the U.S. as a whole is better or worse off after a resource boom.

III.D 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, 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 industry as a whole, and are there differential impacts for the local, tradable, and upstream sectors?

Third, do resource booms affect manufacturing productivity? Within-plant productivity increases identify positive spillovers from resource booms, which per Prediction 7 could moderate or reverse the possibility of Dutch Disease. Furthermore, selection effects from Predictions 5 and 6 could also affect sector-wide average productivity.

IV Data

IV.A 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" in each US county[9] under two different major technologies: pre- and post-fracking. A county's total oil and gas endowment is comprised of three categories of resource: past production, proven reserves, and undiscovered reserves.

Oil and gas production data are from a new county-by-year panel dataset from 1960 to 2011, the first such comprehensive county-level dataset. Much of this data is drawn from the DrillingInfo (a market research company) database of well-level oil and gas production, which we collapse to the county-by-year level. The DrillingInfo data are incomplete, however, so we have acquired county-level oil and gas production data from local authorities in 13 additional states; see Appendix Table A2 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.[10] This allows a substantial improvement over publicly-available proven reserves data used in previous work, which covers only the largest fields.

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].[11] These resources are unaffected by existing or past extraction except insofar as greater prospecting in an area might transfer resources from the "undiscovered" to the "proven" category.[12]

We combine these three categories to our county-level measure of resource abundance: the value

[9]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.

[10]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.

[11]See http://energy.usgs.gov/OilGas/AssessmentsData/NationalOilGasAssessment/Methodology.aspx for more details on assessment methodology.

[12]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.

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:

$$a_i = \frac{\sum_{t=1960}^{T} Production_{it} + Proven\,Reserves_{iT} + Undiscovered\,Reserves_{iT}}{Area\,(Square\,Miles)_i} \tag{14}$$

As discussed in Section II, 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. a_i^{early} measures endowment in the first boom, with $T = 1995$, using the estimates of proven and undiscovered reserves from the late 1990s. a_i^{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_{it}, which takes value a_i^{early} until 2000, and a_i^{total} beginning in 2001. The precise year in which a_i^{early} ends does not make much difference, and we show that the conclusions are not sensitive to using either a_i^{early} or a_i^{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, a_i^{total} also has standard deviation of approximately \$10 million per square mile within the set of counties with non-zero resource. We transform physical units of oil and gas to dollar values using their average prices over 1960-2011: \$34.92 per barrel of oil and \$3.20 per mmBtu of gas.

Table 1 presents descriptive statistics for the resource data, focusing on a_i^{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, a_i^{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 a_i^{total}. Fifth, there is substantial variation in a_i^{total} across counties: the standard deviation across all counties (not just non-zeros) is about three times the mean. This variation is also highlighted in Figures 3 and 4, which show a_i^{total} and $a_i^{total} - a_i^{early}$, respectively.

IV.B Regional Economic Information System

Our primary source of data on employment, earnings, and population is the Regional Economic Information System (REIS). Data are available annually beginning in 1969. 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.[13] Since the REIS data begin in 1969, we collected earnings per worker and employment data from the 1964 and 1968 County Data Books, and population data from the 1960 and 1966 US Census. Data on county area, including both land and water area, are also from the US Census.[14] The top panel of Table 2 describes the REIS data.

IV.C Current Population Survey Data

In order to directly measure wages instead of earnings per worker, we construct two datasets from the Current Population Survey (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 Merged Outgoing Rotation Group (MORG) files 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 two "outgoing rotation" interviews.[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.[16] In regressions with CPS data, we thus use state-level treatment intensity a_{st}, which is constructed analogously to the county-level measure described earlier.

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[13]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 robustness checks available upon request, 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.

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

[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.

IV.D Manufacturing Census Microdata

The Census of Manufactures (CM) includes microdata for all manufacturing establishments (i.e. plants) in the United States. The data include the county where the plant is located, its four-digit SIC 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 every five years beginning in 1967, i.e. 1972, 1977, ..., 2007. We convert all industry codes to four-digit year-1987 SIC codes.

We use plant-level revenue TFP (TFP-R) estimates made available 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.

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 a plant-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.

IV.D.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 "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 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

[17]Employment and earnings data for non-responders and small plants with fewer than five employees is imputed and/or marked as an "administrative record." For these plants, 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.

sum of these two quantities. We define an industry as "upstream" of oil and gas if this upstream 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.[19] 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 A3 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).

V Empirical Strategy

V.A Estimating Equations for County-Level Variables

We measure the magnitudes of our first four predictions using county-level panel data on employment, wages, and other outcomes. Define Y_{it} as an outcome in county i in year t, E_t as national-level oil and gas employment, $\ln \mathbf{Y}_{0i}$ as a vector of baseline values of the outcome from two different years at the beginning and end of the 1960s, and ϕ_{dt} as a vector of Census division-by-year indicator variables, where d indexes Census divisions.[20] We use a reduced-form estimating equation, regressing changes in log outcomes on changes in a measure of resource sector revenue productivity:

$$\Delta \ln Y_{it} = \tau \Delta \ln E_t a_{it} + \kappa a_{it} + \sum_t \varpi_t \ln \mathbf{Y}_{0i} + \phi_{dt} + \varepsilon_{it}. \tag{15}$$

We use robust standard errors and cluster by county.[21]

[19] 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.

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

[21] Because some local labor markets include multiple counties, one might also cluster by Commuting Zone or by state. In alternative regressions available upon request, we conservatively cluster by state. Standard errors actually decrease in just over half of our regressions, because spillovers can cause negative error correlations across counties. For example, unexplained population increases in one county may come from population decreases in a nearby 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 a_{it}. Furthermore, since $\Delta \ln Y_{it} \approx \frac{Y_{it}-Y_{i(t-1)}}{Y_{it}}$ 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 $\Delta \ln E_t a_{it}$ is closely analogous to the Bartik (1991) instruments, except that the cross-sectional variation comes from initial resource abundance instead of an industry's initial employment share. Unlike Blanchard and Katz (1992) and others who use the Bartik instruments, we directly use $\Delta \ln E_t a_{it}$ on the right-hand-side instead of using it as an instrument for changes in employment. We do not report instrumental variables estimates because we do not intend to suggest that the exclusion restriction would be satisfied: as the model shows, resource booms affect local economies through royalties and other channels in addition to changes in oil and gas employment.

V.A.1 Regressions for Graphical Results

We also present graphical evidence on how outcomes vary over time for more or less resource-intensive counties. The estimating equation is identical, except with $\sum_t \tau_t a_{it}$ substituted for $\tau \Delta \ln E_t a_{it}$:

$$\ln Y_{it} = \sum_t \tau_t a_{it} + \kappa a_{it} + \sum_t \varpi_t \ln \mathbf{Y}_{0i} + \phi_{dt} + \varepsilon_{it}. \tag{16}$$

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

V.B Current Population Survey Wage Regressions

While the REIS allows us to measure earnings per worker, 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 per worker could change: if people work more hours during resource booms, earnings per worker would increase even if unit labor costs did not. We use the CPS microdata to measure wage effects directly and test these two potential concerns.

We estimate two parallel specifications for our two CPS datasets, temporarily using i to index individuals. 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 υ_s, month indicators μ_m, and year indicators ν_t. With Y_{ismt} as an outcome variable (either wages or hours worked per week), the specification is:

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

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

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:

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

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

V.C Regressions Using Plant-Level Census Microdata

To measure the latter three predictions from our theoretical framework, we turn to plant-level Census microdata. We estimate two sets of regressions. The first examines how changes in resource booms affect continuing plants. This allows us to test for productivity spillovers from the resource sector to manufacturing, as contemplated in Equation (12) of the model. In the estimating equation, f indexes plants, i again indexes counties, and we also add λ_{nt}, the full interactions of four-digit SIC codes and years. The regression is:

$$\Delta \ln Y_{fit} = \tau \Delta \ln E_t a_{it} + \kappa a_{it} + \phi_{dt} + \lambda_{nt} + \varepsilon_{fit}. \tag{19}$$

In these specifications, Δ denotes a 5-year difference between rounds of the Census of Manufactures. In all Census microdata regressions, standard errors are robust and clustered by county.

Our second microdata specification studies how changes in resource booms affect the set of plants that enter or exit between rounds of the CM. This allows us to test whether resource booms affect the types of plants selecting into production, as in Predictions 5 and 6. In each census round, we identify plants as entrants if they appeared in the CM in the five years since the previous round, and as exiters if they disappear prior to the next CM round five years later. For these regressions, we use the mean national oil and gas employment $\bar{E}_t$ for the past (future) five years for entrants (exiters) as a measure of the resource boom or bust. The regression is:

$$\ln Y_{fit} = \tau \ln \bar{E}_t a_{it} + \kappa a_{it} + \phi_{dt} + \lambda_{nt} + \xi_i + \varepsilon_{fit}, \tag{20}$$

where ξ_i denotes county fixed effects. The sample is limited to either entering or exiting plants.

VI Results

VI.A 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 total 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-fifth 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 coefficients of regressions of natural logs of these variables on oil and gas endowment per square mile a_i^{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 and downstream linkages: a \$10 million increase in oil and gas abundance is associated with a 11.3 percent increase in linked manufacturing employment. By contrast, the relationships between resource endowment and other sub-sectors of the manufacturing industry are insignificant and point estimates are negative.[22]

VI.B Effects on County-Level Aggregates in REIS Data

VI.B.1 Main Results

How do resource booms affect county-level aggregates? 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 in grey against the right axis. 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

[22] 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.

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 4 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 increases national oil and gas employment by 100 log points increases population, employment, and earnings per worker by 1.29, 2.87, and 2.14 percent, respectively, for counties with \$10 million/square mile (i.e. one standard deviation) additional endowment.

Connecting to Prediction 1 of the model, these results show that resource booms significantly affect both population and earnings per worker. This implies that the assumptions for Prediction 3 are satisfied: because wages rise in resource-abundant counties, traded good sectors should contract. The coefficients in Figure 5 show that over the entire period from 1975-1985, earnings per worker are one to 2.5 percent higher than their 1969 levels in counties with one standard deviation additional endowment.

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 4) 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 4 includes two interactions with $\tau \Delta \ln E_t a_{it}$. 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, 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 B.A shows that conditional on our controls, there are no trends in county-level outcome variables over the 1969-1972 period, before the oil price shock in 1973. Appendix Table A4 presents other robustness checks. The results are highly robust to using a_i^{early} or a_i^{total} in place of a_{it}, 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.[23] 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.

VI.B.2 Geographic Spillovers

Section III discussed how resource booms could create cross-county spillovers. Table 5 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 one hand, nearby booming county could draw migrants away from a non-producer county. On the other hand, nearby non-producer counties may also experience labor demand growth if their firms provide goods and services for the resource boom or if income from the boom is redistributed through state taxation.

Column 1 of Table 5 restates the base estimates of Equation 15 from column 2 of Table 4. 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

[23]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 proportional increase in prices than in national oil and gas employment (see Figure 1).

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 firm 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 its home 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.

VI.C Current Population Survey Wage Regressions

Table 6 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 6 illustrates these results, using an approach analogous to Equation (16): we plot the coefficients on the interaction of year indicators with a_{it}, with an omitted interaction for the year 2001. States with \$10 million extra endowment per square mile saw relative wages are five to ten percent higher than their year-2001 equilibrium for the entire eleven-year period between 1977 and 1987. Figure 7 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 6, suggest that the more recent boom has had smaller wage effects than the 1970s-1980s boom. Column 2 of Table 6 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 6 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 reasonable approximations to 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 A5, 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.

VI.D 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 8 presents estimates of Equation (16) with the log of county-level manufacturing sector employment 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 7 presents the formal estimates of the effects of resource booms on manufacturing employment. The columns parallel the columns for county aggregate outcomes in Table 4. A boom that increases national oil and gas employment by 100 log points 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 7 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 REIS estimate for all workers.

To parallel the aggregate results tables, Appendix Tables A6 and A7 present robustness checks and geographic spillovers. Results are similarly robust, except that τ for manufacturing employment 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 5, except that estimates for manufacturing earnings per worker are less precise.

VI.E County-Level Census Dataset: Subsectors and Alternative Outcomes

While manufacturing as a whole is procyclical with resource booms, can we identify Dutch Disease (or particularly positive effects) within different sectors? Table 8 presents estimates of Equation (15) using a county-level Census dataset, which we constructed by collapsing the CM microdata across plants to the county-by-year level. Each panel presents a different outcome, while each column presents estimates with outcomes collapsed from different sectors.

Column 1 presents estimates for all manufacturing plants. The first panel examines employment, confirming the result from Table 7 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 consider revenues ("total value of shipments") and investment instead of employment. Revenues grow much more in percent terms, suggesting that revenues per worker may be increasing, and investment is even more procyclical than revenues.

Do firms adjust to resource booms on the "intensive margin," by hiring more workers within the same plant, or on the "extensive margin," by opening and keeping open more plants? Because opening physical plants may involve larger sunk costs than hiring workers into existing plants, this could affect the persistence of a resource boom's effects. The fifth panel shows that the count of manufacturing plants is indeed procyclical with resource booms, although the coefficient is about 2/3 the size as the coefficient on employment. In that sense, 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 plants 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 plant exit rates have no significant correlation with booms.

Column 2 presents analogous results for plants that are upstream or downstream of oil and gas. For most outcomes, effects are more pro-cyclical than in non-linked sectors. Columns 3, 4 and 5 examine non-linked plants, divided into subsamples that produce more vs. less tradable goods. Non-linked, local industries are generally procyclical. Interestingly, local sectors' births and death rate are both pro-cyclical, implying increased churn, not just growth. This could arise if demand heterogeneity makes previously-viable plants less profitable. Sectors making goods that resource industries and workers tend not to buy could be crowded out by higher wages when demand fails to grow during a boom.

In contrast to the local sector results, column 5 suggests counter-cyclical effects on tradable sectors, although the estimates are imprecise. Point estimates on employment, revenue, and number of plants 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. Remarkably, however, these effects are relatively difficult to detect, and arise only for a subset of manufacturers.

VI.F Effects on Revenue Productivity

Prediction 7 highlighted the potential importance of productivity spillovers, suggesting that spillovers from natural resources to manufacturing could moderate potential Dutch Disease. Such spillovers could help to explain why there is so little evidence that manufacturing contracts during resource booms. Table 9 tests for spillovers by estimating Equation (19) using plant-level data from the Census of Manufactures. Recall that this specification first-differences outcomes within surviving plants across five year periods between each Census of Manufactures round. As in the previous table, each of the two panels 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 value-added results are especially interesting when combined with the logic of the "initial conditions" in Table 3. Plants 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 plant 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 plant produces output for an oil and gas producer but is in a larger industry that typically does not.

Resource booms increase value added for linked plants nationwide, and without industry-by-year fixed effects, our estimates include selection effect of highly (but unobservably) linked plants in less-linked industries having sorted into resource-abundant counties. As we include more disaggregated industry fixed effects, our estimates increasingly focus on local causal effects and less on selection. Using the coefficient movement logic from Altonji, Elder, and Taber (2005), the fact that the TFP-R estimates don't change between the top and bottom panels suggests that the TFP-R effects are spillovers from a local resource boom, not industry-wide effects in unobservably-selected industries.

One concern might be that even though these are within-plant estimates, the productivity increase for linked and local sectors could reflect selection instead of spillovers if plant productivity shocks are serially correlated. Prediction 5 suggests that the local sector productivity threshold is unrelated to resource booms, however, and we see no differential selection below in Table 10. If resource booms did allow lower-productivity firms to operate during booms, a boom would allow more firms to remain in operation even if they receive a negative productivity shock. This potential selection effect would work against our results, which show that the average continuing plant in linked and non-linked local industries experiences a productivity increase during a boom.

One explanation for the results in Table 9 is that they reflect increased markups during booms, and not increased physical productivity (TFP-Q). Given that the CM does not have physical output data for all plants, this is not possible to conclusively test. In Appendix Table A8, we consider the subset of plants that do report physical output. Because physical output can only be reported for relatively homogeneous goods, this subset of plants is both relatively small and relatively unusual. Within this caveat, however, we see no statistically significant effects on price, and the TFP-R estimates in columns 1 and 4 are statistically more positive than the price estimates. This tentatively suggests that the TFP-R effects may reflect TFP-Q. In Appendix Table A8, we also estimate TFP-R effects using 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.

If the results in Table 9 reflect physical productivity spillovers, we can draw some inference on the potential mechanisms. A natural starting point is Marshall's (1890) three types of transport costs: goods, people, and ideas. "Goods" linkages could increase productivity if local economic growth allows goods to be procured from and delivered to more nearby suppliers and buyers, either in the resource sector or in other pro-cyclical local sectors. This is consistent Table 9 results, which show TFP-R growth in linked and local sectors, but not in tradables.

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. The "ideas" channel seems even less likely: much of the oil and gas sector's innovation does not occur at the drilling site, and much of it seems unlikely to translate to non-resource 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 tradable sector plants that would presumably also benefit from any government assistance. Tax cuts and infrastructure take time to implement, so they might be more relevant in a long-term cross-sectional analysis like Michaels (2010) than in a relatively short-term within-county analysis like ours.

VI.G Selection

Aside from affecting the productivity of continuing plants, resource booms could also change the types of plants that are able to operate in the market, as considered in Predictions 5 and 6. Although the theoretical framework only captures entry, we also empirically consider exit. Predictions 5 and 6 would be similar in a multi-period version of the model where actual entrants pay a per-period fixed cost f_{ij} and can later choose to exit if market conditions change and their productivity is too low to merit paying the fixed cost.

Table 10 presents estimates of Equation (20), regressing natural log TFP-R of all entering and exiting plants on the averaged measures of local oil and gas booms in the past (for entrants) and future (for exiters) five years. The results show no statistically significant change in average TFP-R for entrants and exiters, except for in the highly-tradable sectors. This suggests that the productivity threshold φ^* for export production has increased, leading higher-productivity firms to exit. This result, and the lack of a statistically significant change in the local sectors, is consistent with Predictions 5 and 6.[24] This documents how resource booms (or potentially other local economic changes) can affect plant selection, not just overall output and productivity.

VI.H 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 11 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 1973 oil price shock, to 1997, the last round of the CM prior to the beginning of the second resource boom in the early 2000s.

Table 11, sub-table (a), examines the long-term effects of the boom and bust on natural log TFP-R. For the first specification, we collapse plant-level log TFP-R to county means and difference

[24]As we discussed in Section III, Prediction 6 pertains only to the decision to export a traded good from county i. Because county i is small, we interpret this as the relevant margin of selection when comparing the prediction to our empirical results.

between 1972 and 1997 to generate the long-term change outcome. The second specification parallels the first, except using plant-level data for 1972 and 1997. We run a difference-in-differences estimator, controlling for county fixed effects and 4-digit SIC-by-year effects and reporting the interaction of the 1997 year indicator with resource endowment a_i^{early}. Both specifications find no significant differences in productivity in any sector. Thus, the TFP-R effects measured in Table 9, plus any potential longer-term effects, canceled out over the boom and bust of the 1970s and 1980s.

Table 11, sub-table (b), regresses changes in natural log of REIS outcomes from 1972 to 1997 on early period oil and gas endowment a_i^{early}, controlling for Census division dummies and pre-1969 levels and trends of the outcome variable. Again here, 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 essentially offset by the effects of the bust.

VII Conclusion

The rise and fall 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 increases national oil and gas employment by 10 percent increases total employment by 0.29 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-R are actually pro-cyclical with resource booms.

There are four key takeaways. First, our results counter the argument that natural resource extraction is unlikely to drive productivity growth. Instead, our results show that natural resource booms increase TFP-R (and perhaps TFP-Q) in linked and local manufacturing sectors. 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 highly localized demand growth. Third, despite the increase in revenue productivity for local and resource-linked sectors, the boom does not cause an enduring transformation of resource-rich areas. On most outcomes, the bust of the 1980s offset the boom of the 1970s, leaving no permanent effects. Fourth, while Dutch Disease is theoretically possible and wages do rise, our results clearly reject the idea of Dutch Disease within the United States, except for within a more narrowly-defined subset of manufacturing plants.

Would this latter result generalize to larger geographic areas? If manufacturing plants agglomerate at the *county* level, they surely agglomerate at the *country* level. However, tradable sectors would clearly contract more if facing a larger real input cost increase, either if a within-country labor market is less flexible than the U.S. or if the national currency appreciates. Furthermore, our results show that linked manufacturing is an important driver of local growth around oil and gas booms, so our results would be stronger (less strong) for other natural resource industries requiring more (fewer) upstream manufacturing inputs.

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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 ($/barrel)	34.92			
Natural Gas (billion cubic feet)				
Output 1960-2011	244	1102	20,033	1121
Current proven reserves	136	990	30,544	734
Current undiscovered reserves	284	1318	50,538	2287
1960-2011 average price ($/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. Total 1960 oil and gas resource is the product of physical quantities of oil and gas with their average prices over 1960-2011.

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	29.2	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 1969 REIS. Manufacturing employment is from the 1967 Census of Manufactures. Column 2 presents the coefficient of a regression of natural log of the variable on oil and gas endowment per square mile a_i^{early}, controlling for Census division fixed effects. Robust standard errors in parentheses.

Table 4: **Effects of Resource Booms on County-Level Aggregates**

	(1)	(2)	(3)
Population			
Δln(National oil&gas employment$_{t-1}$)$\times$endowment$_{it}$	0.0168***	0.0129***	0.0251***
	(0.0024)	(0.0022)	(0.0050)
Δln(National oil&gas employment$_{t-1}$) $\times$endowment$_{it}$			-0.0116***
$\times$1(ΔNational oil&gas employment$_{t-1}$<0)			(0.0032)
Δln(National oil&gas employment$_{t-1}$) $\times$endowment$_{it}$			-0.0179***
$\times$1(year>2000)			(0.0039)
Employment			
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$	0.0379***	0.0287***	0.0412***
	(0.0055)	(0.0049)	(0.0090)
Δln(National oil&gas employment$_t$) $\times$endowment$_{it}$			0.00242
$\times$1(ΔNational oil&gas employment$_t$<0)			(0.0045)
Δln(National oil&gas employment$_t$) $\times$endowment$_{it}$			-0.0321***
$\times$1(year>2000)			(0.0079)
Wage Earnings/Worker			
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$	0.0334***	0.0214***	0.0152***
	(0.0050)	(0.0041)	(0.0049)
Δln(National oil&gas employment$_t$) $\times$endowment$_{it}$			0.0141**
$\times$1(ΔNational oil&gas employment$_t$<0)			(0.0065)
Δln(National oil&gas employment$_t$) $\times$endowment$_{it}$			-0.0015
$\times$1(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 5: **Geographic Spillover Effects of Resource Booms**

	(1)	(2)	(3)	(4)
	All counties	All counties	Zero endowment counties	All counties
	Population			
$\Delta\ln$(National oil&gas employment$_{t-1}$)	0.0129***	0.0117***		0.0254***
$\times$endowment$_{it}$	(0.0022)	(0.0021)		(0.0035)
$\Delta\ln$(National oil&gas employment$_{t-1}$)			0.0280**	0.0200***
$\times$endowment$_{st}$			(0.0112)	(0.0029)
$\Delta\ln$(National oil&gas employment$_{t-1}$)				-0.0104***
$\times$endowment$_{it}\times$endowment$_{st}$				(0.0016)
	Employment			
$\Delta\ln$(National oil&gas employment$_{t}$)	0.0287***	0.0246***		0.0487***
$\times$endowment$_{it}$	(0.0049)	(0.0047)		(0.0066)
$\Delta\ln$(National oil&gas employment$_{t}$)			0.0747	0.0460***
$\times$endowment$_{st}$			(0.0532)	(0.00621)
$\Delta\ln$(National oil&gas employment$_{t}$)				-0.0176***
$\times$endowment$_{it}\times$endowment$_{st}$				(0.0023)
	Wage Earnings/Worker			
$\Delta\ln$(National oil&gas employment$_{t}$)	0.0214***	0.0173***		0.0362***
$\times$endowment$_{it}$	(0.0041)	(0.0037)		(0.0060)
$\Delta\ln$(National oil&gas employment$_{t}$)			0.0597**	0.0455***
$\times$endowment$_{st}$			(0.0235)	(0.0048)
$\Delta\ln$(National oil&gas employment$_{t}$)				-0.0135***
$\times$endowment$_{it}$ $\times$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 6: **Effects of Resource Booms on Wages in Current Population Survey**

	(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$_{st}$	(0.0092)	(0.0162)	(0.0075)	(0.0098)	(0.0072)
ln(National oil&gas employment$_t$)		-0.0557***			
$\times$endowment$_{st}\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$_{st}$	(0.0187)	(0.0221)	(0.0137)	(0.0188)	(0.0204)
ln(National oil&gas employment$_t$)		-0.0315			
$\times$endowment$_{st}\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 7: **Effects of Resource Booms on Manufacturing Aggregates**

	(1)	(2)	(3)
	Manufacturing Employment		
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$	0.0435***	0.0289***	0.0463**
	(0.0085)	(0.0082)	(0.0187)
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$			0.0002
$\times$1(ΔNational oil&gas employment$_t$<0)			(0.0228)
Δln(National oil&gas employment$_t$) $\times$endowment$_{it}$			-0.0478***
$\times$1(year>2000)			(0.0173)
	Mfg. Earnings/Mfg. Worker		
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$	0.0278***	0.0190***	-0.0035
	(0.0060)	(0.0056)	(0.0075)
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$			0.0421**
$\times$1(ΔNational oil&gas employment$_t$<0)			(0.0193)
Δln(National oil&gas employment$_t$)$\times$endowment$_{it}$			0.0124
$\times$1(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 8: **Effects on Manufacturing Subsectors and Alternative Outcomes**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			Employment		
$\Delta\ln$(National oil&gas employment$_t$)	0.0368**	0.0538**	0.0169	0.0557**	-0.0503*
$\times$endowment$_{it}$	(0.0171)	(0.0255)	(0.0171)	(0.0227)	(0.0290)
			Revenue		
$\Delta\ln$(National oil&gas employment$_t$)	0.0657*	0.0429	0.0474	0.0733	-0.0756
$\times$endowment$_{it}$	(0.0339)	(0.0542)	(0.0641)	(0.0720)	(0.0604)
			Investment		
$\Delta\ln$(National oil&gas employment$_t$)	0.126***	0.126**	0.0611	0.116**	-0.0129
$\times$endowment$_{it}$	(0.0446)	(0.0500)	(0.0568)	(0.0497)	(0.0547)
			Number of Plants		
$\Delta\ln$(National oil&gas employment$_t$)	0.0229***	0.0374***	0.0057	0.0126	-0.0145
$\times$endowment$_{it}$	(0.0067)	(0.0092)	(0.0067)	(0.0095)	(0.0090)
			Plant Births		
$\Delta\ln$(National oil&gas employment$_t$)	0.0455***	0.0562***	0.0274**	0.0311**	0.0103
$\times$endowment$_{it}$	(0.0129)	(0.0138)	(0.0122)	(0.0129)	(0.0107)
			Plant Death Rate		
$\Delta\ln$(National oil&gas employment$_t$)	0.00246	-0.0110**	0.00685	0.00981*	-0.0033
$\times$endowment$_{it}$	(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 five 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 9: **Effects of Resource Booms on Continuing Manufacturing Plants**

	(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$_{it}$	(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$_{it}$	(0.0013)	(0.00162)	(0.0020)	(0.00242)	(0.0031)
N	756,000	280,000	476,000	251,000	225,000

(a) **No Industry Controls**

			Value Added per Worker		
$\Delta\ln$(National oil&gas employment$_t$)	0.0066**	0.0066	0.00574*	0.0094**	0.0011
$\times$endowment$_{it}$	(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$_{it}$	(0.0013)	(0.0017)	(0.0021)	(0.0026)	(0.0029)
N	756,000	280,000	476,000	251,000	225,000

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

Notes: This table presents estimates of Equation (19). All specifications use plant-level differenced outcomes; the time between each Census is five 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 10: **Effects of Resource Booms on Revenue Productivity of Entrants and Exiters**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			Entrants		
ln(National oil&gas employment$_t$)	.0017	0.00004	.00288	0.0019	.0032
$\times$endowment$_{it}$	(0.0017)	(0.0029)	(0.0019)	(0.0026)	(0.0030)
N	359,000	108,000	251,000	120,000	132,000
			Exiters		
ln(National oil&gas employment$_t$)	.0076**	0.0028	.00920**	.00859	0.0098***
$\times$endowment$_{it}$	(0.0031)	(0.0039)	(0.0395)	(0.0064)	(0.0049)
N	303,000	87,000	218,000	99,000	118,000

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 11: **Long-Term Effects of the Boom and Bust of the 1970s and 1980s**

	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			1997-1972 county-level means		
$\text{Endowment}_t^{early}$	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		
$1(\text{year}=1997) \times \text{endowment}_t^{early}$	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

(a) **TFP-R**

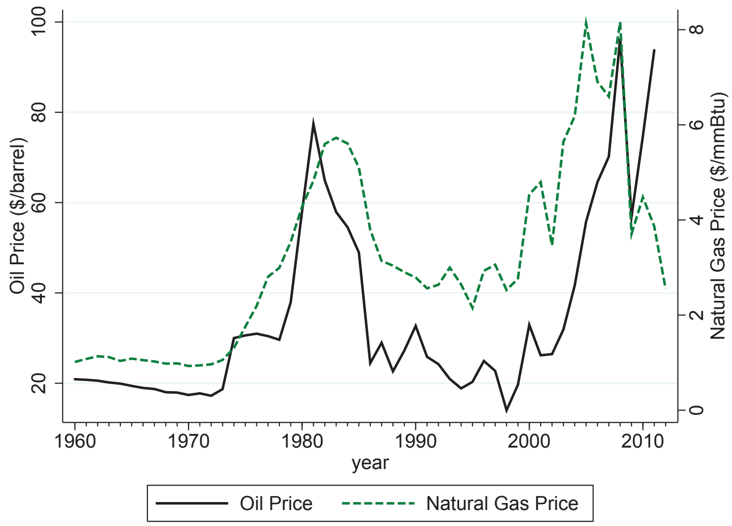
	(1)	(2)	(3)	(4)	(5)
Outcome Variable:	Population	Employment	Wage Earnings/ Worker	Mfg. Employment	Mfg. Earn-ings/Mfg. Workers
$\text{Endowment}_t^{early}$	0.0015	0.0095	0.0006	0.0170	-0.0149*
	(0.0060)	(0.0062)	(0.0023)	(0.0195)	(0.0090)
N	3075	3075	3075	2514	2514

(b) **REIS Outcomes**

Notes: The first specification of sub-table (a) regresses changes in county-average log TFP-R on early period oil and gas endowment. The second specification regresses log TFP-R 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. 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.

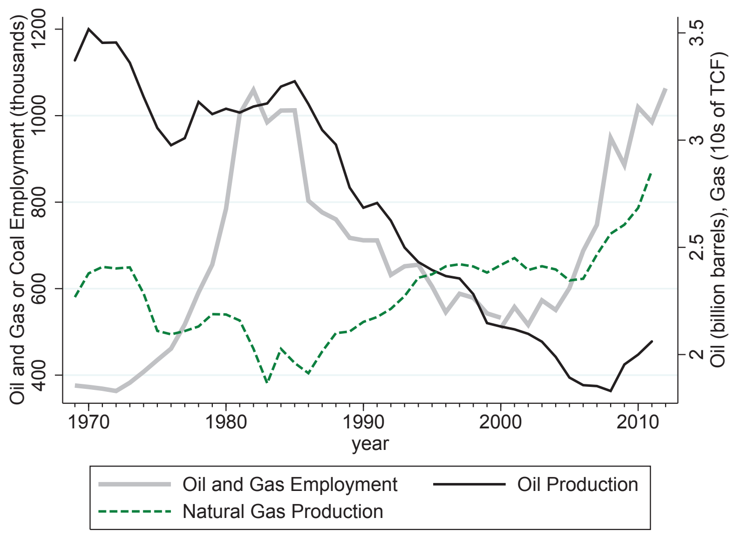
Figures

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



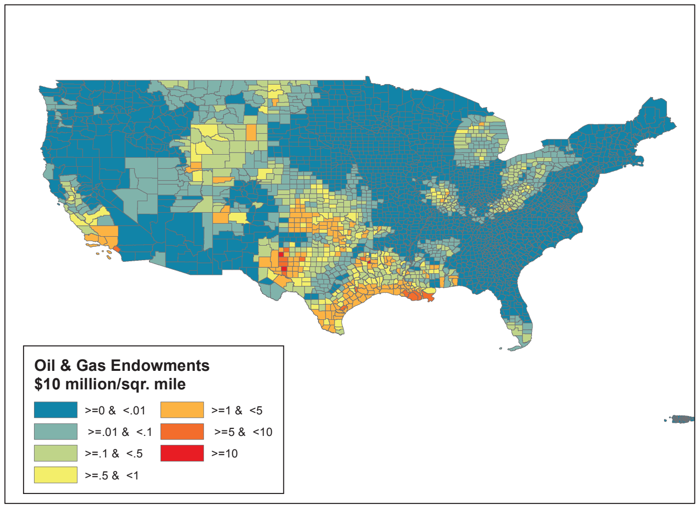
Notes: Prices are in real 2010 dollars.

Figure 2: **Oil and Gas Production and Employment**



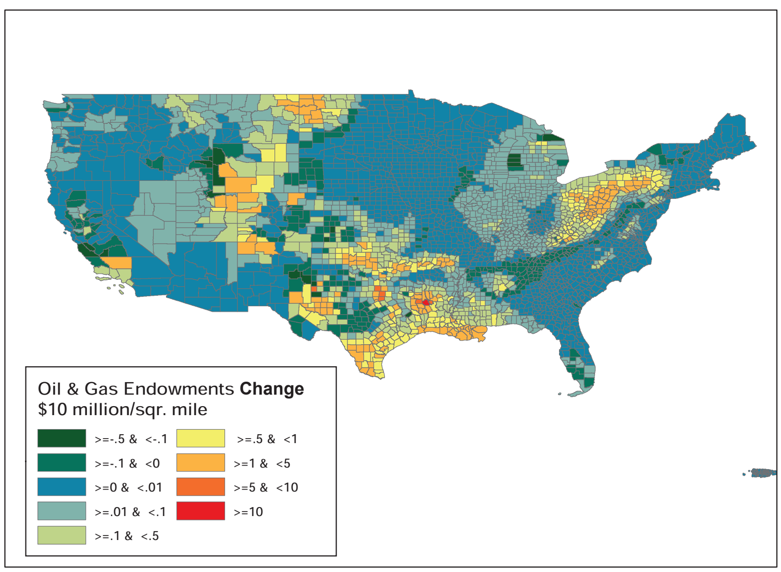
Notes: Oil and gas production data are from the Energy Information Administration. Oil and gas employment data are from the Regional Economic Information System. We switch from the SIC to the NAICS classification system in 2000 and plot both data points in that year.

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



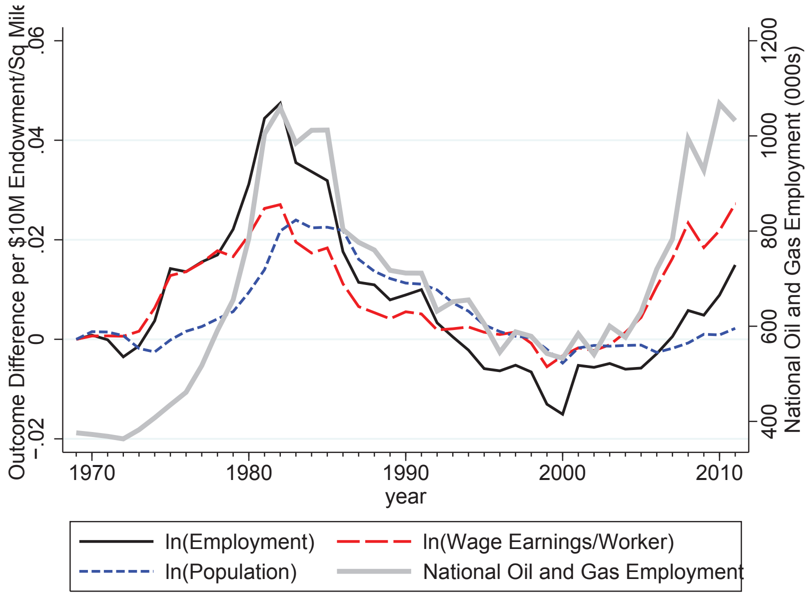
Notes: This figure maps the oil and gas endowment as of 1960 that is economically recoverable during the oil and gas boom of the 1970s and 1980s. See Section IV.A for details of variable construction.

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



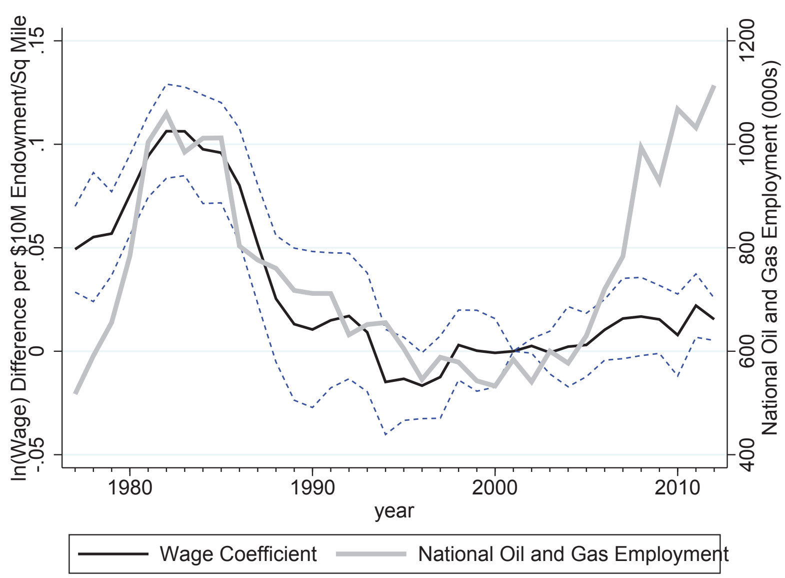
Notes: This figure maps the change between the early period oil and gas endowment in Figure 3 and the total endowment. See Section IV.A for details of variable construction.

Figure 5: **County-Level Aggregates Over Time in Resource-Abundant Counties**



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: **CPS Wages Over Time in Resource Abundant Counties**

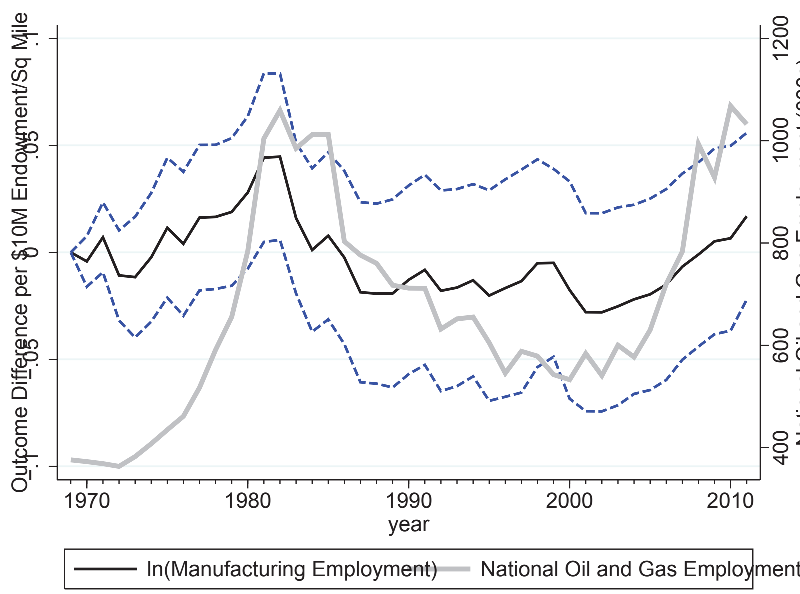


Notes: This figure presents the coefficients and 90 percent confidence intervals on τ_t when estimating Equation (17) after substituting $\sum_t \tau_t a_{st}$ for $\tau \ln E_t a_{st}$, using all workers in the CPS.

Figure 7: **CPS Manufacturing Wages Over Time in Resource Abundant Counties**

Notes: This figure presents the coefficients and 90 percent confidence intervals on τ_t when estimating Equation (17) after substituting $\sum_t \tau_t a_{st}$ for $\tau \ln E_t a_{st}$, using only the sample of manufacturing workers in the CPS.

Figure 8: **Manufacturing Employment Over Time in Resource-Abundant Counties**



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 Model Appendix

A.A Deriving the Productivity Cutoffs

Analogous to a result in Arkolakis *et al.* (2008), we show below in Appendix A.C that the mass of firms that pay to receive productivity draws in each county-sector is proportional to labor input: $M_i^h = \gamma L_i^h$, where $\gamma = \frac{\sigma-1}{f_e\sigma\theta}$. The γ notation parallels Chaney (2008). Fixed costs f_{ij} imply that only potential entrants in county i that draw productivity above a cutoff $\varphi \geq \varphi_{ij}^*$ will sell goods in county j. Here, we derive that productivity cutoff in terms of wages and M_i^h. For notational convenience throughout the appendix, we drop the h superscripts on all variables except for L^h and μ^h.

The cutoff productivity level for selling from county i into county j is the productivity at which the potential entrant earns zero profits: $\pi\left(\varphi_{ij}^*\right) = 0$. Substituting in the pricing rule $p_{ij}\left(\varphi\right) = \tau_{ij}w_i/\varphi\rho$ and Equation (5) gives

$$\varphi_{ij}^* = \left(\frac{R_j}{w_i f_{ij}\sigma}\right)^{\frac{1}{1-\sigma}} \frac{\tau_{ij}w_i}{\rho P_j}. \tag{21}$$

The aggregate price index P_j can be written as a function of φ_{ij}^*:

$$P_j = \left(\sum_{i=1}^{D+1} M_i \int_{\varphi_{ij}^*}^{\infty} p_{ij}\left(\varphi\right)^{1-\sigma} g\left(\varphi\right) d\varphi\right)^{\frac{1}{1-\sigma}}, \tag{22}$$

where $g(\varphi)$ is the probability density function of the Pareto distribution.

Substituting Equation (21) into Equation (22), using the Pareto distributional assumption, and simplifying gives:

$$\left(\varphi_{ij}^*\right)^{\theta} = \lambda_1 \frac{f_{ij}\sigma}{\chi_{ij}^h R_j^h} w_i \sum_{k=1}^{D+1} b_k^{\theta} M_k \chi_{kj} \left(\frac{w_i}{w_k}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}}, \tag{23}$$

where λ_1 is a constant and χ_{ij} is an inverse measure of the trade costs.[25] The productivity cutoff to sell outside of the county is weakly higher than the cutoff to sell within-county, so all firms that "export" also sell locally: mathematically, that is $\tau_{ii} \leq \tau_{ij}$ and $\chi_{ii} \geq \chi_{ij}$, so $\varphi_{ii}^* \leq \varphi_{ij}^*$.

Equation (23) can be simplified for the special cases of local and tradable sectors. For the local sector, we substitute $\chi_{ij} = 0,\ \forall j \neq i$ and simplify. For the tradable sector, we substitute $\chi_{ii} = \chi_{ij},\ \forall i, j$ and simplify.

[25] $\lambda_1 = \theta/\left(\theta + 1 - \sigma\right)$, and $\chi_{ij} = \left(\frac{\rho}{\tau_{ij}}\right)^{\theta}\left(f_{ij}\sigma\right)^{\frac{\sigma-1-\theta}{\sigma-1}}$

$$\text{Local: } (\varphi_{ii}^*)^\theta = \lambda_1 f_{ii} \sigma \frac{w_i}{R_i} b_i^\theta M_i \tag{24}$$

$$\text{Tradable: } (\varphi_{ij}^*)^\theta = \lambda_1 f_{ij} \sigma \frac{w_i}{R_j} b_i^\theta \left(M_i + DM_k \left(\frac{b_k}{b_i}\right)^\theta \left(\frac{w_i}{w_k}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}} \right) \tag{25}$$

If M_i^h is held constant, the wage w_i captures favorability of county i for production: higher wages increase the productivity cutoff φ_{ii}^* and cause more productive firms to withdraw without producing. R_i (or R_j) captures the favorability of county i (or j) for consumption: higher expenditures decrease the productivity cutoff, allowing less productive firms to produce. In Equation (25), the j index could reflect sales into the home county (i) or some other county, and the relative productivity and wage terms that multiply DM_k capture competition from counties k other than i selling varieties into county j. After solving for labor demand L_i^h below, we endogenize M_i^h through the free entry condition and solve for Equations (10) and (11).

A.B Deriving Labor Demand

Total labor demand in sector h and county i is the sum of labor required for all actual entrant firms selling to all markets. Denoting $l_{ij}(\varphi)$ as the labor input for a firm with productivity φ in county i for goods sold in county j, this is:

$$L_i^h = M_i f_e + M_i \sum_{j=1}^{D+1} \int_{\varphi^*}^{\infty} l_{ij}(\varphi) d\varphi \tag{26}$$

After substitutions, we have:

$$L_i^h = M_i f_e + M_i \sum_{j=1}^{D+1} \int \varphi_{ij}^* \left(R_j \left(\frac{1}{P_j}\right)^{1-\sigma} p_{ij}^h(\varphi)^{-\sigma} \frac{\tau_{ij}}{\varphi} + f_{ij} \right) \left(\frac{\theta b_i^\theta}{\varphi^{\theta+1}} \right) d\varphi$$

Substituting in the equation for φ^* and simplifying, this gives total labor demand in sector h in county i as an implicit function of wages, relative wages, and demand in all counties:

$$L_i^h = M_i f_e + \lambda_2 \frac{M_i}{w_i} \sum_{j=1}^{D+1} \frac{b_i^\theta \chi_{ij} R_j}{\sum_{k=1}^{D+1} b_k^\theta M_k \left(\frac{w_k}{w_i}\right)^{\frac{\sigma(1-\theta)-1}{\sigma-1}} \chi_{kj}} \tag{27}$$

where λ_2 is a constant.[26]

[26] $\lambda_2 = (\sigma(\theta-1)+1)/\sigma\theta$

A.C Free Entry

Imposing the free entry condition endogenizes M_i, which allows the productivity cutoff and labor demand equations to be further simplified. Potential entrant firms enter until expected profits exactly equal the fixed cost of entry, f_e, paid in terms of local labor:

$$\sum_{j=1}^{D+1} \Pr\left(\varphi > \varphi_{ij}^{h*}\right) \mathbb{E}\left[\pi_{ij} | \varphi > \varphi_{ij}^{h*}\right] \quad = \quad w_i f_e. \tag{28}$$

Using the following result from the labor market clearing condition

$$M_i f_e + \left(\frac{\sigma(\theta-1)+1}{\theta+1-\sigma}\right) \sum_{j=1}^{D+1} M_i \frac{b_i^\theta f_{ij}}{\left(\varphi_{ij}^*\right)^\theta} \quad = \quad L_i^h \tag{29}$$

yields the relation between the mass of entrants and labor supply:

$$M_i f_e \left(\frac{\sigma\theta}{\sigma-1}\right) = L_i^h. \tag{30}$$

This parallels the result in Arkolakis *et al.* (2008) that the mass of firms that pay to receive productivity draws in each county-sector is proportional to labor input. Substituting this into labor demand in Equation (27) and simplifying gives Equations (8) and (9). The substituting those two equations into the productivity cutoffs from Equations (24) and (25) gives the productivity cutoffs given in Equations (10) and (11).

A.D Impact of Resource Productivity on the Expenditure-to-Wage Ratio

Here we show that a resource boom will increase the ratio of $\frac{R_i^h}{w_i}$ under all but unrealistic parameter assumptions. Dividing consumer expenditures from Equation (4) by the wage, we have:

$$\frac{R_i}{w_i} = \frac{\mu^h\left(w_i L_i + \eta\pi_i^r\right)}{w_i}. \tag{31}$$

The derivative with respect to resource productivity A_i^r is:

$$\frac{d\left(R_i/w_i\right)}{dA_i^r} \quad = \quad \eta\mu^h \frac{\pi_i^r}{A_i^r w_i}\left(\frac{\partial\pi_i^r}{\partial A_i^r}\frac{A_i^r}{\pi_i^r} - \left(1 - \frac{\beta}{1-\alpha-\beta}\frac{\partial L_i}{\partial w_i}\frac{w_i}{L_i}\right)\frac{\partial w_i}{\partial A_i^r}\frac{A_i^r}{w_i}\right). \tag{32}$$

Decreasing returns in the resource sector's Cobb-Douglas aggregate production function implies that profits are

$$\pi_i^r = \frac{\left(p^r A_i^r\right)^{1/(1-\alpha-\beta)}}{1-\alpha-\beta}\left(\left(\frac{\alpha}{P_i^u}\right)^{\alpha}\left(\frac{\beta}{w_i}\right)^{\beta}\right)^{1/(1-\alpha-\beta)}, \tag{33}$$

and thus

$$\frac{\partial \pi_i^r}{\partial A_i^r}\frac{A_i^r}{\pi_i^r} = \frac{1-\beta\frac{\partial w_i}{\partial A_i^r}\frac{A_i^r}{w_i}-\alpha\frac{\partial P_i^u}{\partial A_i^r}\frac{A_i^r}{P_i^u}}{1-\alpha-\beta}. \tag{34}$$

Substituting back into Equation 32 and simplifying yields

$$\frac{d\left(R_i/w_i\right)}{dA_i^r} = \eta\mu^h\frac{\pi_i^r}{A_i^r w_i}\frac{1}{1-\alpha-\beta}\left(1-\alpha\frac{\partial P_i^u}{\partial A_i^r}\frac{A_i^r}{P_i^u}-\left(1-\alpha-\frac{\beta}{\eta}\frac{\partial L_i}{\partial w_i}\frac{w_i}{L_i}\right)\frac{\partial w_i}{\partial A_i^r}\frac{A_i^r}{w_i}\right). \tag{35}$$

Consider the extreme case of inelastic county labor supply, $\frac{\partial L_i}{\partial w_i}\frac{w_i}{L_i} = 0$, and a unit elasticity of upstream input costs, $\frac{\partial P_i^u}{\partial A_i^r}\frac{A_i^r}{P_i^u} = 1$. (Unit elasticity would reflect large changes in P_i^u relative to what we expect and relative to our empirical estimates.) Even in this scenario, $\frac{d(R_i/w_i)}{dA_i^r} > 0$ if $\frac{\partial w_i}{\partial A_i^r}\frac{A_i^r}{w_i} < 1$, a condition that our empirical results suggest is easily satisfied. Allowing for positive labor supply elasticity and less responsive upstream prices would further strengthen the increase in local demand due to increased resource productivity. Thus, it will typically be the case that resource booms increase the ratio $\frac{R_i^h}{w_i}$.

A.E Predictions

Prediction 1

Labor demand in the resource sector $L_i^r\left(p^r A_i^r, w_i, P_i^u\right)$ is increasing in $p^r A^r$ and decreasing in w_i. Similarly, from Equation (27) we see that labor demand in the monopolistically competitive sectors is decreasing in wages, so can be written $L_i^h(w_i)$, with $(L_i^h)' < 0$. Labor market clearance can be rewritten:

$$L_i\left(w_i\right) = L_i^r\left(p^r A_i^r, w_i, P_i^u\right) + \sum_{h=1}^{H+1} L_i^h\left(w_i\right). \tag{36}$$

We now prove by contradiction that A_i^r must increase either wages or total labor supply. Assume that this is not true, i.e. that an increase in A_i^r increases L_i^r but does not affect w_i or total population L_i. Under this assumption, Equation (36) cannot hold, since the first and third terms are constant but the second term increased. Thus, it must be that an increase in A_i^r increases either w_i or L_i. As long as $0 < L_i'\left(w_i\right) < \infty$, both w_i and L_i will increase.

Prediction 3

This prediction holds as long as county i is not too large relative to the overall market. To see this, rewrite Equation (9) as:

$$L_i^h = \frac{R_i}{w_i} + \frac{DR_j}{w_i} - DL_j^h \left(\frac{b_j}{b_i}\right)^\theta \left(\frac{w_i}{w_j}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}} \tag{37}$$

A resource boom (an increase in A_i^r) increases w_i (per Prediction 1) and $\frac{R_i}{w_i}$ (per Appendix A.D). Thus, the effect on labor demand trades off the increase in demand from county i (the first term to the right of the equals sign) with the direct effects of a price increase in the D other counties (the second term) and a loss of competitiveness relative to suppliers from other counties (the third term). Now take the total derivative of Equation (37) with respect to A_i^r and solve for the value of D required for $\frac{dL_i^h}{dA_i^r} < 0$:

$$D > \frac{\frac{d\left(\frac{R_i}{w_i}\right)}{dA_i^r}}{\frac{dw_i}{dA_i^r}} \cdot \left[\frac{R_j}{w_i^2} + \frac{\sigma\theta}{(\sigma-1)}\frac{L_j}{w_i}\left(\frac{b_j}{b_i}\right)^\theta \left(\frac{w_i}{w_j}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}}\right]^{-1}. \tag{38}$$

As long as D is sufficiently large, $\frac{dL_i^h}{dA_i^r} < 0$.

Prediction 4

The upstream sector is analogous to the other monopolistically competitive sectors, except that specifying the resource sector factor demands allow more precise predictions. The resource sector factor demands imply that

$$\frac{R_i^u}{w_i} = \frac{\alpha}{\beta} L_i^r. \tag{39}$$

For clarity, we again focus on the special cases of local and tradable upstream goods. For local sectors, substituting Equation (39) into labor demand from Equation (8) gives

$$L_i^u = \frac{\alpha}{\beta} L_i^r.$$

Thus, if the upstream sector is locally-traded, upstream sector labor is linear in resource sector labor, with the intuitive result that the slope is steeper if the upstream factor share α is larger.

For the perfectly tradable case, we derive an analogue to Equation (38), the condition required for $\frac{dL_i^u}{dA_i^r} < 0$:

$$D > \frac{\frac{\alpha}{\beta}\frac{dL_i^r}{dA_i^r}}{\frac{dw_i}{dA_i^r}} \cdot \left[\frac{R_j^u}{w_i^2} + \frac{\sigma\theta}{(\sigma-1)}\frac{L_j^u}{w_i}\left(\frac{b_j}{b_i}\right)^\theta \left(\frac{w_i}{w_j}\right)^{\frac{\sigma(\theta-1)+1}{\sigma-1}}\right]^{-1}. \tag{40}$$

As in Prediction 3, the local upstream sector is more likely to contract due to competition from other counties where wages have not risen. However, the larger is α, the larger that D must be for this to be satisfied.

Predictions 5 and 6

In Appendix A.C, we discuss how to derive the productivity thresholds to produce in local and tradable sectors.

For Prediction 6, we note that the productivity threshold to sell tradable goods in the *home county* (county i) is

$$(\varphi_{ii}^{*})^{\theta} = \lambda_1 f_{ij} b_i^{\theta} \left(\frac{\sigma - 1}{f_e \theta} \left(1 + D \frac{R_k^h}{R_i^h} \right) \right) \tag{41}$$

Thus, while the model predicts that resource booms decrease overall employment in tradable sectors due to decreased exports, tradable sector firms may continue to produce exclusively to sell in their home counties. Although tradable sector firms in county i are hurt by increased wages relative to producers in other counties, for the lower-productivity tradable goods manufacturers who only sell to the local market, this is more than offset by the increase in home market demand and the decrease in competing potential entrants from county i, M_i^h. This effect is analogous to the reverse of the Melitz (2003) trade selection dynamic: decreasing local competitiveness lowers employment at productive exporters most, allowing less productive firms to continue operating.

B Additional Empirical Results

B.A Pre-Trends

As Figures 1 and 2 in Section II showed, oil and gas prices and employment were relatively steady in the years leading up to the 1973 oil shock. Appendix Table A1 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 A1 are the difference in a logged outcome between 1969 and 1972. Column 1 regresses this on endowment r_i^{early}, with no other controls. Column 2 includes controls for baseline levels $\ln \mathbf{Y}_{0i}$ 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 $\ln \mathbf{Y}_{0i}$ in column 2 substantially reduces the size and significance of the coefficients, with no remaining significant estimates.

Table A1: **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.

B.B Additional Tables and Figures

Table A2: **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 A3: **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 A4: **Effects on County-Level Aggregates: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endowment 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$_{it}$	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$_{it}$	-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$_{it}$	-0.0170***	-0.0124***	-0.0161***		
$\times$1(year >2000)	(0.0035)	(0.0019)	(0.0035)		
Employment					
Δln(National intensity$_t$)$\times$endowment$_{it}$	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$_{it}$	0.0019	-0.0024	-0.0014		
$\times$1(ΔNational intensity$_t$<0)	(0.0047)	(0.0045)	(0.0037)		
Δln(National intensity$_t$)$\times$endowment$_{it}$	-0.0273***	-0.0222***	-0.0258***		
$\times$1(year >2000)	(0.0063)	(0.0038)	(0.0076)		
Wage Earnings/Worker					
Δln(National intensity$_t$)$\times$endowment$_{it}$	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$_{it}$	0.0141**	0.0036	0.0077		
$\times$1(ΔNational intensity$_t$<0)	(0.0067)	(0.0051)	(0.0053)		
Δln(National intensity$_t$)$\times$endowment$_{it}$	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 A5: **Current Population Survey Regressions: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endowment 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$_{st}$	(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$_{st}\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$_{st}$	(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$_{st}\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 A6: **Effects on Manufacturing Aggregates: Alternative Specifications**

	(1)	(2)	(3)	(4)	(5)
	Use early endowment a_i^{early}	Use total endowment a_i^{total}	Measure intensity by wage emp. only	Measure intensity by oil and gas price	Fixed effects
	Manufacturing Employment				
Δln(National intensity$_t$)$\times$endowment$_{it}$	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$_{it}$	-0.0033	-0.0015	-0.0080		
$\times$1(ΔNational intensity$_t$ <0)	(0.0237)	(0.0147)	(0.0202)		
Δln(National intensity$_t$)$\times$endowment$_{it}$	-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$endowment$_{it}$	-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$_{it}$	0.0445**	0.0229**	0.0313**		
$\times$1(ΔNational intensity$_t$ <0)	(0.0196)	(0.0108)	(0.0139)		
Δln(National intensity$_t$)$\times$endowment$_{it}$	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 A7: **Geographic Spillover Effects on Manufacturing Outcomes**

	(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$_{it}$	(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$_{it}$ $\times$endowment$_{st}$				(0.00718)
Mfg. Earnings/Mfg. Worker				
Δln(National oil&gas employment$_t$)	0.0190***	0.0133**		0.0210**
$\times$endowment$_{it}$	(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$_{it}$ $\times$endowment$_{st}$				(0.005)
N	105,568	105,568	29,196	105,568
State-by-year fixed effects	No	Yes	No	No

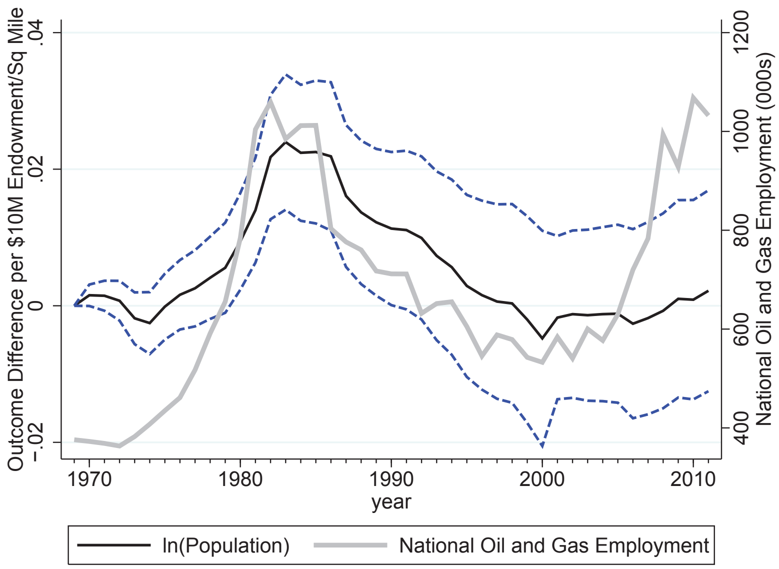
Notes: This table presents alternative estimates of Equation (15), plus additional interaction terms to measure spillovers. It parallels Table 5 but focuses on manufacturing outcomes. All regressions include controls for year interacted with natural log of the outcome variable in two baseline years. *, **, ***: Statistically different from zero with 90, 95, and 99 percent certainty, respectively. Robust standard errors, clustered by county.

Table A8: **Effects of Resource Booms on TFP-R and Price for Plants with Physical Output Data**

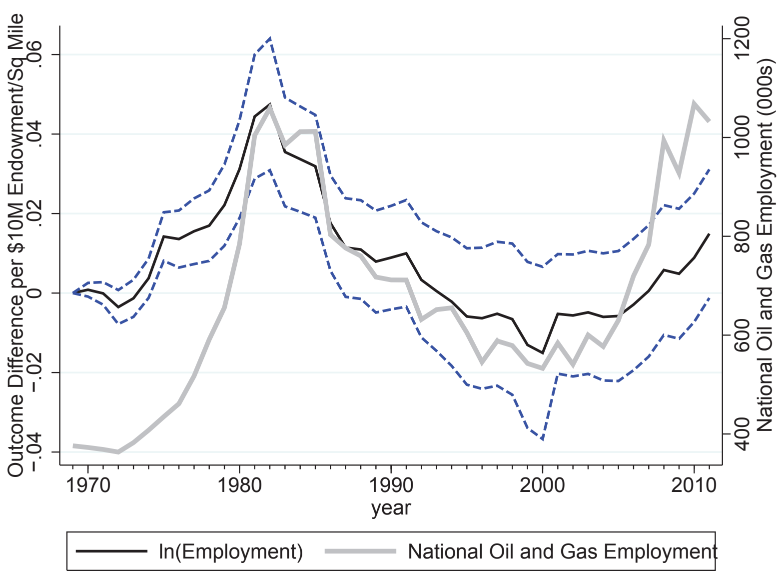
	(1)	(2)	(3)	(4)	(5)
	All	Upstream / downstream	Non-linked	Non-linked and local	Non-linked and tradable
			TFP-R		
Δln(National oil&gas employment$_t$)	0.0042	0.0004	0.00465	0.00753	0.00003
$\times$endowment$_{it}$	(0.0036)	(0.0048)	(0.00376)	(0.00487)	(0.0108)
N	108,000	27,000	81,000	55,000	26,000
			Price		
Δln(National oil&gas employment$_t$)	-0.0043	-0.0097	-0.0014	-0.0026	0.0034
$\times$endowment$_{it}$	(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), with the sample limited to plants that report physical output. Price regressions use data at the product-by-plant-by-year level, while TFP-R regressions use data at the plant-by-year level. All specifications use differenced outcomes; the time between each Census is five 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: **County Aggregates Over Time in Resource Abundant Counties**



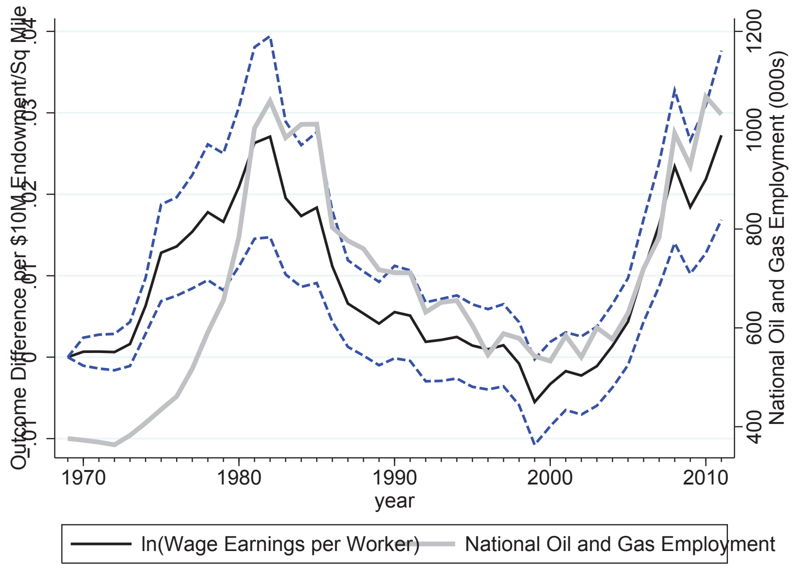
(a) **Population**



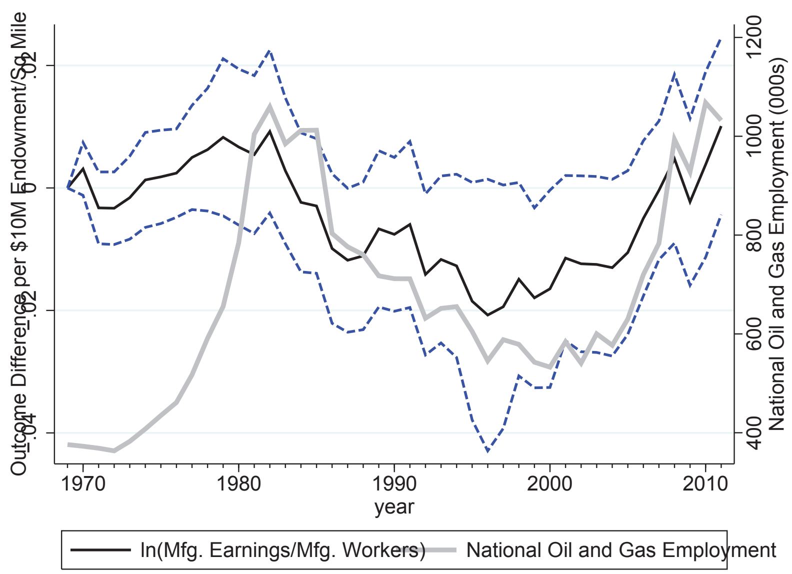
(b) **Employment**

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.