Economics of modern energy boomtowns: do oil and gas shocks differ from shocks in the rest of the economy?

Tsvetkova, Alexandra and Partridge, Mark

Ohio State University

16 July 2015

Economics of Modern Energy Boomtowns:
Do Oil and Gas Shocks Differ from Shocks in the Rest of the Economy?*

by

Alexandra Tsvetkova, Ohio State University
Email: tsvetkova1@osu.edu

Mark D. Partridge, Ohio State University
Email: Partridge.27@osu.edu

July 16, 2015

Abstract: The U.S. shale boom has intensified interest in how the expanding oil and gas sector affects local economic performance. Research has produced mixed results and has not compared how energy shocks differ from equal-sized shocks elsewhere in the economy. What emerges is that the estimated impacts of energy development vary by region, empirical methodology, as well as the time horizon that is considered. This paper captures these dimensions to present a more complete picture of energy boomtowns. Utilizing U.S. county data, we estimate the effects of changes in oil and gas extraction employment on total employment growth as well as growth by sector. We compare this to the effects of equal-sized shocks in the rest of the economy to assess whether energy booms are inherently different. The analysis is performed separately for nonmetropolitan and metropolitan counties using instrumental variables. We difference over 1-, 3-, 6-, and 10-year time periods to account for county fixed effects and to assess responses across different time horizons. The results show that in nonmetro counties, energy sector multiplier effects on total county employment first increase up to 6-year horizons and then decline for 10-year horizons. In metro counties, 1-year differences analysis suggests crowding out though the multipliers are insignificant in longer horizons. We also observe positive spillovers to the nontraded goods sector, while spillovers are small or negative for traded goods. Yet, equal-sized shocks in the rest of the economy produce more jobs on average than oil and gas shocks, suggesting that policymakers should seek more diversified development.

Key words: employment growth, job multipliers, energy boom effects, instrumental variable approach

JEL Codes: O13, Q33, R11

*The authors acknowledge and appreciate the support of the USDA AFRI grant #11400612 titled "Maximizing the Gains of Old and New Energy Development for America`s Rural Communities."

Introduction

The recent shale boom in the U.S. has intensified scholarly interest in how expansion of the resource extraction sector affects local economic performance of impacted areas. Although the so-called resource curse (an inverse relationship between resource sector dependence and long-run economic performance) has been examined for nations, less has been done at the sub-national level in developed counties, though there is increasing interest (Freeman, 2009; Gylfason *et al.*, 1999; James and Aadland, 2011; Papyrakis and Gerlagh, 2007; Sachs and Warner, 1999; Sachs and Warner, 2001). Recent research assesses how a growing energy sector affects short-term local economic performance, at least in the relatively short run of the previous boom decade (Brown, 2014; Weinstein, 2014). It remains to be seen if localities that benefit from resource extraction now will be able to retain some of the gains in a prolonged bust period to avoid a natural resources curse. What is clear is that the conclusions of past research largely depend on the specific settings of the study, such as time frame, sample, etc. (Munasib and Rickman, 2015).[1]

Most U.S. regional research has focused on selected regions (Haggerty *et al.*, 2014; Michaels, 2011; Paredes *et al.*, 2015) or only nonmetropolitan areas (Brown, 2014; Munasib and Rickman, 2015). Detailed studies of the whole country are rare (one exception is Weinstein (2014)). Likewise, academic investigations of the energy sector's employment effects usually concentrate on total employment or just a few sectors (Brown, 2014; Weinstein, 2014). Besides, the existing studies generally fail to explicitly account for the non-uniform temporal association between energy sector and changes in employment growth.

This paper contributes to the literature by presenting what we believe is the most detailed account of the effects of energy sector on local employment. We separately consider U.S. metropolitan and nonmetropolitan areas by examining total employment as well as employment in 14 sectors to assess how energy booms differentially affect regional economies. We also examine the degree to which our analysis is affected by regional heterogeneities. Our timeframe is 1993 to 2013, although most of the analysis takes place after 2000. Tracing the effects through 2013 is crucial for capturing the dynamics of the last decade characterized by rapid expansion in extracting unconventional oil and gas sources.

[1]The academic studies have helped discredit many so-called "economic impact" studies that show very large positive spillovers from energy development, most of which were funded by the energy industry (Kinnaman, 2011).

Finally, we are the first to compare oil and gas shocks to similar sized shocks to assess whether and how energy booms differ from growth in the rest of the economy.

The estimation is based on instrumental variable (IV) technique and first-differencing over 1, 3, 6, and 10 years. We employ two combinations of instruments that are based on geological measures of oil and gas resources as well as historical measures of drilling activity. The differencing approach removes location fixed effects; whereas the IV accounts for possible endogeneity associated with time-varying factors that might affect the location of energy development (e.g., desperately poor economies looking for jobs or pro-business environments). Besides, our empirical strategy examines shocks of various durations to get a clearer picture of how the effects of energy booms evolve over time as supply chains and displacement effects take various amount of time to work their way through regional economies.

The results suggest that growth in the energy sector measured by oil and gas employment has positive net spillovers to a number of other sectors in nonmetropolitan areas. In traded goods sectors, however, there is some evidence of crowding out effects. In metropolitan counties we observe crowding out on average, although the results at the sectoral level show some positive spillovers. Nonetheless, energy shocks have smaller total employment effects than equal-sized standard shocks across the rest of the economy, suggesting that energy has fewer complementarities with other sectors than average. Likewise, population responses to both energy shocks and representative shocks elsewhere in the economy are both small, suggesting limitations in the role of agglomeration economies supporting long-term growth in modern booms. Overall, given that the employment effects of energy booms are relatively modest in magnitude compared to scale of the rest of the economy, local economies would be better off if they were to experience broad-based growth rather than energy booms both in terms of multiplier effects and the enhanced diversity for their economies (with less risk for a possible natural resources curse).

The rest of the paper is organized as follows. The next section reviews literature with specific focus on U.S. subnational studies. Section 3 presents empirical methodology and the data sources followed by the discussion of results in Section 4. Section 5 briefly covers various sensitivity checks, whereas Section 6 contains concluding remarks.

Literature review

The literature regarding the relationship between resource endowment and various measures of socioeconomic performance and well-being at the national level has a long tradition. It often documents negative association between resource dependence and long-run growth (Gylfason *et al.*, 1999; Sachs and Warner, 1999; Sachs and Warner, 2001; Sala-I-Martin *et al.*, 2004). The natural resource curse is linked to the Dutch Disease (Sala-i-Martin and Subramanian, 2013), corruption and low-quality of institutions (Bhattacharyya and Hodler, 2010; Bjorvatn *et al.*, 2012; Sala-i-Martin and Subramanian, 2013); failure to diversify economy and export structure (Murshed and Serino, 2011); lower educational attainment and human capital (Black *et al.*, 2005; Blanco and Grier, 2012; Gylfason, 2001); and crowding out other sectors, entrepreneurship and innovation (Betz *et al.*, 2015; Gylfason, 2000; Sachs and Warner, 1999). Yet, some authors find stimulating effect of resource abundance on growth (Alexeev and Conrad, 2009; Cavalcanti *et al.*, 2011), while others argue that sluggish economic performance may stem from market imperfections that are unrelated to resources (Gylfason and Zoega, 2014; Manzano and Rigobon, 2001).

Recent research on the effects of energy sector has increasingly used subnational data, which reduces the influence of unobserveables such as institutional quality, though there is still heterogeneity across different subnational regions (Fleming and Measham, 2014; Munasib and Rickman, 2015). The expected overall positive impact of greater economic activity in areas endowed with unconventional energy resources on employment and income is not straightforward if one takes into account extensive use of long-distance commuters (Kinnaman, 2011; Munasib and Rickman, 2015), potential adverse health and environmental effects (Sovacool, 2014) that possibly dampen property values in extraction areas (Boxall *et al.*, 2005).

The results for resource rich U.S. states are mixed. Based on cross-sectional analysis, Papyrakis and Gerlagh (2007) conclude that resource dependence measured by the share of primary-sector GSP output does not directly slow growth. Instead, large primary sector is related to lower investments, schooling, openness, R&D and higher corruption, which, in turn, translate into sluggish growth. Using panel data, Boyce and Emery (2011) find a negative association between resource abundance and growth rates but a positive effect on income levels. Freeman (2009) finds that intensity of employment in the primary sector (mining and agriculture) is negatively related to U.S. GSP per capita growth between 1977-2002. James and James (2011) explain the observed negative relationship between resources and economic growth by slower growth in mining compared to other sectors.

When this factor is accounted for in their models, the results suggest that more resource-dependent states enjoyed greater per capita personal income growth between 1980-2000.

Multiple studies point to the stimulating role of natural resource extraction in economic performance. Paredes *et al.* (2015) analyse counties in New York and Pennsylvania using a ban on shale gas fracking imposed in New York as a natural experiment. Their results suggest that unconventional gas wells have positive contemporaneous effect on income and employment, although the coefficients in the former case are rather small. Weber (2012) estimates the impact of gas production value on employment, income and poverty for counties in Colorado, Texas and Wyoming using difference-in-difference and instrumental variable approaches. He concludes that shale gas extraction modestly contributed to employment and income but did not affect poverty rates. Weber (2014) focuses on nonmetropolitan counties in Texas, Louisiana, Arkansas and Oklahoma during the 2000s. According to this analysis, each gas-related mining job was associated with additional 1.4 non-mining jobs. In a comparable analysis that covers a 9-state region of the U.S. Great Plains and Oil Patch, Brown (2014) finds a smaller increase in employment per each additional gas-related mining job (0.7 vs. 1.4 in the previously cited paper). Counties that increased gas production saw small employment gains in construction, transportation, and services, while retail trade and manufacturing were not affected. Based on the analysis of all counties in lower 48 states over years 2001-2011, Weinstein (2014) reports an employment multiplier from shale boom-related labour market restructuring of approximately 1.3. All studies considered use different time periods, as well as samples and measurement of the crucial variables, such as using production to proxy employment and then trying to extrapolate employment even though as noted earlier, production and employment are not necessarily highly linked.

There is some evidence, though, that the relationship between resources and socioeconomic outcomes is not uniform across the country. Munasib and Rickman (2015) find that unconventional oil and gas production in North Dakota has large and statistically significant positive effect on total employment and employment in accommodation and food services, construction, and retail. For Arkansas, positive effects are observable only in four most extraction-intensive counties, while no impact is found in Pennsylvania.

County-level investigations that examine previous energy boom-bust cycles also produce somewhat ambiguous results. On the one hand, James and Aadland (2011) show that personal income growth between 1980 - 1995 was slower in counties with a larger primary sector, thus lending support to the natural resource curse hypothesis. On the other hand, Michaels' (2011) investigation of resource abundance effects on economic performance of counties in the U.S. South during the 1940-1990 period indicate that areas situated over oilfields enjoyed higher employment, income and population density, although the effects lessened after about 1960. In the analysis of more recent years, Peach and Starbuck (2011) find small but positive effect of oil and gas production value on employment and income in New Mexico counties in census years 1960, 1970, 1980, 1990 and 2000. In a study going back to 1960, Allcott and Keniston (2014) find that oil- and gas-endowed (in terms of reserves) counties experience employment growth during energy booms, although these effects quickly reverse in busts. Analysis of income and employment from 1969 to 1998 by Jacobsen and Parker (2014) reveals that oil and gas extracting counties enjoyed employment growth, particularly in mining and non-tradable sectors during the boom but they suffered larger income declines and greater unemployment in the bust. Somewhat different findings comes from Haggerty et al. (2014) who fail to find significant relationship between county specialization in oil and gas, as well as duration of such specialization, on change in employment between 1980 and 2011 in the U.S. West.

Estimation approach, variables and data sources

The impacts of changes in resource industry are likely to depend on the specific setting and time horizon. In this paper we are interested in two important policy indicators, employment and population. We do not consider income because of theoretical concerns about interpretation.[2] In contrast to recent research that focuses on nonmetropolitan areas (Brown, 2014; Munasib and Rickman, 2015; Weber, 2014), we separately study metropolitan and nonmetropolitan areas.[3] While extraction activity predominantly takes place in rural areas, the use of long-distance workers and tendency of energy companies to locate their headquarters in metropolitan areas suggest the need for such a distinction. Existing research usually concentrates on total employment (Paredes *et al.*, 2015; Weber, 2012; Weber, 2014) or considers just a few sectors (Brown, 2014; Weinstein, 2014). We

[2] The standard model used to assess U.S. regional trends is the spatial equilibrium model that assumes highly mobile factors of production and profit and utility maximization Glaeser, E. L. and J. D. Gottlieb (2008) *The economics of place-making policies*, National Bureau of Economic Research.. In this case people tradeoff income with site-specific amenities (e.g., weather, landscape, etc.) so that income is not necessarily a measure of well being. In mining boomtowns with socioeconomic, congestion, remoteness, and environmental concerns, high income is to large extent a compensating differential, while during the bust, some of the income decline reflects less of a need for such compensating differentials. In a cross-country international comparison of (say) the natural resources curse, income differences are more meaningful.

[3] We use the December 2003 Office of Management and Budget (OMB) metropolitan area definitions based on the 2000 Census.

make a step further and trace the effects at a more disaggregated level across many sectors.[4] Various parts of regional economy are likely to respond differently to energy sector expansion. Whereas positive effects can be expected in accommodation and food services or construction, traded goods may be crowded out as suggested by the Dutch Disease literature.

The time path of an energy boom is likely to vary over time as new supply chains are established and other complementary sectors are built out, whereas other sectors and activities are crowded out. To capture the dynamic time path of energy boom we separately employ differencing of the dependent and main explanatory variables over 1-, 3-, 6-, and 10-year periods. This allows us to assess the dynamics of a boom in which the multiplier effects and offsetting displacement effects work at a different pace through the supply chains across different industries and county types. The timespan of the study is from 2001 to 2013 for the former three differences and from 1993 to 2013 for the 10-year difference. Extending the analysis to 2013 is important for capturing recent trends in unconventional oil and gas extraction and makes this examination one of the most current in the literature. A potential weakness of this study (and other recent studies) is our inability to comment on longer-run adverse natural resource curse effects as it relates to the recent "shale revolution" because there was no sustained bust period over the 2000-13 period.

Our empirical approach has several advantages. First, differencing over varying time periods removes the unobservable county fixed effects. Second, there is a possibility that the relative profitability of energy development may be time-varying and location-specific. For example, struggling places or places with pro-business political leadership may welcome energy development, which can change over time. Thus, we use IV approach for relative energy employment growth with instruments that reflect (1) historic energy production (under the notion that shale is often located in the Great Plains with a conventional oil and gas production history and these places may have more supporting infrastructure) and (2) by geological conditions that drive the availability of the resource. A more detailed description of the instruments is provided below.

[4]The specific sectors are: agriculture; manufacturing; construction; transportation and warehousing; retail trade; wholesale trade; accommodation and food services; real estate, finance and insurance; information services; professional, scientific and technical services; tradable industries; non-tradable industries; and industries that are 'upstream' to oil and gas extraction. The definition of all sectors, except for tradable, non-tradable and 'upstream' industries, follows standard NAICS2012 industry classification. The description of tradable, non-tradable and 'upstream' industries is in Appendix A.

A third advantage of our approach is that we use actual energy employment using a proprietary data set described below. In our setting, it is energy employment that directly affects the labour market outcomes of interest. Most of the previous literature used some measures of reserves (which is an instrument in our case) or production data, mostly due to limited data availability. Yet, the first-order effects of the energy resource/reserves on a local economy occur indirectly through their impact on local energy employment. If there is little or no related employment, reserves have a much smaller impact on outcomes—e.g., the shale resource has long been under ground, but did not have any tangible effects until development. Oil and gas production data may be a less suitable measure as it fails to capture employment changes prior to production or as production matures. As Kelsey *et al.* (2014) note, well drilling and the building of associated infrastructure such as pipelines accounts for a disproportionately large share of new jobs created within the expanding energy sector. Many jobs, however, are created before production starts. After production fully matures, energy sector employment needs are much smaller.

Equation (1) presents empirical specification estimated in this paper

$$\Delta Y_{ic} = \beta_0 + \beta_1 \Delta EnVar_c + \beta_2 \Delta DSchock_c + \boldsymbol{X\beta} + \theta_t + \varepsilon_c \qquad (1)$$

where $\Delta Y_{ic} = Y_{ict,t-n} - Y_{ict-n,t-2n}$; $\Delta EnVar_c = EnVar_{ct,t-n} - EnVar_{ct-n,t-2n}$ and $\Delta DSchock_c = DSchock_{ct,t-n} - DSchock_{ct-n,t-2n}$; subscript *i* denotes a sector or total employment, *c* refers to a county, *t* is the end of a period and *t-n* is the beginning of a period with *n*=1,3,6,10, which represents the differencing used for each set of models.

The dependent variable $Y_{ict,t-n} - Y_{ict-n,t-2n}$ is the change in total employment growth rates or changes in sector *i* employment growth rates divided by the total county employment in the base period. We divide the sectoral growth rate in each sector by total employment to scale the sector's growth to the total size of the economy, which helps in calculating multipliers because in this case they are scaled to the same benchmark.

We define oil and gas employment (energy employment) as the sum of employment in two industries, NAICS2111 (Oil and Gas Extraction) and NAICS2131 (Support Activities for Mining). The change in energy employment growth, $\Delta EnVar_c$ (or *DiffEnVar* in tables*)* over the four different time spans is the main explanatory variable. We first calculate $EnVar_{ct,t-n}$ as the difference in total oil and gas employment in a county between the end and beginning periods divided by the initial total county employment, producing the contribution of energy to total employment growth. Differencing *EnVar* over 1-, 3-, 6-, and

10-year periods produces *DiffEnVar*. Because both the energy explanatory variable and dependent variable are divided by total employment, the value of β_1 coefficient is interpreted as a multiplier. For example, when modelling total employment growth as the dependent variable, β_1 that equals 1 means that total employment changes by exactly the same amount as energy employment, or there are no net spillovers of energy employment on other sectors on balance. If β_1 is greater (less) than one, there are net positive (negative) spillovers on the other sectors.[5]

One key control variable is the industry mix measure $DSchock_{ct,t-n}$ that reflects demand shocks in all *other* industries in a county.[6] We calculate *DSchock* as follows.

$$DSchock_{ct} = \sum_i S_{cit-n} NG_{it-n,t}\ , \qquad (2)$$

where S_{cit-n} stands for the employment share of industry *i* (*i* ≠ NAICS2111 or NAICS2131) in county *c* in the beginning period and $NG_{it-n,t}$ refers to the national employment growth rate in industry *i* during the period of interest (*n*=1, 3, 6, 10). The industry mix term represents the predicted growth rate of the county if all of its industries (minus oil and gas) are growing at the national growth rate. This variable is typically presumed exogenous to the modelled relationships, as it utilizes initial industry composition of a county and projects county growth based on the *national* growth rates that are not influenced by growth dynamics of a single county. Controlling for aggregate shocks also accounts for factors that may be correlated with new energy development and may bias the coefficients if omitted. The oil and gas sector is omitted from the industry mix calculation so that we can compare the size of the oil and gas variable coefficient to the industry mix coefficient to ascertain whether an energy shock has a different effect compared to an equal-sized typical shock outside of the oil and gas sector. In equation (1), $\Delta DSchock_c$ $(DiffDSchock)$ is measured at 1-year, 3-year, 6-year and 10-year differences depending on the model.

Our models also include controls for initial-period and deep-lags of socioeconomic conditions ***X*** that are widely used in the literature. These include the 1980 natural log of the population to account for historical agglomeration features that may be correlated with energy development and future population growth. We also include educational attainment (share of adult population with at least 4 years of college and share of adult population with only high school diploma or some college in 2000). To account for

[5] See, for example, Marchand, J. (2012). 'Local labor market impacts of energy boom-bust-boom in Western Canada', *Journal of Urban Economics*, vol. **71**(**1**), pp. 165-174. for a comparable approach. Our coefficients are easier to interpret because we do not use logarithmic transformation.

[6] This measure is sometimes called the Bartik (1991) instrument because it is assumed to be exogenous.

industry composition effects that may affect growth, we include 1990 industry employment shares in manufacturing and agriculture, in which lagging to 1990 avoids any endogeneity due to sorting in anticipation of the shale boom. We also control for the 1985 mining employment share because accounting for the historical size of mining as the 1970s-1980s energy boom came to an end captures any historical energy sector agglomerations that may in turn influence the contemporaneous size of the industry. These include mining and energy legacy effects that are related to the presence of energy infrastructure such as pipelines and service companies or a tradition of a more favourable climate for energy development. Finally we include time period dummies, θ_t.[7]

As noted earlier, local energy employment may be related not only to energy endowments, but also to other factors that possibly influence the dependent variables—e.g., environmentally sensitive residents may object to resource extraction due to its negative quality-of-life effects. To avoid potential endogeneity, we follow other studies (Brown, 2014; Weber, 2012; Weber, 2014; Weinstein, 2014) and employ an instrumental variable (IV) approach based on geological measures to complement our first difference approach. Unlike previous studies that typically use only one instrument and estimate just identified models, we try multiple instrument combinations to possibly improve fit beyond the past literature. A key advantage of using several instruments is our ability to assess over-identification assumptions rather than simply assuming they hold.[8] The use of IV can also alleviate potential measurement-error problems in oil and gas employment data.

We use higher-quality employment data compared to what have been used in the past. The past work often uses mining employment (not oil and gas) and typically extrapolates due to numerous observation at a county level suppressed for confidentiality.[9] Yet, the data we use may still have measurement issues. For one, firms and their workers commuting for work to a nearby county could be counted as employment in their place-of-residence county if the firm is based there. Also, a surge in new jobs that lasts a short period of time or happens at the end of a calendar year might affect the validity of an annual employment average.

[7]We also tried the 1990 share in oil and gas employment to capture long-term legacy effects of oil and gas but the results are very similar to the 1985 mining share.

[8] A popular instrument has been whether the county sits on shale deposits (Brown, 2014; Weber 2102), which would mostly be useful for predicting unconventional oil and gas drilling, whereas our measures would also help us identify conventional drilling as well.

[9] Alternative data used in previous work are place-of-residence Census data, which have their own limitations when used to study employment change at a county level.

For this study we develop five instruments related to the geological abundance and historical legacy: (1) shale oil reserves of the county at the beginning of the decade**;** (2) beginning of the decade shale gas reserves in the county; (3) the county's number of square miles with oil and gas wells in the 1980s; (4) following Weber (2012), per cent of the county that covers shale resources; and (5) average depth of the shale in each "shale play" if the county sits above a play, as depth is a proxy for its quality. These instruments are further described in Appendix B. The geological instruments reflect the exogenous geology or predetermined availability of reserves while drilling intensity in the 1980s reflects whether there is a history of *production* in the county (after conditioning on mining employment after the early 1980s bust). That could also suggest conventional reserves that could be coaxed out with modern technology or suggest better shale reserves given the association of shale and conventional reserves. Following the econometric approach employed by Duranton and Turner (2011), we assume that after conditioning on the size of the 1985 mining sector, the geological variables only indirectly affect contemporaneous energy employment growth by affecting the size of the energy sector employment share, which is the definition of a good instrument. Similarly, conditioning on 1980 population would further account for long-term agglomeration effects that might be correlated with current energy development and contemporaneous job growth.

A practical concern stemming from using multiple observations per county is that the geological/historical scale instruments are fixed over time and might appear to provide no more information than simply considering fixed effects or first differences. Yet, that is not true because shale energy technology evolves over time, suggesting that geological reserves are more important in later time periods with improved technology. Likewise, commodity prices are set on national and world markets and are not affected by one U.S. county's production, so year-to-year changes in the price of oil and natural gas also affect value of the resource and whether extraction is profitable. We include a series of instruments with time interactions to account for the time-varying endogeneity. In theory this may overly increase collinearity and reduce the first-stage strength of the instruments. This is not the case in our study as evidenced by the strength of instruments well above 10 in all cases except for metropolitan subsample in 6-year differenced models.

Given the large number of instrument combinations, after a series of diagnostic tests, two combinations of instruments (and their time interactions) were selected based on their strength in the first stage and whether they pass over-identification tests for the total and sectoral employment models. Instrument I (IV I) includes two measures that approximate thickness of oil and gas shale deposits and the oil and gas drilling intensity in the 1980s at the county level. Instrument II (IV II) supplements IV I with measures of recoverable shale oil and recoverable shale gas reserves. Appendix B describes how instrument components are determined. We estimate equation (1) using 2SLS. Thus, the identification strategy relies on first-differences to eliminate county-level fixed effects of various duration and IV using exogenous (or at least deep-lagged predetermined) instruments to account for any time-varying endogeneity, while accounting for industrial shocks and historical measures to capture long-term agglomeration effects that might affect contemporary drilling.

The primary data source is a proprietary dataset acquired from Economic Modelling Specialists Intl. (EMSI) with information on county employment and earnings disaggregated at 4-digit NAICS level. EMSI data have been successfully used in various studies in recent years (Betz *et al.*, 2015; Dorfman *et al.*, 2011; Fallah *et al.*, 2011; Fallah *et al.*, 2014; Nolan *et al.*, 2011). This allows us to measure oil- and gas-extraction employment, as well as other sectors of interest, more precisely (especially in calculating our energy and industry mix terms). By contrast, detailed employment data from secondary government sources are incomplete because of suppression for confidentiality.[10] We supplement the EMSI data with information from the U.S. Census Bureau, U.S. Energy Information Administration and other publicly available sources described below.

The dependent variables, energy measures, industry mix, and employment shares in manufacturing and agriculture are calculated from the EMSI data. All shale-related indicators are from the geospatial files provided by the EIA.[11] The data on 1980s drilling intensity is aggregated from U.S. Geological Survey geospatial files.[12] The U.S. Census Bureau is the data source for population and educational attainment. The 1985 mining share variable is derived from the U.S. Bureau of Economic Analysis data using the methods described in Partridge and Rickman (2006).

Results and discussion

[10]In deriving their data, EMSI uses several government sources such as the Bureau of Economic Analysis REIS data, *County Business Patterns, and Quarterly Census in Employment and Wages.* Dorfman et al., (2010) provide more details of EMSI's process for deriving the employment figures.

[11]http://www.eia.gov/pub/oil_gas/natural_gas/analysis_publications/maps/maps.htm#geodata

[12] http://certmapper.cr.usgs.gov/geoportal/catalog/search/resource/details.page?uuid=%7B985D2AB7-B159-46C2-BD58-99EC3E366C4F%7D

We first separately describe the total employment results in nonmetropolitan and metropolitan counties (Table 1) followed by discussion of selected sectoral results. Table 1 includes the four different lengths for the time differencing and both sets of instruments, where Appendix C has the descriptive statistics. All models include controls for education, initial economic conditions and time periods in addition to the displayed variables.

Table 1. 2SLS estimation results (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	1.261***	1.309***	0.638***	1.208***	3.605***	3.027***	0.239	1.678***
	(0.173)	(0.165)	(0.196)	(0.173)	(0.673)	(0.240)	(0.436)	(0.271)
DiffDSchock	1.518***	1.518***	2.075***	2.042***	1.573***	1.594***	1.712***	1.813***
	(0.059)	(0.059)	(0.195)	(0.193)	(0.153)	(0.144)	(0.108)	(0.101)
Mining85	0.007	0.007	0.157***	0.134***	0.351***	0.366***	0.316	-0.277*
	(0.007)	(0.007)	(0.027)	(0.026)	(0.068)	(0.063)	(0.201)	(0.141)
Durbin P	0.170	0.079	0.000	0.094	0.026	0.000	0.001	0.563
Overid P	0.932	0.918	0.008	0.000	0.006	0.028	0.929	0.000
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.634*	0.699*	0.402	0.742	-7.977	9.466	0.812	0.473
	(0.377)	(0.370)	(0.540)	(0.534)	(26.840)	(19.130)	(1.438)	(1.408)
DiffDSchock	1.149***	1.149***	1.411***	1.386***	2.495***	2.385***	1.976***	1.971***
	(0.060)	(0.060)	(0.217)	(0.217)	(0.273)	(0.234)	(0.168)	(0.168)
Mining85	0.006	0.006	0.144***	0.135***	0.345	0.677*	-0.085	0.0185
	(0.010)	(0.010)	(0.044)	(0.044)	(0.529)	(0.386)	(0.493)	(0.485)
Durbin P	0.672	0.801	0.211	0.551	0.657	0.646	0.672	0.856
Overid P	0.006	0.048	0.037	0.000	0.044	0.060	0.677	0.663
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include 1980 log of population, 1990 employment shares in manufacturing and agriculture, 2000 shares of adult population with at least four years of college and with some college, as well as time period dummies.

Before turning to the results, the Durbin test results at the bottom of the table suggest that the null hypothesis that the energy variable is exogenous can be rejected in four of the eight nonmetro models and it is never rejected in the metro models. Given that energy is such a small share of metropolitan economies, the latter result is not surprising. Though these results suggest we could use OLS, we still report the 2SLS results. We summarize the OLS results in the Sensitivity Analysis section. Using the rule of thumb that the first-stage F-test should be greater than 10, the instruments are quite strong with the exception of the two cases for the six-year first-differences in metropolitan models. The Sargan over-identification test p-values (Sargan, 1958) imply that some of the equations may not be well identified, especially the metropolitan models. This calls for caution in interpreting the results, although the geological nature of the instruments and the unanticipated nature of the shale revolution (and global energy prices), as well as differencing out fixed effects, suggests our empirical approach is sound.[13]

Results for nonmetropolitan areas. We primarily interested in the results for the nonmetro counties because the shale revolution would have the largest *relative* impacts in less-populated counties. The change in the energy employment variable (*DiffEnVar*) is the main explanatory variable. The nonmetropolitan results in columns [1] and [2] of Table 1 suggest that expanding energy sector employment is associated with greater nonmetro total employment, which indicates net positive spillovers to other sectors. For example, the 1.261 coefficient in column [1] suggests that over the course of one year, for every 100 direct jobs created in the oil and gas sector, another 26.1 jobs are indirectly expected elsewhere in the local economy. In some sense, these are consistent with Brown (2014), who hypothesized that thin labour markets in rural areas may have less slack for expanded employment, which would seem to especially apply in the short-run before migration can take hold. The magnitude of the spillovers modestly depends on the instrument used (with IV II producing larger estimates in all models except for 6-year differences), though the results are generally robust to instrument choice (except in the six-year differenced metropolitan results; which we mostly omit from the discussion due to the weak instruments, except when we discuss the Lewbel (2012) instruments below).

The three-year first difference nonmetropolitan results in columns [3] and [4] indicate that an expanding oil and gas sector has about the same multiplier effects as the one-year models (ignoring the relatively small three-year coefficient in column [3]). However, the six-year first difference models suggest the nonmetric energy multiplier is above three, implying significant spillovers that might relate to a lag between initial drilling and construction build-up in infrastructure such as pipelines. Given that migration takes time to respond, nonmetric labour markets may have larger responses because of in-migrants filling labour demand that create additional spillovers. The ten-year multiplier estimates with instrument set IV I suggest (insignificant) crowding out, whereas instrument set II indicates positive spillovers on net with a multiplier of 1.68.

The overall time path of the expanding energy sector effects appears to be the following: modest short-term positive net spillovers in the one to three-year frame, but

[13]It is particularly curious that the metropolitan models appear the most problematic in terms of the over-identification tests as oil and gas employment is a small proportion of total metro employment.

then rising to a large multiplier of 3 in the course of six years (though the multiplier is smaller in sensitivity analysis). Then the multiplier declines with small positive spillovers in the ten-year timeframe. As noted earlier, because the time period does not include a bust, we cannot assess the longer-run aspects over the boom-bust cycle.

To assess whether energy shocks have similar impacts as equally sized shocks across the rest of the economy, we compare the energy (*DiffEnVar*) and industry mix (*DiffDShock*) coefficients. With the exception of the nonmetro six-year first differences, the industry mix coefficient tends to be larger than the energy coefficient, suggesting that in the shorter one- to three-year range and in the longer ten-year first differences, the energy shocks have smaller net-positive spillovers to other local industries compared to the average shocks elsewhere in the economy. This may happen due to the 'shallow' nature of the input-output energy supply chain in nonmetropolitan areas where even with the relatively high wages in the energy sector together with lease and royalty payments to landowners, much of the inputs are imported from elsewhere. Alternatively, the workers may reside outside of the rural communities and commute in, creating income leakages. For the six-year first differences, the pattern is reversed with the energy sector having larger net positive spillovers, suggesting that the short-term construction of infrastructure effects are important, though temporary.

To provide some perspective, the average nonmetropolitan county gained 0.076% net total employment growth from energy-sector expansion between 2001-2013. Using the one-year-difference coefficients in Table 1, this translates into about 6.5 net jobs per year created by the energy boom when evaluated at the median nonmetropolitan county employment of 6,569, equalling 0.1% increase in total annual job growth. Focusing on the nonmetro counties in the top 20% of energy sector expansion as measured in this paper, total employment growth was 0.337% higher as a direct result of energy employment growth, which translates into about 25.9 net jobs created on an annual basis when evaluated at the corresponding median nonmetro county employment of 5,876. For metropolitan counties, the corresponding numbers of jobs created for the average and metropolitan county in the top 20% of energy producing counties is 33.8 and 42.1 net jobs created due to the energy boom (or a respective increase of about 0.1% annual growth in each case). While any job growth would be welcomed, these numbers are relatively small in the context of the current boom phase of the oil and gas commodity cycle; many or most of the newly created jobs could be lost in a bust as during the 1980s. In sum, given that the average representative shock tends to have larger employment effects and likely leads to a more diversified economy, focusing more broadly on other sectors to promote growth seems to be the best way forward for rural communities desiring economic development.

The 1985 mining share variable accounts for long-term historical effects of having the industry in a location. *A priori,* the expected sign is ambiguous. It could have positive contemporaneous effects as the associated infrastructure is already in place, allowing energy development to occur more easily. However, if the associated infrastructure is at least partially in place, then there is less need for construction and support workers. Table 1 shows that the 1985 mining share coefficient is insignificant in the one-year and ten-year difference models, but there is some evidence of a positive effect on total employment growth for the three- and six-year difference models. This can be interpreted as limited evidence of the positive legacy mining effects.

Results for metropolitan counties. In models for metropolitan counties, the oil and gas multiplier is only statistically significant in the one-year difference models (where the highly unstable six-year difference results reflect extremely weak instruments). For instance, the coefficient suggests that over the course of a year, for every 100 jobs created in the energy sector, only about 63 to 70 net jobs are created in total (depending on the model). This actually means that local economy loses about 30 to 37 jobs per every 100 new energy jobs due to crowding out. As noted by Munasib and Rickman (2015), the impact of changes in energy employment is likely to be less pronounced in metropolitan areas due to the sheer size of their economies. In the longer-period models, the energy variable is insignificant, suggesting that net spillovers are not large or even negative. Likewise, comparing the industry mix coefficient to the energy coefficient again confirms the general pattern that equally-sized shocks in the rest of the economy have larger employment spillovers than oil and gas sector shocks, which is indicative of more crowding out or fewer input-output energy supply-chain complementarities.

Results for Population. Table 2 shows the results where we replace employment growth with population growth as the dependent variable. Considering population growth allows us to assess whether the net job creation primarily goes to commuters or original residents of the county or to outsiders such as new migrants (which do not include "fly-ins" who reside elsewhere). If the newly created jobs are filled by migrants, the potential of the local employment growth to improve local opportunities for those who are underemployed or out of the labour force is undermined.[14]

Table 2. 2SLS estimation results (DV is the differenced change in total population between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	-0.288***	-0.229***	0.183***	0.231***	0.507***	0.255***	0.157***	0.199***
	(0.038)	(0.036)	(0.027)	(0.025)	(0.094)	(0.026)	(0.033)	(0.022)
DiffDSchock	0.064***	0.065***	0.250***	0.247***	0.042**	0.051***	0.057***	0.060***
	(0.013)	(0.013)	(0.027)	(0.027)	(0.021)	(0.015)	(0.008)	(0.008)
Mining85	0.006***	0.006***	0.014***	0.012***	0.018*	0.024***	0.003	-0.014
	(0.002)	(0.002)	(0.004)	(0.004)	(0.009)	(0.007)	(0.015)	(0.012)
IV F-stat	65.44	36.57	114.1	72.89	16.01	64.01	54.10	69.19
Durbin P	0.000	0.000	0.053	0.000	0.000	0.000	0.182	0.000
Overid P	0.000	0.000	0.000	0.000	0.911	0.000	0.020	0.001
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.608***	-0.689***	-0.137	-0.107	2.290	0.620	0.096	0.070
	(0.205)	(0.201)	(0.097)	(0.096)	(5.665)	(3.451)	(0.086)	(0.084)
DiffDSchock	0.004	0.004	0.208***	0.206***	0.0951*	0.106**	0.090***	0.089***
	(0.033)	(0.033)	(0.039)	(0.039)	(0.058)	(0.042)	(0.010)	(0.010)
Mining85	0.006	0.006	0.032***	0.031***	0.090	0.058	0.005	0.013
	(0.005)	(0.005)	(0.008)	(0.008)	(0.112)	(0.070)	(0.030)	(0.029)
IV F-stat	26.94	14.02	50.11	25.51	0.197	0.170	39.35	20.52
Durbin P	0.004	0.001	0.090	0.167	0.617	0.871	0.892	0.863
Overid P	0.139	0.625	0.967	0.475	0.843	0.938	0.832	0.131
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Before describing the specific results, we note that the diagnostic statistics are similar to total employment with (for instance) consistently strong instruments except in the six-year metro models. The one-year difference nonmetropolitan results suggest that there is a small net out-migration in response to energy development, perhaps by those who do not desire some of the negative externalities associated with drilling.[15] Over the three, six, and ten year differences, the population "multiplier" starts at about 0.2, peaking at perhaps as high as 0.5 at six years, before falling to just under 0.2 after 10 years (all statistically significant). Nonetheless, these very small population responses compared to the employment responses in Table 1 suggest that most of the new net jobs created in

[14]Population changes have the advantage of being the most accurate measure compared to estimates of net domestic migration or international migration. It is also the most comprehensive measure.

[15]One possible example of such net out-migration (or at least not strong in-migration) is Bradford County, PA, which has been one of the most exposed Marcellus shale play counties in terms of having over 1,000 wells drilled. Yet, between 2006 (before drilling began in earnest) and 2014, Bradford county population declined from 62,345 to 61,784, while U.S. population rose 6.9%. Of course, this suggests that boomtowns like Williston, North Dakota are far outliers, in which Williams County (Williston is the county seat) went from 20,122 to 29,595 between 2006 and 2013 using U.S. Census Bureau data.

nonmetropolitan areas go either to original residents, commuters from nearby counties, or "fly-ins" who might temporarily reside in the county. The lack of sizable population increase as a result of new energy development limits the positive agglomeration effects that could reduce the population outflow during a bust and permanently help in the long run.

Compared to a representative shock in the economy, the population in-flow response to energy shocks is smaller in the one- and three-year periods and slightly larger in the six- and ten-year periods, though both shocks lead to small population responses. This is consistent with a significant decline in migration responses to economic shocks after the year 2000 reported by Partridge *et al.* (2012). It follows that the long-term agglomeration effects hypothesized by Michaels (2011) are much less likely for modern boomtowns.

For metropolitan counties the one-year first difference results suggest about a -0.6 population multiplier in response to energy shocks, consistent with short-term out migration as a result of oil and gas development. The corresponding multipliers in the models with wider differencing span are statistically insignificant. Thus, energy booms are not associated with large metropolitan population expansion. This is expected because a rapidly growing energy sector employs a tiny fraction of the population in a vast majority of metropolitan counties. By contrast, the representative economy-wide shock is associated with modest population net in-migration that is statistically significant for every period except the one-year models.

Results for selected sectors. Table 3 reports 2SLS results for the traded goods sector defined here as agriculture, mining (except NAICS2111 and NAICS2131), and selected manufacturing industries (Appendix A provides more details).

Table 3. 2SLS estimation results (DV is the differenced change in tradable goods sector employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	-0.112	-0.070	-0.253***	-0.130	-0.056	0.102	-1.327***	-0.529***
	(0.120)	(0.113)	(0.097)	(0.087)	(0.277)	(0.104)	(0.212)	(0.117)
DiffDSchock	0.966***	0.967***	0.841***	0.834***	0.461***	0.455***	0.569***	0.624***
	(0.041)	(0.041)	(0.097)	(0.096)	(0.063)	(0.062)	(0.053)	(0.044)
Mining85	0.001	0.001	0.039***	0.034***	0.033	0.028	0.422***	0.094
	(0.005)	(0.005)	(0.013)	(0.013)	(0.028)	(0.027)	(0.098)	(0.061)
Durbin P	0.346	0.536	0.006	0.110	0.923	0.175	0.000	0.000
Overid P	1.000	1.000	0.485	0.080	0.456	0.818	0.635	0.000
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	

Metropolitan areas								
DiffEnVar	-0.255*	-0.246*	0.127	0.139	-3.916	3.791	-0.860*	-0.914**
	(0.153)	(0.150)	(0.217)	(0.215)	(10.410)	(7.965)	(0.449)	(0.441)
DiffDSchock	0.521***	0.521***	0.232***	0.231***	0.553***	0.504***	0.182***	0.181***
	(0.024)	(0.024)	(0.088)	(0.088)	(0.106)	(0.097)	(0.052)	(0.053)
Mining85	-0.001	-0.000	-0.006	-0.007	-0.137	0.010	0.169	0.185
	(0.004)	(0.004)	(0.018)	(0.018)	(0.205)	(0.161)	(0.154)	(0.152)
Durbin P	0.320	0.341	0.441	0.403	0.650	0.548	0.213	0.161
Overid P	0.983	0.982	0.678	0.853	0.378	0.387	0.500	0.840
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Before turning to the results, note that the first-stage F-statistics imply strong instruments (except for the six-year metropolitan sample; which we do not discuss) and the over-identification tests generally indicate well-identified models. Dutch Disease arguments suggest that energy sector growth bids up wages, reducing growth in the traded goods sector as their costs increase. At the same time, local demand from the energy industries could stimulate manufacturing offsetting the negative impact of increased production costs. The oil and gas coefficient is almost always negative in the nonmetro sample. It is significant in three cases including both ten-year models. By contrast, the industry mix coefficient indicates that the average industry shock has a consistent positive and statistically significant effect on employment in tradable goods industries. A similar pattern also emerges in the metropolitan county results with a negative oil and gas coefficient that is significant in the one- and 10-year models, whereas the industry mix term is consistently positive and significant.[16] Especially when compared to larger positive net response to the average shock elsewhere in the economy, the results suggest that oil and gas development crowds out employment in traded goods industries in the longer-run (and in the short-run in metro areas), weakly consistent with the Dutch Disease hypothesis.

Table 4 reports the results for the non-traded goods sector. The diagnostic statistics suggest the nonmetro models are better identified for the one- and ten-year models, whereas the metro models are best identified for the ten-year models.

[16]Appendix Tables 1D and 2D respectively report estimation results for agriculture and manufacturing. They indicate short-term crowding out in manufacturing and longer-term crowding out in agriculture.

Table 4. 2SLS estimation results (DV is the differenced change in non-tradable goods sector employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I	IV II	IV I	IV II	IV I	IV II	IV I	IV II
Non-metropolitan areas								
DiffEnVar	0.373***	0.379***	-0.109	0.337**	2.661***	1.925***	1.547***	1.538***
	(0.122)	(0.116)	(0.166)	(0.147)	(0.621)	(0.217)	(0.349)	(0.227)
DiffDSchock	0.551***	0.551***	1.234***	1.209***	1.112***	1.138***	1.060***	1.060***
	(0.042)	(0.042)	(0.165)	(0.164)	(0.141)	(0.130)	(0.087)	(0.084)
Mining85	0.006	0.006	0.117***	0.099***	0.318***	0.338***	-0.189	-0.186
	(0.005)	(0.005)	(0.023)	(0.022)	(0.063)	(0.057)	(0.161)	(0.118)
Durbin P	0.004	0.002	0.000	0.303	0.013	0.001	0.080	0.006
Overid P	0.311	0.127	0.003	0.000	0.001	0.003	0.641	0.457
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.110	-0.055	-0.724	-0.397	-5.060	4.675	1.899	1.752
	(0.345)	(0.338)	(0.484)	(0.478)	(21.940)	(15.810)	(1.233)	(1.206)
DiffDSchock	0.628***	0.627***	1.179***	1.155***	1.942***	1.881***	1.617***	1.615***
	(0.055)	(0.055)	(0.195)	(0.194)	(0.223)	(0.193)	(0.144)	(0.144)
Mining85	0.007	0.007	0.151***	0.141***	0.482	0.667**	-0.244	-0.200
	(0.009)	(0.009)	(0.040)	(0.039)	(0.432)	(0.319)	(0.423)	(0.415)
Durbin P	0.981	0.885	0.081	0.296	0.765	0.801	0.170	0.202
Overid P	0.004	0.062	0.073	0.000	0.0413	0.098	0.864	0.920
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

The results for nonmetropolitan counties indicate that oil and gas have a statistically significant stimulating effect (except for one three-year differenced model) on non-traded goods employment. This positive response to energy sector growth is smaller than the average industry mix effect in the one- and three-year models, but it exceeds the average effect in the six- and ten-year models, revealing, most likely, favourable supply chains and induced spending effects take time to develop in energy booms. Thus, unlike the traded goods sector, oil and gas development in nonmetro areas has longer-term positive effects on non-traded goods employment. For metropolitan counties, the models show no impact on non-traded goods employment from the expansion in the oil and gas industry, although in the MSAs that are ‘outliers,’ like Houston and Tulsa, outsized stimulating effects on non-traded employment are likely present. In contrast, the average shock from other industries outside energy consistently boosts non-traded goods employment.

Construction is arguably the non-traded sector that benefits the most from oil and gas development. Table 5 reports the corresponding results for this industry. The nonmetro results suggest a consistent positive response to energy sector growth that exceeds that of the average industry shock, with the exception of the three-year models. The relative magnitude of the effects in Tables 4 and 5 seem to indicate that the positive effect of energy sector growth on non-traded goods sector is mostly through construction. The metro results follow a similar pattern in the one- and ten-year models, though there is no statistically significant pattern in the other periods.

Table 5. 2SLS estimation results (DV is the differenced change in construction employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I	IV II	IV I	IV II	IV I	IV II	IV I	IV II
Non-metropolitan areas								
DiffEnVar	0.289***	0.274***	0.097	0.178***	0.852***	0.494***	0.358***	0.420***
	(0.048)	(0.046)	(0.064)	(0.057)	(0.245)	(0.085)	(0.100)	(0.065)
DiffDSchock	0.094***	0.094***	0.486***	0.481***	0.529***	0.542***	0.290***	0.295***
	(0.016)	(0.016)	(0.064)	(0.064)	(0.055)	(0.051)	(0.025)	(0.024)
Mining85	0.004*	0.004*	0.042***	0.039***	0.119***	0.129***	-0.029	-0.054
	(0.002)	(0.002)	(0.009)	(0.009)	(0.025)	(0.023)	(0.046)	(0.034)
Durbin P	0.000	0.000	0.314	0.702	0.027	0.078	0.346	0.011
Overid P	0.002	0.014	0.059	0.030	0.081	0.097	0.491	0.717
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.428***	0.430***	-0.008	0.081	-2.170	0.332	0.567**	0.575**
	(0.160)	(0.156)	(0.174)	(0.172)	(7.007)	(4.492)	(0.277)	(0.271)
DiffDSchock	0.124***	0.124***	0.595***	0.589***	0.703***	0.687***	0.399***	0.399***
	(0.026)	(0.026)	(0.070)	(0.070)	(0.071)	(0.055)	(0.032)	(0.032)
Mining85	0.000	0.001	0.046***	0.043***	0.134	0.182**	-0.071	-0.073
	(0.004)	(0.004)	(0.014)	(0.014)	(0.138)	(0.091)	(0.095)	(0.093)
Durbin P	0.002	0.001	0.188	0.432	0.684	0.981	0.041	0.034
Overid P	0.052	0.532	0.138	0.004	0.000	0.000	0.879	0.899
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Appendix Tables 3D through 10D report the results for non-traded goods sector by industry. Focusing on some noteworthy results, Appendix Table 3D shows that transportation and warehousing in nonmetro counties consistently enjoys positive employment spillovers from energy sector growth. The large needs for transporting products to well sites, especially water used for shale development likely explain this positive relationship. The retail and wholesale trade industries (Tables 4D and 5D) in rural areas enjoy positive spillovers with a delay of 3 to 6 years, consistent with a lagged agglomeration effect. Given that many of the oil and gas workers live in temporary housing and are likely eat out regularly, it is unsurprising that accommodation and food employment, as well as real estate, are particularly stimulated in nonmetropolitan areas by energy sector development (Tables 6D and 7D).

Table 6 focuses directly on the upstream industries that most intensively supply the oil and gas industry, following the classification described in the Appendix (see Appendix Table 2A). With the exception of the ten-year nonmetro models, the response to oil and gas shocks is statistically insignificant and less than the corresponding size from the average shock (which is consistently statistically significant). Oil and gas development appears to be ineffective at stimulating local employment in supply-chain industries even compared to the average industry. Even at ten years, the energy multiplier for upstream industries only ranges from 0.135 to 0.218, or for every 100 jobs created in the local energy industry, only about 13.5 to 21.8 jobs are expected to be created in upstream supply industries during this period. It may suggest that upstream oil and gas industry suppliers often locate outside of local area.

Table 6. 2SLS estimation results (DV is the differenced change in upstream to energy sector employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I	IV II	IV I	IV II	IV I	IV II	IV I	IV II
Non-metropolitan areas								
DiffEnVar	-0.043	-0.038	-0.017	0.005	0.086	0.024	0.218**	0.135**
	(0.036)	(0.034)	(0.052)	(0.047)	(0.177)	(0.066)	(0.085)	(0.055)
DiffDSchock	0.137***	0.137***	0.209***	0.208***	0.130***	0.132***	0.210***	0.205***
	(0.012)	(0.012)	(0.052)	(0.052)	(0.040)	(0.040)	(0.021)	(0.020)
Mining85	0.001	0.001	0.011	0.010	0.025	0.026	-0.051	-0.017
	(0.002)	(0.002)	(0.007)	(0.007)	(0.018)	(0.017)	(0.039)	(0.029)
Durbin P	0.893	0.758	0.658	0.999	0.880	0.570	0.055	0.149
Overid P	0.169	0.764	0.943	0.966	0.419	0.769	0.967	0.617
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.137	0.124	0.103	0.143	-4.104	-1.723	0.073	0.055
	(0.111)	(0.109)	(0.143)	(0.142)	(7.926)	(4.251)	(0.218)	(0.214)
DiffDSchock	0.112***	0.112***	0.137**	0.135**	0.192**	0.177***	0.359***	0.359***
	(0.018)	(0.018)	(0.058)	(0.058)	(0.081)	(0.052)	(0.026)	(0.026)
Mining85	0.000	0.000	0.017	0.015	-0.017	0.028	-0.001	0.005
	(0.003)	(0.003)	(0.012)	(0.012)	(0.156)	(0.086)	(0.075)	(0.074)
Durbin P	0.368	0.424	0.539	0.358	0.449	0.705	0.683	0.742
Overid P	0.867	0.999	0.537	0.42	0.170	0.208	0.149	0.514
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Sensitivity Analysis

To assess the robustness of our results to changes in model specification, we perform a series of sensitivity analyses that are based on a different modelling approach and variations in the sample. Because most of the Durbin p-values for endogeneity are insignificant in Table 1, perhaps the most natural starting point for any robustness check is using OLS. Table 7 presents the OLS results for total employment. In nonmetro areas, the magnitude of the effects follows the same pattern as the one reported in Table 1 (continuous increase between one and six years followed by decrease in the 10-year analysis). Likewise, the average shock generally has a larger estimated multiplier than the one for the energy sector. One result that stands out is that the six-year OLS energy multiplier is 2.22, which is considerably less than the IV estimate.

For metropolitan counties, unlike the IV results, the *DiffEnVar* coefficient is always statistically significant. It reveals crowding out in the one-year and ten-year samples and positive net spillovers in the three- and six-year models. Given the fact that there is no statistical evidence of endogeneity in the metro models (Durbin p value in Table 1 is universally greater than 0.05), these OLS results may have more validity.

Table 7. OLS results for full models (DV is the differenced change in total energy employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	Non-metro	Metro	Non-metro	Metro	Non-metro	Metro	Non-metro	Metro
DiffEnVar	1.031*** [0.079]	0.790*** [0.194]	1.045*** [.187]	1.478*** [.137]	2.223*** [0.194]	1.779*** [0.506]	1.531*** [0.215]	0.227 [0.832]
DiffDSchock	1.515*** [0.259]	1.148*** [0.099]	1.365*** [0.394]	2.027*** [.251]	1.622*** [0.165]	2.434*** [0.333]	1.802*** [0.119]	1.967*** [0.253]
Mining85	0.008** [0.003]	0.006 [0.004]	0.126** [.046]	0.123*** [0.027]	0.388*** [0.077]	0.531** [0.170]	-0.216^ [0.126]	0.094 [0.438]
R2	0.087	0.176	0.305	0.510	0.349	0.247	0.329	0.317
F	142.17	176.56	157.23	211.74	29.25	24.82	74.89	70.91
Clusters	1,987	1,041	1,987	1,041	1987	1,041	1,987	1,041
Observations	21,846	11,451	5,961	3,123	1,987	1,041	1,987	1,041

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

We then consider the GMM instrumental variable estimation proposed by Lewbel (2012) using Stata's IVREG2H procedure. Intuitively in Lewbel's method, unobserved heterogeneity is reflected in heteroskedasticity of the error terms. This heteroskedasticity is used to form alternative instruments (Carmignani, 2014). When using these constructed instruments in combination with the instruments used in this study, the results follow the same basic patterns as before, though the estimates produced by combined IV I and IV II are more similar (results not shown for brevity). The Lewbel nonmetro energy multipliers tend to be a little smaller and the metro multipliers tend to be a little larger than for the reported results (their significance is typically improved as well) with the instruments also being stronger than before. Yet, one difference is in the six-year difference models in which the nonmetro multipliers are just over 2.2 and the metro energy multipliers are just over 1.8 (consistent with the OLS results). Thus, while these results support the robustness of the IV results (including finding that the average economy-wide multiplier exceeds the energy multiplier), they also tend to suggest the OLS six-year results are more credible.

As the next step we examine a more parsimonious model in which we omit all of the variables except the energy, industry mix, mining share in 1985, and the time period dummies (see Appendix Table 1E). These results are quite similar to the base IV results in Table 1. Next, to test for a nonlinearity in oil and gas multiplier (perhaps either due to agglomeration or crowding out effects), we added *DiffEnVar* squared to the base IV model (see Table 2E in the Appendix). There is a weak evidence of nonlinearity in only a few cases but overall it seems that linear approximation is appropriate, thus we do not consider this model further. As a final sensitivity test, we take the base IV model and omit the 1985 mining share and industry mix variable one by one to see if it affects the results. Like in the previous case, estimates stay very close to the ones reported in Table 1 (Tables 3E and 4E).

Finally, we estimate the model using subsamples that exclude some of the most 'powerful' observations and outliers in terms of oil and gas endowment and production. For the nonmetro sample, we first exclude all counties that are above the Bakken play. These results are displayed in Table 8; they indicate that dropping the Bakken modestly reduces the magnitude of the multipliers estimated by IV II in 3-year and 10-year analysis. Otherwise, the results reported in Table 1 are robust.[17] Dropping large energy centres (Dallas, Houston, Oklahoma City and Tulsa) from the metro sample appreciably changes the energy coefficient in only one case, in which there is a negative relationship between energy sector expansion and total employment using IV I in the 3-year analysis.

Table 7. 2SLS estimation results for alternative samples (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas, no Bakken								
DiffEnVar	1.190***	1.287***	0.490**	0.817***	3.333***	2.614***	0.001	0.672*
	(0.186)	(0.179)	(0.196)	(0.182)	(0.717)	(0.351)	(0.444)	(0.375)
DiffDSchock	1.516***	1.517***	2.025***	2.015***	1.529***	1.529***	1.717***	1.765***
	(0.0591)	(0.059)	(0.191)	(0.190)	(0.145)	(0.140)	(0.104)	(0.102)
Mining85	0.007	0.007	0.142***	0.131***	0.357***	0.352***	0.293	0.046
	(0.007)	(0.007)	(0.026)	(0.026)	(0.063)	(0.061)	(0.185)	(0.162)
Durbin P	0.351	0.124	0.000	0.024	0.0269	0.018	0.060	0.734
Overid P	0.958	0.976	0.004	0.000	0.011	0.033	0.803	0.013
IV F-stat	68.64	37.5	136.9	79.79	25.99	55.07	89.72	64.18
# Obs	21,329		5,820		1,939		1,939	
Metropolitan areas, no Dallas, Houston, Oklahoma City and Tulsa								
DiffEnVar	0.654*	0.745*	-0.956*	-0.325	31.57	32.75	1.183	0.987
	(0.396)	(0.383)	(0.556)	(0.538)	(19.71)	(20.17)	(1.636)	(1.625)
DiffDSchock	1.132***	1.132***	1.390***	1.348***	2.218***	2.209***	1.970***	1.968***
	(0.061)	(0.061)	(0.223)	(0.220)	(0.415)	(0.428)	(0.169)	(0.169)

[17] We also estimated the relationship of interest for nonmetropolitan counties that lie above Bakken, Eagle Ford and Barnett shale plays only. The strength of the instruments in all these models is below 10, so we do not report the results here.

Mining85	0.004	0.004	0.181***	0.161***	0.900***	0.913***	-0.184	-0.130
	(0.011)	(0.011)	(0.048)	(0.048)	(0.340)	(0.349)	(0.517)	(0.514)
Durbin P	0.791	0.975	0.000	0.0107	0.001	0.001	0.636	0.725
Overid P	0.075	0.225	0.03	0.000	0.493	0.726	0.694	0.705
IV F-stat	27.02	14.52	58.416	30.76	1.461	0.739	31.51	15.93
# Obs	11,055		3,015		1,005		1,005	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Conclusions

As observed by others (Munasib and Rickman, 2015; Weber, 2012) impacts of the energy sector on various economic performance metrics is uneven across space, time, and industrial landscape. Our analysis finds considerable heterogeneity in energy sector effects on employment in metropolitan and nonmetropolitan U.S. counties between 1993-2013. The responses also vary across the different time horizons we consider. Even instrument choice can sometimes affect the size of the coefficients.

Estimation results suggest that in nonmetropolitan areas, the energy-sector multiplier on total county employment growth first increases and peaks at six years decreasing afterwards. Only at six years is the typical multiplier response to oil and gas shocks larger than the corresponding response to the average economy-wide shock. Positive energy-sector spillovers to other industries are most pronounced in construction, transportation and warehousing, wholesale trade, accommodation and food, real estate, and nontradable goods. There appears to be some crowding out of traded goods sectors by oil and gas booms, consistent with the Dutch Disease hypothesis. Indeed, even in industries that are close upstream suppliers of the energy sector, oil and gas expansion does not appear to statistically stimulate employment gains until about ten years, and even then, it is no larger than what an equally-sized shock in the average industry would do. Hence, small populations in nonmetropolitan areas do not have the size or scale to support oil and gas supply-chain activities, or alternatively, because these industries have long established themselves in the oil patch, there is less need to create new firms elsewhere.

For metropolitan areas, 1-year differencing analysis suggests crowding out, as an average MSA county lost about 0.3 jobs outside of the energy sector for each additional energy job. This effect is not observable in the differences spanning longer periods. At disaggregated level, only a few sectors respond to changes in oil and gas extraction in metropolitan sample. In the short-run manufacturing declines; while employment in transportation and warehousing together with wholesale trade increase. Some sectors exhibit changing patterns with wider differencing timespans, while traded goods sector and oil and gas supply chain employment are generally insensitive to energy sector growth.

Overall, our results point to the importance of a number of factors, such as the sample, choice of instruments, industries of interest and time frame, that should be explicitly acknowledged in the discussion of energy sector impacts. Arguably, the accumulated evidence to a considerable extent depends on these factors. This makes generalizations of the existing findings in the literature problematic and may explain why extant research comes to conflicting conclusions. For policymakers this points to the need to exercise caution when designing policies. Yet, we can be confident that the local employment spillovers from oil and gas development tend to be more modest than equal-sized shocks from other industries (on average), suggesting less complementarities in the economy. Population responses to both types of shocks are both small, suggesting limitations in the role of agglomeration economies supporting long-term growth in modern booms. Overall, given that energy booms are relatively small in magnitude relative to the rest of the economy, local economies would appear to be better off when they experience broad-based growth rather than energy booms both in terms of multiplier effects and in terms of enhancing the diversity of their economies (with less risk for a possible natural resources curse). Policymakers who look at oil and gas development as a silver bullet for their economic development woes should probably consider other sectors, which on average have larger local employment effects.

References

Alexeev, M. and R. Conrad (2009). 'The elusive curse of oil', *Review of Economics and Statistics*, vol. **91**(**3**), pp. 586-598.

Allcott, H. and D. Keniston (2014) *Dutch Disease or agglomeration? The local economic effects of natural resource booms in modern America*. Available at http://www.nber.org/papers/w20508.

Betz, M., M. Farren, L. Lobao and M. Partridge (2015). 'Coal mining, economic development, and the natural resource curse', *Energy Economics*, vol. **50**, pp. 105-116.

Bhattacharyya, S. and R. Hodler (2010). 'Natural resources, democracy and corruption', *European Economic Review*, vol. **54**(**4**), pp. 608-621.

Bjorvatn, K., M. R. Farzanegan and F. Schneider (2012). 'Resource curse and power balance: Evidence from oil-rich countries', *World Development*, vol. **40**(**7**), pp. 308–1316.

Black, D., T. McKinnish and S. Sanders (2005). 'The economic impact of the coal boom and bust', *The Economic Journal*, vol. **115**(**503**), pp. 449-476.

Blanco, L. and R. Grier (2012). 'Natural resource dependence and the accumulation of physical and human capital in Latin America', *Resources Policy*, vol. **37**(**281-295**).

Boxall, P., W. Chan and M. McMillan (2005). 'The impact of oil and natural gas facilities on rural residential property values: A spatial hedonic analysis', *Resource and Energy Economics*, vol. **27**, pp. 248-269.

Boyce, J. R. and J. C. Herbert Emery (2011). 'Is a negative correlation between resource abundance and growth sufficient evidence that there is a "resource curse"?', *Resources Policy*, vol. **36**(**1**), pp. 1-13.

Brown, J. (2014). 'Production of natural gas from shale in local economies: a resource blessing or curse?', *Economic Review*(**Q I**), pp. 1-29.

Carmignani, F. (2014) *The spatial curse of natural resources*, Griffith University, Department of Accounting, Finance and Economics.

Cavalcanti, T. V. d. V., K. Mohaddes and M. Raissi (2011). 'Growth, development and natural resources: New evidence using a heterogeneous panel analysis', *The Quarterly Review of Economics and Finance*, vol. **51**, pp. 305-318.

Dorfman, J. H., M. D. Partridge and H. Galloway (2011). 'Do natural amenities attract high-tech jobs? Evidence from a smoothed Bayesian Spatial Model', *Spatial Economic Analysis*, vol. **6**(**4**), pp. 397-422.

Duranton, G. and M. A. Turner (2011). 'The fundamental law of road congestion: Evidence from US cities', *American Economic Review*, vol. **101**(**6**), pp. 2616-2652.

Fallah, B., M. Partridge and M. R. Olfert (2011). 'New economic geography and US metropolitan wage inequality', *Journal of Economic Geography*, vol. **11**(**5**), pp. 865-895.

Fallah, B., M. Partridge and D. S. Rickman (2014). 'Geography and high-tech employment growth in US counties', *Journal of Economic Geography*, vol. **14**(**4**), pp. 683-720.

Fleming, D. A. and T. G. Measham (2014). 'Local job multipliers of mining', *Resources Policy*, vol. **41**(**C**), pp. 9-15.

Freeman, D. G. (2009). 'The 'Resource Curse' and regional US development', *Applied Economics Letters*, vol. **16**(**5**), pp. 527-530.

Glaeser, E. L. and J. D. Gottlieb (2008) *The economics of place-making policies*, National Bureau of Economic Research.

Gylfason, T. (2000). 'Resources, agriculture, and economic growth in economies in transition', *Kyklos*, vol. **53**(**4**), pp. 337-361.

Gylfason, T. (2001). 'Natural resources, education, and economic eevelopment', *European Economic Review*, vol. **45**(**4-6**), pp. 847-849.

Gylfason, T., T. T. Herbertsson and G. Zoega (1999). 'A mixed blessing: Natural resources and economic growth', *Macroeconomic Dynamics*, vol. **3**(**02**), pp. 204-225.

Gylfason, T. and G. Zoega (2014) *The Dutch Disease in reverse: Iceland's natural experiment*, Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford. Available at http://EconPapers.repec.org/RePEc:oxf:oxcrwp:138.

Haggerty, J., P. H. Gude, M. Delorey and R. Rasker (2014). 'Long-term effects of income specialization in oil and gas extraction: The U.S. West, 1980–2011', *Energy Economics*, vol. **45**(**0**), pp. 186-195.

Holmes, T. and J. Stevens (2014). 'An alternative theory of the plant size distribution, with geography and intra- and international trade', *Journal of Political Economy*, vol. **122**(**2**), pp. 369-421.

Jacobsen, G. and D. Parker (2014). 'The economic aftermath of resource booms: Evidence from boomtowns in the American West', *The Economic Journal*.

James, A. and D. Aadland (2011). 'The curse of natural resources: An empirical investigation of U.S. counties', *Resource and Energy Economics*, vol. **33**(**2**), pp. 440-453.

James, A. and R. G. James (2011). 'Do resource dependent regions grow slower than they should?', *Economics Letters*, vol. **111**(**3**), pp. 194-196.

Kelsey, T., M. Partridge and N. White (2014) *Unconventional Gas and Oil Development in the United States: Economic Experience and Policy Issues*, University Library of Munich, Germany. Available at http://EconPapers.repec.org/RePEc:pra:mprapa:62154.

Kinnaman, T. (2011). 'The economic impact of shale gas extraction: A review of existing studies', *Ecological Economics*, vol. **70**(**7**), pp. 1243-1249.

Lewbel, A. (2012). 'Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models', *Journal of Business & Economic Statistics*, vol. **30**(**1**), pp. 67-80.

Manzano, O. and R. Rigobon (2001). 'Resource curse or debt overhang?', *National Bureau of Economic Research Working Paper Series*, vol. **No. 8390**.

Marchand, J. (2012). 'Local labor market impacts of energy boom-bust-boom in Western Canada', *Journal of Urban Economics*, vol. **71**(**1**), pp. 165-174.

Michaels, G. (2011). 'The long term consequences of resource‐based specialisation', *Economic Journal*, vol. **121**(**551**), pp. 31-57.

Munasib, A. and D. Rickman (2015). 'Regional economic impacts of the shale gas and tight oil boom: A synthetic control analysis', *Regional Science and Urban Economics*, vol. **50**(**1**), pp. 1-17.

Murshed, S. M. and L. A. Serino (2011). 'The pattern of specialization and economic growth: The resource curse hypothesis revisited', *Structural Change and Economic Dynamics*, vol. **22**(**2**), pp. 151-161.

Nolan, C., E. Morrison, I. Kumar, H. Galloway and S. Cordes (2011). 'Linking industry and occupation clusters in regional economic development', *Economic Development Quarterly*, vol. **25**(**1**), pp. 26-35.

Papyrakis, E. and R. Gerlagh (2007). 'Resource abundance and economic growth in the United States', *European Economic Review*, vol. **51**(**4**), pp. 1011-1039.

Paredes, D., T. Komarek and S. Loveridge (2015). 'Income and employment effects of shale gas extraction windfalls: Evidence from the Marcellus region', *Energy Economics*, vol. **47**(**0**), pp. 112-120.

Partridge, M. and D. Rickman (2006). 'An SVAR model of fluctuations in U.S. migration flows and state labor market dynamics', *Southern Economic Journal*, vol. **72**(**4**).

Partridge, M., D. S. Rickman, M. R. Olfert and K. Ali (2012). 'Dwindling US internal migration: Evidence of spatial equilibrium or structural shifts in local labor markets?', *Regional Science and Urban Economics*, vol. **42**(**1**), pp. 375-388.
Peach, J. and M. Starbuck (2011). 'Oil and gas production and economic growth in New Mexico', *Journal of Economic Issues*, vol. **XLV**(**2**), pp. 511-526.
Sachs, J. and A. Warner (1999). 'The big push, natural resource booms and growth', *Journal of Development Economics*, vol. **59**(**1**), pp. 43–76.
Sachs, J. and A. Warner (2001). 'The curse of natural resources', *European Economic Review*, vol. **45**, pp. 827-838.
Sala-I-Martin, X., G. Doppelhofer and R. I. Miller (2004). 'Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach', *American Economic Review*, vol. **94**(**4**), pp. 813-835.
Sala-i-Martin, X. and A. Subramanian (2013). 'Addressing the natural resource curse: An illustration from Nigeria', *Journal of African Economies, Centre for the Study of African Economies (CSAE)*, vol. **22**(**4**), pp. 570-615.
Sargan, J. D. (1958). 'The estimation of economic relationships using instrumental variables', *Econometrica: Journal of the Econometric Society*, pp. 393-415.
Sovacool, B. (2014). 'Cornucopia or curse? Reviewing the costs and benefits of shale gas hydraulic fracturing (fracking)', *Renewable and Sustainable Energy Reviews*, vol. **37**, pp. 249-264.
Weber, J. G. (2012). 'The effects of a natural gas boom on employment and income in Colorado, Texas, and Wyoming', *Energy Economics*, vol. **34**(**5**), pp. 1580-1588.
Weber, J. G. (2014). 'A decade of natural gas development: The makings of a resource curse?', *Resource and Energy Economics*, vol. **37**(**0**), pp. 168-183.
Weinstein, A. (2014). 'Local labor market restructuring in the shale boom', *The Journal of Regional Analysis and Policy*, vol. **44**(**1**), pp. 71-92.

Appendix A

Tradable industries include agriculture, mining (except NAICS2111 and NAICS2131), and some manufacturing industries. ***Non-tradable industries*** include construction, retail, services, FIRE, government, transport and some manufacturing industries. In order to divide manufacturing into tradable and non-tradable segments, we follow Allcott and Keniston (2014) who define non-traded manufacturing industries if their products sell within approximately 500 miles of the manufacturing facility. This distinction is based on the paper by Holmes and Stevens (2014); industries with distance adjustment elasticity above 0.8 are considered tradable, whereas industries with smaller distance adjustment elasticity are non-tradable. Holmes and Stevens use 6-digit NAICS codes in their analysis. Since our data is at 4-digit NAICS level, we calculate shares of tradable and non-tradable 6-digit NAICS industries in corresponding 4-digit NAICS industries using 2000 County Business Patterns tables from the U.S. Census Bureau. We use these shares to divide manufacturing employment into tradable and non-tradable. Table 1A displays the shares.

Table 1A. Tradable and non-tradable manufacturing industries

NAICS	Tradable	Non-tradable	NAICS	Tradable	Non-tradable
3111	0.000	1.000	3311	1.000	0.000
3112	0.453	0.547	3312	0.638	0.362
3113	0.917	0.083	3313	0.625	0.375
3114	0.899	0.101	3314	0.971	0.029
3115	0.419	0.581	3315	1.000	0.000
3116	0.000	1.000	3321	0.318	0.682
3117	1.000	0.000	3322	1.000	0.000
3118	0.173	0.827	3323	0.000	1.000
3119	0.501	0.499	3324	0.256	0.744
3121	0.219	0.781	3325	1.000	0.000
3122	0.857	0.143	3326	1.000	0.000
3131	1.000	0.000	3327	0.300	0.700
3132	1.000	0.000	3328	0.000	1.000
3133	1.000	0.000	3329	1.000	0.000
3141	1.000	0.000	3331	1.000	0.000
3149	1.000	0.000	3332	1.000	0.000
3151	1.000	0.000	3333	1.000	0.000
3152	0.900	0.100	3334	1.000	0.000
3159	1.000	0.000	3335	1.000	0.000
3161	1.000	0.000	3336	1.000	0.000
3162	1.000	0.000	3339	1.000	0.000
3169	1.000	0.000	3341	1.000	0.000
3211	0.000	1.000	3342	1.000	0.000
3212	0.201	0.799	3343	1.000	0.000
3219	0.127	0.873	3344	1.000	0.000
3221	0.634	0.366	3345	1.000	0.000
3222	0.274	0.726	3346	0.926	0.074
3231	0.292	0.708	3351	1.000	0.000
3241	0.000	1.000	3352	1.000	0.000
3251	0.881	0.119	3353	1.000	0.000
3252	1.000	0.000	3359	1.000	0.000
3253	0.402	0.598	3361	1.000	0.000
3254	1.000	0.000	3362	0.500	0.500
3255	0.304	0.696	3363	1.000	0.000
3256	1.000	0.000	3364	1.000	0.000
3259	0.567	0.433	3365	1.000	0.000
3261	0.736	0.264	3366	1.000	0.000
3262	0.957	0.043	3369	1.000	0.000
3271	0.782	0.218	3371	0.478	0.522
3272	0.381	0.619	3372	1.000	0.000
3273	0.000	1.000	3379	0.000	1.000
3274	0.000	1.000	3391	1.000	0.000
3279	0.242	0.758	3399	0.983	0.017

Upstream industries (Table 2A) sell at least 1% of their output value to Oil and Gas Extraction and Drilling Oil and Gas Wells industries as defined in BEA 2007 Input-Output purchaser value tables.

Table 2A. Upstream industries and their NAICS codes

Industry	NAICS
Nonresidential maintenance and repair	2362
Petroleum and Coal Products Manufacturing	3241

Basic Chemical Manufacturing	3251
All other chemical product and preparation manufacturing	3259
Cement manufacturing	3273
Ground or treated mineral and earth manufacturing	3279
Steel product manufacturing from purchased steel	3312
Valve and fittings other than plumbing	3329
Mining and oil and gas field machinery manufacturing	3331
Cutting and machine tool accessory, rolling mill, and other metalworking machinery manufacturing	3335
Other General Purpose Machinery Manufacturing	3339
Watch, clock, and other measuring and controlling device manufacturing	3345
Pipeline transportation	4860
Depository Credit Intermediation	5221
Nondepository Credit Intermediation	5222
Activities Related to Credit Intermediation	5223
Securities and Commodity Contracts Intermediation and Brokerage	5231
Securities and Commodity Exchanges	5232
Other Financial Investment Activities	5239
Lessors of Real Estate	5311
Offices of Real Estate Agents and Brokers	5312
Activities Related to Real Estate	5313
Management of companies and enterprises	5412

Appendix B

Four measures approximating energy endowment and past energy extraction intensity in a county are used to instrument for the change in energy employment at a county level.

1. Thickness of shale play measure (*Thickness*) is the thickness of shale deposit multiplied by the county's area that lies above that deposit standardized by the sum of such county measures across nation.
2. Recoverable shale oil measure (*Oil*) is the projected recoverable shale oil in a play multiplied by the percentage of that play that is under a county standardized by national projected recoverable shale oil deposits.
3. Recoverable shale gas measure (*Gas*) is identically calculated for shale gas instead of shale oil.
4. Miles under wells measure (*Miles*) is the total number of square miles in a county that had at least one oil or gas well in the 1980s divided by the total number of such miles nationally.

Both IV I and IV II also include all independent variables used in the estimation models, including interactions of the instruments with time dummies.

Appendix C

Table 1C. Descriptive statistics for dependent and explanatory variables

	1-year differences				10-year differences			
Variable	**Mean**	**St.Dev.**	**Min**	**Max**	**Mean**	**St.Dev.**	**Min**	**Max**
Dependent variables								
TotEmp Growth	0.15	4.40	-74.55	309.09	1.03	27.43	-71.01	467.47
Trade Growth	-0.18	2.45	-74.27	291.09	-5.09	8.43	-60.26	183.15
NTrade Growth	0.28	3.36	-48.08	157.29	3.02	20.66	-52.81	252.01
Upstr Growth	-0.01	0.92	-16.78	51.64	-0.25	3.58	-15.57	101.14
Agri Growth	0.02	2.00	-70.23	270.05	-2.72	7.22	-60.15	181.87
Manuf Growth	-0.28	1.59	-24.66	32.84	-1.71	5.05	-34.56	55.80
Constr Growth	-0.03	1.25	-49.35	51.18	0.51	4.10	-18.08	107.89
WSale Growth	0.02	0.52	-19.39	18.51	0.07	1.51	-12.22	31.27
Retail Growth	-0.04	0.71	-26.74	12.67	-0.15	3.49	-14.77	40.25
TrWh Growth	0.03	0.69	-18.44	35.52	0.02	2.94	-20.19	152.10
Info Growth	-0.03	0.28	-13.17	6.19	-0.07	0.88	-13.77	15.92
FinIn Growth	0.00	0.38	-9.82	35.90	-0.02	1.69	-7.83	54.50
ReEst Growth	0.00	0.20	-6.16	6.81	-0.27	2.07	-16.37	35.58
ProfS Growth	0.04	0.71	-18.18	70.61	0.22	2.00	-18.29	40.72
Acc&F Growth	0.07	0.70	-17.28	16.47	0.87	3.47	-36.29	208.40
Explanatory variables								
Energy Growth	0.06	0.67	-15.96	23.99	0.18	2.59	-23.53	93.35
DSchock	0.11	1.60	-13.31	8.06	-1.29	15.23	-46.14	41.18
LnPop 80	10.16	1.28	6.03	15.83	10.16	1.28	6.03	15.83
ManufShare 90	4.79	3.52	0.05	20.60	4.79	3.52	0.05	20.60
AgriShare 90	3.94	2.99	0.00	19.26	3.94	2.99	0.00	19.26
Mining 85	2.45	5.56	0.00	58.75	2.45	5.56	0.00	58.75
CollGradsShare 90	0.16	0.08	0.05	0.60	0.16	0.08	0.05	0.60
SomeCollege 90	0.35	0.07	0.11	0.53	0.35	0.07	0.11	0.53
Instruments								
Thickness	0.0003	0.0032	0.0000	0.1234	0.0003	0.0032	0.0000	0.1234
Oil	0.0003	0.0050	0.0000	0.1994	0.0003	0.0050	0.0000	0.1994
Gas	0.0003	0.0010	0.0000	0.0181	0.0003	0.0010	0.0000	0.0181
Miles	0.0003	0.0008	0.0000	0.0097	0.0003	0.0008	0.0000	0.0097

Abbreviations in the table: TotEmp (total employment), Trade (traded goods industries), NTrade (non-traded goods industries), Upstr (industries upstream to energy sector), Agri (agriculture), Manuf (manufacturing), Constr (construction), WSale (wholesale trade), Retail (retail trade), TrWh (transportation and warehousing), Info (information services), FinIn (finance and insurance), ReEst (real estate), ProfS (professional services), Acc&F (accommodation and food), DSchock (demand shock), lnPop 80 (natural logarithm of population in 1980), ManufShare 90 (share of manufacturing employment in 1990), AgriShare 90 (share of agricultural employment in 1990), Mining 85 (share of mining employment in 1985), CollGradShare 90 (share of adult population with at least four years of college in 1990), SomeCollege 90 (share of adult population with at least some college in 1990).

Appendix D

Table 1D. 2SLS estimation results (DV is the differenced change in agricultural employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Nonmetropolitan areas								
DiffEnVar	-0.0483	-0.022	-0.071	-0.000	-0.182	0.092	-0.837***	-0.373***
	(0.105)	(0.100)	(0.072)	(0.064)	(0.202)	(0.075)	(0.186)	(0.112)
DiffDSchock	0.272***	0.273***	0.118*	0.114	0.131***	0.121***	0.321***	0.354***
	(0.036)	(0.036)	(0.072)	(0.072)	(0.046)	(0.045)	(0.046)	(0.042)
Mining85	-0.000	-0.000	-0.002	-0.005	-0.005	-0.012	0.143*	-0.048
	(0.004)	(0.004)	(0.010)	(0.010)	(0.021)	(0.020)	(0.086)	(0.059)
Durbin P	0.576	0.750	0.125	0.564	0.435	0.092	0.000	0.009
Overid P	1.000	1.000	0.935	0.657	0.641	0.309	0.769	0.003
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.062	0.070	0.248**	0.241**	-4.744	-1.411	-0.738*	-0.754**
	(0.097)	(0.095)	(0.119)	(0.118)	(9.608)	(4.909)	(0.379)	(0.371)
DiffDSchock	0.042***	0.042***	0.006	0.007	0.266***	0.245***	-0.020	-0.021
	(0.016)	(0.016)	(0.048)	(0.048)	(0.098)	(0.060)	(0.044)	(0.044)
Mining85	-0.001	-0.001	-0.009	-0.008	-0.118	-0.055	0.157	0.162
	(0.003)	(0.003)	(0.010)	(0.010)	(0.189)	(0.099)	(0.130)	(0.128)
Durbin P	0.149	0.117	0.046	0.050	0.438	0.766	0.414	0.378
Overid P	0.981	0.745	0.566	0.167	0.916	0.836	0.21	0.639
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 2D. 2SLS estimation results (DV is the differenced change in manufacturing employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	-0.074	-0.056	-0.179**	-0.146**	0.000	-0.016	0.024	-0.008
	(0.058)	(0.055)	(0.079)	(0.071)	(0.214)	(0.080)	(0.143)	(0.093)
DiffDSchock	0.739***	0.739***	0.819***	0.817***	0.546***	0.546***	0.272***	0.270***
	(0.020)	(0.020)	(0.079)	(0.079)	(0.049)	(0.048)	(0.035)	(0.035)
Mining85	-0.000	-0.000	0.023**	0.022**	0.019	0.020	-0.036	-0.022
	(0.002)	(0.002)	(0.011)	(0.011)	(0.022)	(0.021)	(0.066)	(0.048)
Durbin P	0.477	0.680	0.070	0.120	0.995	0.847	0.992	0.725
Overid P	0.360	0.683	0.069	0.057	0.439	0.754	0.736	0.911
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
#Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.463***	-0.456***	-0.108	-0.074	2.816	3.327	-0.086	-0.127
	(0.151)	(0.148)	(0.222)	(0.220)	(9.297)	(7.422)	(0.296)	(0.291)
DiffDSchock	0.604***	0.604***	0.271***	0.268***	0.381***	0.378***	0.282***	0.282***
	(0.024)	(0.024)	(0.089)	(0.089)	(0.095)	(0.091)	(0.035)	(0.035)
Mining85	0.000	0.001	0.010	0.009	0.032	0.042	0.005	0.017
	(0.004)	(0.004)	(0.018)	(0.018)	(0.183)	(0.150)	(0.102)	(0.100)
Durbin P	0.001	0.001	0.001	0.998	0.706	0.562	0.380	0.297
Overid P	0.540	0.954	0.532	0.875	0.217	0.686	0.475	0.772
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 3D. 2SLS estimation results (DV is the differenced change in transportation & warehousing employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.113***	0.125***	0.109***	0.181***	0.450***	0.479***	0.278***	0.304***
	(0.030)	(0.028)	(0.037)	(0.034)	(0.133)	(0.050)	(0.061)	(0.040)
DiffDSchock	0.021**	0.021**	0.019	0.015	0.070**	0.069**	0.043***	0.045***
	(0.010)	(0.010)	(0.037)	(0.037)	(0.030)	(0.030)	(0.015)	(0.015)
Mining85	-0.001	-0.001	0.008	0.005	0.021	0.020	-0.024	-0.034*
	(0.001)	(0.001)	(0.005)	(0.005)	(0.014)	(0.013)	(0.028)	(0.021)
DurbinP	0.048	0.011	0.462	0.002	0.403	0.003	0.426	0.048
Overid P	0.965	0.239	0.273	0.000	0.004	0.033	0.866	0.952
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.160**	0.157**	0.111	0.110	0.152	2.044	-0.028	-0.048
	(0.070)	(0.068)	(0.082)	(0.081)	(3.264)	(3.317)	(0.139)	(0.136)
DiffDSchock	0.061***	0.061***	0.035	0.035	-0.006	-0.018	0.020	0.020
	(0.011)	(0.011)	(0.033)	(0.033)	(0.033)	(0.041)	(0.016)	(0.016)
Mining85	0.002	0.002	0.026***	0.026***	0.097	0.133**	0.085*	0.091*
	(0.002)	(0.002)	(0.007)	(0.007)	(0.064)	(0.067)	(0.048)	(0.047)
Durbin P	0.000	0.000	0.470	0.473	0.982	0.464	0.451	0.352
Overid P	0.980	1.000	0.176	0.462	0.631	0.740	0.689	0.852
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 4D. 2SLS estimation results (DV is the differenced change in retail employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I	IV II	IV I	IV II	IV I	IV II	IV I	IV II
Non-metropolitan areas								
DiffEnVar	0.0274	0.026	-0.031	0.009	0.239**	0.221***	0.259***	0.286***
	(0.029)	(0.028)	(0.036)	(0.032)	(0.122)	(0.045)	(0.071)	(0.046)
DiffDSchock	0.045***	0.045***	0.124***	0.121***	0.122***	0.122***	0.148***	0.150***
	(0.010)	(0.010)	(0.036)	(0.036)	(0.028)	(0.027)	(0.017)	(0.017)
Mining85	-0.000	-0.000	0.008*	0.007	0.037***	0.037***	-0.069**	-0.080***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.012)	(0.012)	(0.033)	(0.024)
Durbin P	0.933	0.961	0.032	0.261	0.238	0.004	0.040	0.000
Overid P	0.188	0.267	0.359	0.020	0.019	0.117	0.751	0.953
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.013	-0.012	-0.136	-0.109	-1.054	0.085	0.25	0.217
	(0.082)	(0.080)	(0.112)	(0.111)	(4.918)	(3.469)	(0.207)	(0.202)
DiffDSchock	0.009	0.010	0.056	0.054	0.232***	0.225***	0.186***	0.186***
	(0.013)	(0.013)	(0.045)	(0.045)	(0.050)	(0.042)	(0.024)	(0.024)
Mining85	-0.000	-0.000	0.009	0.008	0.022	0.044	-0.068	-0.058
	(0.002)	(0.002)	(0.009)	(0.009)	(0.097)	(0.070)	(0.071)	(0.070)
Durbin P	0.799	0.944	0.391	0.544	0.796	0.991	0.225	0.286
Overid P	0.155	0.420	0.123	0.116	0.881	0.832	0.38	0.685
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 5D. 2SLS estimation results (DV is the differenced change in wholesale employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.040*	0.037*	0.057**	0.060**	0.187**	0.113***	0.103**	0.109***
	(0.023)	(0.022)	(0.027)	(0.024)	(0.087)	(0.032)	(0.043)	(0.028)
DiffDSchock	0.020***	0.020***	0.084***	0.084***	0.067***	0.070***	0.025**	0.025**
	(0.008)	(0.008)	(0.027)	(0.027)	(0.020)	(0.019)	(0.011)	(0.011)
Mining85	0.000	0.000	0.003	0.003	0.006	0.008	-0.009	-0.011
	(0.001)	(0.001)	(0.004)	(0.004)	(0.009)	(0.008)	(0.020)	(0.015)
Durbin P	0.138	0.141	0.492	0.361	0.299	0.631	0.747	0.446
Overid P	0.998	1.000	0.768	0.879	0.853	0.331	0.589	0.617
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.037	-0.034	0.185***	0.191***	0.453	0.764	0.183	0.194*
	(0.056)	(0.055)	(0.069)	(0.068)	(2.586)	(2.080)	(0.117)	(0.115)
DiffDSchock	0.025***	0.025***	0.043	0.043	0.035	0.033	0.025*	0.025*
	(0.009)	(0.009)	(0.028)	(0.028)	(0.026)	(0.025)	(0.014)	(0.014)
Mining85	0.000	0.000	0.004	0.004	0.0311	0.037	-0.009	-0.012
	(0.001)	(0.001)	(0.006)	(0.006)	(0.051)	(0.042)	(0.040)	(0.040)
Durbin P	0.500	0.533	0.12	0.096	0.896	0.739	0.195	0.156
Overid P	0.285	0.961	0.875	0.978	0.918	0.994	0.175	0.559
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
#Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 6D. 2SLS estimation results (DV is the differenced change in accommodation and food employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.082***	0.0844***	0.076**	0.100***	0.309***	0.196***	0.118**	0.158***
	(0.029)	(0.027)	(0.033)	(0.030)	(0.106)	(0.038)	(0.051)	(0.033)
DiffDSchock	0.008	0.008	0.102***	0.101***	0.034	0.038*	0.052***	0.055***
	(0.010)	(0.010)	(0.033)	(0.033)	(0.024)	(0.023)	(0.013)	(0.012)
Mining85	0.000	0.000	0.003	0.002	0.001	0.004	-0.003	-0.020
	(0.001)	(0.001)	(0.004)	(0.004)	(0.011)	(0.010)	(0.023)	(0.017)
Durbin P	0.012	0.006	0.471	0.092	0.040	0.009	0.591	0.030
Overid P	0.213	0.660	0.419	0.084	0.010	0.032	0.935	0.159
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.062	-0.049	-0.156	-0.105	-1.471	-2.944	0.137	0.048
	(0.093)	(0.092)	(0.113)	(0.112)	(4.535)	(4.607)	(0.439)	(0.430)
DiffDSchock	-0.011	-0.011	0.029	0.025	0.099**	0.108*	0.037	0.036
	(0.015)	(0.015)	(0.045)	(0.045)	(0.046)	(0.056)	(0.051)	(0.051)
Mining85	0.001	0.001	0.011	0.009	0.062	0.035	-0.012	0.015
	(0.002)	(0.002)	(0.009)	(0.009)	(0.089)	(0.093)	(0.151)	(0.148)
Durbin P	0.687	0.786	0.424	0.749	0.717	0.334	0.823	0.988
Overid P	0.907	0.993	0.818	0.022	0.329	0.872	0.883	0.781
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 7D. 2SLS estimation results (DV is the differenced change in real estate employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.035***	0.032***	0.017*	0.023***	0.115***	0.055***	0.202***	0.089***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.035)	(0.012)	(0.041)	(0.025)
DiffDSchock	0.006**	0.006**	0.044***	0.043***	0.053***	0.055***	0.163***	0.155***
	(0.003)	(0.003)	(0.009)	(0.009)	(0.008)	(0.007)	(0.010)	(0.009)
Mining85	0.000	0.000	0.004***	0.003***	0.012***	0.014***	-0.041**	0.005
	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.019)	(0.013)
Durbin P	0.015	0.039	0.422	0.845	0.018	0.198	0.000	0.076
Overid P	0.271	0.161	0.001	0.009	0.005	0.004	0.248	0.001
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.073***	0.080***	-0.095***	-0.081**	-0.732	-0.717	0.078	0.086
	(0.025)	(0.025)	(0.032)	(0.032)	(1.591)	(1.200)	(0.113)	(0.111)
DiffDSchock	0.008*	0.008*	0.056***	0.055***	0.087***	0.087***	0.245***	0.245***
	(0.004)	(0.004)	(0.013)	(0.013)	(0.016)	(0.015)	(0.013)	(0.013)
Mining85	0.000	0.000	0.010***	0.010***	0.024	0.024	0.017	0.014
	(0.001)	(0.001)	(0.003)	(0.003)	(0.031)	(0.024)	(0.039)	(0.038)
Durbin P	0.0267	0.01	0.000	0.001	0.546	0.438	0.607	0.551
OveridP	0.387	0.936	0.15	0.007	0.198	0.623	0.608	0.915
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 8D. 2SLS estimation results (DV is the differenced change in finance and insurance employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.003	0.006	-0.027*	-0.022*	0.084*	0.016	0.048	0.031
	(0.012)	(0.012)	(0.014)	(0.013)	(0.046)	(0.017)	(0.034)	(0.022)
DiffDSchock	0.004	0.004	0.033**	0.033**	0.017*	0.020**	0.066***	0.064***
	(0.004)	(0.004)	(0.014)	(0.014)	(0.010)	(0.010)	(0.008)	(0.008)
Mining85	-0.000	-0.000	0.001	0.000	0.001	0.003	-0.030*	-0.023**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.004)	(0.016)	(0.011)
Durbin P	0.287	0.188	0.247	0.395	0.107	0.876	0.257	0.329
Overid P	0.605	0.551	0.772	0.914	0.682	0.316	0.914	0.838
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.063	-0.073	-0.090	-0.080	-2.537	-1.894	-0.003	-0.012
	(0.073)	(0.071)	(0.076)	(0.075)	(4.863)	(3.104)	(0.152)	(0.149)
DiffDSchock	0.004	0.004	0.088***	0.088***	0.080	0.076**	0.111***	0.111***
	(0.012)	(0.012)	(0.031)	(0.031)	(0.050)	(0.038)	(0.018)	(0.018)
Mining85	0.000	0.000	0.007	0.007	-0.034	-0.021	-0.028	-0.025
	(0.002)	(0.002)	(0.006)	(0.006)	(0.096)	(0.063)	(0.052)	(0.051)
Durbin P	0.234	0.173	0.091	0.118	0.371	0.383	0.764	0.812
Overid P	1.000	1	0.963	0.992	0.510	0.878	0.674	0.919
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 9D. 2SLS estimation results for (DV is the differenced change in information services employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	-0.014	-0.014	-0.019	-0.012	0.043	0.016	0.0383	0.021
	(0.011)	(0.010)	(0.013)	(0.012)	(0.049)	(0.018)	(0.027)	(0.017)
DiffDSchock	0.015***	0.015***	0.0171	0.017	0.024**	0.025**	0.015**	0.014**
	(0.004)	(0.004)	(0.013)	(0.013)	(0.011)	(0.011)	(0.007)	(0.006)
Mining85	0.000	0.000	-0.000	-0.000	-0.003	-0.003	-0.012	-0.005
	(0.000)	(0.000)	(0.002)	(0.002)	(0.005)	(0.005)	(0.012)	(0.009)
Durbin P	0.177	0.140	0.218	0.435	0.503	0.739	0.210	0.360
Overid P	1.000	0.995	0.862	0.831	0.085	0.080	0.899	0.049
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	-0.096**	-0.103**	0.075*	0.081*	0.445	-0.087	0.090	0.070
	(0.041)	(0.041)	(0.042)	(0.041)	(1.827)	(1.253)	(0.074)	(0.072)
DiffDSchock	0.015**	0.015**	0.053***	0.052***	0.062***	0.065***	0.040***	0.039***
	(0.007)	(0.007)	(0.017)	(0.017)	(0.019)	(0.015)	(0.009)	(0.009)
Mining85	-0.000	-0.000	-0.002	-0.002	0.014	0.004	-0.052**	-0.046*
	(0.001)	(0.001)	(0.003)	(0.003)	(0.036)	(0.025)	(0.025)	(0.025)
Durbin P	0.020	0.010	0.036	0.023	0.759	0.982	0.331	0.483
Overid P	0.000	0	0.785	0.777	0.365	0.689	0.743	0.528
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 10D. 2SLS estimation results (DV is the differenced change in professional services employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	0.026	0.016	-0.026	-0.015	0.036	0.055	0.131***	0.068**
	(0.032)	(0.030)	(0.045)	(0.041)	(0.122)	(0.046)	(0.050)	(0.032)
DiffDSchock	-0.041***	-0.041***	0.036	0.035	0.032	0.032	0.126***	0.121***
	(0.011)	(0.011)	(0.045)	(0.045)	(0.028)	(0.028)	(0.012)	(0.012)
Mining85	0.000	0.000	0.007	0.006	0.029**	0.029**	-0.053**	-0.027*
	(0.001)	(0.001)	(0.006)	(0.006)	(0.012)	(0.012)	(0.023)	(0.017)
Durbin P	0.552	0.769	0.275	0.339	0.919	0.881	0.061	0.384
Overid P	0.998	1.000	0.823	0.985	0.333	0.725	0.525	0.039
IV F-stat	65.44	36.57	114.10	72.89	16.01	64.01	54.10	69.19
# Obs	21,846		5,961		1,987		1,987	
Metropolitan areas								
DiffEnVar	0.054	0.072	0.101	0.132*	0.346	0.421	0.065	0.018
	(0.061)	(0.060)	(0.077)	(0.077)	(2.769)	(2.125)	(0.135)	(0.132)
DiffDSchock	0.008	0.008	0.089***	0.087***	0.093***	0.092***	0.175***	0.174***
	(0.010)	(0.010)	(0.031)	(0.031)	(0.028)	(0.026)	(0.016)	(0.016)
Mining85	0.002	0.001	0.010	0.009	0.035	0.036	-0.035	-0.021
	(0.002)	(0.002)	(0.006)	(0.006)	(0.055)	(0.043)	(0.046)	(0.046)
Durbin P	0.350	0.205	0.253	0.115	0.926	0.875	0.797	0.917
Overid P	1.000	1.000	0.990	0.496	0.632	0.773	0.905	0.299
IV F-stat	26.94	14.02	50.11	25.51	0.20	0.17	39.35	20.52
# Obs	11,451		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 1E. 2SLS estimation results for parsimonious models (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	1.260***	1.310***	0.647***	1.205***	3.940***	3.105***	0.357	1.674***
	(0.173)	(0.165)	(0.195)	(0.172)	(0.665)	(0.240)	(0.436)	(0.272)
DiffDSchock	1.509***	1.510***	2.091***	2.069***	1.321***	1.332***	1.644***	1.758***
	(0.058)	(0.058)	(0.192)	(0.190)	(0.141)	(0.131)	(0.084)	(0.076)
Mining85	0.009	0.009	0.124***	0.103***	0.301***	0.315***	0.290	-0.250*
	(0.007)	(0.007)	(0.0238)	(0.023)	(0.062)	(0.057)	(0.196)	(0.136)
Durbin P	0.172	0.078	0.000	0.088	0.005	0.000	0.005	0.505
Overid P	0.932	0.911	0.007	0.000	0.006	0.010	0.728	0.001
IV F-stat	65.46	36.59	115.1	73.96	17.94	66.03	54.67	71.20
# Obs	21,846	21,846	5,961	5,961	1,986	1,986	1,986	1,986
Metropolitan areas								
DiffEnVar	0.635*	0.703*	0.412	0.757	20.28	10.80	1.988	1.995
	(0.377)	(0.370)	(0.543)	(0.536)	(32.89)	(17.92)	(1.606)	(1.602)
DiffDSchock	1.151***	1.149***	1.522***	1.499***	2.431***	2.490***	2.291***	2.291***
	(0.060)	(0.060)	(0.216)	(0.215)	(0.331)	(0.218)	(0.159)	(0.159)
Mining85	0.001	0.003	0.063	0.0527	0.799	0.621*	-1.000*	-1.002*
	(0.010)	(0.010)	(0.043)	(0.043)	(0.643)	(0.361)	(0.560)	(0.559)
Durbin P	0.674	0.807	0.234	0.599	0.358	0.555	0.129	0.127
Overid P	0.006	0.043	0.026	0.000	0.082	0.092	0.391	0.591
IV F-stat	26.95	14.03	50.35	25.68	0.248	0.216	38.36	19.25
# Obs	11,451	11,451	3,123	3,123	1,041	1,041	1,041	1,041

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; the model includes industry mix variable, share of mining employment in 1985 and time period dummies as controls.

Table 2E. 2SLS estimation results for models with squared energy employment growth (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	1.218***	1.308***	0.699***	0.999***	4.268***	2.814***	0.105	-0.903
	(0.177)	(0.165)	(0.218)	(0.192)	(1.236)	(0.471)	(1.533)	(0.717)
DiffEnVarSq	-0.0326	-0.002	-0.011	0.0235**	0.0657	0.006	0.006	0.054***
	(0.028)	(0.021)	(0.017)	(0.009)	(0.042)	(0.011)	(0.066)	(0.0137)
DiffDSchock	1.516***	1.518***	2.054***	2.093***	1.572***	1.603***	1.704***	1.639***
	(0.059)	(0.059)	(0.199)	(0.194)	(0.263)	(0.146)	(0.142)	(0.121)
Mining85	0.0164	1.308***	0.172***	0.103***	0.0115	0.343***	0.302	0.158
	(0.011)	(0.165)	(0.036)	(0.029)	(0.245)	(0.077)	(0.254)	(0.192)
IV F-stat	22.19	20.40	32.04	55.54	2.429	14.92	0.635	14.55
Durbin P	0.226	0.208	0.000	0.124	0.001	0.001	0.067	0.001
Overid P	0.950	0.900	0.005	0.000		0.012		0.249
# Obs	11,451		5,961		1,986		1,986	
Metropolitan areas								
DiffEnVar	0.542	0.666	0.429	0.755	3.748	24.83	2.679	0.133
	(0.426)	(0.414)	(0.545)	(0.537)	(25.70)	(34.36)	(5.427)	(3.998)
DiffEnVarSq	-0.073	-0.027	-0.071	-0.031	1.089**	0.934	-0.240	0.045
	(0.156)	(0.151)	(0.134)	(0.131)	(0.507)	(0.822)	(0.663)	(0.493)
DiffDSchock	1.154***	1.150***	1.423***	1.392***	2.523***	2.376***	1.974***	1.971***
	(0.061)	(0.061)	(0.220)	(0.218)	(0.256)	(0.386)	(0.194)	(0.167)
Mining85	0.016	0.010	0.194*	0.156	-0.013	0.471	0.670	-0.125
	(0.024)	(0.023)	(0.104)	(0.101)	(0.522)	(0.663)	(2.166)	(1.657)
IV F-stat	3.858	2.048	6.270	3.247	0.014	0.148	0.635	0.204
Durbin P	0.829	0.953	0.397	0.815	0.191	0.102	0.0668	0.205

Overid P	0.004	0.039	0.022	0.000		0.489		0.453
# Obs	21,846		3,123		1,041		1,041	

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 3E. 2SLS estimation results for models that exclude mining in 1985 (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	1.267***	1.313***	0.860***	1.331***	4.299***	3.077***	0.651***	1.192***
	(0.173)	(0.164)	(0.188)	(0.169)	(0.710)	(0.243)	(0.229)	(0.195)
DiffDSchock	1.518***	1.518***	2.004***	1.985***	1.556***	1.600***	1.785***	1.756***
	(0.059)	(0.059)	(0.194)	(0.193)	(0.166)	(0.146)	(0.098)	(0.096)
IV F-stat	65.57	36.62	122.3	76.41	17.01	63.80	173.6	122.2
Durbin P	0.160	0.075	0.000	0.259	0.001	0.000	0.000	0.150
Overid P	0.917	0.911	0.000	0.000		0.000		0.000
# Obs	21,846		5,961		1,986			
Metropolitan areas								
DiffEnVar	0.652*	0.715*	0.780	1.085**	-37.64	-28.02	0.648	0.542
	(0.376)	(0.369)	(0.520)	(0.515)	(29.68)	(21.82)	(0.794)	(0.789)
DiffDSchock	1.149***	1.148***	1.361***	1.341***	2.681***	2.621***	1.969***	1.971***
	(0.060)	(0.060)	(0.216)	(0.216)	(0.560)	(0.437)	(0.165)	(0.165)
IV F-stat	27.02	14.06	53.65	27.27	0.979	0.559	116.1	58.86
Durbin P	0.704	0.832	0.518	0.978	0.000	0.001	0.619	0.724
Overid P	0.006	0.045	0.002	0.000		0.508		0.663
# Obs	11,451		3,123		1,041			

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.

Table 4E. 2SLS estimation results for models that exclude industry mix variable (DV is the differenced change in total employment between periods divided by total county employment)

	1-year differences		3-year differences		6-year differences		10-year differences	
	IV I [1]	IV II [2]	IV I [3]	IV II [4]	IV I [5]	IV II [6]	IV I [7]	IV II [8]
Non-metropolitan areas								
DiffEnVar	1.089***	1.126***	0.684***	1.242***	3.331***	3.111***	0.542	1.480***
	(0.176)	(0.167)	(0.197)	(0.175)	(0.680)	(0.248)	(1.528)	(0.291)
Mining85	0.008	0.008	0.141***	0.119***	0.364***	0.370***	0.410	0.216
	(0.008)	(0.007)	(0.027)	(0.0261)	(0.0684)	(0.065)	(0.518)	(0.146)
IV F-stat	65.51	36.60	114.3	73	15.81	64.21	39.51	69.87
Durbin P	0.693	0.518	0.000	0.127	0.092	0.000	0.744	0.814
Overid P	0.432	0.473	0.003	0.000		0.335		0.000
# Obs	21,846		5,961		1,986			
Metropolitan areas								
DiffEnVar	0.822**	0.906**	0.720	1.063**	-7.583	-4.653	-0.375	0.494
	(0.383)	(0.375)	(0.536)	(0.530)	(28.07)	(20.48)	(0.473)	(1.500)
Mining85	0.005	0.005	0.127***	0.117***	0.357	0.413	0.951***	0.425
	(0.010)	(0.010)	(0.044)	(0.044)	(0.553)	(0.412)	(0.211)	(0.511)
IV F-stat	26.97	14.04	51.30	26.12	0.199	0.159	56.38	20.50
Durbin P	0.958	0.778	0.457	0.942	0.691	0.728	0.000	0.764
Overid P	0.000	0.008	0.023	0.000		0.394		0.998
# Obs	11,451		3,123		1,041			

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors in parentheses; all models include a full set of controls and time period dummies described in text and note to Table 1.