Fracking Growth

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Abstract

This paper estimates the effect of the shale oil and gas boom in the United States on local economic outcomes. The main source of exogenous variation to be explored is the location of previously unexplored shale deposits. These have become technologically recoverable through the use of hydraulic fracturing and horizontal drilling. I use this to estimate the localised effects from resource extraction. Every oil- and gas sector job creates about 2.17 other jobs. Personal incomes increase by 8% in counties with at least one unconventional oil or gas well. The resource boom translates into an overall increase in employment by between 500,000 - 600,000 jobs. A key observation is that, despite rising labour costs, there is no Dutch disease contraction in the tradable goods sector, while the non-tradable goods sector contracts. I reconcile this finding by providing evidence that the resource boom may give rise to local comparative advantage, through locally lower energy cost. This allows a clean separation of the energy price effect distinct from the local resource extraction effects.

Keywords: resource boom, fracking, shale, spillovers, natural gas, energy prices
JEL Codes: Q33, O13, N52, R11, L71

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1 Introduction

The role of energy prices and its relationship with economic aggregates such as employment, wages, and output has been a key concern for academic economist since the oil price shocks in the 1970s (Berndt and Wood (1975)). A second literature that developed around the same time was studying the impact of resource booms on economic outcomes, originally at the aggregate level (Bruno and Sachs (1982), Corden and Neary (1982a)) and then increasingly through micro-econometric studies (see Michaels (2011), Black et al. (2005)). The key empirical observation from this literature was that resources can be, both a blessing and a curse. This paper aims to link these two strands of literature. I exploit the recent energy boom in the US as a window through which I can study both, the local effects of lower energy prices and the local effects of the extraction activity itself. I show that it may be the combination of these two forces that can help explain why a resource boom may be a disease for some and a blessing for other countries.

The identification will rely on two sources of arguably exogenous variation. First, I exploit spatial variation in resource extraction of shale deposits that became recoverable due to technological advances in drilling technology. The second source of exogenous variation is driven by the implied changes in the energy production geography of the US; moving natural gas production from the South to the Mid West and the North East of the country does not have the existing pipeline capacity to take the produce to market where the willingness to pay is highest; this generates distinctly lower gas prices.

In the last step, I combine the findings from these empirical approaches and highlight that they may help us understand why there is no resource curse in sectors that may be particularly vulnerable to it.

It is important to highlight the context in which this recent energy boom is happening. Since the early 2000s, US domestic natural gas and oil production was in decline and the imports of crude and natural gas became even more important as they had already been. Employment in the natural gas and oil extraction sector was at its lowest since 1972.

In 2012, the picture is vastly different. The transition that was achieved in the last 7 years falls short from being a miracle. The US, in 2012, is least dependent on foreign energy imports than it ever was since 1973. This is attributed to improvements in energy efficiency and the development of biofuels. However, the most important contributing factor is the development of unconventional resource extraction technology known as hydraulic fracturing or "fracking" that has lead to a mining boom across the US. The hydraulic fracturing technology, together with horizontal drilling made vast shale deposits accessible, that could previously not be economically exploited. As a consequence, employment in the mining sector has reached levels not seen since the early 1990s. But do these employment gains have significant spill-over effects into different sectors at the locations where resource extraction is actually taking place? It is - by no means - clear, whether one should expect significant employment gains in the non-mining sectors. The development literature has highlighted that it strongly depends, among others, on the type of resources (Boschini (2007), Mehlum et al. (2006)), the quality of the institutions (Vicente (2010),Sala-i Martin and Subramanian (2003),Robinson et al. (2006),Monteiro (2009), Caselli and Michaels (2012), Ross (2006)), the potential for input demand linkages (see Aragón and Rud (2013)) and the extent to which revenues are invested locally (Caselli and Michaels (2012)).

The first contribution of this paper is to quantify the extent of the local effects due to the recent resource boom. I show that many economic aggregates, such as local employment, payroll, labour force participation and unemployment respond quite significantly. In the next step I highlight that this is driving up local wages across the sectors, giving rise the the possibility of there being a resource curse. In the third step I find no evidence that the manufacturing sector suffers from Dutch disease style contraction, while the non-tradable goods sector does.

In the last section I explore whether locally cheaper energy may explain this finding. Energy is a key factor of production for many production processes - both directly and indirectly, through intermediate goods consumption. The literature on electricity prices and provision has highlighted the relevance and importance of cheap and in particular, reliable energy (see e.g. Rud (2012), Abeberese (2012) and Fisher-Vanden et al. (2012)) or Dinkelman (2011), who studies the labour market effects of electrification in South Africa. In the case of the US, Kahn and Mansur (2013) show that electricity prices affect firm location decisions, while Severnini (2013)'s analysis suggests that low energy prices in the historical context may have created agglomeration clusters. I proceed to show that indeed - energy intensive tradable goods sectors - do expand, giving initial credence to this mechanism.

Following this I show that natural gas and electricity become significantly cheaper in counties with shale deposits from the mid 2000s onwards, suggesting that higher labour costs may be offset with lower energy bills. I show that the effect is particularly pronounced in places that face significant pipeline capacity constraints. Binding outflow capacity forces the additionally extracted natural gas to be consumed locally, putting downward pressure on local prices.

In the last step I provide a small back of the envelope calculation that indicates that the drop in energy prices offsets the increase in labour costs, which may explain why the local non-tradable goods sector contracts, while the tradable goods sector doesn't. This highlights that a key to understanding whether Dutch disease style contractions do occur, depends on the nature of the resource and whether there are significant trade costs associated with the export of the latter. This ties in well with the arguments in Boschini (2007), who argue that the type of resource matters for whether a country actually suffers from a resource curse. They mainly argue that this is driven by the degree to which the resource can be appropriated. The mechanism I explore here highlights that it depends on the extent of trade costs and frictions, as these create locally lower energy prices.

The paper is organised as follows. I begin with a very brief conceptual framework to guide the empirical analysis. In the third section I discuss the main data sources used. The fourth section then proceeds to establish the main results, while the fifth section focuses on the proposed mechanism of lower natural gas prices. The last section concludes.

2 Conceptual Framework

Before discussing the data used in this paper and the empirical specifications, I want to present a simple conceptual framework to fix some ideas and to motivate the empirical analysis.

I build on the simple partial-equilibrium framework in Corden and Neary (1982b). I assume that there are three sectors: the resource or energy production sector, a tradable goods sector and a non-tradable goods sector. These are indexed with E, T, NT and have production functions $E = Ah(N_E)$, $Y_{NT} = Bg(N_{NT})$ and $Y_T = f(N_T, E)$. This simple formulation implicitly assumes that the tradable goods sector is relatively more energy intensive than the non-tradable goods sector. All three sectors compete for an immobile factor labour. The price of tradable goods serves as the numeraire. In the first exercise, I assume that energy prices and the price of tradables is fixed and only wages and the price of non-tradables may respond to a productivity shock in the resource extraction sector. This mimics the case of a small open economy and gives rise to the classical results as in Corden and Neary (1982b). In the second exercise, I model a wedge in local energy prices that is a function of the bindingness of pipeline capacity constraints (e.g. a lack of takeaway capacity). This generates a local market for energy and thus implies that there is a feedback from lower energy prices. Households have simple Cobb-Douglas utility over consumption of tradables and non-tradables.

$$u(Y_T, Y_{NT}) = \alpha_T log(Y_T) + \alpha_{NT} log(Y_{NT})$$

Income in this economy is simply $y = w + \theta\pi^E$, where π^E are the profits that accrue in the energy production sector and θ is a measure indicating the extent to which these profits go to local owners of the mineral resources. The demand functions for non-tradables is simply $Y_{NT}^d = \alpha_{NT} \frac{y}{p_{NT}}$. The market clearing condition in the labour market requires:

$$N_{NT}^d + N_T^d + N_E^d = 1$$

.

where the labour- and energy demand functions solve the following first order conditions.

$$p_E A h'(N_E^d) = w$$

$$p_{NT} B g'(N_{NT}^d) = w$$

Two for the tradable sector:

$$p_T f_1(N_T^d, E^d) = w$$

$$p_T f_2(N_T^d, E^d) = p_E$$

For fixed energy prices, an increase in the productivity in the resource extraction sector, has three effects. Firstly, the increase in productivity is going to lead to an overall increase in aggregate economic activity and GDP per capita. The second and third effects are concerned about the effect on wages and the implied impact on the allocation of labour across sectors. First, there is the *resource movement* effect. As labour demand by the resource sector increases, overall wages go up. This implies that the marginal cost of production for non-tradables and tradables increase. Hence, the employment shares of these sectors contract. There is a direct factor price induced structural transformation. Graphically this is indicated in Figure 1.

The second effect is the so-called *spending effect*. Higher equilibrium wages drive up local incomes y, which is inducing an outward shift in the demand for tradables- and non-tradables for a given level of prices. This increased demand leads to an increase in production in the non-tradables sector, thus, partly offsetting the implied contraction due to the resource movement effect. Wages increase even further and thus, lead to a further contraction of the tradable good sector. The sum of the spending and resource movement effect suggests an unambiguous increase in wages and thus, a contraction in the tradable goods sector, but not necessarily in the non-tradable goods sector due to the spending effect. The degree to which the spending effect may offset the resource movement effect depends on the elasticity of demand for non-tradables with respect to income.

Consider now the case of variable energy prices. In particular, I assume that en-

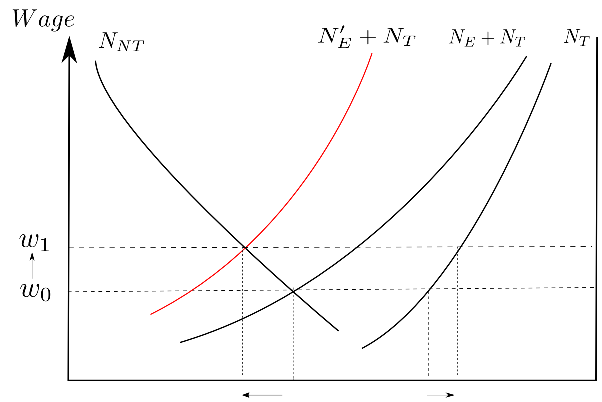

Figure 1: Resource Movement Effect

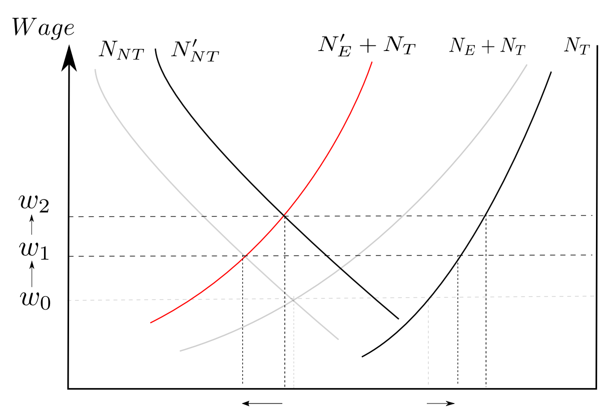

Figure 2: Resource Movement and Spending Effect

ergy prices $\bar{p}_E$ are exogenously given, but local energy prices p_E may be lower than $\bar{p}_E$. Local energy price differentials reflect the extent to which energy is tradable. For energy, such as natural gas or electricity there are mechanic trade costs, as the transport of the commodity uses up part of the commodity itself.[1] I assume that local energy prices are given as:

$$p_E = \tau(E)\bar{p}_E$$

with $\tau(E) < 1$. The degree of the price wedge depends on a set of characteristics, such as pipeline transmission constraints and the physically implied transport costs.

Given this reduced form representation of the local energy market, there is now a distinct margin through which an increase in productivity in energy production affects the tradable goods sector. With endogenous local energy prices, the increase in the productivity of the energy production sector is correlated with lower local energy prices, which may provide insurance against the increase in labour costs. A reduction in the energy prices does not have a direct effect on the non-tradable goods sector, but it does have an impact on the energy and the tradable goods sector. First, it is going to moderate the initial movement of labour into the energy sector as the marginal returns are now decreasing in the level of output and second, the lower energy price is going to increase the demand for labour by the tradable sector depending on the degree of complementarity. This further increases wages, while hurting the non-tradable goods sector, as the latter is not able to benefit from lower energy prices; the key observation is that an energy price effect may now generate ambiguous effects for all three sectors.

The degree of ambiguity depends on the relative strength of the resource-movement effect compared to the spending effect and the energy price effect. The key variables of interest here are the labour intensity relative to the labour intensity for the interplay of the energy price effect and the spending effect and the income elasticity of demand for non-tradables, which measures the degree to which the spending effect affects the non-tradable goods sector.

The ambiguous predictions for the relative employment shares make this very much an empirical question. I will proceed in three steps that follow naturally from this analysis.

[1] For natural gas, 11% of the extracted natural gas is used in the transmission process by compressor stations along the natural gas pipeline grid. For electricity, aggregate transmission losses account for 7% of gross electricity generation.

3 Data

Shale Plays, Oil- and Gas Well Location Data

The key empirical design will be simple intention-to-treat exercises exploiting geographic variation in the availability of unconventional oil and gas resources. This data was obtained from the Energy Information Administration and the US Geological Survey and is presented as the grey areas in Figure 3.

The second main source of data is a set of geocoded locations of actual unconventional oil or gas wells where unconventional techniques involving horizontal drilling and hydraulic fracturing are applied. This data was derived from various state-level sources and the data disclosure website Frac Focus. The data is discussed in further detail in Appendix A.1. Based on these data I construct a cross-sectional dummy indicating the presence of an unconventional well in a county by 2012. This dummy variable provides cleaner treatment assignment and does not merely reflect the intention to treat, since not all shale resources are currently being actively pursued. The resulting map of well locations is presented in Figure 3. The reason for using the cross-section of well locations is one of data constraints; not for all wells in the sample do I have data on the actual timing of when a well was constructed. The unconventional shale gas and oil boom commenced in 2005, however, the timing varies across shale plays. I have the exact dates of when drilling operations commenced for a set of states, appendix A.1 shows that new well construction is significantly occurring from the mid 2000s onwards, which coincides well with the anecdotal accounts.

Sectoral Employment

They key outcome variables studied in this paper is annual sectoral employment, as obtained from the the Longitudinal Employer-Household Dynamics dataset maintained by the US Census Bureau (see Davis et al. (2006) for a discussion). This dataset produces Quarterly Workforce Indicators (QWI) that provide details up to 4-digit NAICS industry codes. The data covers 96% of all employment in the US and is developed to provide researchers with a very fine spatial- and temporal resolution that can be further disaggregated by firm- characteristics, such as firm size and age or by individual employee characteristics such as age, educational attainment and race. The second key variable of interest is the earnings per worker data, which provides the average monthly earnings for a worker in a sector and county in a given quarter, provided that this worker has been with the firm for the duration of the whole quarter. This variable will be used as a proxy for wages. Since estimating high dimensional fixed effects can be computationally very heavy, I reduce the

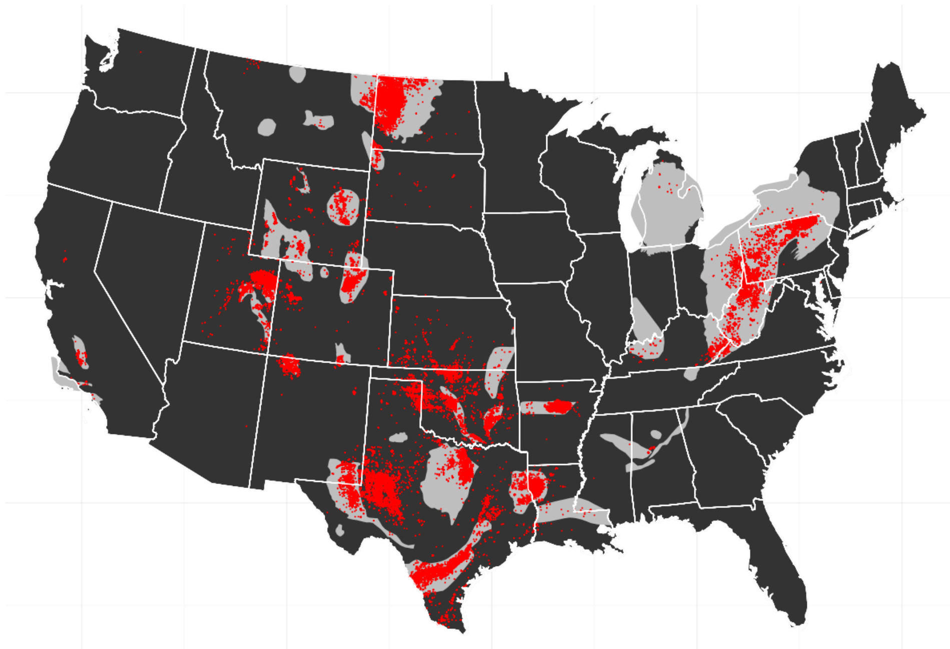

Figure 3: Location of Unconventional Wells in 2012 (red dots) and Shale Plays (grey)

time-dimension by a factor of four by constructing sector specific annual average employment figures. This induces a loss of signal, however, it makes it feasible to run the regressions on a simple desktop computer.

Due to non-disclosure constraints there are some issues as the data is infused with noise. These are discussed in detail in A.4 and all results are robust when accounting for these non-disclosure constraints. A second caveat is that the data are not available for all states from 1998 onwards. As a robustness check, I construct a balanced panel filling the missing observations with the county-business patterns database that has been extensively used in the past (see e.g. Kahn and Mansur (2013), Mian and Sufi (2011), or Rosenthal and Strange (2001)).

Energy Price Data

I construct county-level annual electricity and natural gas prices using two sources. For the electricity prices I use the Annual Electric Power Industry Report by the Energy Information Administration, which provides for each of the roughly 3,000 electric utility companies the revenues and the quantity of electricity sold to commercial, residential and industrial customers. This is used to construct an average price per supplier. The majority of the utility companies serve individual municipalities or relatively small spatial areas. Using data on the location of electricity delivery equipment, I construct the service area of each municipality and the compute the average price charged.

I proceed similarly for the natural gas prices using data collected by the Energy Information Administration under Form EIA-176. This provides revenues and quantities of gas sold in a state and year for a local distribution company. The service areas were constructed based on confidential data from the EIA; it is only available for the year 2008, implying that changes in the service areas are not reflected in my data. The average price of gas in a county is proxied by the simple averages of the prices charged by local distribution companies that service customers in a county. More details on the construction of these data are detailed in appendix A.3.

Pipeline Capacity Constraints

The Energy Information Administration provides data on state-to-state physical pipeline capacity at an annual level as well as annual state-to-state pipeline flows. Figure A4 plots the resulting net physical capacity flows. For each state the annual data provides information how much natural gas is flowing to all its neighbouring states. Based on this, I can compute a state level measure of the bindingness of the existing physical outflow- and inflow capacity. Let $\mathcal{P}$ be the set of states that are neighbouring state s, and C_{ps} be the direct physical pipeline capacity connecting state $p \in \mathcal{P}$ with state s, while F_{ps} is the actually observed flow.

I simply compute

$$O_s = \frac{\sum_{p \in \mathcal{P}} F_{ps}}{\sum_{p \in \mathcal{P}} C_{ps}}$$

as a measure of the bindingness of outflow capacity. Similarly, I compute I_s as a measure of the bindingness of inflow capacity. It is well-established that a key ingredient driving local natural gas prices is the bindingness of pipeline capacity constraints; for electricity markets, this is very similar and has recently been analysed by Ryan (2013) in the Indian context.[2]

I construct the measure using the average capacity for the period 2000-2005 and the average flows for that period. Averaging helps remove year-on-year variation e.g. induced by weather phenomena or other shocks, such as hurricanes, which may adversely affect production in the outer continental shelf in the Gulf of Mexico.

The key intuition behind the various measures is that relatively binding outflow capacity leads to locally lower natural gas prices, as additional local production needs to be locally consumed. This variation will be exploited to identify the effect

[2]On the natural gas spot market, the role of transmission constraints were very visible in recent months due to the strong winter driving up energy demand. Natural gas prices on the Algonquin Citygate, near Boston, peaked at \$ 95.00, averaging at \$ 11 per cubic foot; prices in Louisiana peaked only at \$ 9.00 and averaged at \$ 4.55 per cubic foot.

of the shale boom on local energy prices.

I now proceed to present the main estimating equation along with the key results in turn.

4 Empirical Strategy and Results

This section presents the main estimation strategy along with the key results. I use two main specifications throughout the paper. The first one is to illustrate the overall effect of the recent shale-gas and oil boom. For this, I consider the left-hand side variables in levels as the conceptual framework indicates an overall economic expansion due to the technological progress in the resource extraction sector. For these exercises I use a simple instrumental variables exercise using the presence of shale-resources (the intention to treat) as an instrument for the cross section of unconventional wells that were present by the end of 2012.

$$y_{cist} = \alpha_{ci} + b_{st} + \sum_i \gamma_i \times Shale_c + X'\beta + \nu_{cist} \tag{1}$$

where α_{ci} is a set of county industry fixed effects, b_{st} is a set of state-time fixed effects, X is a set of other controls[3] and $Shale_c$ measures the share of the land area in a county that is covered by unconventional shale resources. Standard errors will be clustered at the state-level unless otherwise stated.

The main instrumental variables specification is

$$y_{cist} = \alpha_{ci} + b_{st} + \sum_t \eta_t \times Year_t \times Anywell_c + X'\beta + \epsilon_{cist} \tag{2}$$

where $Anywell_c$ is a dummy variable that is equal to 1 in case there is an unconventional well located in a county by 2012. These are instrumented with the set of interactions $Year_t \times Shale_c$. These specifications will allow the visual presentation of most regression results, however, I also report less demanding specifications where I split the data into a pre- and post period with 2008 being the cutoff year.

The second set of exercises aims to highlight the impact of the expansion of the mining sector and how this affects the labour allocation across sectors. For this exercise, I instrument the share of mining sector employment with a post 2008 variable interacted with the share of a county's surface that has shale resources. That is the specification becomes:

[3] I construct a set of heating- and cooling degree days controls using the daily minimum- and maximum temperature data based on the PRISM dataset, which comes at a spatial resolution of roughly 4 x 4 kilometres. See appendix A.6 for more details.

$$y_{cist} = \alpha_{ci} + b_{st} + \eta \widehat{MiningSectorShare} + X'\beta + \epsilon_{cist} \qquad (3)$$

where the first stage is

$$MiningSectorShare_{cst} = \alpha_c + b_{st} + \gamma \times Post2008 \times Shale_c + X'\beta + \nu_{cist} \qquad (4)$$

As the prediction of the conceptual framework for the labour market was about the relative sector sizes, this design mimics the conceptual framework closely.

The empirical analysis will proceed in three steps. First, I show that there is indeed a significant expansion of oil- and gas employment in areas with shale resources, and an overall economic expansion in other economic aggregates such as local area income, and employment. Most of the effect is driven by increased labour force participation and less unemployment, while I do not observe significant gains in population. I will use the boom in the mining sector to measure the extent of spill-overs. This is a margin that is not incorporated by the simple model, which, however, moderates any Dutch disease style contraction in the non- mining sectors. I then show that the mining sector expansion is correlated with significantly higher monthly earnings across most sectors; this is the only unambiguous prediction from the conceptual framework, however, there is some heterogeneity due to the different skill requirements across sectors. In the third step, I present results on the employment shares, which highlights that the simple logic of the resource-movement and spending effect do not provide the expected results. I then try to reconcile these findings by providing evidence of distinctly lower energy prices facing the tradable goods sector. A small back-of-the envelope calculation suggests that indeed - lower energy costs may explain why there is no contraction in the tradable goods sector relative to the non-tradable goods sectors.

Step 1: Shale Resources and Economic Expansion

I first present evidence on the impact of shale resources on overall economic expansion. I document this in three individual steps. First, I show that there is a dramatic expansion in oil- and gas sector that sets on from about 2005 onwards.

In the next step, I study overall local labour market outcomes. I document dramatic increases in overall employment, labour force participation and a significant reduction in unemployment rate. I show that this expansion extends beyond the mining sector, indicating that there are significant spill-overs. I use this to estimate a job-creation elasticity, indicating the number of jobs that are created for each oil- and gas sector job.

The third part documents the impact on local area income and payroll; this

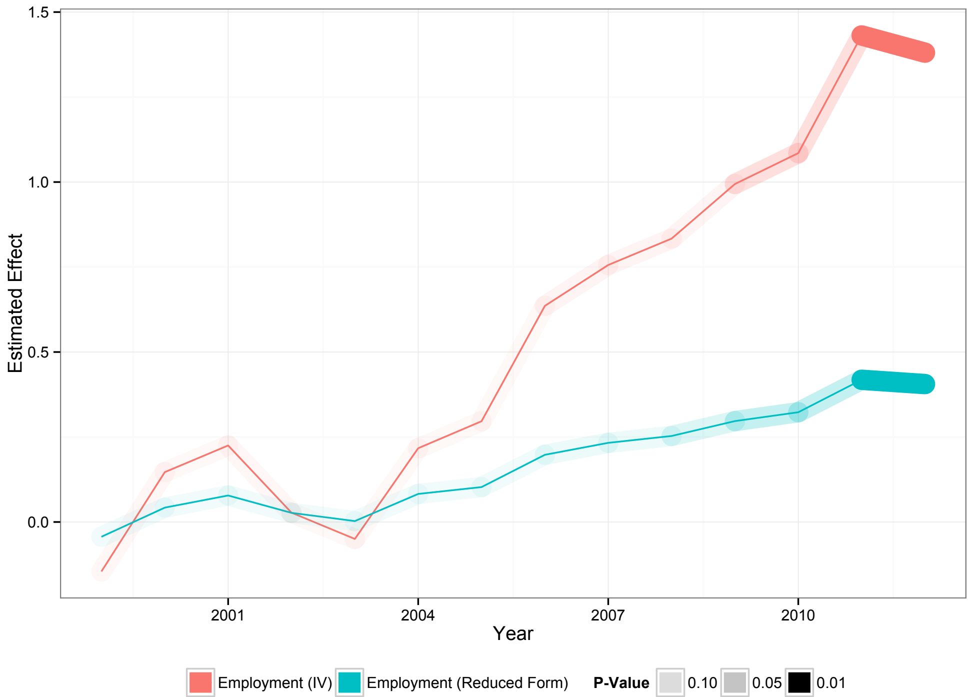

Figure 4: Expansion of Oil- and Gas Extraction Sector Employment

highlights that there is an overall increase in economic activity.

The results from estimating models 1 and 2 are best presented graphically by plotting the estimated coefficients $\hat{\eta}_t$ and $\hat{\gamma}_t$, all accompanying tables can be found in the online appendix.

Oil and Gas Sector Expansion Figure 4 presents the results from estimating models 1 and 2, where I use the log of employment in the mining sector as the dependent variable. The pattern is very similar when using the share of oil- and gas sector employment as the dependent variable.

The coefficient plots are slightly unconventional. The line presents the estimated coefficients in the different years for the IV specification in red and the intention-to-tread reduced form in blue. The shade around the line becomes less opaque as the estimated coefficients approach p-values near conventional significance levels. This highlights that the estimated effects are insignificant before 2006, which coincides well with the general accounts that fracking has only become a widespread technology used from the mid 2000s onwards.

The estimated effects indicate how dramatic the expansion has been. The IV coefficient suggests that places with unconventional oil or gas extraction activity have experienced a growth in mining sector employment by 1.38 log points in 2012 relative to control counties.[4] The intention-to-treat estimates are, as expected, significantly lower suggesting an increase by 0.4 log points or 49% in 2012. Table 1 presents the results from pooling into a pre- and post 2008 period. This year was chosen as the dynamics in most of these controls appear to be picking up from this point onwards. The results do not change significantly, if I use a different break year. Clearly, there are some concerns about the onset of the financial crisis with Lehman brothers collapse in late 2008. This will be addressed in detail in various robustness checks. Column (1) presents the results for the mining sector, giving very similar results, suggesting an increase in mining sector employment by around 1 log points.

Overall Local Economic Activity In the simple conceptual framework, the only source for change in overall levels of local income is due to the technological progress in the oil- and gas sector. Hence, the increase in employment in the oil- and gas sector is not sufficient to highlight that there is indeed a local economic expansion that can be ascribed to the boom in the oil and gas sector.

I now document that many economic aggregates respond to the boom in the mining sector, indicating that there is indeed an increase in overall economic activity. The key variables I consider are measures of labour market activity, such as unemployment, overall employment, non-mining sector employment, local area income and local area overall payroll.[5]

Figure 5 presents the core results for a set of economic indicators. The top panel presents the IV results, while the bottom panel draws the estimated coefficients for the intention to treat exercises. The opacity of the line is proportional to the p-value of the estimated regression coefficient. The pattern that emerges is consistent.

Columns (2)-(7) of table 1 presents a regression version of the graphs. The results indicate a significant expansion in non-mining sector expansion (see column 3). This expansion is coming from increased labour force participation and significantly lower unemployment, as is indicated in columns (4) and (5). The coefficient suggests that overall unemployment on counties with unconventional oil and gas is about 1.1 percentage points lower than for control counties.

Columns (6) and (7) explore the effects on local incomes. Personal incomes

[4]Note that the big increases can not simply be converted to proportional increases due to Jensen's inequality, see Kennedy (1981). Thats why I leave them as log-points. For small values, the linear approximation is reported.

[5]The local unemployment data is drawn from the Bureau of Labor Statistics Local Area Unemployment Rate database, while the local area income data comes from the Bureau of Economic Analysis Regional Economic Accounts. The remaining data is from the Quarterly Workforce Indicators described in the data section.

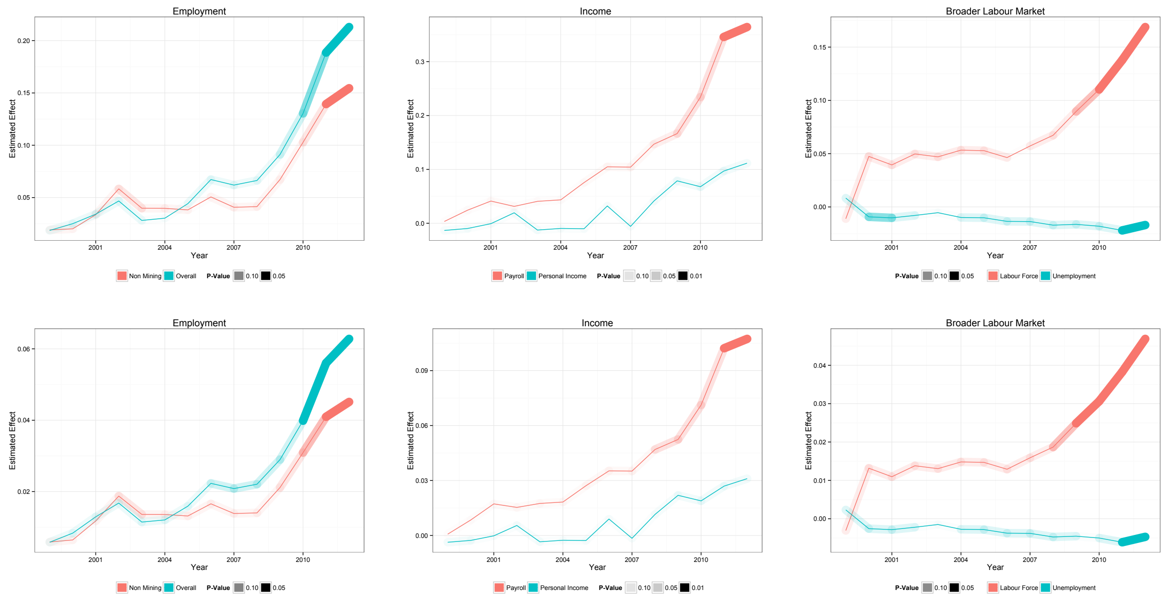

Figure 5: Overall Effects on Employment, Non-Mining Employment and Local Income Variables

increase by around 8%, while the payroll increases by roughly 20%. This already indicates that wage levels must be rising, as the overall employment increase in column (2) is just 10%, suggesting that wages must have gone up at least to some extent to bridge the difference.[6]

I now turn to exploring the extent to which the expansion in the oil and gas sector creates spill-over job growth and the extent thereof. This is a particular mechanism not incorporated in the simple conceptual framework, which may moderate any Dutch disease style contraction for local non-tradable goods producers.

Spill-Overs and Local Job Creation The expansion in the mining sector can be used as an instrument to estimate local multipliers for job creation, as e.g. explored in Moretti (2010). This is important in this context as positive spill-overs indicate that local non-tradable goods sectors, who benefit from such spill-overs due to demand linkages, may not actually contract in response of an expansion of the oil and gas sector, as they are benefiting directly through increased demand on top of the spending effect. In order to evaluate this, I use as instrument for oil and gas sector employment an interaction term $Post2008 \times Shale_c$. This gives rise to the estimates in column (2) of table 2.

[6] An alternative explanation is increased working hours driving up overall payroll; this is a mechanism that is, unfortunately, unobservable.

In the third column I use the estimated elasticity from column (2) and multiply this by the means of the respective employment variables.[7]

I study four sectors separately. The first is the overall-non mining sector employment. This suggests that for every oil and gas sector job, on average, 2.17 non-mining sector jobs are created. The effect is mainly driven by growth in construction- and transportation sectors, which are strongly linked with the oil and gas industry. The other main employment categories do not experience statistically significant spill-overs. Given that overall employment in the oil and gas sector has more than doubled between 2004 and 2013, increasing by 264,900 from 316,700 to 581,500 this translates into an increase in overall employment by around 574,833 due to the shale oil and gas boom. This represents a significant share of roughly 0.4% of all employment in the US in 2012.

Step 2: Response of Wages and Earnings

The preceding results already indicate that there must be an increase of local wages in response to the resource boom, since the overall payroll increases more than the overall employment as indicated in 5. I now document the effect on real wages, highlighting that the estimated effect is a real wage increase, rather than a nominal one, as predicted by the simple framework. [8]

I estimate specification 3, predicting the share of mining sector employment with the interaction term $Post2008 \times Shale_c$ as before.

The results are presented in table 3. Column (1) suggests that an increase in the mining sector share by one percentage point increases monthly earnings in that sector by 6 percentage points. Columns (2) - (6) provide the respective effects for the different sectors. Column (3) and (4) present the results for the construction and transportation sector wages. These are directly linked to the mining sector through mining sector demand.[9] The local manufacturing and service sector wages respond in similar fashion: a 1 percentage point increase in the mining employment share

[7] I only include observations up to the 95% percentile of the total non-mining sector employment. This becomes necessary as the employment and population data is highly skewed, distorting the means when including the upper quantiles. In the regressions, the skewness is taken care of by using logarithmic transformation, making conditional mean regressions appropriate.

[8] I construct local price-indices by combining a series of Consumer Price Indices for metropolitan statistical areas, Census regions and Census region by city size drawn from the Bureau of Labour Statistics. I assign the CPI level to a county provided it falls in one of the metropolitan statistical areas that have its own dedicated CPI series. For the remaining ones, I compute the weighted average of the CPI using the Census region and city size CPI series using as weights the population of a county that falls in each town-size class for which a separate CPI value for that respective region is available.

[9] The New York Department of Energy Conservation estimates that the construction of each well requires between 895 to 1350 truck loads, see `http://www.dec.ny.gov/energy/58440.html`, accessed on 15.08.2013.

increases their respective wages by about 1.8 and 1.9 percentage points respectively.

Since the mining sector share increased by around 3 percentage points on average, suggests that real wage costs for manufacturing firms increased by roughly 5 percentage points. These results suggest that there is some heterogeneity in the extent of the wage increase. The effect is weaker for sectors with less of a factor demand linkage. However, overall, wages do increase significantly, which mirrors the findings of Allcott and Keniston (2013), who study the effects of oil and gas booms on the manufacturing sector over the last thirty years. In the appendix, Table A4 presents the reduced form results by education group, confirming that the strongest dynamics are observed for relatively low educational attainment levels.

The observed increase in real wages sets up the possibility for there to be a Dutch disease style contraction in the tradable and non-tradable local sectors. In the next step I provide results that highlight that reallocation of labour across sectors in the manner suggested by the simple conceptual framework does not occur. The manufacturing sector does neither contract nor expand, while the non-tradable service goods sector contracts.

Step 3: Employment Shares and Labour Reallocation

The conceptual framework without endogenous local energy prices, suggest that there be an unambiguously negative effect on the tradable goods sector, while the response of the relative size of the non-tradable goods sector is ambiguous. The latter depends on the strength of the spending effect.

I now explore the evolution of the sectoral shares over time. The results are presented in table 4. The first column presents the result from specifications 2. This gives a sense of the overall impact of well-construction on shale deposits on the share of mining sector employment; overall, mining sector employment increased by around 3 percentage points, more than doubling the initial mining sector employment share of roughly 2%. Columns (2)-(6) use the share of mining sector employment as a right hand side, instrumented for by the interaction Post 2008 x Shale as in specification 3.

Column (2) indicates that the manufacturing sector appears not to be contracting. The coefficient on the share of manufacturing employment is negative but far form being statistically significant. Column (3) suggests that a one percentage point increase in mining sector employment increases the construction employment share by 0.453 percentage points. The stark observation is that for locally consumed services (column (5) and (6)), the coefficient is unambiguously negative. This suggests that the reallocation of labour across sectors happens at the expense of the local non-tradable goods sector, rather than at the expense of the tradable goods sector.

This is quite at odds with the conceptual framework, which suggested that the local non-tradable goods sector might even expand if the spending effect is sufficiently strong. The results presented here suggest that this is not the case, i.e. the spending effect appears to be quite week.

The next section highlights that the local tradable goods sector may even expand, despite rising labour cost. I argue that this is driven by the fact that local energy prices drop dramatically in response of the oil and gas boom. As tradable goods sectors are more energy intensive, this offsets the increase in labour costs. This ties in well with the arguments in Boschini (2007), which argue that the type of resource matters for whether a country actually suffers from a resource curse. They mainly argue that this is driven by the degree to which the resource can be appropriated. The mechanism I explore here highlights that it depends on the extent of trade costs and frictions.

5 Local Energy Prices and Sectoral Change

In this section I focus on one key mechanism that may explain why tradable goods sectors do not appear to contract, while other non-tradable goods sector appear to suffer from a Dutch disease style contraction. I first present evidence that supports this mechanism: local sectors that are energy intensive do not contract. This holds up when controlling for the extent to which the sectors are linked to the resource extraction sector producing inputs for the latter, and a wide array of other control variables at the three digit industry level.

I then document that local energy prices do indeed contract significantly. Places with unconventional oil- and gas extraction experience drops in the costs of natural gas by almost 30%. Similarly, local electricity prices go down significantly. I document that these effects are particularly pronounced in locations that are export constraint by the existing natural gas pipeline network, suggesting that trade costs can indeed be made responsible for these lower factor prices.

This suggests that in the short run, the boom in the resource extraction sector may not necessarily crowd out local tradable goods producers. It may even attract further producers of energy intensive goods. There are anecdotal accounts suggesting that this is happening in the heart of America, with fertiliser producers building up capacity in the West of the US, taking advantage of lower energy prices there.[10]

In order to compare the degree to which different sectors vary in their use of energy as a source of input, I refer to the 2002 input-output tables developed by the Bureau of Economic Analysis. Based on these, I construct measures of natural-gas

[10]See e.g. `http://www.agweek.com/event/article/id/21548/publisher_ID/80/` for recent fertiliser plant construction in North Dakota.

intensity and overall utility intensity at the three digit industry sector level, as there is significant variation within two digit industry.[11]

Using the same data-source, I also compute the labour cost shares as well as the degree to which each sector is linked to the mining sectors by providing inputs for the latter. This is an important control variable as it has been identified earlier that there are significant spillovers in the non-mining transportation- and construction sectors, which may moderate any labour cost induced contraction. In the appendix, Table A1 provides these respective cost shares at the two-digit industry level.

All intensity measures are at the three digit level. Unfortunately, the input-output tables do not have the same sectoral break-up as the employment data. In particular, the retail- and wholesale trade sectors are all pooled together at the two digit industry level. Thats why I focus the main results on just the manufacturing sector as there I have significant variation in energy intensity. I then successively add more sectors in the control group to highlight that the estimated coefficient and patterns stay virtually the same and the results become even stronger.

Energy Intensity and Sector Specific Expansion In order to capture the sector specific variation in energy intensity, I modify the estimating equation 1 by adding interaction terms with the sector specific energy intensity. The estimating equation then becomes:

$$\begin{aligned} y_{cist} &= \alpha_{ci} + b_{st} + \kappa \times Post2008 \times Shale_c \times EnergyIntensity_i \\ &+ \gamma \times Post2008 \times EnergyIntensity_i + X'\beta + \nu_{cist} \end{aligned}$$

where as left-hand side I use the log of sector specific employment. In order to capture heterogeneity by different factor input intensities, I add further interactions. The results can be found in table 5.[12]

The first four columns constrain the analysis to only include the tradable goods

[11] In order to measure this, I compute the cost shares of natural gas in the input costs. For natural gas, I sum up all the purchased values from companies working in the Natural Gas Distribution, Oil- and Gas Extraction 21100 and the Natural Gas Pipeline Transportation sectors (NAICS Codes 221200, 21100, 486000 respectively). This gets as close as possible to the input cost shares of natural gas. For the broader utility cost shares, I include all the above sectors and all electric utilities, that is private Electric Power Generation, Transmission and Distribution and State and local government electric utilities (NAICS Codes 2211000 and S00101, S00202).

I construct both measures of direct utility consumption as well as indirect utility consumption, indirectly used through the consumption of intermediary inputs.

[12] Note that the standard errors are clustered at the Workforce Investment Board Area level (WIA). This are regional entities created to implement the Workforce Investment Act of 1998. There are about 7-8 counties per workforce investment board area, rendering them spatially still significant in size to account for spatial correlation. An appealing feature of the WIA is that they are designed to include counties with similar economic structure, to ensure that the services under the Workforce Investment Act can be direct to the local needs.

industries.[13] While the coefficient on the simple interaction of the time dummy with the shale deposit indicator is negative but insignificant, the coefficient on the energy intensity interaction is positive and statistically significantly different from zero. This coefficient does not change when adding more interactions as control variables, such as the downstream linkages or the labour cost share. Columns (5) - (7) include subsequently more sectors. In column (5) I add the non-tradable goods sector as control. As expected, the results get stronger.

This suggests that energy intensive tradable goods sector are actually benefiting from being on the shale. In the next section I highlight that this may be due to significantly lower energy prices, which allows tradable goods producers to compete despite rising labour costs.

Trade Costs and Local Energy Prices I show that local energy prices actually go down significantly. This reduction in energy prices is particularly observed for states with shale deposits but that have relatively little slack natural gas pipeline outflow capacity.

I estimate specifications 1 and 2 as before, however, now using local utility and electricity prices as left-hand side variables.

Figure 6 displays the estimated coefficients for local natural gas prices. It appears that well before 2008 - if anything - natural gas prices in counties with shale deposits had actually been higher than in the rest of the US. From 2008 onwards, this picture changes. By 2012, natural gas on places with shale deposits and active resource extraction, was - on average - almost 30 percent cheaper than in the rest of the US.

Table 5 presents the reduced form results when exploring this relationship in a more systematic manner. In column (1) I present the reduced form effect of being on the shale on natural gas prices by all uses. This suggests that counties with shale deposits had - on average - 2.2% lower natural gas price. Column (2) refines this to focus on industrial use gas prices, which are particularly relevant for tradable goods producers. This highlights that the overall effect is driven by the price for industrial users. This makes sense as the latter is a lot more flexible as prices to residential consumers are typically regulated and quite sticky.

In column (3) and (4) I explore that it is actually a lack of physical pipeline capacity (and thus trade costs), that drive a significant portion of the observed natural gas price drop. States with relatively binding outflow capacity observe stronger price drops. This is intuitive. An increase in local production has to

[13]The classification is based on the four digit sector classification used in Mian and Sufi (2011). I exclude the mining sector and the 3-digit sector 324, Petroleum and Coal Products Manufacturing, as this sector captures the 144 oil refineries that are extremely concentrated in a few counties; furthermore,it represent a significant outlier as more than 70% of their input costs are direct costs for oil.

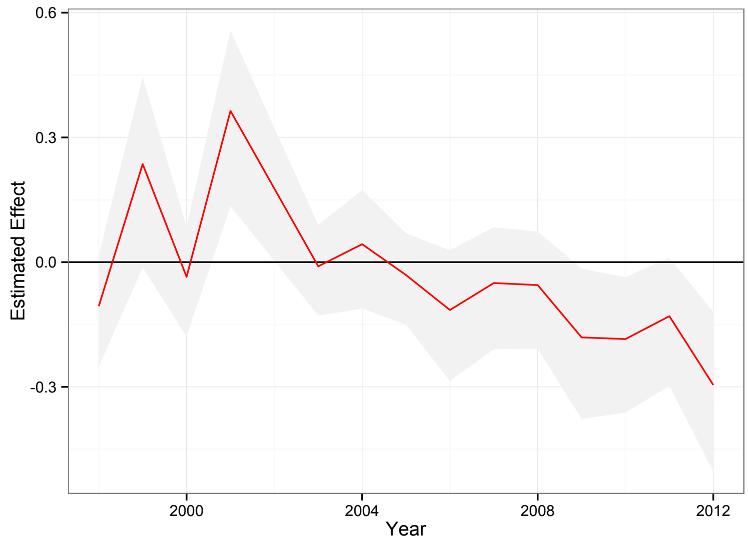

Figure 6: Natural Gas Prices for Industrial Consumers for Counties on Shale Deposits with a well by 2012

reduce local prices if the additional production can not be exported. In column (5) I use the relative bindingness of outflow-capacity to inflow-capacity. This measures the overall degree to which a state has slack capacity available, where that slack capacity could be indicating that local production is displacing imports or can not be exported due to outflow constraints.

Columns (5)-(7) present the results for average electricity prices. The results are similar, but statistically a lot weaker. This is obvious as one way to avoid pipeline capacity constraints is through the conversion of natural gas into electricity, where transmission constraints may be less binding. Hence, this suggests that the results may be driven mostly by lower natural gas prices.[14]

I now present a small back of the envelope calculation to see whether the observed energy price drops may indeed offset the labour cost increases.

Mining Sector Expansion and Local Energy Prices In the third step, I estimated the effect of the relative expansion of the mining sector on sectoral wages. This suggested that manufacturing wages increased by 1.6 percentage points for every 1 percentage point increase in the share of mining sector employment.

In Table 7 I present the results from the same analysis, however, replacing the

[14]This is confirmed when performing the same analysis for the overall energy intensity presented in table 5, but now focusing only on the directly consumed natural gas. The results are presented in the appendix in table A5.

electricity and gas prices on on the left hand side. The results are quite strong: column (1) studies overall natural gas prices. An increase in mining sector share by 1 percentage points reduces natural gas prices by 2.4 percentage points. This effect is even stronger for industrial use natural gas prices, where the elasticity is 6, evidenced in column (2). Column (3) looks at electricity prices, again I see a significant negative effect.

Can the drop in energy prices offset the increased labour costs and thus, moderate a Dutch disease style contraction in energy intensive sectors as is suggested by the results presented in the previous section? Given that the overall energy intensity is 5.3 percent for the manufacturing sector, while the labour cost share is 19.2%, this implies that the energy costs must go down by 3.6 times the amount that labour costs have gone up in order to compensate the labour cost increases.[15]

The results presented here are well in this ball-park. The increase in labour costs was estimated to be around 1.6 percent, while industrial gas prices have gone down by around 6 percent for a one percentage point increase in mining sector employment. Hence, the factor is actually $\frac{6}{1.6} = 3.75$, suggesting that total operating costs may actually have stayed the same - i.e. there is full compensation in form of lower energy costs offsetting the labour costs.

This does not affect the non-tradable goods sectors, who may benefit from lower energy prices but too a lesser extent as their average energy cost shares are significantly lower.

6 Conclusion

The existing literature has highlighted that resource booms tend to benefit the local service sector (see Kuralbayeva and Stefanski (2013); Michaels (2011); Sachs and Warner (1999). Depending on the institutional environment, there is some suggestive evidence that resource booms create fiscal surpluses which may induce growth in public sector employment (see e.g. Robinson et al. (2006), Baland and Francois (2000)). Lastly, resource booms, depending on the degree of local demand linkages should lead to a boost in sectors that provide inputs for the mining industry (see e.g. Marchand (2012) and Black et al. (2005)). On the other hand, the literature on Dutch disease has highlighted that there may be adverse effects on local tradable goods producers, as they can not pass on higher labour costs on to final goods consumers.

In this paper I provide evidence that sectoral reallocation appears not to happen as described in the classic Dutch disease literature. I do not explore whether

[15]Refer to table A1 for the average utility cost shares at the two digit sector level derived from the input-output tables.

agglomeration externalities may explain why this does not happen (as e.g. Allcott and Keniston (2013)), but focus on a different and much more simple mechanism. First, my results suggest that the spending effect, which positively affects the non-tradable goods sector share is quite weak. In addition to the resource movement effect, my results indicate that local energy prices may explain why there is no contraction in the tradable goods sector, while there is for the non-tradables sector. The argument is simple. The resource boom creates a local comparative advantage in form of lower energy prices. It is questionable whether this is an effect that persists. This depends on the nature of the transport cost induced energy price differentials. If the price differentials are purely due to a lack of transmission capacity, arbitrage conditions will imply that these missing transmission links will be build to arbitrage the price differences away. On the other hand, a significant share of energy costs are due to transmission losses, which would make locally lower energy prices a persistent feature. Further research is needed to highlight whether this is the case.

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Tables for the Main Text

Table 1: Economic Expansion in Key Variables

	Overall Employment			Broader Labour Market		Incomes	
	(1) Oil & Gas	(2) Overall	(3) Non Oil & Gas	(4) Unemployment	(5) Labourforce	(6) Personal Income	(7) Payroll
Instrumental Variables:							
Anywell x	0.910***	0.100**	0.065*	-0.011**	0.077**	0.080**	0.200***
(Year≥2008)	(0.269)	(0.045)	(0.035)	(0.006)	(0.034)	(0.040)	(0.071)
Reduced Form:							
Shale x	0.256***	0.028**	0.018*	-0.003*	0.021**	0.022*	0.056**
(Year≥2008)	(0.068)	(0.013)	(0.010)	(0.002)	(0.011)	(0.012)	(0.022)
Clusters	48	48	48	48	48	48	48
Observations	33944	43259	39496	45601	45601	45611	43358
R-squared	.912	.997	.998	.901	.998	.998	.996
First Stage	19.68	18.17	18.27	18.22	18.22	18.23	18.17

Notes: All regressions include state-time fixed effects and county fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Spillovers from the Mining Sector Expansion

	(1) OLS	(2) IV	(3) Job Creation (IV)
Overall Non Oil Gas	0.008***	0.054**	2.172**
	(0.002)	(0.027)	(1.100)
Manufacturing	-0.002	0.112	0.586
	(0.005)	(0.098)	(0.514)
Construction	0.016**	0.376***	0.872***
	(0.007)	(0.123)	(0.284)
Transportation	0.020**	0.277*	0.342*
	(0.009)	(0.158)	(0.195)
Local Services	0.010***	0.038	0.328
	(0.003)	(0.054)	(0.471)
Education and Health	0.006**	-0.002	-0.020
	(0.003)	(0.033)	(0.358)

Notes: All regressions include state-time fixed effects and county fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Effects of Mining Expansion on Sectoral Wages

	QWI Data					
	(1) Mining	(2) Manufacturing	(3) Construction	(4) Transportation	(5) Local Services	(6) Education and Health
Instrumental Variables:						
Mining Sector Share	6.475**	1.609*	2.912**	2.756**	1.899*	0.346
	(3.011)	(0.955)	(1.175)	(1.122)	(1.064)	(0.321)
Ordinary Least Squares:						
Mining Sector Share	1.519***	0.564***	0.425*	0.647*	0.301**	0.119**
	(0.267)	(0.149)	(0.253)	(0.361)	(0.127)	(0.056)
Weak Identification	7.26	6.87	7.25	7.21	7.07	7.13
R-squared	.756	.875	.862	.799	.961	.927
Clusters	46	46	46	46	46	46
Observations	32102	36844	37399	37099	74762	74668

Notes: The dependent variable is the log of real monthly earnings for the sectors given in the column head. Education and Health comprise the two digit sectors 61,Educational Services and 62,Health Care and Social Assistance, while Local Services comprise 44-45,Retail Trade, 71,Arts, Entertainment, and Recreation and 72,Accommodation and Food Services. All regressions include state-time fixed effects and county-industry fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effects of Mining Expansion on Sector Shares

	(1) Mining	(2) Manufacturing	(3) Construction	(4) Transportation	(5) Local Services	(6) Education and Health
Instrumental Variables:						
Anywell x Year≥2008	0.029***					
	(0.010)					
Mining Sector Share		-0.014	0.453***	0.049	-0.337*	-0.694**
		(0.363)	(0.150)	(0.140)	(0.213)	(0.341)
Ordinary Least Squares:						
Shale x Year≥2008	0.008***					
	(0.003)					
Mining Sector Share		-0.074***	-0.063*	-0.008	-0.168***	-0.312***
		(0.027)	(0.035)	(0.040)	(0.027)	(0.043)
Mean of Dependent Variable	.02	.15	.06	.03	.2	.25
Clusters	48	48	48	48	48	48
Observations	39496	33534	33903	33800	33944	33944
Instrument	18.27	7.32	7.8	7.63	7.82	7.82
R-squared	.915	.943	.845	.834	.92	.613

Notes: The dependent variable is the share of overall employment of the sectors given in the column head in a county. The sectors are defined at a two digit level. Education and Health comprise the two digit sectors 61,Educational Services and 62,Health Care and Social Assistance, while Local Services comprise 44-45,Retail Trade, 71,Arts, Entertainment, and Recreation and 72,Accommodation and Food Services. All regressions include state-time fixed effects and county-industry fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Energy Intensity and Manufacturing Sector Expansion

	Tradable Goods Sector Only				Additional Sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reduced Form							
Energy Intensity x Shale	1.656*	1.654*	1.645*	1.755**	1.707**	1.414*	1.694***
	(0.856)	(0.852)	(0.855)	(0.852)	(0.821)	(0.794)	(0.441)
Labour Intensity x Shale		0.091	0.126	0.085	−0.010	0.124	−0.004
		(0.202)	(0.206)	(0.204)	(0.123)	(0.087)	(0.056)
Downstream Linkage x Shale			−0.415	0.038	−0.172	1.018***	0.617***
			(0.751)	(0.722)	(0.654)	(0.298)	(0.192)
Shale	−0.012	−0.031	−0.033	−0.035	−0.016	−0.058	−0.013
	(0.027)	(0.054)	(0.054)	(0.053)	(0.049)	(0.036)	(0.022)
Clusters	366	366	366	366	366	366	366
Sectors	19	19	19	19	30	36	82
Observations	440,981	440,981	440,981	440,981	867,554	1,108,577	2,490,087
Adjusted R^2	0.915	0.915	0.915	0.917	0.939	0.942	0.947

Notes: The dependent variable is the log of the number of people employed in the three digit sub sectors. All control variables presented are interactions with a post 2008 dummy. All regressions include state-time and county-industry fixed effects. Robust standard errors clustered at the workforce-investment board area are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Natural Gas and Electricity Prices

	Natural Gas				Electricity		
	All uses	Industrial Gas Prices			Average Electricty Price		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post 2008 Interactions:							
Shale	-0.022**	-0.055***	-0.081**	-0.028	-0.002*	-0.008**	-0.002
	(0.011)	(0.019)	(0.037)	(0.020)	(0.001)	(0.004)	(0.001)
Outflow Capacity x Shale			-0.140***			0.010	
			(0.039)			(0.006)	
Inflow Capacity x Shale			0.255***			0.003	
			(0.061)			(0.006)	
Inflow/Outflow Capacity x Shale				-0.022***			-0.000
				(0.005)			(0.000)
Weather Variables:							
HDD	-0.000**	-0.000**	-0.000**	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CDD	0.000	0.000**	0.000	0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clusters	339	339	339	339	367	367	367
Observations	30896	31468	30399	30823	44505	43305	43305
R-squared	.954	.899	.954	.898	.886	.88	.88

Notes: All regressions include state-time and county fixed effects. Column (1) uses the log of average gas prices in a county, where the consumer, commercial and industrial gas prices are weighted by their national consumption shares. In column (2)-(4) I only study the price charged to industrial consumers. Column (3)-(6) is the level of average electricity prices, where consumer, commercial and industrial prices are weighted by their respective national consumption shares. HDD stands for heating degree days, while CDD measures cooling degree days. Robust standard errors clustered at the workforce-investment board area are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Mining Sector Expansion and Local Energy Prices

	(1) Average All Use Gas	(2) Industrial Gas Use	(3) Electricity All Use
Instrumental Variables:			
Mining Sector Share	-2.409*	-6.067**	-0.188*
	(1.262)	(2.453)	(0.113)
Reduced Form:			
Shale x Post 2008	-0.022**	-0.055***	-0.002*
	(0.011)	(0.019)	(0.001)
Ordinary Least Squares:			
Mining Sector Share	-0.059	-0.033	-0.003
	(0.069)	(0.149)	(0.005)
Clusters	337	337	364
Observations	24187	24620	33849
Instrument	15.09	14.99	15.79
R-squared	.953	.898	.885

Notes: All regressions include state-time fixed effects and county fixed effects. Column (1) uses the log of average gas prices in a county, where the consumer, commercial and industrial gas prices are weighted by their national consumption shares. In column (2) I only study the price charged to industrial consumers. Column (3) is the level of average electricity prices, where consumer, commercial and industrial prices are weighted by their respective national consumption shares. Robust standard errors clustered at the workforce investment board area are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Tables

Table A1: Sector Specific Cost Shares

	NAICS2	Sector	Utility Cost	Natural Gas	Labour	Mining Linkage
1	11	Agriculture, Forestry, ...	0.020	0.004	0.120	0.004
2	31-33	Manufacturing	0.053	0.042	0.192	0.225
3	54	Professional, Scientific,..	0.004	0.001	0.450	0.102
4	55	Management of Companies	0.007	0.001	0.524	0.127
5	44-45	Retail Trade	0.014	0.001	0.378	0.000
6	61	Educational Services	0.038	0.017	0.475	0.000
7	62	Health Care and Social Assistance	0.008	0.001	0.508	0.000
8	71	Arts, Entertainment, and Recreation	0.016	0.002	0.357	0.000
9	72	Accommodation and Food Services	0.025	0.003	0.373	0.002
10	81	Other Services	0.010	0.002	0.342	0.004
11	48-49	Transportation and Warehousing	0.008	0.003	0.387	0.005
12	21	Mining,Oil and Gas Extraction	0.042	0.023	0.156	0.123
13	22	Utilities	0.196	0.196	0.174	0.060
14	23	Construction	0.004	0.001	0.380	0.072
15	42	Wholesale Trade	0.006	0.001	0.377	0.001
16	51	Information	0.005	0.002	0.249	0.006
17	52	Finance and Insurance	0.001	0.000	0.307	0.042
18	53	Real Estate and Rental and Leasing	0.017	0.001	0.087	0.214
19	56	Administrative and Support ...	0.004	0.001	0.515	0.011

Table A2: Economic Expansion in Key Variables

	Overall Employment			Broader Labour Market		Incomes	
	(1) Oil & Gas	(2) Overall	(3) Non Oil & Gas	(4) Unemployment	(5) Labourforce	(6) Personal Income	(7) Payroll
Shale × 1999	-0.043	0.006	0.006	0.002	-0.003	-0.004	0.001
	(0.038)	(0.006)	(0.006)	(0.002)	(0.003)	(0.003)	(0.009)
Shale × 2000	0.042	0.008	0.006	-0.003	0.013	-0.003	0.009
	(0.101)	(0.012)	(0.011)	(0.002)	(0.008)	(0.006)	(0.018)
Shale × 2001	0.078	0.013	0.012	-0.003	0.011	-0.000	0.017
	(0.100)	(0.014)	(0.014)	(0.002)	(0.008)	(0.006)	(0.017)
Shale × 2002	0.027	0.017	0.019	-0.002	0.014	0.005	0.015
	(0.108)	(0.015)	(0.014)	(0.002)	(0.009)	(0.007)	(0.019)
Shale × 2003	0.003	0.011	0.014	-0.002	0.013	-0.003	0.018
	(0.111)	(0.016)	(0.015)	(0.002)	(0.009)	(0.006)	(0.021)
Shale × 2004	0.083	0.012	0.014	-0.003	0.015	-0.003	0.018
	(0.127)	(0.017)	(0.016)	(0.002)	(0.010)	(0.009)	(0.022)
Shale × 2005	0.103	0.016	0.013	-0.003	0.015	-0.003	0.027
	(0.139)	(0.018)	(0.018)	(0.002)	(0.010)	(0.010)	(0.022)
Shale × 2006	0.198	0.022	0.017	-0.004	0.013	0.009	0.035
	(0.157)	(0.019)	(0.019)	(0.003)	(0.011)	(0.013)	(0.022)
Shale × 2007	0.233	0.021	0.014	-0.004	0.016	-0.002	0.035
	(0.153)	(0.018)	(0.017)	(0.003)	(0.012)	(0.011)	(0.021)
Shale × 2008	0.253*	0.022	0.014	-0.005	0.019*	0.012	0.047**
	(0.151)	(0.017)	(0.016)	(0.003)	(0.011)	(0.012)	(0.022)
Shale × 2009	0.297**	0.029	0.021	-0.005	0.025**	0.022	0.053**
	(0.145)	(0.018)	(0.018)	(0.004)	(0.012)	(0.016)	(0.024)
Shale × 2010	0.323**	0.040**	0.031*	-0.005	0.031**	0.019	0.071**
	(0.149)	(0.020)	(0.018)	(0.003)	(0.014)	(0.014)	(0.029)
Shale × 2011	0.418***	0.056**	0.041**	-0.006**	0.038**	0.027	0.102***
	(0.149)	(0.023)	(0.020)	(0.003)	(0.017)	(0.019)	(0.035)
Shale × 2012	0.406***	0.063**	0.045*	-0.005**	0.047**	0.031	0.107**
	(0.153)	(0.028)	(0.024)	(0.002)	(0.022)	(0.021)	(0.045)
Observations	33944	43259	39496	45601	45601	45611	43358
R-squared	.912	.997	.998	.901	.998	.998	.996

Notes: All regressions include state-time fixed effects and county fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Economic Expansion in Key Variables

	Overall Employment			Broader Labour Market		Incomes	
	(1) Oil & Gas	(2) Overall	(3) Non Oil & Gas	(4) Unemployment	(5) Labourforce	(6) Personal Income	(7) Payroll
Shale × 1999	-0.145	0.019	0.019	0.008	-0.011	-0.013	0.003
	(0.132)	(0.020)	(0.019)	(0.006)	(0.009)	(0.011)	(0.026)
Shale × 2000	0.147	0.025	0.020	-0.009*	0.047	-0.010	0.025
	(0.272)	(0.034)	(0.032)	(0.005)	(0.030)	(0.020)	(0.051)
Shale × 2001	0.226	0.034	0.034	-0.010	0.040	-0.001	0.042
	(0.287)	(0.045)	(0.043)	(0.007)	(0.030)	(0.020)	(0.055)
Shale × 2002	0.028	0.047	0.058	-0.008	0.050	0.020	0.032
	(0.321)	(0.047)	(0.048)	(0.007)	(0.034)	(0.025)	(0.058)
Shale × 2003	-0.050	0.028	0.040	-0.005	0.047	-0.012	0.041
	(0.346)	(0.050)	(0.049)	(0.007)	(0.032)	(0.021)	(0.066)
Shale × 2004	0.217	0.030	0.040	-0.010	0.053	-0.009	0.044
	(0.388)	(0.052)	(0.050)	(0.008)	(0.037)	(0.030)	(0.070)
Shale × 2005	0.297	0.044	0.038	-0.010	0.053	-0.010	0.076
	(0.419)	(0.056)	(0.055)	(0.008)	(0.039)	(0.034)	(0.071)
Shale × 2006	0.636	0.067	0.051	-0.014	0.046	0.032	0.105
	(0.485)	(0.060)	(0.059)	(0.009)	(0.042)	(0.047)	(0.077)
Shale × 2007	0.756	0.062	0.041	-0.014	0.057	-0.006	0.105
	(0.485)	(0.056)	(0.054)	(0.009)	(0.043)	(0.036)	(0.075)
Shale × 2008	0.834*	0.066	0.041	-0.017*	0.067	0.041	0.147*
	(0.488)	(0.058)	(0.055)	(0.010)	(0.042)	(0.044)	(0.081)
Shale × 2009	0.994**	0.091	0.067	-0.016	0.090**	0.079	0.167**
	(0.462)	(0.059)	(0.058)	(0.013)	(0.044)	(0.053)	(0.079)
Shale × 2010	1.085**	0.130**	0.103*	-0.018*	0.110**	0.068	0.235**
	(0.485)	(0.066)	(0.063)	(0.011)	(0.048)	(0.047)	(0.092)
Shale × 2011	1.431***	0.189**	0.139**	-0.022**	0.138**	0.097	0.346***
	(0.466)	(0.075)	(0.066)	(0.011)	(0.059)	(0.062)	(0.113)
Shale × 2012	1.380***	0.213**	0.155**	-0.017**	0.169**	0.112*	0.365***
	(0.476)	(0.090)	(0.076)	(0.008)	(0.074)	(0.067)	(0.138)
Observations	33942	43251	39488	45586	45586	45596	43350
R-squared	.909	.997	.998	.898	.998	.998	.996

Notes: All regressions include state-time fixed effects and county fixed effects. Robust standard errors clustered at the state level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Monthly Earnings By Sector and Educational Attainment

	Employment			Earnings		
	(1) Overall	(2) Mining	(3) Non-Mining	(4) Overall	(5) Mining	(6) Non-Mining
Shale x After 2012 x	0.077***	0.349***	0.051***	0.085***	0.157***	0.050***
Workers younger 24	(0.014)	(0.070)	(0.014)	(0.011)	(0.034)	(0.010)
Shale x After 2012 x	0.071***	0.219***	0.040***	0.040***	0.060***	0.030***
Less than high school	(0.013)	(0.061)	(0.013)	(0.008)	(0.023)	(0.008)
Shale x After 2012 x	0.058***	0.176***	0.018	0.038***	0.062***	0.029***
High school or equivalent, no college	(0.011)	(0.061)	(0.011)	(0.007)	(0.023)	(0.007)
Shale x After 2012 x	0.052***	0.196***	0.023**	0.028***	0.033	0.021***
Some college or Associate degree	(0.011)	(0.061)	(0.011)	(0.007)	(0.024)	(0.007)
Shale x After 2012 x	0.025**	0.218***	0.003	0.014**	0.033	-0.001
Bachelor's degree or advanced degree	(0.011)	(0.060)	(0.012)	(0.007)	(0.027)	(0.008)
County x Education Group FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	586247	234458	306147	571829	375433	306147
States	2525	1677	2251	2525	2219	2251

Notes: All regressions include state-time fixed effects and county fixed effects. Robust standard errors clustered at the county level are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Natural Gas Intensity and Manufacturing Sector Expansion

	Tradable Goods Sector Only				Additional Sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reduced Form							
Natural Gas Intensity x Shale	3.252*	3.491*	3.571*	3.739*	3.798**	3.218**	3.539***
	(1.966)	(1.992)	(1.993)	(1.990)	(1.918)	(1.629)	(1.005)
Labour Intensity x Shale		0.151	0.190	0.153	0.067	0.157*	0.027
		(0.206)	(0.210)	(0.207)	(0.141)	(0.089)	(0.055)
Downstream Linkage x Shale			−0.491	−0.042	−0.271	0.884***	0.556***
			(0.747)	(0.717)	(0.657)	(0.283)	(0.190)
Shale	−0.002	−0.036	−0.038	−0.040	−0.024	−0.054*	−0.012
	(0.024)	(0.055)	(0.055)	(0.055)	(0.051)	(0.031)	(0.020)
Clusters	366	366	366	366	366	366	366
Sectors	19	19	19	19	30	36	82
Observations	440,696	440,696	440,696	440,696	867,104	1,108,037	2,488,857
Adjusted R^2	0.914	0.914	0.914	0.916	0.939	0.942	0.947

Notes: The dependent variable is the log of the number of people employed in the three digit sub sectors. All control variables presented are interactions with a post 2008 dummy. All regressions include state-time and county-industry fixed effects. Robust standard errors clustered at the workforce-investment board area are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Data Appendix

A.1 Oil and Gas Well Data

Wyoming Data on horizontal wells that are mainly used for fracking purposes were obtained upon request fromthe Wyoming Oil and Gas Conservation Commission (WOGCC).[16] It contains data on 1541 wells; the date on which a well was first dug is used to construct an annual panel of active wells.

West Virginia Data on gas well drilling permits for the Marcellus Shale and Utica Shale permits issued by the West Virginia Department of Environmental Protection. [17] It contains data on 3,176 permits for drilling that were issued up to May 2013 commencing in 2005. The time variable used is the date the permit was issued.

Utah Data on gas and oil wells constructed were obtained from the Division of Oil, Gas and Mining - Department of Natural Resources.[18] It contains data on 32,176 wells completed since the 1950s. The paper uses data on unconventional horizontally drilled wells, the time variable is the date the well was completed.

South Dakota Data on gas and oil wells exploring shale deposits were obtained from the Minerals Mining Program, Division of Environmental Services, Department of Environment and Natural Resources.[19] It contains data on 292 wells completed since 2000. The paper uses data on unconventional horizontally drilled wells, the time variable is the date the well was spudded.

Virginia The data on horizontal wells comes from the Virginia Department of Mines, Minerals, and Energy Division of Gas and Oil and contains all horizontal wells drilled as of June 6, 2013.[20] The data starts from 2007 onwards and comprises 93 wells in total. The type of well (i.e. whether oil or gas is produced is provided).

Pennsylvania The data used is for unconventionally drilled wells, which typically include all horizontal wells and all wells that use hydraulic fracturing. The data were obtained from reports filed under the Pennsylvania Oil and Gas Act which requires unconventional well operators to submit production reports to the

[16] See `http://wogcc.state.wy.us/`, accessed on 14.07.2013.

[17] See `http://tagis.dep.wv.gov/fogm/`, accessed on 14.07.2013.

[18] See `http://oilgas.ogm.utah.gov/Data_Center/LiveData_Search/well_data_lookup.cfm`, accessed on 14.07.2013.

[19] See `http://denr.sd.gov/des/og/oghome.aspx`, accessed on 14.07.2013.

[20] See `http://www.dmme.virginia.gov/dgoinquiry/`, accessed on 14.07.2013

Department of Environmental Protection.[21] The data is as of December 2012 and includes data from 2005 onwards. The time variable used is the date at which drilling commences. The type of well, i.e. whether oil or gas is produced is provided.

Oklahoma Data on shale-wells obtained from the Oklahoma Corporation Commission through the Oklahoma Geological Survey, containing details on unconventional wells. It contains data on 2694 wells from 2000 onwards. The time variable used is the well-completion date, from which point onwards the well commences production.

Ohio Data on shale gas well drilling for the Mascellus and the Utica Shale were obtained from the The data contains 16 drilling sites for the Marcellus shale and 367 locations for the Utica Shale as of September 2013 starting in 2006. The time variable is the date that the permit was issued

New York Data on 63 horizontal wells from the Marcellus, Utica, and Upper Devonian were obtained from the New York State Department of Environmental Conservation.[22] The time variable used is the date that drilling began.

New Mexico Data on 1078 wells that were hydraulically fractured between 2009 and 2012 are included in the dataset. The data was obtained from the state fracking liquids disclosure. The time vasiable is the daue in which a weml was fractured.

North Dakota Data on gas wells were extracted from the North Dakota Industrial Commission, Oil and Gas Division and the Current Confidential Well List.[23] It contains data on 7,982 wells; data from 2000 onwards is used. The time variable used is the date!the drilling of the well began.

Data on county-level oil and gas production was obtained from the Oil and Gas Division of North Dakota. Unfortunately, well-level production data is not available in the public domain (free of charge).

Arkansas Data on shale gas well drilling for the Faye Shale was obtained from the Arkansas Geological Survey.[24] It contains data on 5,577 permits for drilliog that

[21]See https://www.paoilandgasreporting.state.pa.us/publicreports/Modules/Welcome/Agreement.aspx, accessed on 14.07.2013.

[22]See http://www.dec.ny.gov/imsmaps/navigator/md_oil_gas.html, accessed on 14.07.2013.

[23]See https://www.dmr.nd.gov/oilgas/, accessed on 14.07.2013.

[24]See http://www.geology.ar.gov/fossilfuel_maps/fayetteville_play.htm, accessed on 14.07.2013.

were issued up to May 2013 commencing in 2001. The time variable used is the date the permit was issued.

Louisiana Data on shale gas well drilling for the Haynesville Shale was obtained from the Louisiana Department of Natural Resources.[25] It cootains data on 2,451 wells issued up to June 2013. The time variable used is the date when drilling began.

Kentucky Data on 1,447 horizontal wells were extracted from data provided by the Kentucky Geological Survey as of July 2013. The time variable used is the date that drilling was completed.

Kansas Data on horizontal wells piercing the Mississippian Lime Play were obtained from the Kansas Geological Survey as of July 2013 Data on 1,447 horizontal wells were extracted from data provided by the Kentucky Geological Survey as of July 2013. The time variable used is the date that drilling was completed.

Frac Focus Disclosure Data For the remaining states I rely on a cross-section of data from FracFocus. This is a voluntary disclosure website, where oil and gas companies disclose the date, time, type of liquid and location of the well that was fracked. Clearly, this dataset is complementing the other data-sources, filling gaps where no data was publicly available from the state level agencies.

Figure A1 plots the spatial distribution of newly constructed wells that are part of this study. The clusters for the various shale plays highlighted in **??** is very visible.

As the identification strategy rests on an interaction between a time fixed effect and a cross-sectional variable indicating whether a county has unconventional deposits, I need to justify the choice of the particular year that is used as reference year. For the parts where I allow the effect of a county having shale resources to flexibly vary over the years, the data makes this judgement call. However, in some specification I divide the data into two regimes, one before 2008 and one after 2008 to estimate the pooled effect across these years.

In order to justify this choice, I use the data on the timing of well construction for the set of states for which this data is available. I can then estimate the simple non-parametric specification and plot the coefficients over time.[26]

[25] See `http://dnr.louisiana.gov/index.cfm?md=pagebuilder&tmp=home&pid=442`, accessed on 14.07.2013.

[26] The estimated specification is as in the main part of the paper, i.e.

$$WellConstruction_{cist} = \alpha_{ci} + b_{st} + \sum_i \gamma_i \times Shale_c + \nu_{cist} \quad (5)$$

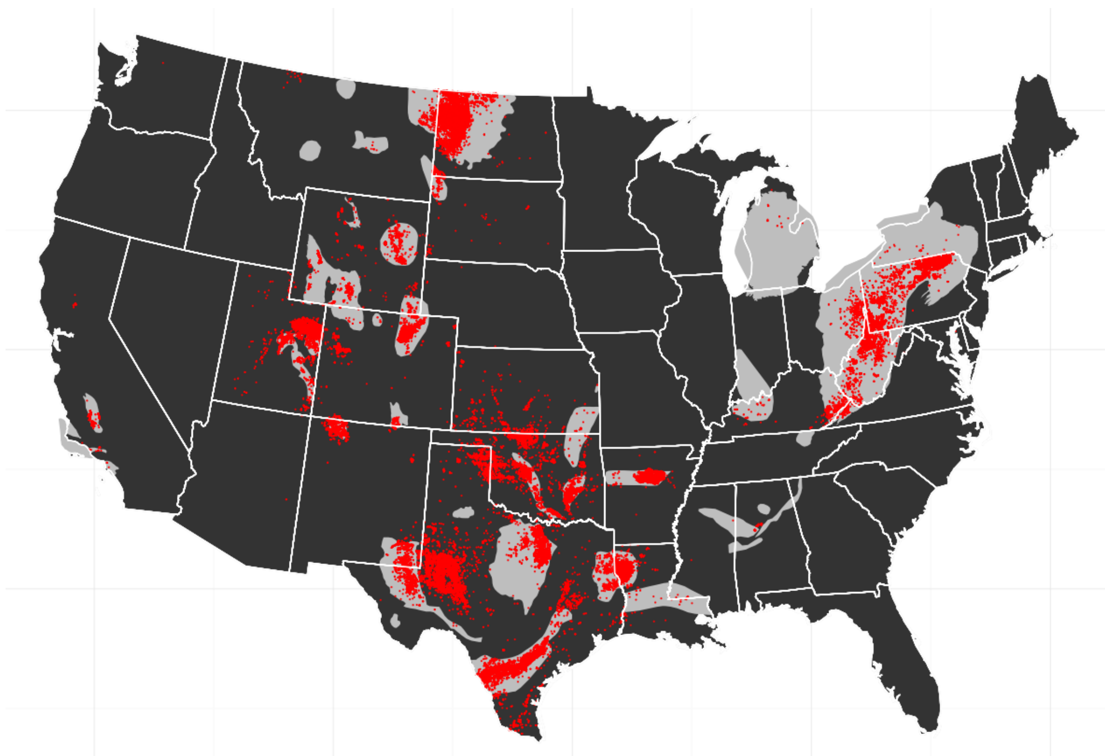

Figure A1: Spatial Distribution of Well Construction: Each Point Represents a Newly Constructed Well.

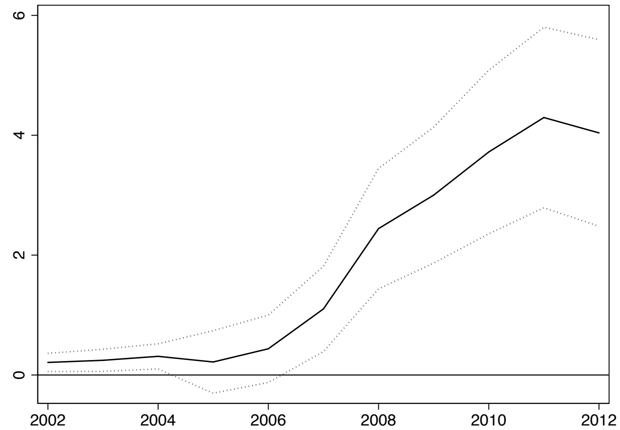

Figure A2: New Oil and Gas Well Construction on Shale Deposits Over Time

Figure A2 presents the results from this exercise. It becomes evident that the bulk of new well construction is occurring in the second part of the 2000s, making the choice of 2008 as a cutoff year a feasible candidate.

A.2 Oil, Gas and Shale-Plays

Data for the location and extent of known oil, gas and shale-oil and shale-gas fields were obtained from the U.S. Geological Survey and the U.S. Energy Information Administration.[27] The shape files used are the basin boundaries (as of September 2011), the tight gas maps and the shale gas and oil maps.

A.3 Gas Price Data and Geographic Matching

I use two main sources to obtain county-level natural gas prices. The first source is the Energy Information Administration annual reports filed under Form EIA-176. This provides detailed data for each firm that sells natural gas to final consumers. The data pertain to the revenues and sales volume of natural gas to residential-, commercial-, industrial and electric power generation users.

The utility companies typically serve, what is referred to, a "Utility Service Territory". The territories are set up, either by regulators or may be a type of natural monopoly that exists due to the high economies of scale implied by the network technology for delivery. A lot of the utility firms are publicly owned. Hence, there

[27]See `http://www.eia.gov/pub/oil_gas/natural_gas/analysis_publications/maps/maps.htm`, accessed n 13.07.2013.

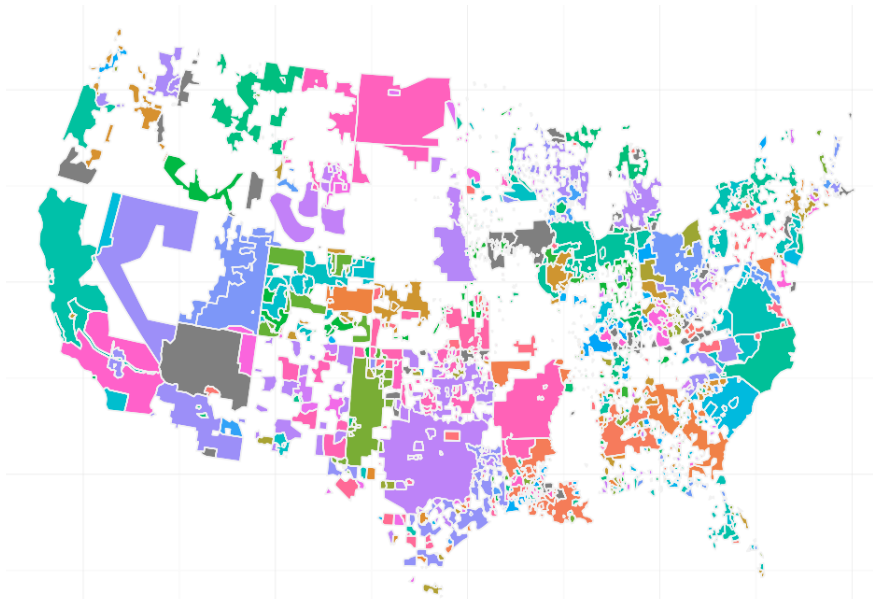

Figure A3: Service Areas for Natural Gas Utility Companies.

is quite a degree of variation in the price policies. Public utilities typically hold regular public meetings in which prices are determined.

There exists no dataset at county level that provides an energy price-time series for the US. However, there does exist a register of all firms involved in the natural gas sector, with there annual commercial and private customer revenues and turnover.

I obtained data from the Energy Information Administration under Form EIA-176. This provides revenues and quantities of gas sold in a state and year for a local distribution company. This allows the construction of an average price for each utility company operating in a particular state.

I obtained non-publicly available data on utility company service areas from the EIA; the service areas can be drawn on a map, as is presented in **??**. Each colour refers to a separate utility company. It is quite obvious that some utility companies service huge areas, though it is unlikely that all individuals living in a particular service area can actually be served with piped utility gas, as the service area are most likely representing a convex hull. The map of service areas is only available for 2008, implying that changes in the service areas are not reflected in my data. Based on the state- by utility company average prices, I compute a county level simple average utility gas price.

A.4 Employment Data

Data on industry specific employment per quarter is obtained from the Longitudinal Employer-Household Dynamics dataset maintained by the US Census Bureau. In particular I use the Quarterly Workforce Indicators (QWI) that provide details up to 4-digit NAICS industry codes on county-level quarterly employment, payroll, earnings and job creation and destruction.

The source that feeds into the QWI is the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata, which in turn is derived from the Unemployment Insurance (UI) wage records. The data has been available from the late 1990s onwards thanks to a data-sharing arrangement between the Census Bureau and participating states.

The database roughly covers 95% of private sector employment. The core data is drawn from administrative records in the participating states and submitted once a quarter. The QWI used here are public use products, while firm- and individual level data can only be physically accessed at the US Census Bureau data centres.

A concern is measurement error in the employment data due to noise-infusion or non-reporting of employment data at county level if employment in categories is too low. The noise-infusion is multiplicative, where the infused noise generates non-systematic measurement error in the employment figures, payroll and earnings. Abowd and Gittings (2012) show that the noise infusion does not create any systematic bias, nor does it distort the time-series properties of the employment data.

More problematic are the strictly binding non-disclosure constraints which require that employment counts be not reported in case there are fewer than 3 individuals- or fewer than 3 employers in a sub-geography and sector cell that contribute to the data (Abowd (2005)).

This is particularly problematic even for employment at the 2-digit industry level for the mineral resource sector, as there are typically few firms operating in this sector due to the high capital intensity.

The key binding constraint is the rigid minimum 3 employer per sector and county rule. For the sample I am working with, only 35.2% of the county report employment figures in the mining sector that are regularly distorted. 24.3% of the observations are considered significantly distorted. The overall mean employment for the significantly distorted data is roughly 1/3 of the mean for the moderately distorted data. This hints that a significant amount of employment is not accounted for. 40.1% of the observations do not meet the minimum disclosure condition of there being at least 3 employers in the county in the given sector.

This data can indirectly, but noisily, be inferred from the payroll- and earnings figures. For 91.3 % of the non-reported employment counts, the data reports earn-

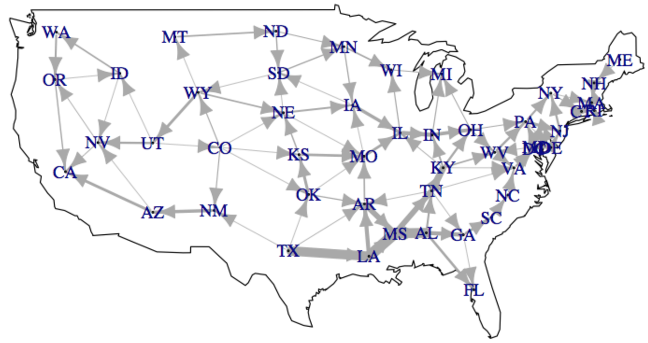

Figure A4: Physical Natural Gas Pipeline Net Inflow Capacity in 2002

ings and payroll. This data itself, is distorted. Since the noise-infusion is symmetric and random, the measure $E^f = Payroll/Earnings$ is a consistent estimator for the actual employment figure E^*.

Data generating process can be described as:

$$E^*_{it} = \phi(f(E_{it}))$$

where f is the data filter function:

$$f(E_{it}) = \begin{cases} 1 & \text{if } E_{it} < \tau \\ missing & \text{if } E_{it} \geq \tau \end{cases}$$

and $\phi()$ is the noise-infusion function.

This implies a type of sample selection bias, which can be corrected for using Heckman-style sample selection models.

A.5 Natural Gas Pipeline Network

A.6 PRISM Weather Data

In the paper I use some temperature controls to make sure that the observed variation can is not attributed to weather fluctuations or trends that differentially occur on places with shale deposits. This is important as temperature in particular is a driver for the demand of energy, but may also indirectly affect economic aggregates through a productivity channel.

I use the daily PRISM dataset, which provides for every day the mean, minimum and maximum temperature on a 4 by 4 kilometre grid. The data is described in more detail in Daly et al. (2008). Instead of relying on reanalysis data that comes at fairly coarse resolution, the PRISM dataset relies on the dense network of weather stations in the US; it uses 13 000 stations for precipitation and 10 000 points for temperature every day.

Based on the daily minimum-, maximum and average temperatures, I can compute two measures that are often used to capture residential demand for energy: the heating degree days (HDD) and cooling degree days (CDD). This constitutes an improvement, as most papers tend to use HDD or CDD derived from average temperature. This is clearly problematic, as it significantly underestimates the within-day variation in temperatures.

I use the formula's developed by the UK Meterological Office, using as base temperature $\bar{T} = 15$ degrees centigrade. Please refer to Mourshed (2012) or Day and Karayiannis (1999) for details. The formulas for heating degree days is given as:

$$HDD = \begin{cases} 0 & \text{if } T_{min} > \bar{T} \\ \frac{\bar{T}-T_{min}}{4} & \text{if } T_{min} < \bar{T} \ \& \ \frac{T_{max}+T_{min}}{2} > \bar{T} \\ \frac{\bar{T}-T_{min}}{2} - \frac{\bar{T}-T_{min}}{4} & \text{if } T_{min} < \bar{T} \ \& \ \frac{T_{max}+T_{min}}{2} \leq \bar{T} \ \& \ T_{max} \geq \bar{T} \\ \bar{T} - \frac{T_{min}+T_{max}}{2} & \text{if } T_{min} < \bar{T} \ \& \ \frac{T_{max}+T_{min}}{2} \leq \bar{T} \ \& \ T_{max} < \bar{T} \end{cases}$$