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# ECONOMICS

# LOCAL EMPLOYMENT IMPACT FROM COMPETING ENERGY SOURCES: SHALE GAS VERSUS WIND GENERATION IN TEXAS

by

**Peter R Hartley**
**Rice University and**
**University of Western Australia**

**Kenneth B Medlock III**
**Rice University**

**Ted Temzelides**
**Rice University**

**Xinya Zhang**
**Rice University**

**DISCUSSION PAPER 14.15**

# Local Employment Impact from Competing Energy Sources: Shale Gas versus Wind Generation in Texas*

Peter Hartley† Kenneth B. Medlock III‡ Ted Temzelides§

Xinya Zhang¶

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†Department of Economics, Rice University and Economics Department, University of Western Australia Business School

‡James A. Baker III Institute for Public Policy, Rice University

§Department of Economics, Rice University

¶Department of Economics, Rice University

**Abstract**

The rapid development of both wind power and of shale gas has been receiving significant attention both in the media and among policy makers. Since these are competing sources of electricity generation, it is informative to investigate their relative merits regarding job creation. We use a panel econometric model to estimate the historical job-creating performance of wind versus that of shale oil and gas. The model is estimated using monthly county level data from Texas from 2001 to 2011. Both first-difference and GMM methods show that shale-related activity has brought strong employment to Texas: 77 short-term jobs or 6.4 full-time equivalent (FTE) jobs per well. Given that 5482 new directional/fractured wells were drilled in Texas in 2011, this implies that about 35000 FTE jobs were created in that year alone. We did not, however, find a corresponding impact on wages. Our estimations did not identify a non-negligible impact from the wind industry on either employment or wages.

# 1 Introduction

Following the dramatic increase in natural gas supplies, and the corresponding decrease in natural gas prices resulting from the development of shale gas, there is an ongoing discussion about the relative merits of renewable energy versus those of natural gas. Proponents of renewable energy emphasize its potential to reduce $CO_2$ emissions and point to other benefits, including the potential of renewable energy to increase employment opportunities and economic growth. We hear less about the employment effects of shale gas production, but a review of the employment experience of different states over the last recession suggests that the effects may be non-negligible. We examine this experience in more detail using detailed microeconomic data from the state of Texas, which has seen substantial development of both shale and wind energy.

Since energy produced through renewable sources is still more expensive than that produced through fossil fuels, governments around the world have been providing tens of millions of dollars in subsidies to the renewable energy industry. More than half of all states in the U.S. have established Renewable Portfolio Standards to promote electricity generation from renewable sources.[1] Federal production tax credits and grants also contributed to increases in renewable capacity and generation between 2001 and 2011. Partly as a result, the renewable energy sector has developed rapidly in the past 12 years. In particular, since wind generation is currently the most competitive non-hydroelectric renewable source, as Figure **??** shows it has grown rapidly in recent years. Other sources of non-hydroelectric renewable electricity generation, including biomass, geothermal, and wood, have remained relatively stable since 2000.[2]

[1]Renewable portfolio standards (RPS), also referred to as renewable electricity standards (RES), require or encourage electricity producers within a given jurisdiction to supply a certain minimum share of electricity from designated renewable resources.

[2]In 2011, in the United States, biomass accounted for about 11% of the total renewable electricity generation, wind accounted for 23%, solar (photovoltaics and concentrating solar power) accounted for 1%, and geothermal for 3%.

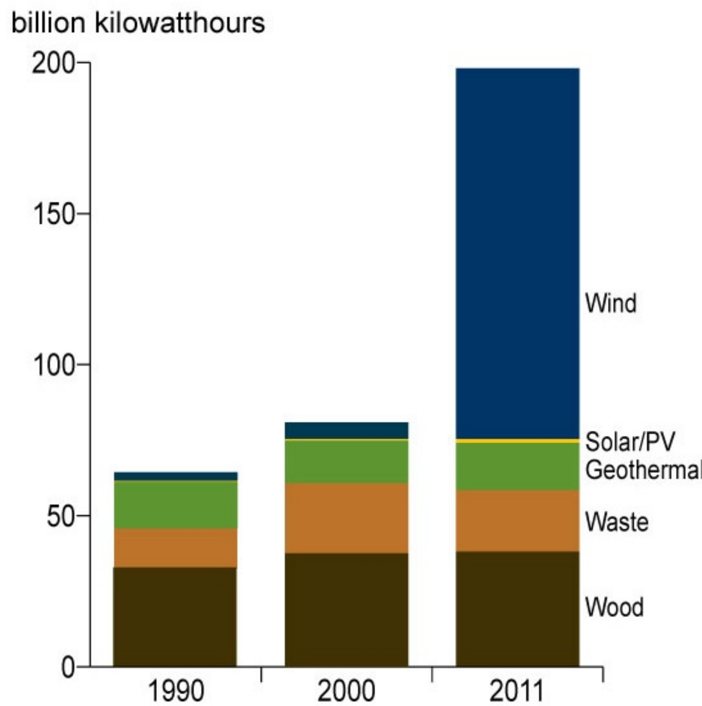



Figure 1: Non hydro-power renewable energy generation, 1990-2011. Data source: EIA

While economists usually concentrate on objectives related to economic efficiency and growth rather than job creation, policy makers often emphasize the job-creating potential of renewable energy sources. Wind energy production, and especially the construction and installation of physical plants and facilities, has the potential to increase domestic employment. Indeed, domestic wind-turbine and component manufacturing capacity has increased recently. Eight of the ten wind turbine manufacturers with the largest share of the U.S. market in 2011 had at least one manufacturing facility in the United States at the end of 2011. By contrast, in 2004 only one utility-scale wind-turbine manufacturer (GE) assembled nacelles in the United States.[3] In addition, both foreign and domestic firms announced or opened new wind turbine and component manufacturing facilities in 2011. The American Wind Energy Association (AWEA) estimates that the entire wind energy sector directly or indirectly employed 75,000 full-time workers in the United States at the end of 2011.

[3]See 2011 Wind Technology Market Report by the U.S. Department of Energy.

At the same time as wind capacity has been expanding, oil and gas companies have demonstrated that the vast resources of shale gas and oil in North America can be exploited at reasonable cost. This "shale revolution" is a result of cost-effective technological developments such as horizontal drilling and hydraulic fracturing. The combination of these techniques caused U.S. production of shale oil and gas to boom.

From the perspective of competition with wind, we are most interested in the increase in natural gas production since very little oil is now used to generate electricity. The Energy Information Administration's 2012 Annual Energy Outlook (?) projects that the share of shale gas in total U.S. natural gas production will increase from 4 percent in 2005 to 34 percent by 2015 and 49 percent by 2025. As shown in Figure ??, shale gas is the largest contributor to natural gas production growth; there is relatively little change in production levels from tight formations, coal-bed methane deposits, and offshore fields.

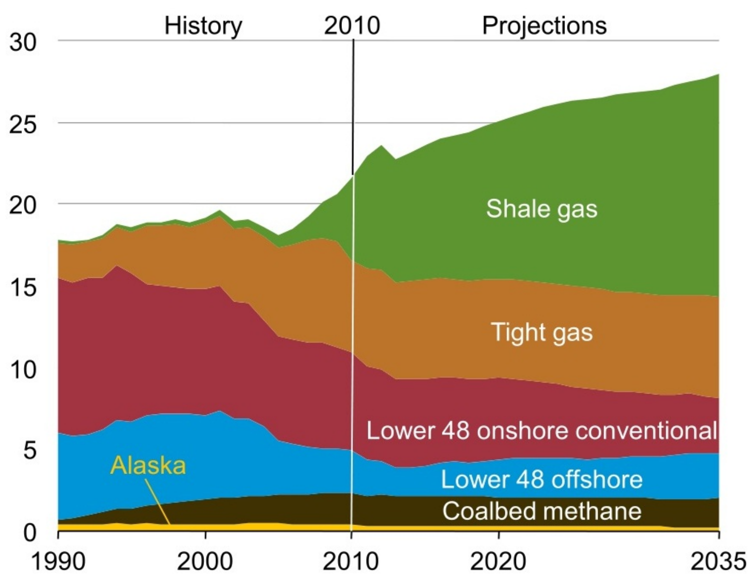
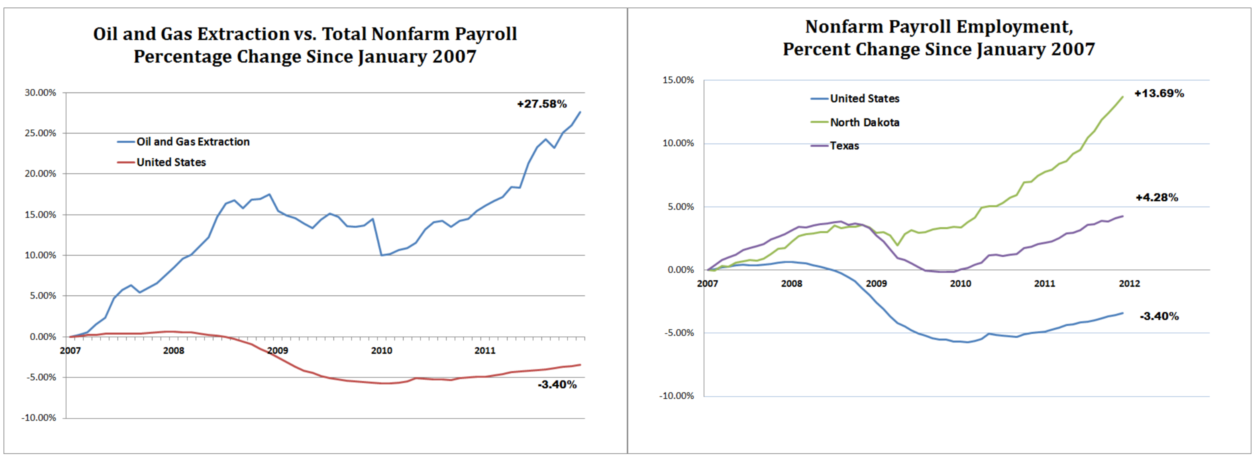



Figure 2: Natural gas production by source, 1990-2035 (TCF). Data source: EIA

The development of shale oil and gas resources has created an investment boom in the oil and gas industry and led to economic revitalization in places like North Dakota, Texas, Alberta, West Pennsylvania, and Louisiana to name a few. During 2007-2011, employment in the oil and gas extraction sector grew at an annual rate of 4.99 percent, or, 27.58 percent in total. By comparison, during the same period, total employment declined 3.40 percent below its starting value (Figure ??). Meanwhile, there is anecdotal evidence that states with more shale oil and gas production have experienced increased employment, while the nationwide employment growth rate remains negative (Figure ??). Furthermore, the relatively low prices resulting from the expanded natural gas supply are stimulating downstream investment in manufacturing,[4] as well as in electricity generation (Figure ??) and in transportation.




(a) (b)

Figure 3: U.S. employment growth (a) by sector (b) by state, 2007-2011. Data source: BLS

While the aggregate effect on employment from developing different energy sources is an important question, it cannot be readily answered in the context of traditional macroeconomic models. As these models assume market clearing, they cannot account for variations in unemployment rates and, thus, are not well suited to study the employment consequences of alternative government policies or other shocks.

Generally speaking, there are two existing approaches to analyzing the employment impacts of the energy industry. The first uses an input-output (I/O) model. The second

[4]This is especially relevant for those sectors that are sensitive to energy costs, such as basic chemicals, plastics & rubber, pharmaceuticals, aluminum, pesticides, paints, and fertilizers.

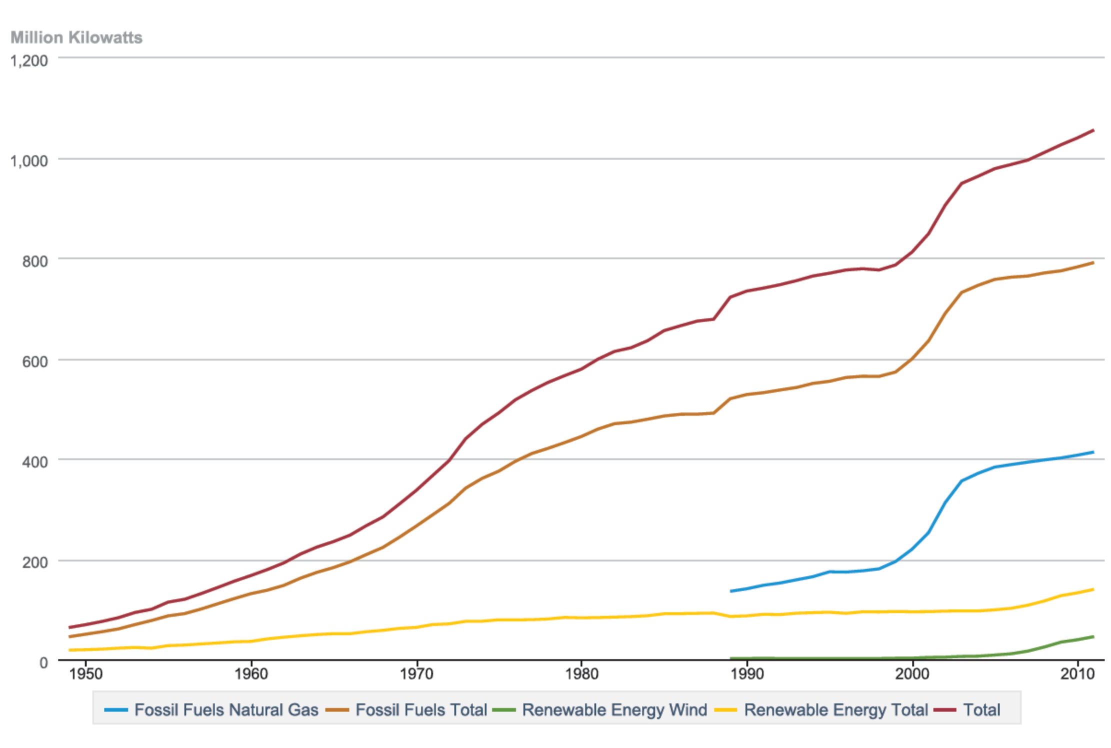



Figure 4: Electricity net summer capacity by source (all sectors), 1949-2011. Data source: EIA

approach is based on survey responses from employers, and uses simple descriptive techniques.[5] In this study, we collect data on the historical job creation and unit of energy produced by each energy source. We then use an econometric model to estimate the historical job-creating performance of wind versus that of shale gas. Like the survey approach, our analysis focuses on localized employment effects rather than more distant impacts. However, the econometric analysis allows us to compare the employment impacts in a more systematic and consistent way across the two energy sources.

[5]See Section **??** for a detailed discussion.

## 2 Literature Review

In the last few years, a large number of reports have emerged studying employment in the shale and wind industries. While non-government organizations and consulting firms conducted most of these studies, a few peer-reviewed journal articles have also been published on this topic.

The I/O model focuses on the use of various inputs to production and how the goods and services produced are allocated between various industrial sectors and consumers. I/O models attempt to account for the economy as a whole. They capture employment multiplier effects, as well as the macroeconomic impacts of shifts between sectors. Hence they could account for losses in one sector (e.g., conventional oil industry) created by the growth in another sector (e.g., wind energy). One drawback is that collecting data for an I/O model is highly labor-intensive. As a result, the calibration process for default multiplier parameters can be biased due to lack of information.

Two widely used I/O studies of the oil and gas industry are the IMPLAN model (see **?**, **?**, **?**, and **?**) and the RIMS II model, used by the U.S. Bureau of Economic Analysis (BEA) (see **?**).[6] These studies typically find significant positive effects from the shale oil and gas sectors on jobs, income, and economic growth.

A study of the Eagle Ford Shale (**?**) estimates that in 2011 shale activity raised output in the local (14-county) region by just under $20 billion dollars and supported 38,000 full-time jobs. If the region is extended to 20 counties, the study finds that 47,097 full-time jobs were supported. A nationwide shale industry report (**?**) has found that the shale gas industry supported 600,000 jobs in 2010. This is projected to grow to nearly 870,000 in 2015, and to over 1.6 million by 2035. Two reports on the Marcellus shale by Pennsylvania State

[6]The IMPLAN model uses a national input-output dollar-flow table called the Social Accounting Matrix (SAM) to model the way a dollar injected into one sector is spent and re-spent in other sectors of the economy. RIMS II provides I/O multipliers that measure the effects on output, employment, and earnings from any changes in a region's industrial activity.

University (?) and by West Virginia University (?) show that the oil and gas industry in Pennsylvania generated \$3.8 billion in value added, and over 48,000 jobs in 2009. In West Virginia, the economic impact of the oil and natural gas industry in 2009 was estimated to be \$3.1 billion in total value added, while approximately 24,400 jobs were created.

The Jobs and Economic Development Impact (JEDI) model developed by the National Renewable Energy Laboratory (NREL) is a series of spreadsheet-based I/O models that estimate the economic impacts of constructing and operating power plants, fuel production facilities, and other projects at the local (usually state) level. **?** validate (or test) the JEDI Wind Energy Model using data from NextEra's Capricorn Ridge and Horse Hollow facilities. They then use the model to examine the economic impact of large-scale wind-farm construction. They found that the JEDI model overestimates local jobs during the construction phase in smaller, rural counties, and that it underestimates by more than 50% the number of jobs in large, urban counties. This is because the JEDI model sets the local share of employment attributable to wind to be the same for all counties. In addition, the JEDI model assumes 100% local share for operations and maintenance (O&M) jobs, which might be implausible, especially in small rural counties.

An alternative approach to I/O models uses "bottom up" estimates based on industry/utility surveys of project developers and equipment manufacturers, and on primary employment data from companies across manufacturing, construction, installation, and O&M. For wind energy, most reports are analytical-based studies, and only calculate direct employment impacts. As an example, a case study on the economic effects of the Gulf wind project in Texas reports the estimated creation of 250 - 300 jobs during the peak construction period (9 months), and 15 - 20 permanent jobs.[7]

A report on the wind industry from the Natural Resources Defense Council (NRDC) measures the number of direct jobs that a typical wind farm may create across the entire value

[7]Gulf Wind: Harnessing the Wind for South Texas

chain. They analyze each of the 14 key value-chain activities independently to determine the number of workers involved at each step in building the wind farm. They find that a typical wind farm of 250MW would create 1079 jobs over the lifetime of the project. Similarly, the Renewable Energy Policy Project (REPP) has developed a spreadsheet-based model using data based on a survey of current industry practices. They use it to calculate the number of direct jobs from wind, solar photovoltaic, biomass, and geothermal activities that would result from the enactment of a Renewable Portfolio Standard. They find that every 100 MW of wind power installed creates 475 jobs in total (313 manufacturing jobs, 67 installation jobs, and 95 jobs in O&M).

# 3 Data

We use data from the state of Texas. Texas has rich shale gas and oil resources and, at the same time, it is the national leader in wind installations and a manufacturing hub for the wind energy industry. According to EIA, Texas accounted for 40 percent of U.S. marketed dry shale gas production in 2011, making it the leading unconventional gas producer in the U.S. Meanwhile, Texas leads the nation in wind-powered generation capacity and it is the first state to have reached 10,000 megawatts of wind capacity.

In Texas, there are 254 counties.[8] For each county $i = 1, \dots, 254$, we have collected observations for $T = 132$ months, or a total of 11 years (2001 - 2011), making the panel balanced.

We use total employment in all industries as one dependent variable. We did not restrict the data to specific industries since we want to measure total employment effects, including indirect job-creation. This includes jobs created in upstream and infrastructure supplying industries, as well as induced jobs, such as jobs added in sectors supplying consumer items (food, auto, housing, etc.) and services. Another dependent variable of interest is the average

[8] Out of these, 77 are urban counties.

weekly wage since, unless the supply of labor is perfectly elastic, it should also be impacted by an increase in the demand for workers. We use monthly employment data and quarterly wage data from the Quarterly Census of Employment and Wages (QCEW) Database of the Bureau of Labor Statistics (BLS).[9] The latter has been adjusted to a real wage using the implicit price GDP deflator (IPD) from BEA.[10]

In order to evaluate the impact from shale and wind development on employment and on the local economy, we need to measure activity in the shale and wind industries. The key explanatory variables we use are the number of unconventional wells completed and the newly installed wind capacity in each county and each month, respectively.

Of course, other variables could also be used to reflect other aspects of new activity in the shale industry. These include the number of permits issued, changes in rig counts, the number of wells spudded, and the change in total shale gas production. We chose the number of wells completed because the well completion date indicates the end of the construction period for each well. We suspect that more direct and on-site jobs are created during that period. To fully describe the impact of shale on employment, especially the multiplier effects on job creation in the local economy, we allow well drilling activities to affect employment with a lag, and we study both pre-completion and post-construction effects.

In the shale industry, the entire process from spudding to producing marketed output can take up to 3-4 months. Horizontal drilling itself currently takes approximately 18-25 days from start to finish. Then wells are fractured to release the gas or oil before the well is completed. The well is then connected to a processing facility and pipelines, which transport the products to market. Among these activities, hydraulic fracturing and completion are the

[9]The QCEW employment and wage data is derived from micro data summaries of 9.1 million employer reports of employment and wages submitted by states to the BLS in 2011. These reports are based on place of employment rather than place of residence. Average weekly wage values are calculated by dividing quarterly total wages by the average of the three monthly employment levels and then dividing the result by 13, as there are 13 weeks in a quarter.

[10]The implicit price GDP deflator is the ratio of the current-dollar value of GDP to its corresponding chained-dollar value multiplied by 100.

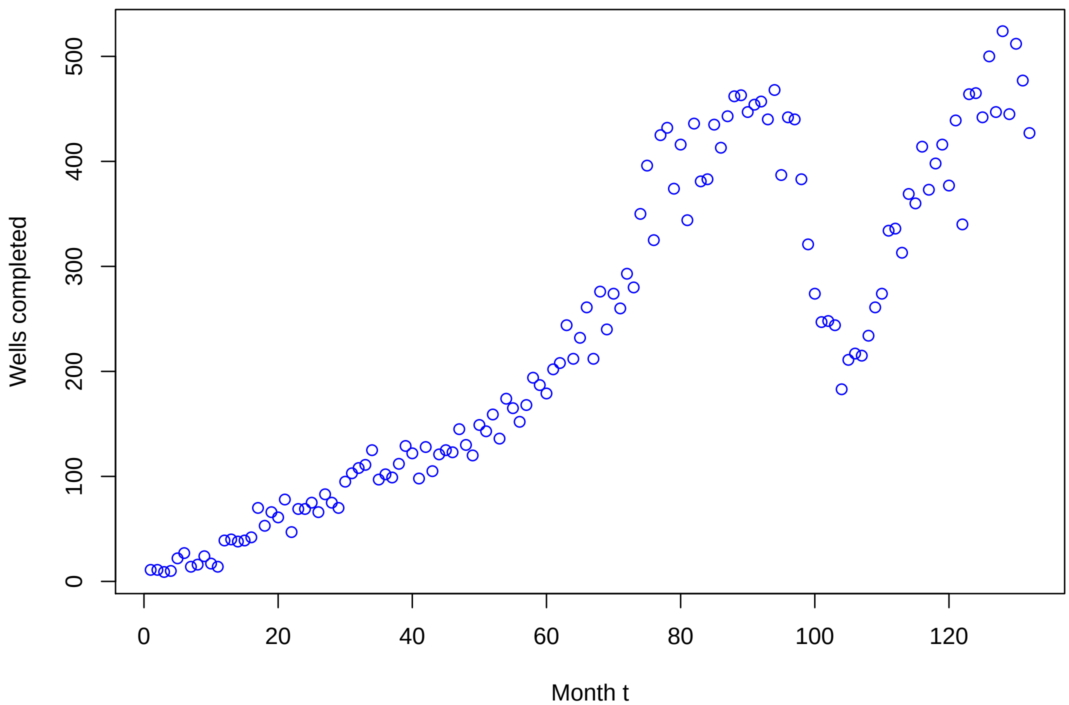



Figure 5: Number of completed directional-drilled/fractured oil and gas wells per county per year, Jan, 2001 - Dec, 2011

most labor intensive. Hence, we expect "number of wells completed" to have a peak impact on employment in the month of well completion.

We use the Drilling Info Database for information about oil and gas wells. We concentrate our study on wells that are both directional/horizontally drilled and hydraulically fractured.[11] Thus, we exclude conventional oil/gas wells from our data set. There were 31,050 directional/horizontal and fractured wells completed in 174 Texas counties during 2001 - 2011, including 25,467 gas wells, 4,963 oil wells, and 620 wells classified as "other types." Figure **??** indicates that shale gas and oil developed very quickly in the past 12 years, from 1 well per month in Jan, 2001 to around 500 in 2011. The completion date and

[11]This filter option is only available for Texas data.

location of each well are used to count the number of wells completed in each county each month.

To measure wind activity in each county we use the installed nameplate capacity brought online in each month. We do not use the change in power generated,[12] as more jobs are created during the construction period than during the O&M period. The installed capacity and online year for new wind projects in Texas throughout the period 2007-2011 is taken from the American Wind Energy Association (AWEA). For wind projects before 2007, we used EIA electricity data on plant level output and a wind industry progress report by *Wind Today*. To find the online month and county location for each new wind project, we needed to refer to additional sources, such as project websites or local news stories. For wind farms covering several neighboring counties, we divided newly installed capacity equally between each of the counties involved. Until 2011, as shown in Figure **??**, we found that 125 wind projects had been constructed in 40 counties, with a total installed capacity of 10,006MW (compared to 6 counties and 920MW in 2001).

To test for non-stationarity, we consider the following model written in difference form:

$$\Delta y_{it} = \rho y_{i,t-1} + \sum_{L=1}^{p_i} \delta_i \Delta y_{i,t-L} + \alpha_0 + \alpha_1 t + u_{it},\ t = 1, 2, \ldots \qquad (1)$$

where $i$ indexes the county and $t$ the month. We then test the hypothesis that $\rho = 0$. Note that the term $\alpha_0 + \alpha_1 t$ allows for a constant and deterministic time trend. When $\rho = 0$, the series $y_{it}$ has a unit root and it is a random walk. When $\rho < 0$, $y_t$ is covariance stationary. Since the $t$-statistic for testing $H_0 : \rho = 0$ does not have the usual distribution, we use the Im, Pesaran, and Shin (IPS) test (**?**) to test for $\rho = 0$. This test is based on the estimation of the above augmented Dickey-Fuller (ADF) regression for the time series in each county. A statistic is then computed using the $t$-statistics associated with the lagged variable. The

[12] Although this would represent the change in monthly wind velocity distribution in addition to the number of generators, it could be argued that wear and tear, and thus the need for maintenance, is likely to be a function of power generated.

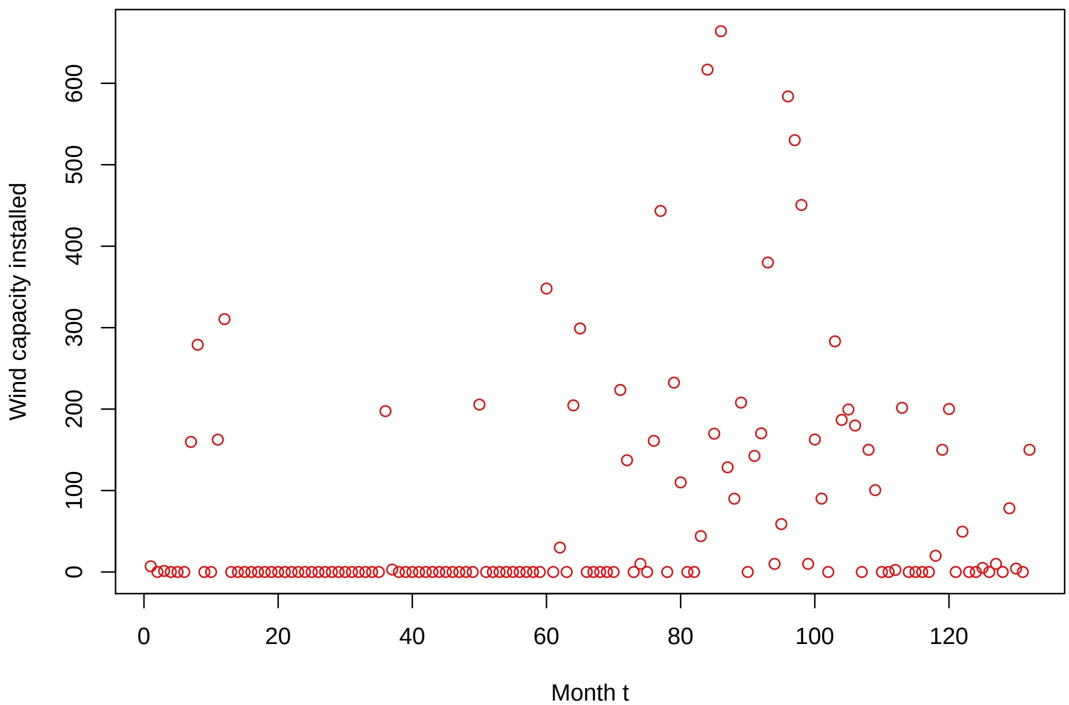



Figure 6: New wind capacity installed during Jan, 2001 - Dec, 2011

null hypothesis is that all series have a unit root, and the alternative is that some have a unit root while others have different values of $\rho_i < 0$. To run the test, we must first determine the optimal number of lags, $p_i$, for each time series in the panel. Since we are working with monthly data, we set the maximum $p_i$ at 14, which is slightly larger than an annual cycle. We then use both the Swartz information criteria (SIC) and the Akaike information criteria (AIC) to determine the optimal value of $p_i$. For both the employment and the wage series, we found that the $p$-value of the IPS test is close to zero. Hence, $H_0$ is rejected and we conclude that some counties may not have unit roots.[13]

[13]We also used a test based on **?** that does not rely on the ADF regression. The Hadri statistic is formed as the cross-sectional average of the individual KPSS statistics, standardized by their asymptotic mean and standard deviation. In our data set, the Hadri test also rejects $H_0$, implying that at least one county has a unit root.

In summary, we conclude that the employment and wage series have unit roots in some counties, while others are stationary. After applying the Dickey-Fuller Generalized Least Squares test (DF-GLS) (at 5% level) and the KPSS test (at 10% level) to each county, we found that in 156 counties, the DF-GLS test cannot reject a unit root, while the KPSS test shows the presence of a unit root. In 34 counties we reject the unit root hypothesis in both tests. In the remaining 64 counties, one test shows the presence of a unit root and the other rejects it.

# 4 Econometric Issues

Working with panel data allows us to study dynamic relationships, which we cannot do using a single cross section. It also allows us to test for the presence of specific effects in counties with shale and wind activities versus those without. This mitigates a potential problem with pure time series analysis, whereby many exogenous factors can change at the same time, making it difficult to attribute an outcome to any one particular change. The panel analysis presumes these other factors affect all counties symmetrically. In addition, a panel data set also allows us to control for unobserved heterogeneity across counties.

## 4.1 Assumptions

We start with a static linear unobserved effects model:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \theta_t + c_i + u_{it}, t = 1, 2, \ldots, T, \tag{2}$$

where $y_{it}$ is a scalar, $\mathbf{x}_{it}$ is a $1 \times K$ vector for $t = 1, 2, \ldots, T$, and $\boldsymbol{\beta}$ is a $K \times 1$ vector. Here, $c_i$ indicates a time-invariant unobservable county effect, and $\theta_t$ represents a series of time fixed effects.

The first issue we need to address is whether the county effects $c_i$ should be taken as fixed or random. A Hausman test yields a statistic $\chi^2_{(2)} = 29632$ with a $p$-value close to zero, indicating that the random effects approach is inconsistent. We therefore assume that the $c_i$ are fixed.

To make the model more realistic, we allow for arbitrary dependence between the unobserved effects, $c_i$, and the observed explanatory variables, $\mathbf{x_{it}}$. For example, underground geology characteristics would be included in $c_i$, and these could be correlated with the number of wells drilled in county $i$. Also, wind capacity highly depends on the climate, and especially the wind resource of the county, which is also part of the variable $c_i$.

With a fixed effects (FE) or first difference (FD) approach, the explanatory variables are allowed to be arbitrarily correlated with $c_i$, but strict exogeneity conditional on $c_i$ is still required. The assumption of strict exogeneity, introduced by **?**, requires that

$$E(u_{it}|\mathbf{x}_i, c_i) = 0, t = 1, 2, \ldots, T. \quad (3)$$

That is, once $\mathbf{x_{it}}$ and $c_i$ are accounted for, $\mathbf{x_{is}}$ has no partial effect on $y_{it}$, for $s \neq t$. In addition, $u_{it}$ has zero mean conditional on all explanatory variables in all time periods. This is a stronger assumption than contemporaneous exogeneity, which requires that $E(u_{it}|\mathbf{x_{it}}, c_i) = 0$. In particular, the latter assumption says nothing about the relationship between $\mathbf{x_s}$ and $u_t$ for $s \neq t$. Sequential exogeneity, which requires that $E(u_{it}|\mathbf{x_{it}}, \mathbf{x_{i,t-1}}, \ldots, \mathbf{x_{i1}}, c_i) = 0$, for $t = 1, 2, \ldots, T$, is stronger than contemporaneous exogeneity. It implies that $\mathbf{x_s}$ is uncorrelated with $u_t$ for all $s \leq t$, but imposes no constraints on the correlation between $\mathbf{x_s}$ and $u_t$ for $s > t$. The pooled OLS estimator for $\boldsymbol{\beta}$ is consistent only if the explanatory variables satisfy contemporaneous exogeneity and zero correlation with the unobserved individual effects.

The idea behind the fixed effects approach is to transform the equations by removing the intertemporal mean, thereby eliminating the unobserved effects. One can then apply pooled

OLS to get FE estimators. Similarly, the FD approach transforms the equations by lagging the model one period and subtracting, then applying pooled OLS to get FD estimators. As we mentioned at the end of the previous section, we found that more than half of the counties have highly persistent employment series. Using time series with a unit root process in a regression equation could cause a spurious regression problem. In that case, first differencing should be used to remove any potential unit roots.

It is standard to assume zero contemporaneous correlation; i.e., that $u_{it}$ is uncorrelated with the number of wells drilled, or the wind capacity installed at $t$. But what about the correlation between $u_{it}$ and, say, $\mathbf{x_{i,t+1}}$? Does future well drilling activity or wind-farm construction depend on past shocks to the county's employment? We do not believe that such feedback is important for our study, since almost all energy produced is sold outside the county and total employment in a county is not the main goal of energy companies. Therefore, it seems reasonable to assume that past county employment across all industries has a negligible effect on energy companies' future plans.

Another issue is that a correlation might exist between $u_{it}$ and past $\mathbf{x_{i,t-1}}, \ldots \mathbf{x_{i,1}}$, leading to a failure of sequential exogeneity. This would be the case if well-drilling activity and wind farm construction have lasting effects on local employment. One way to deal with this kind of correlation is to include lags of the explanatory variables into the model. Strict exogeneity may then hold if enough lags are included.[14]

A test of strict exogeneity is based on **?**, 10.7.1.

$$\Delta y_{it} = \mathbf{\Delta x_{it}} \boldsymbol{\beta} + \mathbf{w_{it}} \boldsymbol{\gamma} + \Delta u_{it}, t = 2, \ldots, T, \tag{4}$$

In the above equation, $w_{i,t}$ is a subset of $x_{i,t}$. Under strict exogeneity, none of the $\mathbf{x_{it}}$s should be significant explanatory variables in the first difference (FD) equation. That is, we should find support of the hypothesis $H_0 : \gamma = 0$. Carrying out this test, the $F$ statistic on $\gamma$ is

[14] Another remedy is to use instrumental variables, but it is often difficult to find suitable instruments.

0.32, with $p$-value 0.5695. Thus, we could not reject $H_0$.

We have not ruled out serial correlation in the idiosyncratic error $u_{it}$, that is, $Corr(u_{it}, u_{is}) \neq 0$, $t \neq s$. If one allows for the $u_{it}$s to be serially correlated over time, the usual pooled ordinary least squares (OLS) and fixed effects (FE) standard errors are not valid, even asymptotically. To test for the existence of serial correlation in the $u_{it}$s, we use the Breusch-Godfrey/Wooldridge LM test and the Wooldridge first difference test (**?**). Rather than interpreting serial correlation as a technical violation of the OLS assumption, we take it as evidence of dynamic responses. This leads us to consider including lagged dependent variables on the right hand side.

Observe that the strict exogeneity assumption necessarily fails in models with unobserved effects and lagged dependent variables. The reason is that $y_{it}$ is correlated with $u_{it}$ and would show up as part of explanatory variables at $t+1$, implying that $E(u_{it}|\mathbf{x_{i,t+1}}) \neq 0$. Additional care is required when we include lagged dependent variables as explanatory variables on the right hand side.

## 4.2 The Finite Distributed Lag (FDL) Model

A finite distributed lag model is appropriate if the impact of the explanatory variables lasts over a finite number of periods, $q$, and then stops. The FDL unobserved effects model expands equation (**??**) to the following form:

$$E_{it} = \sum_{k=0}^{q} \beta_k wells_{i,t-k} + \sum_{k=0}^{q} \delta_k wcap_{i,t-k} + c_i + \theta_t + u_{it} \tag{5}$$

where $E_{it}$ denotes total employment, $wells_{it}$ denotes the number of directional/fractured wells drilled, and $wcap_{it}$ indicates wind capacity installed, in county $i = 1, 2, \ldots, 254$ and month $t = 1, 2, \ldots, T$. Our interest lies in the pattern of coefficients $\{\beta_k, \delta_k\}_{k=0}^{q}$. The values of $\beta_0$ and $\delta_0$ capture the immediate change in $E_i$ due to the one-unit increase in $wells_i$ and

$wcap_i$, respectively, at time $t$. Similarly, $\beta_k$ and $\delta_k$ capture the changes in $E_i$, $k$ periods after the new activity. At time $t+q$, $E_i$ has reverted back to its initial level, $E_{i,t+q} = E_{i,t-1}$.

The unit root tests in section **??** found employment and wage series have unit roots in over half of the counties. Although we have a short panel that only covers 11 years and unit root problems should not be a major concern, we will deal with this issue by taking first differences of the variables in the model.

## 4.3 The Autoregressive Distributed Lag (ADL) Model

We are also interested in allowing for a long-lasting change in $E_i$ in response to a change in any of the explanatory variables.[15] In principle, one could do this by allowing for a large number of lags of the explanatory variables. In practice, however, the inclusion of many lagged variables will reduce degrees of freedom. In addition, the fact that the resulting explanatory variables are likely to be correlated might lead to severe multicollinearity.

The multicollinearity problem can be bypassed by including one or more lags of the dependent variable. The model becomes an autoregressive distributed lag (ADL) model, which is similar to the FDL model, except that the effects of the explanatory variables persists over time at a geometrically declining rate. Denoting the number of lagged dependent variables by $p$, an ADL$(p,q)$ model with unobserved effects has the form:

$$E_{it} = \sum_{j=1}^{p} \lambda_j E_{i,t-j} + \sum_{k=0}^{q} \beta_k wells_{i,t-k} + \sum_{k=0}^{q} \delta_k wcap_{i,t-k} + c_i + \theta_t + u_{it} \tag{6}$$

where $\{\lambda_j\}_{j=1}^{p}$ are the autoregressive coefficients. Provided that the process is stationary, the ADL model eventually reaches a new equilibrium employment in response to a change in $wells$ equal to 1 that is

$$\frac{\sum_{k=0}^{q} \beta_k}{1 - \sum_{j=0}^{p} \lambda_j} \tag{7}$$

[15]The right lag length is rarely known in advance, or pinned down by theory.

higher than the original equilibrium.

Another advantage of the ADL model is that the inclusion of a lagged dependent variable can often eliminate serial correlation, particularly if enough lags of the dependent variable are included. Lags of the independent variables may also help eliminate serial correlation in the error term.[16] Hence, once we introduce lagged values of $y_{it}$, a correct dynamic specification implies sequential exogeneity. However, the strict exogeneity assumption is false, as we discussed above. In this case, both the fixed effects (FE) estimator and the first difference (FD) estimator are inconsistent.[17]

## 4.4 The Spatial Panel Model

In this section, we discuss cross-sectional dependence (XSD) in panels. This can arise, for example, if spatial diffusion processes are present causing different panel members to be related. In our case, shale or wind farm activity in one county could affect employment in neighboring counties. Spatial interaction effects could be due to competition or complementarity between counties, spillovers, externalities, regional correlations in industry structures, or shocks affecting similar industries (for example, similar weather shocks affect different agricultural activities in both counties), as well as many other factors.

The $CD$ and $CD(p)$ tests (**?**) are used to detect XSD. These tests are based on the averages over the time dimension of pairwise correlation coefficients for each pair of cross-sectional units. The $CD(p)$ test also takes into account an appropriate subset of neighboring cross-sectional units in order to check the null of no XSD against dependence between neighbors only. To do so, a spatial weights matrix, $W$, is needed for the $CD(p)$ test.

[16] An interpretation is that the serial correlation is present in the simple model because that model ignores the dynamic adjustment process. Once the dynamic adjustment process is correctly specified, the serial correlation disappears.

[17] Deciding which model to use and how many lags to include is complicated by the fact that we are unlikely to have a theory to distinguish between the different models. As a result, **?** and others have advocated starting with a general model like the ADL and testing down to a more specific model, including the optimal values for $p$ and $q$.

Matrix $W$ in our case will be a $254 \times 254$ non-negative matrix, in which the element $w_{ij}$ expresses the degree of spatial proximity between the pair of objects $i$ and $j$. Following **?**, the diagonal elements $w_{ii}$ are all set to zero, to exclude self-neighbors. Furthermore, only neighborhood effects are considered in this paper, that is, $W$ is a contiguity matrix:[18]

$$w_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are neighbors}, i \neq j \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

In our data set, both the $CD$ and $CD(p)$ tests (the latter with the above $W$ matrix) show the presence of XSD at 0.000 level.

The contiguity matrix $W$ is than transformed into row-standardized form, which assumes that the impacts on a given county from all neighboring counties are equal. Given a spatial weights matrix $W$, a family of related spatial econometric models can be expanded from equation (**??**):

$$E_{it} = \rho \sum_{j=1}^{N} w_{ij} E_{jt} + \beta_1 wells_{it} + \beta_2 wcap_{it} + u_{it}, \tag{9}$$

where $\rho$ is the spatial autoregressive coefficient and $N$ is the number of neighbors. We specify the composite error $u_{it}$ following **?**. They assume that spatial correlation applies to both unobserved individual effects and the remainder error components. In this case, $u_{it}$ follows a first order spatial autoregressive process of the form:

$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \epsilon_{it} \tag{10}$$

and $\epsilon$ follows an error component structure

$$\epsilon_{it} = c_i + \nu_{it} \tag{11}$$

[18] $W$ is also called as adjacency matrix.

to further allow $\epsilon_{it}$ to be correlated over time.

# 5 Results

## 5.1 The FDL model

In this section we drop all lagged dependent variables and use the FDL approach. We verified that the strict exogeneity assumption holds as long as enough lags of the explanatory variables are included.

To obtain a first difference (FD) estimator, lag the model in (**??**) by one period and subtract to obtain:

$$\Delta E_{it} = \sum_{k=0}^{q} \beta_k \Delta wells_{i,t-k} + \sum_{k=0}^{q} \delta_k \Delta wcap_{i,t-k} + \theta_0 + \theta_t + \Delta u_{it},\ t = 2, 3, \ldots, T \tag{12}$$

Note that rather than dropping an overall intercept and including the differenced time dummies $\Delta\theta_t$, we estimated an intercept and then included the time dummies $\theta_t$, for $T-2$ of the remaining periods. Because the regressors involving the time dummies are non-singular linear transformations of each other, the estimated coefficients on the other variables do not change.

Next, we test for the presence of serial correlation in $\Delta u_{it}$ using the Breusch-Godfrey and Wooldridge tests for serial correlation in panels. Both tests reject $H_0$ and show that serial correlation remains in the idiosyncratic errors. We then increased $p$ up to $p = 36$. The results showed that serial correlation remained no matter how many lags of the explanatory variables were included. This serial correlation may imply that the model does not fully capture the actual dynamic adjustment process.

We proceed by computing a robust variance matrix for the FD estimator, which accommodates a fully general structure with respect to heteroskedasticity and serial correlation in

$\Delta u_{it}$. Following **?**, this robust variance matrix is consistent. To determine the appropriate lag length, $q$, we posited a maintained value that should be larger than the optimal $q$. Here we use $q = 24$. We then performed sequential $F$ tests on the last $24 > p$ coefficients. We stopped when the test rejected the $H_0$ that the coefficients are jointly zero at a 5% level. Using a robust variance matrix to calculate the $F$ statistics, we drop 18 lagged explanatory variables and assign $q = 6$.

| **Variable** | **Coefficient** | **(Std. Err.)** | **(Robust SE.)** |
|---|---|---|---|
| $wells_{it}$ | 16.31 | (5.396)$^{**}$ | [6.06]$^{**}$ |
| $wells_{i,t-1}$ | 13.17 | (6.666)$^{*}$ | [7.081]$^{\cdot}$ |
| $wells_{i,t-2}$ | 0.932 | (7.025) | [2.929] |
| $wells_{i,t-3}$ | -5.519 | (7.127) | [6.006] |
| $wells_{i,t-4}$ | 12.23 | (7.119)$^{\cdot}$ | [8.705] |
| $wells_{i,t-5}$ | 17.89 | (6.875)$^{**}$ | [11.13] |
| $wells_{i,t-6}$ | 22.46 | (5.686)$^{***}$ | [12.91]$^{\cdot}$ |
| $wcap_{it}$ | -0.756 | (1.235) | [0.923] |
| $wcap_{i,t-1}$ | -0.755 | (1.653) | [0.594] |
| $wcap_{i,t-2}$ | -0.739 | (1.864) | [0.332]$^{*}$ |
| $wcap_{i,t-3}$ | -0.212 | (1.923) | [0.323] |
| $wcap_{i,t-4}$ | 0.111 | (1.865) | [0.374] |
| $wcap_{i,t-5}$ | 0.250 | (1.654) | [0.432] |
| $wcap_{i,t-6}$ | -0.178 | (1.236) | [0.266] |
| $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$ | | | |

Table 1: FD Estimation Results, $q = 6$

The estimation results are reported in Table **??**, with both robust standard errors and the usual FD standard errors.[19] Using robust standard errors, we find that five out of seven coefficients of the wind installed capacity are negative and all but one are statistically insignificantly different from zero.[20] A joint $F$-test on $H_0 : \delta_k = 0$ for $k = 0, 1, \ldots, 6$ gives $F(7, 31734) = 0.78$ with $p$-value $= 0.6001$. Thus, we cannot reject the hypothesis that the impact of wind activity on employment is not statistically significantly different from zero.

[19]Note that $R^2 = 0.00084$. Since oil and gas-related employment is only 2.6% of the total employment in Texas, a low explanatory power of the regression model is perhaps to be expected.

[20]The order-2 lag is negative and statistically significantly different from zero at a 5% level.

Using robust standard errors we also find that all coefficients on the *wells* variables except for the contemporaneous one are not statistically significantly different from zero at 0.05 level. The contemporaneous one is significant at the better than 0.01 level. Since substantial correlation might exist in *wells* at different lags (multicollinearity), it can be difficult to obtain precise estimates for the individual $\beta$s. However, we found $wells_t$, $wells_{t-1}$,... and $wells_{t-6}$ to be jointly significant: the $F$ statistic has a $p$-value equal to 0.0007. Adding the estimated coefficients of the current and lagged variables, we obtain long-term multipliers $LRP_{wells} = 77.46$. Assuming that all the jobs created are short-term (they only last for 1 month), we divide $LRP_{wells}$ by 12 to obtain the number of annual full-time equivalent (FTE) jobs: 6.42.[21] Given that 5482 new directional/fractured wells were drilled in Texas in 2011, the estimates imply that about 35,000 FTE jobs would have been created.[22]


(a) (b)

Figure 7: FD estimation results with $q = 6$: (a) wells (b) wind capacity

We graph the point estimates of the short-run impact of $wells_k$ and $wcap_k$ as a function of $k$ in Figure **??**. The lag distribution summarizes the dynamic effects on the dependent variable of a temporary increase in the explanatory variables .

[21] This allows us to avoid re-counting the same person working on several different short-term jobs within a full calender year.
[22] The total employment in Texas in 2010 was $10,182,150$.

Figure ?? shows a mainly declining trend in the impact of wells in the first three months. This may be because workers leave after the well completion. Employment then increases starting with month 4. This could be the result of the emergence of new business opportunities in the area, resulting from the well-drilling activity. We find that the largest effect is with the first and the last lag.

Figure ?? shows the impact from the added new wind capacity. The employment effect is estimated to be negative at first, and then increase, peaking about five months after the wind farm construction. However, given the estimated standard errors, we cannot establish a relationship between wind farm construction and county employment.

## 5.2 The ADL model

Since the ADL model involves lagged dependent variables, the strict exogeneity assumption is violated and both the FE and the FD estimators are inconsistent.[23] To overcome this, we use a generalized method of moments (GMM) estimator.

We again need to assign appropriate $p$ and $q$ to the model before we estimate it. When we include one lagged dependent variable, $E_{i,t-1}$ (so $p = 1$), Wooldridge's test for serial correlation gives $\chi^2_{(1)} = 30.189$, with $p$-value $= 3.919e^{-8}$. The strong serial correlation implies that the dynamic data generation processes has not been fully captured. When we include one more lagged dependent variable, $E_{i,t-2}$, the test result changes to $\chi^2_{(1)} = 0.0081$, with $p$-value $= 0.9285$. We conclude that the error term, $u_{it}$, is now serially uncorrelated. Henceforth, we set $p = 2$.

As in the previous section we begin by setting $q = 6$. We then proceed to estimate the two-way Arellano-Bond GMM regression. The full results are shown in Table ?? in Appendix ??. Both the Wald and the joint $F$ tests cannot reject that the coefficients for

[23]If we maintain the contemporaneous exogeneity assumption, the FE estimator's inconsistency shrinks to zero at the rate $1/T$, while the inconsistency of the FD estimator is essentially independent of $T$ (Wooldridge, 2002).

wind capacity $\delta_0 = \ldots = \delta_6 = 0$. Thus, we again do not find any statistically significant effect of wind farm construction on county employment. Figure ?? graphs the point estimate of the dynamic response of employment to a unit increase in $wells_{it}$ and $wcap_{it}$ under six lags. It is noteworthy that these response patterns are quite similar to the ones found for the FDL estimates and graphed in figure ??. However, due to the persistence of the impacts in the ADL model, the long run propensity as calculated by the formula $\sum_{k=0}^{6} \hat{\beta}_k/(1 - \hat{\lambda}_1 - \hat{\lambda}_2)$ is 3 times larger, that is, 228.93. Then the number of FTE jobs is 19.


(a) (b)

Figure 8: GMM estimation results with $p = 2$, $q = 6$: (a) wells (b) wind capacity

The estimate of the long run effect is sensitive to the values of $\hat{\lambda}_1$ and $\hat{\lambda}_2$. The sum of the two estimated coefficients for the lagged dependent variables is 0.98. Although the test $\lambda_1 + \lambda_2 = 1$ is rejected at the 1% level, employment might still follow a unit root process. To address this issue, we re-estimated the same estimation using data from only the 38 counties with stationary employment series. We obtained similar estimates: $\hat{\lambda}_1 + \hat{\lambda}_2 = 0.98$. We believe that the large persistence in employment is probably due to the small explanatory power of well drilling. Since employment in the shale gas sector is a rather small component of total employment, most of the systematic component of employment variation would appear in the error term. It is not surprising that this error is highly serially correlated.

### 5.3 Spatial Panel Models

Including the lagged dependent variable as a regressor in the spatial autoregression (SAR) model introduces simultaneity bias and the OLS estimator is no longer unbiased and consistent. Including the lagged dependent variable as a regressor in the spatial error model (SEM) yields an OLS estimator that is unbiased, but inefficient. Therefore, maximum likelihood estimation is used to estimate the parameters of both models.

Both the SAR and SEM models are estimated allowing for two-way fixed effects. The results are reported in Table **??** in Appendix **??**. We find that the spatial interaction coefficients of both models are statistically significantly different from zero and very similar: $\rho = 0.1730$, $\lambda = 0.1734$. Also, both models show large and statistically significant coefficients for $wells$, and coefficients for $wcap$ that are not statistically significantly different from zero.

Following **?**, the expectation of the dependent variable $y$ in the SAR model $y = \rho W y + X\beta + \epsilon$ is

$$E(y) = (I_N - \rho W)^{-1} X\beta \tag{13}$$

Employment in county $i$ depends on developments in neighboring counties, as a result of the various spatial spillover effects discussed previously.

The own- and cross-partial derivatives in the SAR model take the form of an $N \times N$ matrix that can be expressed as:

$$\partial y / \partial x'_r = (I_N - \rho W)^{-1} I_N \beta_r \tag{14}$$

These partial derivatives measure how drilling/wind activities in county $j$ influence employment in county $i$. For the $r$th explanatory variable, the average of the main diagonal elements of this matrix is labeled as the "direct effect." It measures how wells drilled in a particular county affect employment in that same county. The average of the cumulative off-diagonal elements over all observations corresponds to the "indirect" or spillover effect. The average total effect will be the sum of the two. We use equation (**??**) to calculate both the direct and the indirect effects resulting from well-drilling activity.

The SAR model implies that the direct effect of well-drilling activity on employment is 225, and it is significant at the 0.000 level. The result shows that about 225 jobs would be created per well drilled in the same county. The estimated indirect effect of well drilling activity is 46, which increases the total effect to 271. Thus, if we only consider the direct effect, the results would be underestimated by 17%. The result is significantly higher compared to the FDL and even ADL estimation results (77 and 228), indicating that spatial correlation effects are important. The FTE jobs would be 22.

Similarly, the estimated direct and indirect effects of wind activity are 0.05 and 0.01, respectively, but neither coefficient is statistically significantly different from zero. Hence, wind farm installation and construction was not found to have an impact on total county employment in this data set.

## 5.4 Wage Effects

In this section, we examine whether there is any evidence in our data set suggesting that shale gas and wind developments affect average weekly wages. We again employ the FD approach. Sequential F-tests determine that $q = 12$. The results appear in Table **??** in Appendix **??**. The results show that the coefficients of the $4^{th}$ and $9^{th}$ lagged wells are statistically significantly different from zero at the 0.05 level. For wind capacity, the coefficients of lag 1 and lag 10 are statistically significantly different from zero at the 0.05 level, while coefficients on lags 11 and 12 are statistically significantly different from zero at the 0.01 level.

Figure **??** graphs the resulting dynamic response of wages to a unit increase in $wells_{it}$ and $wcap_{it}$ (12 lags). The impact from wells drilled rises and falls with a 6 month cycle. The peaked value is about 0.3. The impact from wind capacity installation shows a quite different trend: it increases over time from near zero to 0.13.

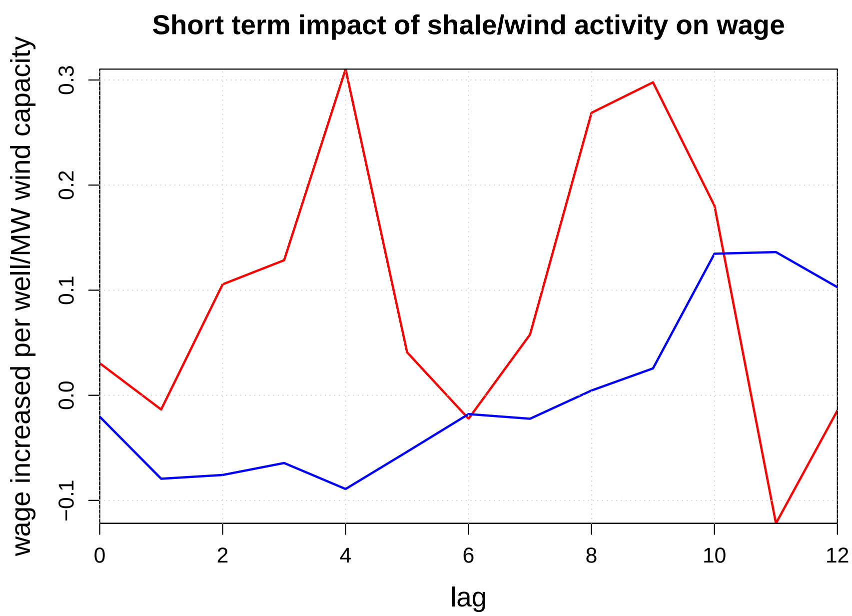



Figure 9: Short run impact of shale/wind activity on wage

The spatial panel regression results for wages are shown in Table **??** in Appendix **??**. The results corroborate in line with those derived in the absence of spatial interaction effects. According to the SAR model, the estimate of $\beta_1$ is 0.18 and statistically significantly different from zero at the 0.05 level, while the estimate of $\beta_2$ is 0.06 and not statistically significantly different from zero. Additionally, the results show a strong spatial correlation: $\rho = \lambda = 0.26$. Interestingly, the spatial correlation effects in wages are even larger than in employment: 26% of the increase in average wages is due to indirect effects from neighboring counties, while we found such effects are responsible for only 17% of the change in employment.

The direct and indirect effects of well drilling activity on wages are 0.18 and 0.06, respectively. Alternatively, the total effect on wages is 23 cents per well drilled, of which 18 cents are due to drilling activity in the same county, while 6 cents are attributed to drilling activity in neighboring counties. The total effect from wind activity is 8 cents per MW, of which about 6 cents are due to the direct effect, while 2 cents are due to the indirect effect.

# 6 Conclusion

We followed an econometric approach to compare job creation in wind power versus that in the shale gas sector in Texas. We have discussed the advantages and disadvantages of a number of different models. We then estimated them using county level data in Texas from 2001 to 2011. The results were quite consistent. Both first-difference and GMM methods show that shale development and well-drilling activity have brought strong employment to Texas: 77 - 271 short-term jobs or 6 - 22 FTE jobs per well. Given that 5482 new directional/fractured wells were drilled in Texas in 2011, an estimated 35,000 - 120,000 FTE jobs were created. In contrast, we did not find a large effect on wages. The effect on wages corresponds to a 30-cent increase in month 4 and month 9 after each well completion.

All our estimations show that the impact from wind industry development on employment is not significantly different from zero. Its impact on wages increases gradually after construction and peaks about one year later. We found that 13 cents are added to wages in months 10 to 12 after construction.

While this study by no means examines all economic issues surrounding the development of wind farms, the effects on employment in Texas counties over the period examined appear to be insignificant. By contrast, unconventional gas production appears to be a significant force behind employment growth in Texas counties during the same period. Further research is needed to confirm these effects in other states and over different time periods.

# A Tables of Estimation Results

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| $E_{i,t-1}$ | 0.88241 | 0.0056054*** |
| $E_{i,t-2}$ | 0.1005518 | 0.0056067*** |
| $wells_{it}$ | 15.86961 | 5.586163** |
| $wells_{i,t-1}$ | -.8539942 | 5.714926 |
| $wells_{i,t-2}$ | -15.90933 | 5.853195** |
| $wells_{i,t-3}$ | -8.917589 | 5.964613 |
| $wells_{i,t-4}$ | 14.38985 | 5.922299 * |
| $wells_{i,t-5}$ | 4.476252 | 5.851388 |
| $wells_{i,t-6}$ | 3.622863 | 5.794333 |
| $wcap_{it}$ | -9.00e-06 | 0.0000248 |
| $wcap_{i,t-1}$ | -0.0000184 | 0.0000243 |
| $wcap_{i,t-2}$ | 0.0000239 | 0.0000237 |
| $wcap_{i,t-3}$ | 0.0000107 | 0.0000236 |
| $wcap_{i,t-4}$ | 0.0000242 | 0.0000237 |
| $wcap_{i,t-5}$ | -0.0000129 | 0.0000243 |
| $wcap_{i,t-6}$ | -9.63e-06 | 0.0000249 |
| Signif. Code: *** 0, ** 0.01, * 0.05, · 0.1, 1. | | |

Table 2: GMM Estimation Results, $p = 2$, $q = 6$

| SAR Coefficients: | | | | |
|---|---|---|---|---|
| | Estimate | Std. Error | t-value | $\Pr(>\|t\|)$ |
| $\rho$ | 0.1730 | 0.0081 | 21.43 | $< 2e-16^{***}$ |
| wells | 224.72 | 12.99 | 17.29 | $< 2e-16^{***}$ |
| newcap | 0.05 | 6.366 | 0.0079 | 0.9937 |
| SEM Coefficients: | | | | |
| $\lambda$ | 0.1734 | 0.0081 | 21.42 | $< 2e-16^{***}$ |
| wells | 235.81 | 13.63 | 17.30 | $< 2e-16^{***}$ |
| newcap | 0.47 | 6.374 | 0.704 | 0.4814 |
| Significant Code: $^{***}$ 0, $^{**}$ 0.01, $^{*}$ 0.05, $^{\cdot}$ 0.1, 1. | | | | |

Table 3: Spatial interaction effects on employment

| SAR Coefficients: | | | | |
|---|---|---|---|---|
| | Estimate | Std. Error | t-value | $\Pr(>\|t\|)$ |
| $\rho$ | 0.26 | 0.01 | 33.88 | $< 2e-16^{***}$ |
| wells | 0.18 | 0.09 | 2.04 | $0.0412^{*}$ |
| newcap | 0.06 | 0.04 | 1.51 | 0.1319 |
| SEM Coefficients: | | | | |
| $\lambda$ | 0.26 | 0.01 | 33.87 | $< 2e-16^{***}$ |
| wells | 0.12 | 0.09 | 1.27 | 0.20 |
| newcap | 0.07 | 0.04 | 1.60 | 0.11 |
| Significant Code: $^{***}$ 0, $^{**}$ 0.01, $^{*}$ 0.05, $^{\cdot}$ 0.1, 1. | | | | |

Table 4: Spatial interaction effects on wage

| Variable | Coefficient | Robust SE. | t-value | $Pr(>\|t\|)$ |
|---|---|---|---|---|
| $wells_t$ | 0.030579 | 0.112459 | 0.2719 | 0.785688 |
| $wells_{t-1}$ | -0.013512 | 0.149363 | -0.0905 | 0.927917 |
| $wells_{t-2}$ | 0.105605 | 0.160727 | 0.6570 | 0.511159 |
| $wells_{t-3}$ | 0.128526 | 0.159170 | 0.8075 | 0.419399 |
| $wells_{t-4}$ | 0.310342 | 0.132325 | 2.3453 | 0.019018 * |
| $wells_{t-5}$ | 0.040933 | 0.119525 | 0.3425 | 0.732003 |
| $wells_{t-6}$ | -0.022280 | 0.128208 | -0.1738 | 0.862040 |
| $wells_{t-7}$ | 0.057849 | 0.121926 | 0.4745 | 0.635176 |
| $wells_{t-8}$ | 0.268792 | 0.137164 | 1.9596 | 0.050047 . |
| $wells_{t-9}$ | 0.297772 | 0.133959 | 2.2229 | 0.026232 * |
| $wells_{t-10}$ | 0.180401 | 0.108571 | 1.6616 | 0.096603 . |
| $wells_{t-11}$ | -0.121860 | 0.155113 | -0.7856 | 0.432095 |
| $wells_{t-12}$ | -0.014441 | 0.144573 | -0.0999 | 0.920434 |
| $wcap_t$ | -0.020312 | 0.022022 | -0.9224 | 0.356349 |
| $wcap_{t-1}$ | -0.079381 | 0.039836 | -1.9927 | 0.046304 * |
| $wcap_{t-2}$ | -0.075806 | 0.057576 | -1.3166 | 0.187978 |
| $wcap_{t-3}$ | -0.064414 | 0.053879 | -1.1955 | 0.231889 |
| $wcap_{t-4}$ | -0.089130 | 0.058455 | -1.5248 | 0.127325 |
| $wcap_{t-5}$ | -0.053716 | 0.051733 | -1.0383 | 0.299123 |
| $wcap_{t-6}$ | -0.017880 | 0.041650 | -0.4293 | 0.667710 |
| $wcap_{t-7}$ | -0.022297 | 0.065829 | -0.3387 | 0.734828 |
| $wcap_{t-8}$ | 0.004571 | 0.056724 | 0.0806 | 0.935773 |
| $wcap_{t-9}$ | 0.025598 | 0.058720 | 0.4359 | 0.662890 |
| $wcap_{t-10}$ | 0.134719 | 0.058776 | 2.2921 | 0.021907 * |
| $wcap_{t-11}$ | 0.136272 | 0.042045 | 3.2411 | 0.001192 ** |
| $wcap_{t-12}$ | 0.102829 | 0.035770 | 2.8748 | 0.004046 ** |
| Significant Code: $^{***}$ 0, $^{**}$ 0.01, $^{*}$ 0.05, $\cdot$ 0.1, 1. | | | | |

Table 5: FD estimation results with robust se. on wage, $q = 12$

Editor, UWA Economics Discussion Papers:
Ernst Juerg Weber
Business School – Economics
University of Western Australia
35 Sterling Hwy
Crawley WA 6009
Australia

Email: ecoadmin@biz.uwa.edu.au

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