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The regional economic impact of oil and gas extraction in Texas

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HIGHLIGHTS

- Economic impacts and multiplier effects differ between oil and gas wells in Texas.
- Interactions among local economies raise employment and income effects.
- Impacts persist over time, raising the long-run multipliers.
- Greater economic impacts from newly drilled wells than legacy wells.

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ABSTRACT

This paper empirically investigates the regional economic impact of oil and gas extraction in Texas during the recent shale oil boom. Regressions with county-level data over the period 2009–2014 support smaller multiplier effects on local employment and income than corresponding estimates drawn from popular input–output-based studies. Economic impacts were larger for extraction from gas wells than oil wells, while the drilling phase generated comparable impacts. Estimates of economic impacts are greater in a dynamic spatial panel model that allows for spillover effects across local economies as well as over time.

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1. Introduction

1.1. Background

More than a century after the discovery of the Spindletop oilfield in 1901, Texas experienced another oil boom along with other oil-rich regions across the United States. The Lone Star state is arguably the most interesting case not only because of its historical reliance on natural resources, but also because of its leading role in the overall size of proven reserves as well as the volumes of crude oil and natural gas production from its various formations.

The recent oil boom, which began to unfold in 2008, was an extension of the so-called shale revolution. In contrast to conventional techniques, drilling of shale, or tight, oil and natural gas has been driven primarily by advances in technologies called hydraulic fracturing and horizontal drilling. After nearly a decade of development in shale gas extraction, shale oil production also accelerated in the wake of soaring oil prices, which reached record levels more than US$100 in mid-2008 before falling by half within the following year. Crude oil production in Texas more than tripled between 2008 and 2014, according to U.S. Energy Information Administration (EIA).

In the wake of the 2007–2009 Great Recession, much of the United States struggled with relatively slow economic recovery. Meanwhile, the shale oil boom was widely perceived as a “game changer” for Texas’s statewide economy as well as its local communities. A number of private consultants and university researchers (e.g., Scott, 2009; PerrymanGroup, 2009, 2011; Tunstall, 2011, 2012, 2013, 2014; Ewing et al., 2014) have documented the regional economic impacts of the surging oil and gas drilling activity in the state’s major shale formations, notably the Barnett, Permian Basin and Eagle Ford. Those studies, which received substantial media attention, were typically commissioned by government officials and business associations, which rely on the findings to make public policy and business decisions.

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The conventional approach of those so-called "impact" studies draws on an input–output model customized for the region under investigation. Those findings have been subjected to criticism in the academic literature. For instance, input–output analysis relies on the assumption that the economy operates with excess capacity, including elastic labor supply (Dwyer et al., 2000), and no crowding out or leakage effects can occur (Carlson and Spencer, 1975; Kinnaman, 2011; Lee, 2015). For this reason, *ex-ante* estimates based on popular input–output models may misrepresent the actual economic impacts of a sizable change in economic activity. Nevertheless, since the shale oil boom evolved in the aftermath of the Great Recession, those modeling assumptions may not be especially restrictive as a representation of regional communities with substantial economic slack.

An alternative empirical methodology is econometric analysis with cross-sectional data of local economies. The literature concerning *ex-post* economic effects of the recent shale revolution is, however, confined mostly to natural gas extraction (e.g., Brown, 2014; Paredes et al., 2015; Weber, 2012, 2014; Hartley et al., 2015). Given the short history of the recent shale oil boom, econometric-based analysis concerning its regional economic impacts is absent.

The recent shale oil boom in the United States might have ended in late 2014 as crude oil prices fell precipitously from above US$100 in July 2014 to below US$50 by January 2015. It would therefore be interesting to account for what this oil cycle brought to the regional economies of the top producing regions. To this

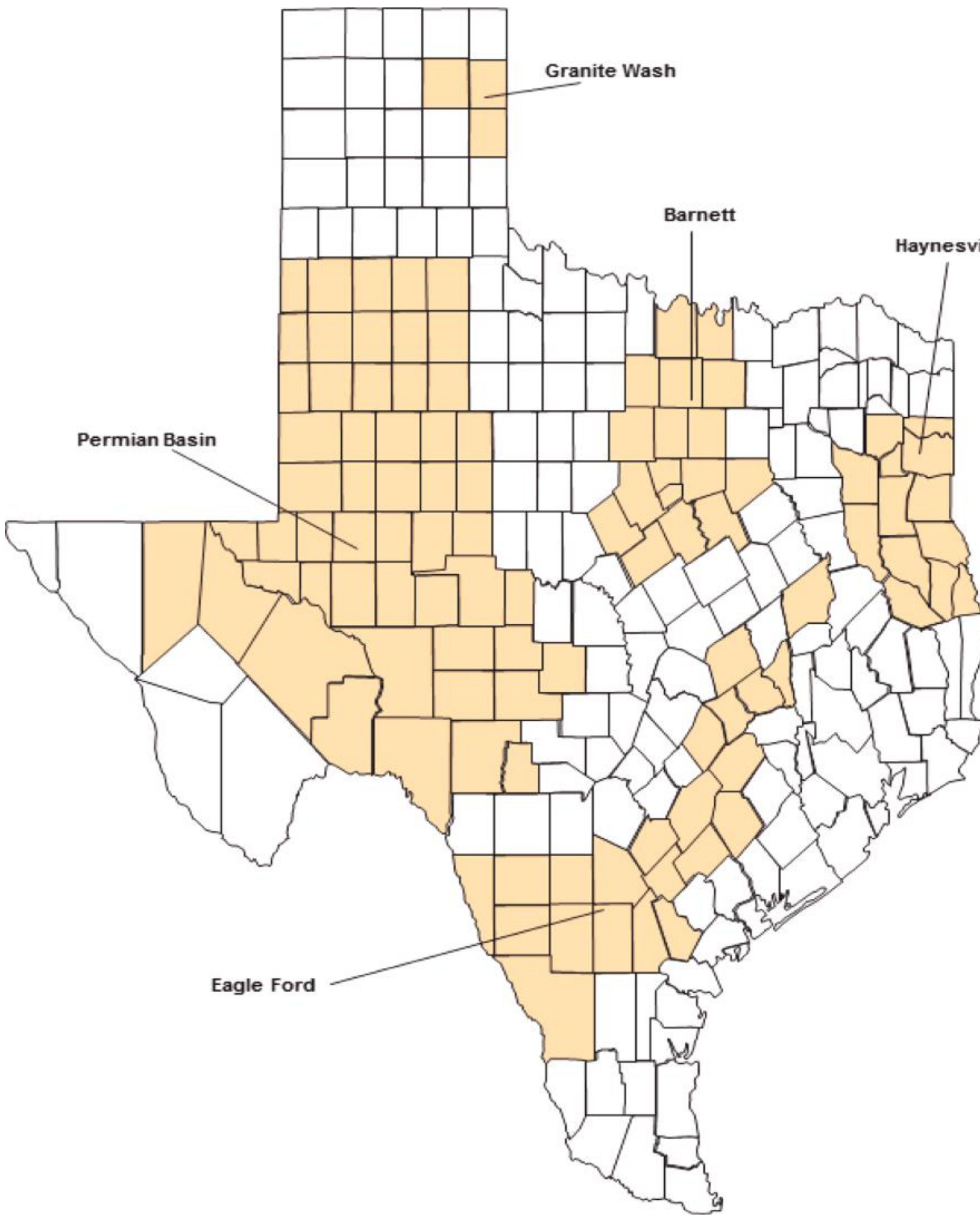

Fig. 1. Texas shale formations.

end, our objective is to quantitatively measure the effect of Texas's shale oil and gas extraction on the state's local economies.

1.2. Shale formations

The five major shale formations in Texas are Barnett, Eagle Ford, Granite Wash, Haynesville and Permian Basin. Fig. 1 contains a map of those formations by county. The counties atop each formation are obtained from Texas Railroad Commission and Baker Hughes. Those are commonly known as core regions.

Among the five shale Texas formations, the Permian Basin in western Texas covers the largest geographical area with the largest number of counties. On the contrary, the Granite Wash shale is the smallest formation with only three Texas counties. This play is split about equally between the Texas Panhandle and Oklahoma.

The Barnett shale lies underneath a total of 17 counties in north central Texas. That formation arguably has the most producible reserves among all onshore natural gas fields in the United States, and drilling activity in that play began as early as the late 1990s. Unlike other shale formations which are located mostly in rural areas, parts of the Barnett Shale play cover the urban areas surrounding the Dallas–Fort Worth Metroplex.

The Haynesville shale is located between East Texas and western Louisiana. Similar to the Barnett shale in size, this formation has reserves mostly in natural gas (Kaiser, 2012). The Eagle Ford shale is the most recently discovered formation. The first well in this 23-county region was drilled in La Salle County in 2008. The Eagle Ford play is distinct from other Texas shale plays for its oil in addition to gas deposits. Along with the Permian Basin, this formation accounted for the majority of growth in shale oil production in Texas during the recent oil boom.

1.3. Related literature

Until recently, measures of the regional economic impact of oil or gas drilling activity had not been a popular academic research topic. Most so-called "impact" studies have been conducted by private consultants commissioned by the public sector in support of planning or policy formulation. Instead of the common methodology in academic research that relies on econometric analysis with historical data, those case studies typically provide *ex ante* or forecast estimates using input–output models customized to a specific region. The leading regional input–output models are BEA's RIMS II (Scott, 2009) and IMPLAN Group's IMPLAN (PerrymanGroup, 2009, 2011; Tunstall, 2011, 2012, 2013, 2014). One interesting outcome of those models is the estimate of the multiplier effect, which represents the change in aggregate income or employment within a region in response to an exogenous change of spending or output (commonly known as the direct impact) in one particular industry.

There are several input–output based studies for the oil and gas drilling industry in Texas's major shale formations. Multipliers can be computed using the reported impact on the regional oil and gas industry and the reported impact on the whole regional economy. For instance, Tunstall (2011) published "impact" reports for the Eagle Ford shale in 2011, followed by annual updates (Tunstall, 2012, 2013, 2014). In the 2012 update, the estimates for the so-called "core" Eagle Ford region of 15 counties imply an average multiplier of 2.2 for employment and 1.3 for wage income. For the counties in the Permian Basin, Ewing et al. (2014) produced corresponding economic impact estimates, which imply an average multiplier of 1.9 for employment and 1.47 for wage income.

Tunstall's 2014 update also includes impact estimates for six counties surrounding the core region. Partly because some of those "peripheral" counties, such as Nueces and San Patricio, are within a metro area, their estimated multiplier effects are remarkably larger than the estimates for the core counties, most of which represent rural communities. More specifically, the employment multiplier for those peripheral counties is 4.5 on average. IHS Global Insight also reported a comparable multiplier of 4.1 for the impact of shale gas production on the entire United States.

However, estimates of the multiplier effects among numerous "impact" studies have been found to be grossly overstated (e.g., Kinnaman, 2011; Weber, 2012; Lee, 2015; Paredes et al., 2015). For instance, the PerrymanGroup (2009) evaluated the economic impact of natural gas drilling in the Barnett shale. Given the estimate of about 7000 jobs in the crude oil and natural gas mining industry along with a total regional employment impact of about 130,000, the employment multiplier is nearly 20. Similarly, Scott (2009) reported that nearly 33,000 jobs were associated with fewer than 500 gas drilling jobs in the Haynesville shale perhaps as a result of lease and royalty payments.

Discrepancies across those implied multipliers might reflect the fragility of input–output analysis, but also estimates of the *direct* impact, which represents a given exogenous shock. Kinnaman (2011) argued that lease and royalty payments to households are considered windfall earnings, which would more likely be saved than spent. Furthermore, "impact" studies tend to ignore the purchases of goods that are not produced with local resources. In the case of capital expenditures, the amounts of direct spending are typically overstated because of underestimation of imports from suppliers outside the region under investigation. As a result of such leakages, the amounts of direct spending as well as measures of secondary effects are exaggerated.

As Weber (2012) pointed out, input–output analysis also tends to ignore supply constraints that are particularly relevant to small regional economies. Supply constraints result in potential crowding-out effects from large increases in direct spending (e.g., Carlson and Spencer, 1975; Lee, 2015). In input–output analysis, multipliers are typically larger for a higher regional level. A larger region tends to have a smaller leakage to imports and fewer supply constraints. As compared to individual counties, the state of Texas better captures interactions or spillovers between counties within that state. A larger region also tends to have a more diversified economy, as more goods and services are available within the region. Weber (2014) used a spatial model to take into account of spillover effects of gas production in one Texas county on its adjacent counties. The regression results indicated that one gas mining job generates 1.4 additional jobs, although there was little evidence of spatial effects. Using a similar spatial model but also allowing for the lagged effect in the dependent variable, Hartley et al. (2015) showed that spatial correlation effects account for as much as 17% of the total employment impact of gas drilling activity.

Input–output analysis is particularly sensitive to the estimate of direct employment. Tunstall (2014) indicated that a new well in the Bakken Shale of North Dakota generated 3 full-time-equivalent direct jobs in the oil and gas industry. It is, however, important to distinguish the different phases of well development. Brundage et al. (2011) indicated that most of the oil and gas industry workforce (13 jobs) is employed during the well drilling phase, and only a small portion (0.2 job) is needed during the extraction phase. The Marcellus Shale Education and Training Center (Marcellus Shale Education & Training Center, 2009) reported similar workforce requirement estimates. The number of direct jobs reduces further for additional wells in multi-well pads. The nature of employment also varies over the lifetime of a given well. Activities like constructing the rig, drilling and hydraulic fracturing occur only once before oil and gas extraction begins. Oil and gas extraction, on the contrary, is a recurring operation throughout the productive life of the well.

Against the above background, econometric studies with historical data have unequivocally generated smaller multiplier estimates than comparable multipliers derived from input–output studies. The bulk of the academic literature, however, focuses on natural gas production. In light of the recent oil boom, this paper seeks to shed light on the economic impacts of oil production in comparison with gas production.

2. Methods

2.1. Data

To explore the effect of oil and gas extraction on local employment and income, we look at annual Texas county-level data. Despite its popularity in the related literature, county-level data are by no means perfect for measuring the local impacts of an oil boom. This level of data disaggregation is more suitable for discerning "local" effects than more aggregated measures at the metro area or state level. Counties are the smallest geographical areas for which the U.S. government regularly reports economic data. However, differences in county size and commuting pattern can potentially affect the observed local economic effects due to disparities in labor and capital mobility. In this paper, we attempt to capture the possible geographical effects of economic interactions and labor mobility using a spatial regression model as described below.[1]

Most data are obtained from the U.S. Bureau of Economic Analysis (BEA). The income and employment data are obtained from the BEA's Local Area Personal Income and Employment database. Income is measured by personal income by place of residence. The employment measures include full-time, part-time, and self-employed workers. As opposed to income, wage and salary employment is on a place-of-work basis. In this study, the oil and gas industry refers specifically to activities related to oil and gas extraction (NAICS 211), and support activities for oil and gas extraction (NAICS 213). Employment and personal income in the oil and gas industry are measured correspondingly.

2.2. Oil and gas wells

We measure the intensity of oil and gas extraction by the numbers of oil and gas wells. Data on the numbers of oil and gas wells are obtained from the Texas Railroad Commission. Although the majority of Texas wells contain both crude oil and natural gas, the oil or gas well designation depends on what a well is drilled primarily for. As explained by Hartley et al. (2015), the number of wells completed captures the peak impact of shale drilling on employment as the date of well completion indicates the end of the construction period and the beginning of its production. While activity during the more lengthy production phase is important for public policy formulation, most "impact" studies focus on the drilling of *new* wells. From this perspective, we report results for the number of new wells drilled in addition to the total number of active wells.

For a particular well, the full-time-equivalent workforce needs are found to be substantially greater in the drilling phase than the production phase (Brundage et al., 2011; Marcellus Shale Education & Training Center, 2009). However, according to Marcellus Shale Education & Training Center (2009), the workforce needs are much more difficult to pinpoint for a specific area, like a county, during the drilling phase than the production phase. The direct workforce needed to drill one well involves more than 400 individuals in 150 occupations typically working for a few months as opposed to a full year. Their workplace locations or residency also depend on a number of factors. By contrast, most direct workers during the production phase are based at offices near the wells and their jobs are considered permanent positions. For these reasons, we expect different local economic impacts between newly drilled wells and legacy wells.

In addition to the total number of wells, the economic effects of oil wells are considered separately from those of gas wells. Unlike crude oil prices, which tended to rise over the observation period between 2009 and 2014, natural gas prices hovered around relatively low levels below $5 per million BTU. As a result of the increase in the price of oil relative the price of natural gas, the U.S. production of shale oil increased during that period while gas production remained flat. Beginning in 2011, the number of gas wells in the Permian Basin declined over time in response to low natural gas prices. Likewise, fewer gas wells were drilled in the Haynesville shale after 2012. The different trends between natural gas prices and crude oil prices might have generated different economic impacts between oil and gas wells among Texas shale formations.

According to the U.S. Energy Information Administration (2013), nearly half of new wells in recent years contained both crude oil and natural gas, oil and gas producers increasingly targeted those wells for oil as opposed to gas production. Hydrocarbon products in the liquid state at the wellhead are treated as oil, and unprocessed gas products are treated as natural gas.

2.3. Summary statistics

Table 2 presents summary statistics of the key variables in our empirical work. Out of the total 254 Texas counties, 107 counties lie within one of the five shale formations. All statistics other than the last two columns are averages of the counties within the specific regions. The numbers of counties comprising each region are listed at the top the table. The first panel shows the average county employment levels in 2009 and 2014, as well as the annual percentage changes over the periods of 2009–2014 and 2000–2009. The 2009–2014 period, which represents the time horizon of the U.S. shale oil boom, is the focus of our regression analysis. Data in the 2000–2009 period represent historical trends prior to the oil boom. Except for the Barnett shale, the employment size of shale counties is on average smaller than the statewide average. This can be explained in part by the fact that the majority of shale oil and gas wells are located in rural communities with a smaller population and workforce.

Texas county employment tended to grow more rapidly during the shale oil boom than the preceding 10-year period. Counties in the Eagle Ford shale experienced the strongest overall employment growth between 2009 and 2014, when local employment in the oil and gas industry expanded by more than 50% per year on average. Meanwhile, counties in the Permian Basin also witnessed dramatic growth in oil and gas employment exceeding 60% annually, but their overall annual employment growth was only close to the statewide average of 2%.

The Barnett shale is the only region with overall employment growing at a relatively slower pace during the oil boom period of 2009–2014. Oil and gas employment growth also slowed down to 11.6% annually from 18.4% in the decade prior to 2009. As pointed out in the preceding section, this formation has predominantly natural gas proved reserves as opposed to oil. In other shale regions with more oil reserves, oil and gas employment grew at least twice as fast during the shale oil boom period than earlier.

Table 1 also shows the averages of counties' total personal income as well as income in the oil and gas industry. Total personal

[1] In the cases that industry level data are suppressed to avoid disclosure of confidential information, we entered a zero because the data are typically very small (less than 5).

Table 1
County data statistics.

	Shale formation (average)						Texas		
	Barnett	Eagle Ford	Granite Wash	Haynes-ville	Permian Basin	Total	Average	Minimum	Maximum
No. of counties	17	23	3	13	51	107	254	254	254
Employment									
2009 Level	66,159	12,777	1426	23,285	8405	20,133	39,537	45	2,015,702
2014 Level	74,252	14,622	1787	24,608	9665	22,586	43,874	44	2,248,285
Annual Chg. 2009–14	2.2%	7.2%	5.1%	1.0%	2.1%	3.1%	2.0%	−9.8%	50.0%
Annual Chg. 2000–09	2.4%	1.6%	4.3%	0.7%	1.1%	1.5%	1.5%	−2.2%	8.9%
Oil & gas employment									
2009 Level	946	283	167	818	592	597	758	0	79,167
2014 Level	1453	755	325	1113	1097	1060	1121	0	91,680
Annual Chg. 2009–14	11.6%	50.3%	18.0%	14.7%	66.0%	43.8%	27.8%	−20.0%	1780.8%
Annual Chg. 2000–09	18.4%	4.9%	9.5%	7.2%	4.1%	7.1%	5.0%	−11.1%	128.5%
Personal income									
2009 Level, $ mil	6965	1073	139	1978	713	1922	3608	4	177,157
2014 Level, $ mil	9048	1418	231	2448	1061	2552	4704	3	237,913
Annual Chg. 2009–14	6.0%	9.8%	11.1%	4.4%	9.1%	8.2%	6.8%	−4.1%	29.6%
Annual Chg. 2000–09	6.5%	6.6%	5.3%	5.6%	5.9%	6.1%	6.0%	−2.3%	15.8%
Oil & gas income									
2009 Level, $ mil	171	28	15	110	84	87	155	0	20,679
2014 Level, $ mil	408	89	38	232	219	217	326	0	36,166
Annual Chg. 2009–14	40.0%	57.5%	31.1%	45.8%	30.9%	41.0%	36.2%	−20.0%	202.7%
Annual Chg. 2000–09	45.2%	15.4%	18.3%	11.9%	4.3%	14.5%	9.3%	−11.1%	295.5%
Oil & gas wells									
Oil Wells, 2009	418	492	255	486	1509	958	618	0	7228
Oil Wells, 2014	463	830	321	487	1859	1206	729	0	10,312
Gas Wells, 2009	1014	369	1705	1187	394	620	391	0	5932
Gas Wells, 2014	1252	450	1858	1196	392	680	408	0	5895
Net earnings by place of work/personal income									
2009	−6.4%	0.3%	−7.5%	−1.4%	−0.2%	−1.4%	−2.3%	−104.2%	124.8%
2014	−5.9%	0.2%	−8.7%	−2.2%	−0.2%	−1.5%	−2.0%	−86.8%	108.1%

income includes wage earnings and other types of incomes, such as oil and gas operators' lease and royalty payments to private households. Whereas the patterns of income statistics correspond to those of employment statistics, the growth of local income far exceeded the growth of local employment, reflecting in part the wage pressure in the increasingly tight local labor markets, especially for skilled labor in the oil and gas industry. Despite overall strong employment and income growth across the five shale regions between 2009 and 2014, a number of counties in Texas suffered losses in employment or income during that period.

Table 1 also lists the numbers of active oil and gas wells in 2009 and 2014. The average numbers of active oil or gas wells per county varied widely across the five shale formations. Counties in the Granite Wash and Barnett regions had the most gas wells, whereas counties in the Permian Basin had the most oil wells. Andrews County in the Permian Basin had the most oil wells in both 2009 and 2014. Sutton County also in the Permian Basin had the most gas wells.

The bottom panel of Table 1 lists the average amounts of net earnings by place of work, as opposed to by place of residence, as a share of total personal income. Net earnings by place of work represent the adjustment to BEA's personal income by residence with the net flow of compensation of interstate commuters. Positive numbers are found only for Eagle Ford counties. A positive number for a particular county indicates that the number of people traveling to that county for work exceeds that county's residents working in other counties within Texas. In addition to the extent of commuting, much of the Eagle Ford shale was operated with a transient workforce living in temporary housing units commonly known as "man camps." For the Barnett and Granite Wash regions, on the contrary, net earning flows were negative. Because the BEA reports such data only at the aggregate level of a county but not at the local industry level, the data will not be included in our econometric work for the purposes of evaluating multiplier effects. The data of net earnings by place of work represent anecdotal evidence in support of the extent of labor mobility and other economic interactions across counties.

2.4. Empirical models

2.4.1. Baseline model

Our empirical analysis begins with regressions using cross-sectional data. This is the approach adopted recently by Weber (2012, 2014) in studying the U.S. natural gas boom over the period 1999–2007. The general form of the regression is:

$$y_i = \alpha + \boldsymbol{X}_i\beta + \boldsymbol{C}_i\gamma + \varepsilon_i \tag{1}$$

where y_i is the dependent variable representing an economic outcome within county i over a specific period, $\boldsymbol{X}_i = [x_{1i,t}, \ldots, x_{Li,t}]'$ is a $(1 \times L)$ vector that includes measures of local activities directly related to oil and gas extraction, and $\boldsymbol{C}_i = [c_{1i,,t}, \ldots, c_{Ki,t}]'$ is a $(1 \times K)$ vector of control variables that allow different characteristics of the local economy to have different effects on y_i. The last term in Eq. (1) is a random error $\varepsilon_i \sim N(0,\sigma^2)$. The other terms $(\alpha,\ \beta$ and $\gamma)$ contain free parameters for estimation.

Following the literature on regional economic impacts, the dependent variables are alternatively employment and personal income. The measure of economic effects by income versus employment allows us to explore the effect on local household incomes associated with royalty payments from the drilling activity. For the explanatory variables, we follow recent studies on the regional effects of oil and gas extraction, such as Paredes et al. (2015) and Weber (2012). The key explanatory variables in $\boldsymbol{X}_i$ are the numbers of active oil and gas wells located within a county. Unconventional and, in particular, horizontal wells dominated the growth in Texas's oil and gas production during the recent shale oil boom.

The number of oil and gas wells, the key explanatory variable, may be correlated with omitted variables that affect oil and gas drilling activities as well as the local economy. Regression excluding those confounding factors would result in biased estimates due to endogeneity in the explanatory variables. Following recent studies (e.g., Weber, 2012, 2014; Brown, 2014), the control variables in $\boldsymbol{C}_i$ capture a multitude of local labor market, economic and geographic characteristics that might have affected the intensity of oil and gas extraction as well as the local economy. The first set of control variables reflect the structure of the local economy, including the shares of total income earnings accounted for by the agricultural, construction, manufacturing, and retail sectors.

Each county's pre-existing economic condition is captured by per capital income in the base year. Heterogeneity across counties is also captured by the population density, which tends to be higher in urban or metro areas. Energy companies may lease land for less in economically depressed areas. Similarly, because proximity to oil or gas wells tends to lower property values and the quality of life, wealthier communities might have more incentive and capability to fight fracking wells (Weber, 2012).

Geological characteristics, such as reserves, would also affect energy companies' decision to drill in a particular area. Those factors are captured by a set of binary dummy variables for the five shale formations. Different shale plays have different recovery rates for oil or gas extraction, and their output differs by density and other quality factors. Following Weber (2012, 2014) and Fetzer (2014), we will also consider a similar variable, which is measured by the percent of a county covering a shale formation.

As Weber (2012) pointed out, there is a considerable lag between the time a well is first drilled and the time oil or gas flows out of the ground. Moreover, it takes time to build the capital infrastructure for the drilling activity as well as a logistical network for transporting the oil or gas supplies to refineries or storage sites. From those perspectives, we attempt to capture the cumulative effects of oil and gas extraction by looking at changes in economic variables over the 6-year period between 2009 and 2014. This sample period captures the interval of the shale oil boom. As such, the dependent variable y_i in the cross-section model is the difference between the county employment or income levels between 2009 and 2014.

2.4.2. Difference-in-difference regressions

Despite our efforts to control for factors that might have affected local economic conditions across counties beyond oil and gas extraction, the regression model as captured by Eq. (1) does not allow for the possibility that shale counties might have overall been performing better or worse than other counties prior to the oil boom. To account for the effects of past trends, we adopt the difference-in-difference approach (see, e.g., Weber, 2012; Lee, 2015), which replaces the dependent variable with a relative measure. More specifically, the transformed dependent variable is defined as $y_{i,2009} \times \left[(y_{i,2014}/y_{i,2009}) - 5/9 \times (y_{i,2009}/y_{i,2000})\right]$, which assumes a linear growth trend. In words, the transformed variable equals the growth rate of economic activity between 2009 and 2014 less the growth rate of economic activity between 2000 and 2009, the latter of which is scaled to conform to the shorter time interval under investigation. This difference-in-difference specification is equivalent to controlling for the counterfactual condition that a county's economy was growing at its historical pace. Data of oil and gas well counts are transformed accordingly. Accordingly, the base year for the control variables is set at 2000.

Our cross-sectional data model has a major drawback, nevertheless. Despite our efforts to control for heterogeneity across counties and endogeneity in drilling activity, it is difficult to ascertain that regression results are free of the potential bias due to unobserved omitted variables. One common strategy to mitigate those potential effects is the panel data approach, which pools time series and cross-sectional data together.[2]

2.4.3. Panel data models

This subsection outlines the panel data models for our empirical work. For county i ($i = 1, 2, \ldots, N$) in year t ($t = 1, 2, \ldots, T$), the basic panel data framework can be expressed as:

$$y_{it} = \boldsymbol{Z}_{it}\boldsymbol{\Theta} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where $\boldsymbol{Z}_{it} = \left[1, x_{1i,t}, \ldots, x_{Li,t}; c_{1i,t}, \ldots, c_{Ki,t}\right]'$ is a $(L+K+1)$ vector of explanatory variables, and $\boldsymbol{\Theta} = [\theta_0, \theta_1, \ldots, \theta_{L+K}]$ is a corresponding $(L+K+1)$ vector of unknown parameters. The term μ_i captures the so-called individual effects, which represent time-invariant, or cross-sectional, heterogeneity across counties. The term λ_t captures time effects, which represent time-varying factors that are common to all counties in the sample. The last term ε_{it} represents a purely random shock.

In panel regressions, the time-invariant effects can be treated as fixed effects or random effects. In line with the econometric literature that analyzes geographical or spatial effects in the panel setting (see below), we have followed the popular approach of the two-way fixed-effects estimator, which treats both individual effects and time effects with dummy variables. The individual effects in μ_i are eliminated from Eq. (2) by demeaning the variables on both sides of the equation. The intercept term θ_0 is also eliminated as a result. The dependent variable after the transformation becomes $y_{it}^{*} = y_{it} - \bar{y}_i$ where $\bar{y}_i$ is the sample mean. The fixed time effects λ_t are eliminated analogously but over the time dimension. The coefficients in $\boldsymbol{\Theta}$ without the intercept can be estimated by ordinary least squares (OLS). An alternative strategy to eliminate the unobserved time-invariant effects is taking the first differencing transformation of Eq. (2), so that the dependent variable after transformation is $y_{it}^{*} = y_{it} - y_{it-1}$. This treatment is analogous to the above difference-in-difference approach to cross-sectional data.

To explore lasting effects in economic activity over time, we extend the static panel data model to a first-order autoregressive AR(1) representation:

$$y_{it} = \rho y_{it-1} + \boldsymbol{Z}_{it}\boldsymbol{\Theta} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where the new coefficient ρ captures the temporal effects given the introduction of the lagged dependent variable.[3] The first-difference model specification is equivalent to $\rho = 1$. However, unlike the specification in Eq. (2), the OLS estimator of $\boldsymbol{\Theta}$ in Eq. (3) with fixed-effects is inconsistent. Hsiao (2003) indicated that the demeaning procedure creates a correlation between the demeaned lagged dependent variable and the demeaned error term. Hsiao et al. (2002) further showed that this bias can be resolved with a maximum-likelihood (ML) procedure based on the model's unconditional likelihood function. In addition to capturing the lagged effects in the dependent variable, Eq. (3) allows us to measure the long-run effect of a change in the explanatory variable. For instance, the long-run response of y_{it} to x_{it} is measured as $\theta_i/(1 - \rho)$.

Eq. (3) captures two distinct characteristics in panel data, namely the temporal effects through the inclusion of the lagged dependent variable, and the time-invariant cross-sectional effects through the fixed-effects estimator. However, the regression model ignores spatial interactions among counties at each time period. Spatial interactions can occur in the form of spillover and

[2] Nevertheless, the difference-in-difference approach deserves attention. As a referee pointed out, our cross-sectional model corresponds to differencing panel data and thus it is not the conventional cross-sectional models that capture only variations across space without the time dimension.

[3] Conceptually, additional autoregressive lags as well as lags in the independent variables can be added to the model. Preliminary analysis, however, shows that those terms are not statistically significant, meaning that the AR (1) model adequately describes the dynamics of the data.

Table 2
Direct estimations of multipliers.

	Employment	Income
(A) Cross-sectional data		
OLS	5.89**	3.51*
	(2.26)	(11.79)
IV	6.90*	4.10*
	(6.28)	(14.78)
(B) Panel data		
Fixed effects	4.63*	2.63*
	(2.88)	(16.08)
First difference	3.01*	2.39*
	(2.24)	(27.33)

Notes: * and ** represent statistical significance at the 1% and 5% levels, respectively. Absolute *t*-statistics are in parentheses.

feedback effects, externality, or competition in labor or capital resources. To capture spatial interactions in addition to time dynamics, we consider a dynamic spatial panel data model (Le Sage and Pace, 2009):

$$y_{it} = \rho_0 y_{i,t-1} + \boldsymbol{Z}_{it}\boldsymbol{\Psi} + \sum_{j=1}^{N} w_{ij}\boldsymbol{Z}_{jt}\boldsymbol{\Phi} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where w_{ij} is an element of an $N\times N$ matrix $\boldsymbol{W}=\{w_{ij}\}$ with prespecified spatial weights that reflect the spatial arrangements of the counties in the sample. More specifically, w_{ij} is equal to one if county i and county j are physically adjacent counties, and zero otherwise. To exclude the self-neighbor effect, the diagonal elements of $\boldsymbol{W}$ are set to zero.

The spatially lagged term $\sum_{j=1}^{N} w_{ij}\boldsymbol{Z}_{jt}$ introduces contemporaneous spatial correlation to the independent variables. The vector of coefficients $\boldsymbol{\Phi}$ captures the spatial effects in the independent variables, while the vector of coefficients $\boldsymbol{\Psi}$ measures the response to a change in the independent variables without spatial effects. By comparison, the term $\boldsymbol{Z}_{it}$ contains own-area characteristics, whereas the linear combination of the spatially lagged term captures characteristics of neighboring areas. In our case, the spatially lagged term will capture the response of one county to the average change in wells of its contiguous neighbors.

One common approach in the spatial econometric literature is to apply a model that includes a corresponding spatially lagged dependent variable ($\sum_{j=1}^{N} w_{ij}y_{j,t-1}$) along with the spatially lagged covariates. However, Gibbsons and Overman (2012) underscored the potential problem of identifying the causal effects of the independent variables of interest in the presence of the spatially lagged dependent variable. As in Weber (2014), we adopt their recommendation and include only $\sum_{j=1}^{N} w_{ij}\boldsymbol{Z}_{jt}$ in the empirical model. For estimation, we apply the ML procedure suggested by Anselin et al. (2006) and Elhorst (2010, 2014).

Eq. (4) allows us to measure, for instance, employment in one particular county in relation to the drilling activity in that county as well as the drilling activity in its neighboring counties. To explore the extent of spatial or "indirect" effects, we use the partitioning technique suggested by Le Sage and Pace (2009). Let $\boldsymbol{y}_t = [y_{1t}, y_{2t} \dots, y_{Nt}]'$, $\boldsymbol{y} = [\boldsymbol{y}_1', \boldsymbol{y}_2', \dots, \boldsymbol{y}_T']'$, $\boldsymbol{Z}_t = [\boldsymbol{Z}_{1t}', \boldsymbol{Z}_{2t}', \dots, \boldsymbol{Z}_{Nt}']'$, and $\boldsymbol{Z} = [\boldsymbol{Z}_1', \boldsymbol{Z}_2', \dots, \boldsymbol{Z}_T']'$. The "direct" and "indirect" effects for the rth explanatory variable are drawn from an $N\times N$ matrix of partial derivatives associated with a change in each of the explanatory variables:

$$\partial\boldsymbol{y}/\partial\boldsymbol{Z}_r' = I_N\boldsymbol{\Psi}_r + \boldsymbol{W}\boldsymbol{\Phi}_r \tag{5}$$

where the subscript r denotes the rth row of a matrix. For the rth explanatory variable, the average of the diagonal elements of this matrix represents the "direct" effect, which measures how the explanatory variable in one county affects the dependent variable of that county (own-partial derivatives). The "indirect" effect is measured by the average of the cumulative sum of the matrix's off-diagonal elements (cross-partial derivatives). The "total" effect is the sum of the "direct" and "indirect" effects.

3. Results and discussions

This section summarizes the estimation results of the models outlined in the preceding section. The cross-sectional sample consists of the 254 counties in the state of Texas. The dependent variable is measured alternatively by employment and personal income. For each of the two alternative economic outcomes, regressions were run for the county total and again for the oil and gas industry. Standard errors in all regressions are robust to arbitrary heteroskedasticity.

The key explanatory variables of our interest are oil and gas well counts as measures of drilling and extraction activities. Our measures of the multiplier effects equal the ratios of the estimated coefficients (total effects) on well counts in the regressions for total economic outcomes over the corresponding coefficients (direct effects) in the regressions for outcomes in the oil and gas industry. This is the common approach among recent econometric-based studies on the economic impacts of the oil and gas industry (e.g., Brown, 2014; Weber, 2014; Hartley, et al., 2015).

3.1. Direct estimation of multipliers

Instead of separate regressions for total employment and employment in the oil and gas industry, employment multipliers can be obtained "directly" by regressing total employment on oil and gas employment. The coefficient on that key explanatory variable represents the response of total employment to a change in oil and gas employment, other things being equal. For comparison purposes, we began our empirical work with those regressions.

Table 2 shows the key results of the "direct" regressions with cross-sectional and panel data. The cross-section model was estimated alternatively with the OLS and instrumental variable (IV) methods. Total county employment and income are the alternative dependent variables. The table displays the coefficient estimates for county employment and income in the oil and gas industry as alternative explanatory variables. Regressions were run along with all control variables ($\boldsymbol{C}_i$) discussed in the previous section. More specifically, the OLS regressions include local per capita income, population density, the income shares of four major economic sectors, and dummy variables representing different shale formations. In the IV regressions, the above control variables serve as instruments. Following Weber (2012, 2014) and Fetzer (2014), we replaced the dummy variables with the percent of a given county covering a shale formation as an instrument. The set of instruments were found to be relevant based on the *F*-tests for the instruments in explaining the key explanatory variables. The *F*-statistic is 19.10 for industry employment, and 90.04 for industry income. Both statistics are statistically significant at the 1% level. According to the table, the employment multipliers are about 6 and the income multipliers are about 4. By comparison, the IV multiplier estimates are slightly larger than their OLS counterparts.

Instead of cross-sectional data, we also ran corresponding regressions with panel data. We also applied the two-way fixed-effects and first-difference estimators as discussed in Section 2 above. The point estimates of the fixed-effects regressions are close to the OLS estimates, albeit slightly smaller in size. By comparison, the first-difference regressions generate even smaller point estimates for the multipliers.

Those "direct" regressions, however, do not distinguish possible differential effects between oil wells and gas wells. As shown

Table 3
Difference-in-difference regressions with cross-sectional data.

	(A) Combined oil & gas wells				(B) Separate oil & gas wells			
	Δ Employment		Δ Income ($mil)		Δ Employment		Δ Income ($mil)	
	Total	**Oil/gas**	**Total**	**Oil/gas**	**Total**	**Oil/gas**	**Total**	**Oil/gas**
Intercept	−2304.06***	−1079.15***	−843.49**	−612.25	−1934.70***	−1069.97**	−765.86***	−595.42
	(1.90)	(2.26)	(2.06)	(1.35)	(1.78)	(2.09)	(2.09)	(1.36)
Δ Oil/gas wells	1.31**	0.32*	0.27***	0.01				
	(1.95)	(2.88)	(1.78)	(1.53)				
Δ Oil wells					1.19**	0.49***	0.26***	0.22**
					(2.20)	(1.91)	(1.85)	(2.15)
Δ Gas wells					3.18**	0.53***	2.97**	0.93***
					(2.32)	(1.73)	(1.96)	(1.92)
Per capita income	33.82	20.76**	20.90**	10.62**	10.31	19.13***	15.96***	8.99**
	(0.97)	(2.03)	(2.43)	(2.36)	(0.31)	(1.93)	(1.81)	(2.05)
Pop. density	57.15*	1.82***	13.55*	2.47**	59.44*	1.97***	14.03**	2.64**
	(4.94)	(1.88)	(4.10)	(2.27)	(4.96)	(1.89)	(3.99)	(2.29)
% Farm income	51.91***	−12.82	12.44	5.21	54.73**	−11.24	13.03	7.00
	(1.83)	(0.98)	(1.60)	(0.77)	(1.92)	(0.90)	(1.63)	(0.96)
% Construction income	77.98**	20.05*	18.03***	12.27*	61.25**	19.00*	14.52***	10.92*
	(2.13)	(2.42)	(1.74)	(2.48)	(2.11)	(2.48)	(1.80)	(2.64)
% Manufacturing income	−49.64	−11.83***	−5.19	2.07	−60.39	−12.53***	−7.45	0.92
	(1.00)	(1.69)	(0.50)	(0.40)	(1.18)	(1.79)	(0.72)	(0.19)
% Retail income	−340.63	83.18	−98.07	−7.91	−328.79	85.97	−95.58	−6.26
	(1.10)	(1.21)	(1.15)	(0.19)	(1.09)	(1.26)	(1.15)	(0.16)
Barnett dummy*100	−24.42	−1.05	−5.26	−2.92	5.79	1.39	1.09	−0.04
	(0.99)	(0.31)	(0.91)	(1.06)	(0.60)	(0.46)	(0.53)	(0.03)
Eagle Ford dummy*100	19.45**	2.95***	3.31	1.51	25.13***	3.43***	4.50	2.02
	(2.30)	(1.91)	(1.30)	(1.34)	(1.85)	(1.68)	(1.34)	(1.38)
Granite Wash dummy*100	−0.02	−2.71	−1.96	−1.87	26.37	−0.44	3.58	0.61
	(0.00)	(0.86)	(0.64)	(1.14)	(1.16)	(0.14)	(0.61)	(0.25)
Haynesville dummy*100	−18.98	0.59	−3.62	0.25	−14.48	0.82	−2.67	0.49
	(1.33)	(0.60)	(1.03)	(0.27)	(0.90)	(0.80)	(0.69)	(0.49)
Permian Basin dummy*100	9.46***	1.33***	2.05	−0.02	6.64***	0.97	1.45	−0.41
	(1.93)	(1.79)	(1.50)	(0.03)	(1.80)	(0.44)	(1.22)	(0.47)
Adjusted R^2	0.79	0.30	0.76	0.48	0.82	0.32	0.78	0.49
Multiplier: oil & gas		4.09**		19.10				
Multiplier: oil						2.41**		1.18**
Multiplier: gas						6.04***		3.20***

Notes: *, **, and *** represent statistical significance at the 1%, 5%, and 10% levels, respectively. Absolute *t*-statistics are in parentheses.

below, this distinction is important for understanding developments during the recent shale oil boom. For this reason, those results in Table 2 simply serve as a robustness check for the empirical work to be presented below.

3.2. Cross-sectional data

Table 3 shows the estimation results for the difference-in-difference model specification as detailed in Section 2 above. To reiterate, the dependent variables and the key explanatory variables (oil wells and gas wells) are measured relative to its historical trend over the 2000–2009 period. The key variables of interest are changes (Δ) in the numbers of active oil wells and gas wells between 2009 and 2014 relative to the 2000–2009 period. As discussed above, the control variables are per capita personal income, population density, and the percentages of personal income in the agriculture, construction, manufacturing, and retail sectors.[4] Regressions were applied to a cross-section of 254 Texas counties.

Panel A of Table 3 contains estimates with the combined oil and gas well counts as a single explanatory variable. The second and third columns display, respectively, estimates for the regressions with a county's total employment and employment in the oil and gas industry as alternative dependent variables. Except for the oil and gas income equation, the estimates of the intercept term are statistically significant and negative, meaning that those local economies on average would have fared worse in 2014 than in 2009 without oil and gas activities. According to the regression results, 0.3 direct job was added when a county drilled one additional well, and the well brought one additional job across non-mining industries. The corresponding estimates for the personal income equation in the fourth and fifth columns are weaker in statistical sense. About $0.3 million in county total income was associated with one additional well. The estimate for income in the oil and gas industry, however, is not statistically different from zero.

As explained in Section 2 above, the coefficient estimates for well counts in the “total impact’ and “direct impact” regressions can be used to calculate the employment and income multipliers. The bottom of panel A shows those multiplier estimates. For employment, the multiplier of 4.09 (=1.31/0.32) is comparable to the “implied” multipliers derived from some popular “impact” studies (e.g., IHS Global Insight, 2011) but smaller than other studies (e.g., PerrymanGroup, 2009; Scott, 2009). For income, however, the multiplier is not statistically meaningful.

Table 3 also lists coefficient estimates for the control variables. According to the estimates in panel A, local per capita income, population density and different aspects of industrial composition can meaningfully explain employment growth. While drilling activity occurred largely in rural areas, the results suggest that economic impacts were larger in more developed communities with higher per capita income levels or higher population density. This implies that more developed areas, which tend to have more capital and labor resources as well as more developed infrastructure, are more ready to reap the potential impact of a positive economic shock.

The estimates for the dummy variables suggest that oil and gas wells in the Eagle Ford and Permian Basin formations tended to generate more jobs than other shale formations. The estimates for the other regions are not significantly different from zero. Oil and gas production grew more rapidly in those two plays as a result of newly drilled wells, which were more productive than “legacy” wells more commonly found in other plays. By comparison, the larger estimates for the Eagle Ford play reflect its more rapid expansion in new wells. Moreover, in contrast to the Permian Basin, which had both conventional and unconventional wells, the Eagle Ford play had mostly unconventional or horizontal wells that required more labor and capital to drill than conventional wells.

Instead of estimations with active oil and gas wells together, panel B of the table shows estimates for oil wells and gas wells as separate explanatory variables. Gauged by the adjusted R^2's, the specification with those separate variables (panel B) provides marginally more explanatory power than aggregating the two types of wells (panel A). The different economic impacts can be realized in the coefficient estimates. For oil wells, the four coefficient estimates are close to those in panel A. For gas wells, however, the corresponding point estimates are noticeably larger.

A comparison of the respective estimates for the two types of wells indicates overall higher employment and income impacts from gas wells relative to oil wells. The bottom of panel B shows the implied multipliers calculated from the coefficient estimates for wells. The employment multiplier is 6.04 for gas wells, compared with 2.41 for oil wells. The estimate for oil wells are comparable to Weber's (2014) multiplier estimate for gas wells. Interestingly, the corresponding multiplier in panel A is between those two estimates. Similarly, the income multiplier for gas wells is more than double that for oil wells. While those estimates are overall comparable to the estimates from “direct” estimations in Table 2, the disparities between oil and gas wells are interesting.

The findings concerning higher economic impacts from gas wells than oil wells are, however, counterintuitive. Capital spending is largely the same for developing a gas well as for an oil well. However, developments in the output markets might have affected the average productivity of the two types of wells in Texas and thus their economic impact on local economies. Between 2009 and mid-2014, crude oil prices followed a steady upward trend while natural gas prices remained relatively low. Meanwhile, the total number of new oil wells in Texas grew exponentially, and the number of new gas wells remained relatively steady or declined in different counties. Higher crude oil prices provided energy companies more incentives to drill new oil wells and refrack old wells that would otherwise be uneconomical to operate. On the contrary, companies might have responded to low natural gas prices by shutting down less productive gas wells and drilling only most productive wells. In this case, the average production rate of the existing gas wells would increase.

The existing infrastructure across Texas might have also played a role in the differential economic impacts between oil and gas production. Natural gas production across the shale formations has leveraged some well-established networks of pipelines in that region. Similar logistical infrastructure was, however, lacking for oil production in the earlier years of the boom. Particularly for the Eagle Ford play, much of the crude oil production was transported in relatively long distance to refineries by trucks before the pipeline capacity was developed to accommodate the production surge. Roadways and other logistical facilities were also less developed in rural areas where much of the shale drilling activity occurred. The potential impact of oil production might have been limited by such logistical disadvantages, which were more prevalent during the beginning of the oil boom.

3.3. Dynamic panel models

This subsection presents results of panel data regressions that allow for dynamic interactions in economic variables in both time and space. Table 4 shows the results of a panel regression model represented by Eq. (3) above. The right hand side of the equation includes a lagged dependent variable to capture the possible lasting effects in economic outcomes. As discussed above, as a result of the application of the fixed effects and first-difference

[4] In preliminary analysis, we also included interaction terms and other control variables, such as a dummy variable for a county being part of a metro area. Their estimates are not statistically significant and thus they are omitted in our reported results.

Table 4
Panel data regressions.

	(A) Combined oil & gas wells				(B) Separate oil & gas wells			
	Employment		Income ($mil)		Employment		Income ($mil)	
	Total	Oil/gas	Total	Oil/gas	Total	Oil/gas	Total	Oil/gas
Fixed effects								
Lagged dependent variable	0.99*	0.73*	0.82*	0.73*	0.99*	0.58*	0.81*	0.73*
	(15.68)	(6.98)	(30.37)	(11.15)	(14.36)	(5.39)	(30.87)	(13.40)
Oil/gas wells	0.41**	0.12*	0.03**	0.01**				
	(1.96)	(2.43)	(2.14)	(2.02)				
Oil wells					0.25*	0.24*	0.08*	0.06*
					(2.13)	(4.35)	(2.56)	(2.70)
Gas wells					2.98*	0.87*	0.25	0.14
					(2.40)	(2.57)	(2.23)	(1.89)
Multiplier: oil & gas		3.33**		3.93**				
Multiplier: oil						1.05*		1.41*
Multiplier: gas						3.44*		2.96*
Pesaran CD test	8.21*	7.67*	5.36**	3.75***	6.84*	6.39*	4.46**	3.13***
First difference								
Lagged dependent variable	0.55*	0.47*	0.56*	0.51*	0.57*	0.16**	0.55*	0.47*
	(7.62)	(3.18)	(4.93)	(3.64)	(9.75)	(1.93)	(6.05)	(7.81)
Oil & gas wells	2.02**	0.59*	0.24**	0.06**				
	(2.30)	(3.15)	(2.19)	(1.91)				
Oil wells					0.44**	0.29**	0.11	0.05**
					(2.00)	(2.02)	(1.62)	(2.15)
Gas wells					3.85**	0.67***	0.36***	0.09**
					(2.26)	(1.64)	(1.68)	(2.14)
Multiplier: oil & gas		3.41**		3.98**				
Multiplier: oil						1.53**		2.17**
Multiplier: gas						5.75**		3.83**
Pesaran CD test	7.33*	6.97*	4.84**	3.25*	6.11*	5.81*	3.72***	2.50***

Notes: *, **, and *** represent statistical significance at the 1%, 5%, and 10% levels, respectively. Absolute *t*-statistics are in parentheses.

estimators, the intercept and all time-invariant variables dropped out of the regressions. With six panels between 2009 and 2014, and a cross-section of 254 counties, the total number of observations ($N \times T$) is equal to 1524.

Panel A of Table 4 shows the estimates for lagged dependent variable and the combined active oil and gas wells. The resulting multipliers are similar between the two alternative regression techniques. In particular, the two implied employment multipliers slightly below 3.5 are comparable to the previous regressions estimated with panel data (Tables 2 and 3). The income multiplier about 4.0, by comparison, is relatively larger than the corresponding estimate in "direct" estimations (Table 2).

Panel B of Table 4 shows the corresponding estimation results for treating active oil wells and gas wells as separate explanatory variables. As for the cross-sectional data in Table 3, the point estimates for gas wells are appreciably larger than the corresponding estimates for oil wells, and the corresponding estimates for oil and gas wells together (panel A) fall between those separate estimates.

In addition to disparities between oil and gas wells, Table 4 highlights the time and spatially lagged effects. The dynamic effects in the time dimension are captured by the coefficients on the lagged dependent variables. Most estimates for those autoregressive coefficients are close to one in the fixed-effects regressions with data in levels. The estimates are much smaller when the data take a first-differencing transformation. Based on the Im et al. (2003) tests for a unit-root in panel data, the null hypothesis of a unit root across all counties in the sample cannot be rejected for the employment and income data. In light of those test results, the dependent variables are not stationary and thus regressions with data in levels may generate spurious estimates.

However, in Table 4, even the first-difference model ignores the presence of spatial effects. To examine the statistical significance of spatial effects, we applied Pesaran's (2004) test for cross-sectional dependence (CD) in the residuals of regressions in Table 4. The CD statistics under the null of cross-sectional independence are reported at the bottom of the two panels. The null hypothesis is uniformly rejected in all cases, giving strong motivation for modeling spatial effects in the panel data models.

Table 5 shows the regression results of a dynamic spatial model represented by Eq. (4). This model captures spatial interactions in addition to temporal dynamics. The table presents results for oil wells and gas wells as separate explanatory variables, given the strong evidence of their differential effects (Table 4). In light of the unit-root test results discussed above, the employment, income and well data are in first-difference form instead of their levels. In addition to results in panel A, which shows estimates for changes in the numbers of all active wells as in Tables 3 and 4, panel B lists corresponding estimates for changes in the numbers of wells being drilled.

The coefficient estimates for the lagged dependent variables confirm that a county's current employment and income growth are strongly correlated with their patterns in the previous year. In panel A, the coefficient estimates for oil and gas well counts are comparable to their corresponding estimates in the first-difference model in Table 4 above. The point estimates for the spatially lagged explanatory variables are noticeably smaller than the corresponding estimates without the spatial weight. The finding of a relatively small response of a county's employment or income to an additional well in its neighboring counties corroborates with Weber (2014). The particularly small coefficient estimates for oil and gas wells underscore the relatively isolated effects of local drilling activity. Nevertheless, as found in Hartley et al. (2015), such spillover effects are statistically meaningful, especially in the presence of an autoregressive term.

In light of the coefficient estimates for active oil and gas wells in the dynamic spatial model, the bottom of the table shows the

Table 5
Dynamic spatial model regression results.

	(A) Active wells				**(B) Newly drilled wells**			
	Δ Employment		**Income**		**Δ Employment**		**Δ Income**	
	Total	**Oil/gas**	**Total**	**Oil/gas**	**Total**	**Oil/gas**	**Total**	**Oil/gas**
Regression estimates								
Lagged dependent variable	0.54*	0.27*	0.53**	0.42*	0.67*	0.27*	0.53*	0.41*
	(7.03)	(2.60)	(2.41)	(10.99)	(7.30)	(2.59)	(2.47)	(10.83)
Δ Oil wells	0.39**	0.24**	0.08**	0.03**	14.61*	8.07*	2.10***	2.12**
	(2.18)	(2.11)	(1.92)	(2.03)	(2.75)	(3.64)	(1.74)	(1.98)
Δ Gas wells	3.26**	0.62***	0.34**	0.09**	15.18***	9.84*	2.24*	1.20**
	(2.13)	(1.86)	(2.06)	(1.99)	(1.92)	(5.18)	(6.11)	(2.26)
$\boldsymbol{W} \times (\Delta$ Oil wells)	0.05**	0.03***	0.03**	0.01**	0.28*	0.15*	0.23***	0.05***
	(2.06)	(1.87)	(2.07)	(2.02)	(2.59)	(3.21)	(1.77)	(1.86)
$\boldsymbol{W} \times (\Delta$ Gas wells)	0.39**	0.06**	0.11**	0.02***	0.42***	0.22*	0.37*	0.03**
	(2.24)	(1.96)	(1.98)	(1.86)	(1.87)	(5.46)	(5.89)	(2.20)
Log likelihood	−8405.06	−7509.13	−7130.58	−6431.72	−8459.83	−7556.26	−7175.66	−6479.70
Multiplier effects								
Oil wells								
Total effect (coefficient)	0.44**	0.26**	0.11**	0.05**	14.89*	8.22*	2.33**	2.17**
Short run multiplier		1.68**		2.39**		1.81*		2.00**
Long run multiplier		2.65**		2.99**		3.99*		2.51**
Gas wells								
Total effect (coefficient)	3.65**	0.68**	0.45***	0.11**	15.60**	10.05*	2.61*	1.22**
Short run multiplier		5.35**		4.19**		1.55*		2.13**
Long run multiplier		8.42**		5.24**		3.41*		2.68**

Notes: *, **, and *** represent statistical significance at the 1%, 5%, and 10% levels, respectively. Absolute *t*-statistics are in parentheses.

implications of the dynamic effects in both spatial and time dimensions. In the context of spatial dynamics, a "total effect" coefficient captures a county's response of one additional well in its area as well as its adjacent counties. According to those measures computed using the procedure explained in Section 2.4 above, the employment impact of one county's oil and gas wells increases by about 10% when the "indirect spatial effect" of other counties are also taken into consideration. This finding is in line with the results reported by Hartley et al. (2015) for gas production. The extent of such neighborhood effects is even larger (over 25%) for income.

The bottom part of Table 5 lists measures of the short-run, or impact, multipliers using the ratios of the respective "total effect" coefficients. The identified spatial effects raise in varying degrees the "total" impacts of oil and gas wells on both the region as a whole as well as the oil and gas industry. The resulting short-run multipliers are comparable to the corresponding estimates in Table 4 (first-difference model). Measures of the regional economic impacts of oil and gas extraction are even larger if the temporal effect is also taken into consideration. As explained in Section 2.4 above, the long-run multipliers can be computed using the "total effect" coefficients and the autoregressive coefficients.

The multiplier measures in Table 5 suggest that one job in oil extraction generates another 1.65 jobs in other industries in the long run. By comparison, the long-run economic impacts are larger for gas wells than for oil wells. One additional active gas well supports a total of 3.65 jobs within a county in the short run, with 0.68 job directly associated with drilling and extraction. Such findings corroborate with the results in Hartley et al. (2015). The long-run multiplier is 8.42 for employment and 5.24 for income.

As an alternative to changes in the numbers of active wells, panel B of Table 5 lists estimation results using changes in the numbers of new wells drilled as the key explanatory variables.[5] Compared with corresponding estimates in panel A, the estimates for employment and income impacts are much higher when the data of newly drilled wells are used. In line with the engineering-based workforce assessments reported by Brundage et al. (2011) and Marcellus Shale Education & Training Center (2009), the estimate for the "direct" employment impact is nearly 10 local jobs for drilling one additional gas well within a particular county. About 5 more jobs are created among other industries in that county. The inclusion of neighborhood effects captured by the spatially lagged term generates another 0.42 job.

Similar to the results for employment, the estimated impacts of drilling one additional well on income are larger than their corresponding estimates using the numbers of all active wells. However, in contrast to those estimates in panel A, the coefficient estimates are similar between oil and gas wells because there is little difference between the construction as well as drilling these two types of wells. This implies that their differences are attributable mainly to differences during the production phase of those wells (recall Section 3.2). With similar coefficient estimates for the economic outcomes between oil and gas wells, the resulting multipliers for gas wells are now comparable to those for oil wells.

4. Conclusions and policy implications

In this paper, we have estimated the impact of oil and gas extraction on local economies during the most recent Texas shale oil boom period between 2009 and 2014. We first applied conventional cross-section and panel data models to county-level employment and income data. We first found that local communities in Texas would have lost jobs and income during that period if not for shale energy boom.

We also found evidence in support of larger economic impacts from gas wells than oil wells. One interpretation for this finding stems from the different price dynamics between oil and natural gas markets during the oil boom period. This echoed the more recent episode of falling oil prices beginning in late 2014. In response to developments in oil markets, the number of operating

[5] Only the current values of well counts are included in estimations as past values have been found to be not statistically significant. Similar estimation results for newly drilled wells have been obtained for the models presented in Tables 3 and 4, but they are not reported here in order to save space.

oil rigs fell precipitously without corresponding reductions in crude oil production. As least productive oil wells were shut down, the average production rate of the remaining oil wells and their average income impact rose as a result.

Despite relatively robust estimates from the basic panel data models, we investigated the roles of temporal and spatial effects in local economies within a dynamic spatial framework. The allowance for spatial interactions across counties raises the estimates of oil and gas wells' total economic impacts in Texas. Measures of the employment and income effects rise further when the time dynamic effect is also taken into consideration.

Policymakers typically rely on input–output-based analysis to assess how changes of an industry affect local economies. Such methodology has been subject to criticisms in the academic literature (e.g., Carlson and Spencer, 1975; Lee, 2015). Similarly, consulting reports that have been adopted for designing public policy targeting recent development in the shale industry are found to grossly overstate the regional economic effects of that industry in various shale gas formations (e.g., Kinnaman, 2011; Weber, 2012; Paredes et al., 2015). We have shown that the total regional employment impact of oil and gas activity could be as much as 10% larger if we allow for economic interactions among counties. This neighborhood effect is even greater when economic impact is measured by income instead of employment. Moreover, in line with previous findings (e.g., Brundage et al., 2011; Marcellus Shale Education & Training Center, 2009), we have found remarkably larger economic impacts from newly drilled wells than legacy wells, highlighting the changing role of a particular well in different stages.

Our finding of spatial effects in oil and gas activity has a direct bearing on public policy toward sustainable regional economic development. For instance, local governments should monitor closely the economies of their neighboring communities in addition to their own economies. While more developed local areas tend to be more ready to reap the full impact of a positive economic shock, state or federal governments can boost the extent of economic impacts at a regional level by promoting more economic interactions among local communities. Among other things, logistical networks might have played a role in explaining the differential impacts of oil and gas wells during the recent shale boom. Geographical spillover or feedback effects may expand with a more developed infrastructure network that facilities resource mobility and other logistics.

Despite the consideration of regional spillover effects and long-run dynamics, the estimates of employment and income multipliers remain below corresponding multipliers implied by popular input–output based studies (e.g., PerrymanGroup, 2009; Scott, 2009). Those input–output based studies analyze the regional economic effects of all developments related to oil and gas drilling and production instead of focusing on changes in the oil and gas industry alone. Discrepancies with our findings would therefore reflect in part the significance of factors other than the industry multipliers embedded in input–output models, including royalty and lease payments, and public infrastructure spending associated with development of that industry.

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