Short-Term Spillover Effects: Examining the Industry Spillover Effects of the 2008-2009 Coal Boom and Bust in Kentucky and West Virginia

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May 4, 2015

Abstract:
A fixed-effects model is employed to quantify the industry spillover effects of the 2008-2009 short-term shock in the coal industry. Two equations are used in this paper, one to show the changes in employment data in the coal industry and another to measure the difference in employment data for the service, retail-trade, construction and manufacturing industries between coal and non-coal producing counties. The dependent variables in both models are the number of employed people, average weekly wages and total wages in each respective industry. My results prove a significant change in coal employment during the boom and bust. However, only the employment in the service industry shows spillover effects from this change in the coal labor market.

JEL Codes: E24, J21, L71

Introduction:

Industry spillover effects, where the changes in employment in one sector affect the labor markets in others, drive growth in local economies across America. Increases in the wage or employment rate in one sector can benefit the whole community due to increased economic activity for local businesses. However, changes in sector labor markets can also adversely affect local sectors due to increased competition in wages and therefore reduced employment. Further, in rural communities, changes in one industry should lead to larger overall changes in their economy due to their relatively less diverse economies when compared to urban areas. The energy sector plays a particularly important part in these rural economies because they are generally home to America's energy resources. Therefore, changes in specific energy sectors should also lead to overall changes in rural communities.

In this paper, I test for industry spillover effects in Kentucky and West Virginia resulting from the 2008-2009 coal boom and bust. Compared to previous shocks in energy markets, the changes in the coal industry during this time were extremely short-lived. While there have been numerous studies examining the spillover effects of long-term changes in the energy sector, little has been explored about very short-term shocks. Therefore, the contribution of this paper is to see if a short-term shock in the energy sector will also affect other industries in a local economy.

In 2008, while U.S. consumption decreased, coal prices and production increased from heightened international demand. Figure 1 highlights the rise in coal prices by plotting coal prices in Central Appalachia from 1997 to 2012. Before 2008 Q1, coal prices in the Central Appalachian region were relatively stable. However, due to increased demand

from European and Asian markets, U.S. coal exports increased by 37.8% in 2008. In addition, the large shock in international demand caused coal prices to increase by 39.0% (Freme, 2008). The resulting boom in production and prices was the result of supply disruptions from historically coal producing countries such as Australia, South Africa, Indonesia, Vietnam and Russia.

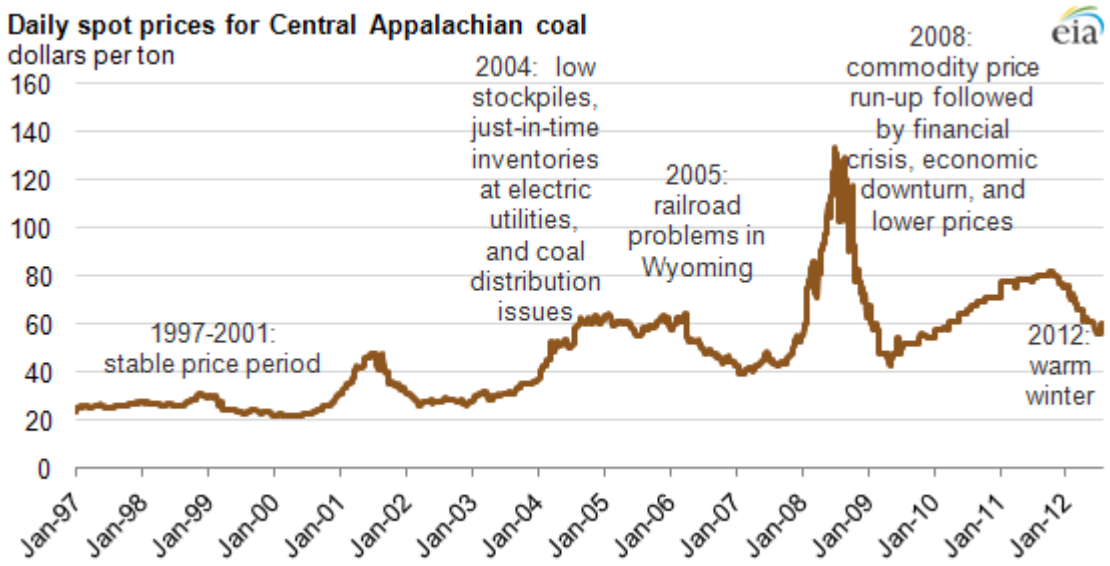

Fig. 1: *Daily Spot Price for Central Appalachian Coal,* 1997 – 2012
Source: EIA

However, in 2009, coal production in the Appalachian region dropped by 13.0% to its lowest levels in almost 50 years. In addition, international exports in 2009 dropped 27.5% from 2008 and returned to 2007 levels (Freme, 2009). The overall economic downturn in America and abroad, in addition to lower natural gas prices, drove this downward trend for the coal industry in 2009.

The short-term boom and then resulting bust in the coal industry creates ideal conditions to analyze short-term shocks in local labor markets. Figure 2 illustrates the

overall changes in coal mining employment in America. Following the changes in real prices, coal mining employment increased by about 10% in 2008 and then decreased by 10% in 2009. This very tight influx and reduction motivated me to explore its potential spillover effects into other industries.

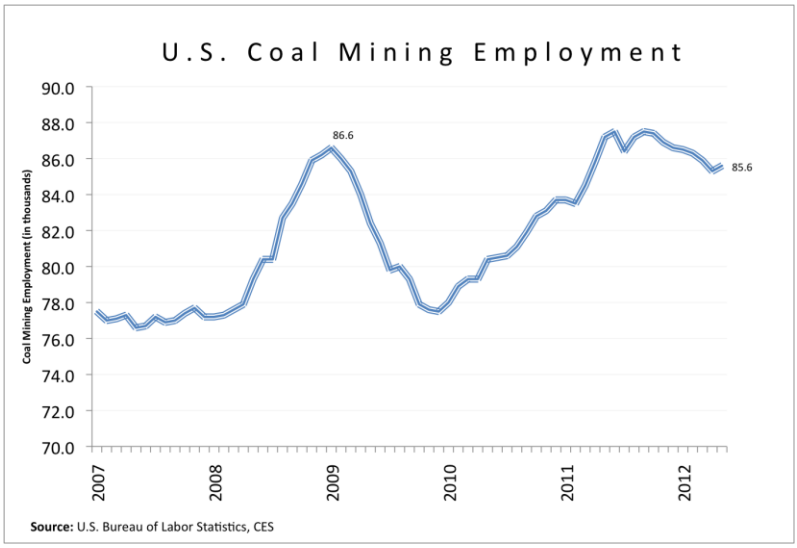

Fig. 2: *U.S. Coal Employment:* 2007 – 2012
Source: Boettner (2012)

Using panel data and a fixed-effects estimation, I examine the difference between coal producing counties and non-coal producing counties in growth rates for employment, average weekly wages and total wages in the construction, manufacturing, service and retail industries. In addition, I also use employment data across all industries in each county. I found that when aggregated across all industries, employment and total wages grew at a higher rate (2.29% and 2.47% respectively) for coal counties relative to non-coal counties during the boom.

However, there is little evidence that the coal industry caused economic changes to the observed sectors during this short-term shock. The only significant difference between

coal and non-coal counties during the boom is in the service industry. I believe this is caused by the increased number of coal workers who are engaging the local service industry.

Literature Review:

In this paper, I closely replicate Black, McKinnish and Sanders (2005), who examined the industry spillover effects of the coal boom and bust in the 1970s and 80s. In their study, they look at annual, county-level employment data in West Virginia, Ohio, Pennsylvania and Kentucky. To examine the spillover effects from the coal industry, they divided the counties into groups based on their coal activity. The high coal producing counties are determined by their percentage of total wages coming from the coal industry, which they set at 10%. The non-coal group is counties with zero coal production and similar population sizes as the high coal counties. In addition, they created groups for low and medium coal counties, which have less than 10% of their total wages coming from coal but still produce coal. They also created three different time groups, *Boom, Peak* and *Bust*, to highlight the different phases of the coal boom and bust.

To analyze the spillover effects of the coal boom and bust into other industries, Black et al. (2005) used the following model:

$$\Delta \ln(y)_{ist} = \sum_{j=1}^{3} \beta_j \left(T_i P_{jt}\right) + \ (State_s Year_t)\emptyset + \ \varepsilon_{ist}$$

T is an indicator for the high coal producing counties and *P* is an indicator for the time-periods. For control variables, they only included interacted State and Year dummy variables, which capture changes that vary over time at the state level. The dependent variables in this model are employment, earnings and earnings per worker in four different

sectors (construction, manufacturing, service and retail trade). By examining these variables for each sector against dummy variables for coal counties, Black et al. (2005) captured the difference in the growth rates of the employment data between coal and non-coal counties.

The results of this model support industry spillover effects from the coal boom and bust. Employment in the construction and services industry increased at a higher rate for coal counties during the boom. Subsequently, the growth rate for employment in the construction, service and retail sectors was smaller in coal counties than non-coal counties during the bust. In addition, while earnings per worker yielded insignificant results during the boom, its growth rate for the construction, service and retail sectors was smaller in coal counties during the bust. Therefore, the results proved that during the 1970s and 1980s there were some spillover effects from the coal industry.

In addition, Black et al. (2005) includes an IV analysis to determine the magnitude of the spillover effects. These results further support spillover effects since it finds that one additional mining job created 0.174 local sector jobs during the boom and one lost mining job reduced local sector jobs by 0.349 during the bust.

The results and methodology in Black et al. (2005) helped guide me through the data work and regressions. I will discuss the specific influences this paper had on my model throughout the paper.

Weber (2012) examines the employment impacts of the natural gas boom in Colorado, Texas and Wyoming from 1993 to 2008. Similar to Black et al. (2005), the author also used county-level data and created groups based on their natural gas production. In addition, Weber used a differentiated model by employing a triple difference approach to

control for differences in trends between gas and non-gas counties before the boom. His results support modest spillover effect in employment, wage and salary income and median household income for gas counties. While his findings suggest growth in employment data, it also shows that prior findings may have overestimated the employment effects of natural gas development.

DeLeire, Eliason and Timmins (2014) also analyze the effects of shale gas development on local employment. They used data on employment and earnings in specific industries within Pennsylvania counties that are situated on the Marcellus shale. Using a distributed lag model they found that the natural gas boom in the Marcellus shale leads to a modest but statistically significant increase in local employment. However, earnings are unaffected by the fracking boom in all observed industries except mining, quarrying, and oil and natural gas production.

Fetzer (2014) examines the changes in employment in different sectors that results from increased shale production from the use of unconventional wells. He employed cross-sectional data on areas across the United States with previously unexplored shale deposits. Fetzer (2014) found that every additional oil/gas job created 2.17 local jobs. In addition, personal incomes increased by 8% in counties that contained at least one unconventional well.

Deller and Schreiber (2012) observe the effects of non-oil and gas mining on economic growth in nonmetropolitan U.S. counties from 2000 to 2007. By using data on non-oil and gas mining, the authors hoped to examine the effects of the increased production of “frack sand” caused by the natural gas boom. However, due to the structure of their dataset, it also included coal mining. Their results suggest little spillover effects

from increased mining production. Deller et al. uses total population growth, total employment growth and per capita income growth as their dependent variables to measure economic growth in rural counties. Unlike the previous paper, the authors do not analyze the effects of a resource boom on specific industries but instead the aggregate effect on local economic growth. They find that non-oil and gas mining leads to lower population growth, increased per capita income and no impact on employment growth.

Data:

The initial sample for this study includes all 175 counties in Kentucky and West Virginia. I chose to study Kentucky and West Virginia due to their geographic proximity and similar coal industries. Furthermore, coal employment in both Kentucky and West Virginia changed in 2008 and 2009, following the shock in the coal industry. Figure 3 and Figure 4 show these fluctuations in coal employment for Kentucky and West Virginia, respectively. In addition, I wanted to closely replicate the model used by Black et al. (2005), who examined employment data from Kentucky, West Virginia, Ohio and Pennsylvania. I did not include Ohio and Pennsylvania in my model because they had lower coal production and larger overall economies compared to Kentucky and West Virginia. I believe by focusing on just Kentucky and West Virginia, my findings may highlight larger spillover effects due to their coal industries accounting for a larger proportion of their overall economy.

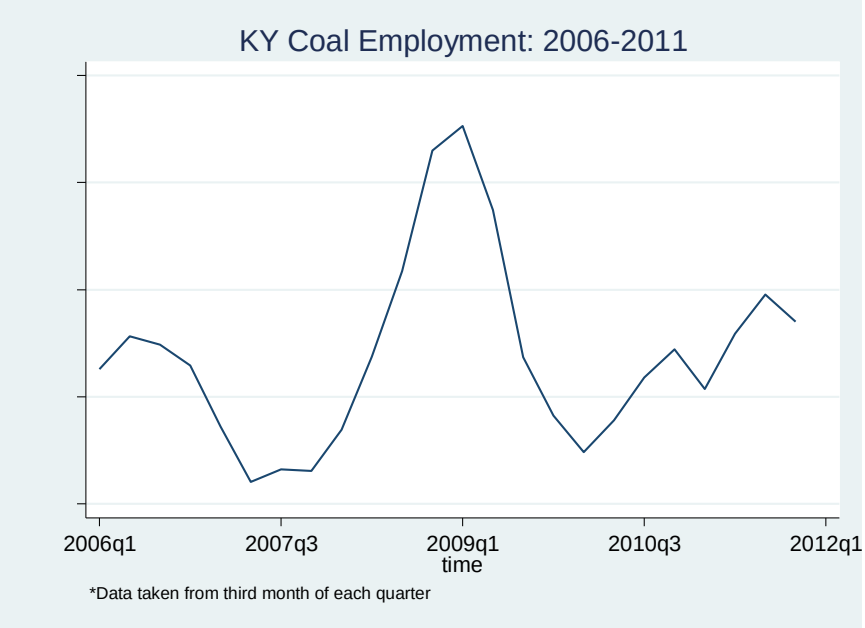

Fig. 3: *Kentucky Coal Mining Employment*, 2006 Q1 – 2011 Q4

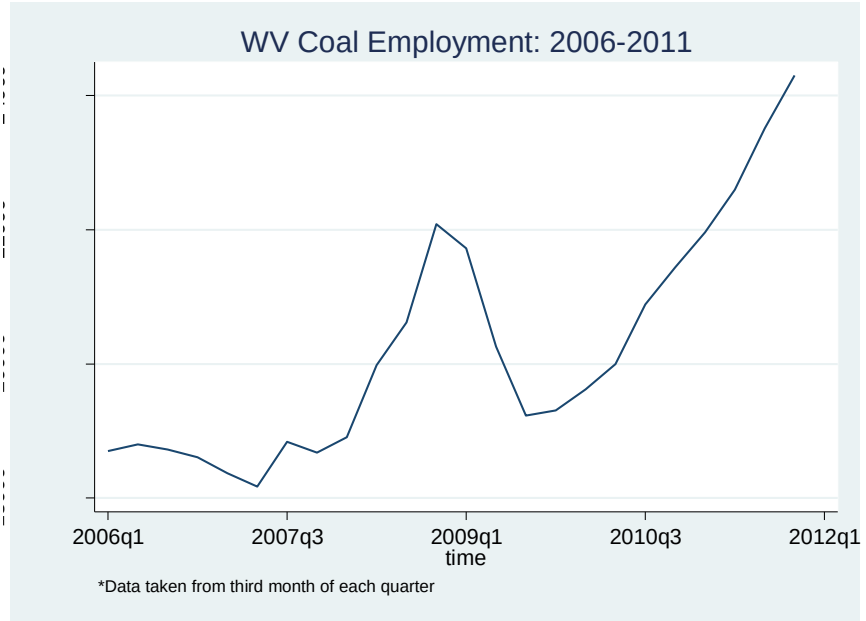

Fig. 4: *West Virginia Coal Mining Employment*, 2006 Q1 – 2011 Q4

To analyze the changes in labor markets, I use county-level data on employment levels, average weekly wages and total wages for all industries and the coal, service, retail trade, construction and manufacturing industries in each quarter from 2006 to 2011. The

dataset, all industries, is an aggregate measure of total employment data in each county. In addition, to control for the coal industry influencing changes in the all industries dataset, I created another variable with the coal industry subtracted from all industries. I only did this for employment data and total wages data because subtracting coal wages from all industries' average wages would have created negative observations.

These employment metrics are from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages database. Table 1 specifically defines each of these metrics. I choose to examine these four industries for spillover effects because Black et al. (2005) used them in his models. Further, these industries intuitively seem like industries that would compete for jobs with coal mining (manufacturing and construction) or would be affected by changes in the local economy (construction, service, and retail-trade). It should be noted that the retail-trade industry is included in the service industry dataset. While it is repeating the same data, it will allow me to more specifically examine the changes in the service industry.

Table 1:
Definition of Dependent Variables Used in Model

Variable	Definition
Employment	The number of people employed in each industry
Average Weekly Wages	The average weekly wage for employees in each industry
Total Wages	Total wages paid in each industry

For employment in each sector, the dataset contained only monthly data and not averages for each quarter. To create quarterly data, I used the last month of each quarter as a proxy for quarterly employment. While Black et al. (2005) and other authors examining

spillover effects use annual data, I use quarterly data to increase the number of observations due to the short period of my study.

The unemployment data used in my model is from the Bureau of Labor Statistic's Local Area Unemployed Statistics database. It includes non-seasonally adjusted monthly data on the total number of unemployed people in each county. To make the coefficients larger and more meaningful, I rescaled this variable to 100s of people unemployed. Similar to the employment data, I used the last month of each quarter to convert the monthly data to quarterly unemployment data in each county.

The population data for each county is from the U.S. Census Intercensal Estimates database. These data points are estimated annual population levels for each county between census-taking years. I divided the population data by male and female because 94% of all coal miners are male (Profile of the U.S. Coal Miner – 2013, 2014). I also only examined the working age population, which I set to be from 20 years to 69 years old. I used a high upper-bound for age because of the high average age of coal miners, which was 55 in West Virginia in 2006 (Brook, 2006). Similar to unemployment data, I also rescaled population data to 100s of people. Due to the lack of data on county-level population data, I could not obtain quarterly or monthly population data. However, I believe, despite using quarterly data throughout my model, it is not important to have quarterly population data because the changes would be small.

While I initially started with 4,200 observations (175 counties x 6 years x 4 quarters) in my dataset, I dropped 2,019 observations due to missing employment. I did not use any further datasets within the service industry because it would have caused me to drop too many observations during this step. I kept retail-trade in my model because it

was used by Black et al. (2005) and there were enough observations to not significantly change my dataset. I only dropped observations with missing coal data if it was coded as missing or non-disclosed in the original dataset from BLS. I did not drop all of the missing coal observations because I did not want to delete counties that did not have any coal production and therefore zero employment data. I recoded these counties as having "0" for coal employment data.

To control for counties that potentially had coal activity but non-disclosed missing data, I used 2006 coal mine data as another indicator for coal production. The coal mine data is from the Energy Information Agency (EIA), and reports the number of coal mines in each county in 2006. I dropped counties that had at least one coal mine but no coal employment data. Therefore, I am confident in recoding missing coal employment as zero since these counties have zero coal production. These total cuts in my dataset reduced the number of observed counties from 175 to 129.

I generated four different time groups to isolate the effects of the boom and bust period in my model. These groups are *Pre-Boom*, *Boom*, *Bust* and *Post-Bust*. I used Figure 3 and 4 to determine which quarters will be included in each period. The *Pre-Boom* group is from 2006 Q1 to 2007 Q4 and comprises of the time leading up to the boom in the coal industry. The *Boom* period is from 2008 Q1 to 2008 Q4 and captures the period during which coal employment increased in both Kentucky and West Virginia. The *Bust* period is from 2009 Q1 to 2010 Q1 and includes quarters during the decrease in coal employment. Lastly, the *Post-Bust* group includes all quarters after the bust and is from 2010 Q2 to 2011 Q4.

To inspect the industry spillover effects, I created two groups of counties, coal producing and non-coal producing counties. Because I am most interested in observing the counties which were most affected by the coal shock, I limit my coal group to counties that had at least 5% of its total wages coming from the coal industry at some point from 2006 to 2011. While this percentage is less than Black et al. (2005), I believe it reflects that counties are more economically diverse since the 1970s and that coal is becoming a less significant energy source in America. Using a 5% threshold creates a sample size of 318 observations and 24 counties.

However, after observing the data, I dropped Pike Country, KY and Boone County, WV because they were outliers in coal employment and were missing data for the boom and bust period. While I would have liked to include them in the model because of their large coal economies, their missing data in 2008 and 2009 would bias the coal group. In addition, I dropped two more counties, Grant County, WV and Morgan County, KY, because they only contained one observation. Therefore, my final coal counties group contains 298 observations and 20 counties. Since these high coal-producing counties were most affected by the coal shock in 2008, they are also referred to as the "Treatment" counties.

The comparison group is counties that have 0% of its total wages derived from the coal industry. Since coal production tends to be in rural areas, I restrict the comparison counties to similar population ranges as the treatment group. In the first year of the data (2006), treatment counties' population ranged from 11,834 to 78,178 people. Therefore, I limited the comparison group to counties that contained between 10,000 and 80,000 people in 2006. These parameters create a comparison group with 1,182 observations and 66 counties. Figure 5 and Figure 6 map the counties in the treatment and comparison

counties for Kentucky and West Virginia, respectively. Creating dummy variables for coal groups and time groups will allow me to isolate the differences in employment data between these two county groups in each period.

Initially, I followed the methodology of Black et al. (2005) by creating groups for counties that produce minimal amounts of coal. However, after examining the small number of counties and observations in these groups, I dropped them from my model. These counties are not important for my study since they would have the least effect from changes in the coal labor market. This paper only focuses on the differences between high coal producing counties and counties that have zero coal production.

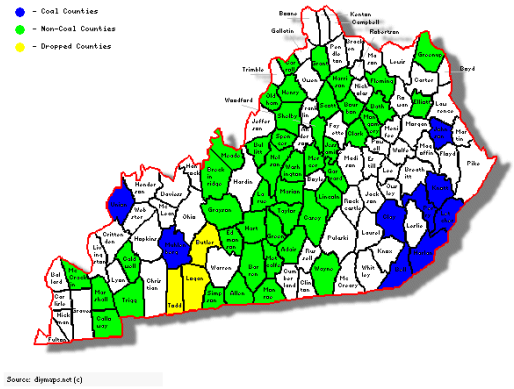

Fig. 5: *Map of Treatment and Comparison Counties: Kentucky*

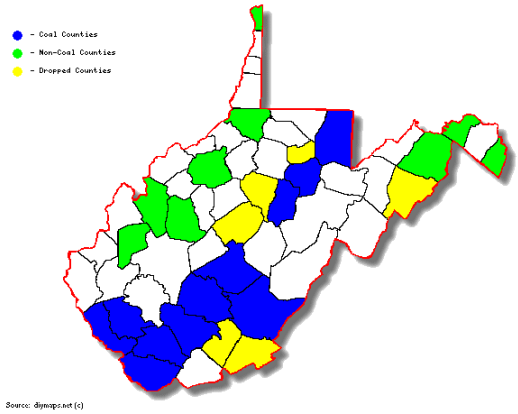

Fig. 6: *Map of Treatment and Comparison Counties: West Virginia*

Treatment counties and comparison counties tend to be geographically separated from each other, with treatment counties on the east side and comparison counties on the west side of each state. However, a few comparison counties border treatment counties. If the economic benefits (or losses) from the shocks in the coal industry spill over to these neighboring counties with no coal production, it will lead to an underestimated effect of the boom and bust. Therefore, following Weber (2012), I drop all comparison counties that share a border with a treatment county. Accounting for this potential bias reduces the comparison group to 57 counties and 1,053 observations.

Methodology:

To estimate the industry spillover effects of the coal boom and bust, I examine its effects on the quarterly rate of change in employment, average weekly wages and total wages in coal counties versus non-coal counties. However, before examining the spillover effects, I analyze the direct effect of the boom and bust on the coal industry to establish a precedent. I calculate the average percentage change in growth rates for coal mining employment, average weekly wages and total wages in three different periods (*Boom*, *Bust* and *Post*). I purposely omitted the *Pre-Boom* period so it is the baseline for comparison. To examine the changes in employment data I use the following model:

Equation (1)

$$\Delta \ln(y)_{it} = \beta_1 Boom_t + \beta_2 Bust_t + \beta_3 Post_t + \delta_1 Q2_t + \delta_2 Q3_t + \delta_3 Q4_t + \beta_4 Femalepop_{it} + \beta_5 Malepop_{it} + \beta_6 Unemployed_{it} + \varepsilon_{it}$$

Y_{it} is employment, average weekly wage and total wage for the coal industry for county *i* in quarter *t*. Before running the model, I dropped all counties that had "0" for coal employment data because I only wanted to examine the high coal producing counties. I differentiated the dependent variable because it creates a more logical interpretation. Rather than showing the percentage change in magnitude between periods, my model shows the percentage change in the growth rate for each period relative to the *Pre-Boom* group. This allows me to capture the trend in employment data during the boom and bust, which should be positive and negative, respectfully. In addition, this follows Black et al. (2005) who differentiated the dependent variable in all of his models.

In this model, I control for seasonal variations in the labor market by including dummy variables for each quarter. I included these seasonal controls because coal average weekly wages show seasonal fluctuations over time. Figure 7 and 8 show these changes by plotting the state-level average weekly wage in the coal industry over time for Kentucky and West Virginia. By controlling for seasonal changes, I prevent the *Boom* and *Bust* periods from picking up the effects of mere seasonal changes. I left out Q1 to be consistent with dropping the earliest period (*Pre-Boom* group).

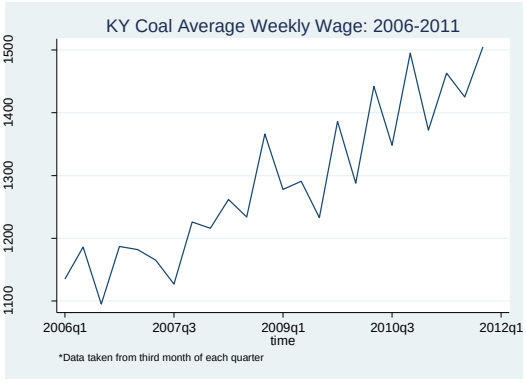

Fig. 7: *Graph of Average Weekly Wage in the Coal Industry: Kentucky,* 2006 – 2011

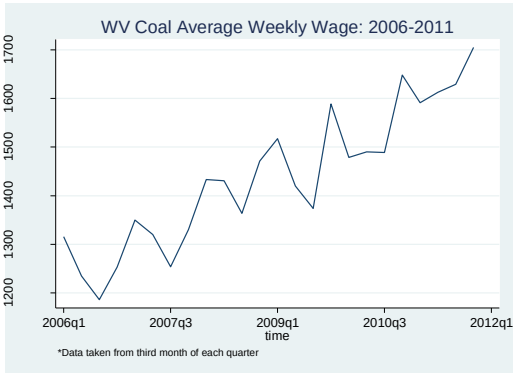

Fig. 8: *Graph of Average Weekly Wage in the Coal Industry: West Virginia,* 2006 – 2011

I also included continuous variables for male and female population to control for the effects of changes in population on employment data. I wanted to ensure that the changes in coal employment data were not due to fluctuations in county population.

Lastly, I account for the number of unemployed people in each county. I believe by adding unemployment to my model, it will account for changes in employment coming from the unemployed finding work. I initially included state and year interaction dummies to follow the model used by Black et al. (2005). However, I did not include these dummies in my final model due to their high colinearity with the time period dummies. Therefore,

unemployment will also pick up many of the same macroeconomic effects included in the state and year dummies.

To determine the spillover effects of the coal boom and bust I use a model similar to Equation (1), but include treatment county dummies to differentiate between coal and non-coal counties.

Equation (2)

$$\Delta \ln(y)_{it} = \beta_1 Boom_t + \beta_2 Bust_t + \beta_3 Post_t + \beta_4 Treatment\ x\ Boom_{it} + \beta_5 Treatment\ x\ Bust_{it} + \beta_6 Treatment\ x\ Post_{it} + \delta_1 Q2_t + \delta_2 Q3_t + \delta_3 Q4_t + \beta_7 Femalepop_{it} + \beta_8 Malepop_{it} + \beta_9 Unemployment_{it} + \varepsilon_{it}$$

Like Equation (1), the dependent variable is also total employment, average weekly wages and total wages. However, these employment variables are now for all industries and the construction, service, retail and manufacturing industries in each county. When using employment data for all industries as the dependent variable, I did not include unemployment in the model because of its high correlation with total employment.

I included interaction terms for treatment counties and the time periods because the data used in this model now includes both comparison and treatment counties. Therefore, these new interaction terms capture the additional change in the growth rate for high coal producing counties relative to counties with zero coal production for each time period.

Results:

Table 2 shows the results from running Equation (1), which tests for the direct effects of the coal boom and bust on the coal industry.

Table 2

Growth in Coal Mining Employment, Average Weekly Wages and Total Wages Treatment Counties, 2006-2011

	(1) Employment	(2) Average Weekly Wage	(3) Total Wages
boom	0.0480*	0.0270	0.0770**
	(0.0271)	(0.0214)	(0.0324)
bust	-0.0761*	0.00351	-0.0729
	(0.0406)	(0.0321)	(0.0486)
post	0.000752	0.0365	0.0465
	(0.0389)	(0.0307)	(0.0466)
Q2	-0.0295	0.0161	-0.0144
	(0.0254)	(0.0201)	(0.0304)
Q3	-0.0146	-0.0132	-0.0478
	(0.0256)	(0.0202)	(0.0307)
Q4	-0.0265	0.0934***	0.0698**
	(0.0260)	(0.0205)	(0.0310)
malepop100	0.0354	-0.00478	0.0261
	(0.0214)	(0.0169)	(0.0256)
femalepop100	-0.0375	0.0168	-0.0234
	(0.0238)	(0.0187)	(0.0284)
unemployed100	0.00364	-0.00216	0.00230
	(0.00620)	(0.00489)	(0.00741)
_cons	0.159	-1.206	-0.317
	(2.250)	(1.775)	(2.691)
N	267	267	267
R^2	0.078	0.161	0.160

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results using coal employment data yield significance for the boom and bust period. During the boom, the growth rate for coal employment was 4.80 percentage-points higher than during the pre-boom period. This shows that during the boom, coal employment grew more quickly than the pre-boom period. Expectedly, during the bust, the

growth rate for coal employment decreased by 7.61 percentage-points relative to the pre-boom period. This means that during the bust the employment in the coal industry grew at a slower rate compared to before the boom.

There were no significant results when looking at the average weekly wage in the coal industry. The coal boom and bust therefore had no effect on weekly wages since Model (2) shows that there is no statistical difference in the growth rate for wage during any of the periods relative to before the boom. However, total wages yielded significant results during the boom period. During the boom, the growth rate for total wages was 7.70 percentage-points higher than during the pre-boom period. While there are no significant findings for average wages, the positive coefficients for both employment and total wages during the boom and subsequent negative coefficient for employment during the bust, indicate an increase in coal labor during the boom period and a contraction during the bust.

Now that I have shown a change in the coal industry during both the boom and bust periods, I can test to see if these changes spillover to other industries. Table 3 reports the results from running Equation (2) with the three employment metrics for both all industries and all industries minus the coal sector. When looking at employment across all industries with the coal industry, there is a statistical difference between coal and non-coal counties during the boom period. During the boom period, the growth rate for employment in all industries was 2.29 percentage-points higher for coal counties relative to non-counties. Further, the growth rate for employment during the boom dropped 1.43 percentage-points for non-coal counties relative to the pre-boom period. In contrast, during the boom for coal counties, the growth rate for employment in all sectors increased 0.86 percentage-points relative to before the boom.

In addition to employment, total wages for all industries yielded a statistically significant difference between coal and non-coal counties during the boom. During the boom, the growth rate in total wages was 2.47 percentage-points higher in coal counties than non-coal counties. However, there is not a statistical difference in the growth rate for total wages between the two county groups during the bust period. Further, the average weekly wages for all industries yield no significant difference between coal counties and non-coal counties.

Model (4) in Table 3 shows the results for the growth rate in employment after removing the coal industry. By removing coal from all industries, it controls for the coal industry biasing the change in overall employment. While less, there still is a significant difference between the coal counties and non-coal counties in their growth rate for total employment during the boom. During the boom, the growth rate for coal counties was 1.87% larger than non-coal counties. Since this difference deceases after removing coal, it confirms that the coal industry biased the initial results in Model (1). However, total employment for coal counties grew faster compared to non-coal counties during the boom. This difference suggests that the increase in coal production may have led to higher growth rates in other sectors during the boom. It should also be noted that subtracting the coal industry eliminates the significant difference in total wages between coal and non-coal counties during the boom period. This suggests that the coal industry drove the difference found in Model (3).

Table 3

Spillover Effects for Employment, Average Weekly Wage and Total Wages for All Industries and All Industries minus the Coal Industry, 2006-2011

	(1) Employment	(2) Average Weekly Wage	(3) Total Wages	(4) Employment With No Coal	(5) Total Wages With No Coal
boom	-0.0143***	0.00497	-0.00232	-0.0143***	-0.00181
	(0.00328)	(0.00495)	(0.00555)	(0.00329)	(0.00555)
bust	-0.0138***	-0.00139	0.00366	-0.0138***	0.00508
	(0.00334)	(0.00742)	(0.00832)	(0.00335)	(0.00832)
post	0.00125	0.00653	0.0229***	0.00121	0.0223***
	(0.00333)	(0.00618)	(0.00692)	(0.00334)	(0.00692)
treatmentboom	0.0229***	0.0109	0.0247**	0.0187***	0.0120
	(0.00720)	(0.0107)	(0.0120)	(0.00721)	(0.0120)
treatmentbust	0.00643	-0.00566	-0.00423	0.0115*	-0.000629
	(0.00689)	(0.0102)	(0.0115)	(0.00690)	(0.0115)
treatmentpost	0.00382	0.00553	0.00808	0.00220	0.00360
	(0.00717)	(0.0106)	(0.0118)	(0.00718)	(0.0118)
Q2	0.0396***	0.0915***	0.147***	0.0404***	0.156***
	(0.00283)	(0.00418)	(0.00469)	(0.00284)	(0.00468)
Q3	0.00592**	0.0895***	0.114***	0.00560**	0.122***
	(0.00283)	(0.00420)	(0.00471)	(0.00283)	(0.00471)
Q4	0.000880	0.159***	0.171***	0.000801	0.177***
	(0.00285)	(0.00422)	(0.00472)	(0.00286)	(0.00472)
malepop100	0.00108	0.00934***	0.0119***	0.000571	0.0114***
	(0.00238)	(0.00352)	(0.00394)	(0.00239)	(0.00394)
femalepop100	-0.000474	-0.00889***	-0.00912**	-0.0000143	-0.00864**
	(0.00223)	(0.00329)	(0.00369)	(0.00223)	(0.00369)
unemployed100	-	-0.000213	-0.00353***	-	-0.00347***
		(0.000861)	(0.000965)		(0.000965)
_cons	-0.0664	-0.115	-0.324***	-0.0630	-0.332***
	(0.0592)	(0.0939)	(0.105)	(0.0592)	(0.105)
N	1236	1236	1236	1236	1236
R^2	0.249	0.577	0.607	0.252	0.621

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 reports the results when using employment data by sector as the dependent variable. Except for the service industry, there is not a significant difference between the growth rates for coal and non-coal counties for any time period. During the boom, the growth rate for employment in the service industry was 1.4 percentage-points larger for coal counties than non-coal counties. Relative to before the boom, the growth rate in service employment for coal counties was 0.514 percentage-points larger during the boom. This contrasts with non-coal counties, which relative to before the boom, their growth rate in service employment decreased 0.926 percentage-points in the boom period. Therefore, there appears to be modest spillover effects in the service industry from the coal industry since employment grew at a higher rate during the boom for coal counties, while employment grew at a slower rate during the boom for non-coal counties. However, while there are spillover effects in the service industry, the total effects of the coal boom and bust on employment appears to be limited since no other observed industry yields significant results.

Table 4

Spillover Effects for Employment by Sector, 2006-2011

	(1) Construction	(2) Retail Trade	(3) Service	(4) Manufacturing
boom	-0.0216	-0.00820**	-0.00926**	-0.0118
	(0.0134)	(0.00405)	(0.00382)	(0.00784)
bust	0.00237	-0.00928	0.00469	0.0257**
	(0.0201)	(0.00608)	(0.00573)	(0.0118)
post	0.0186	-0.00433	0.00689	0.0399***
	(0.0167)	(0.00505)	(0.00477)	(0.00978)
treatmentboom	0.0189	0.00276	0.0144*	0.00389
	(0.0288)	(0.00874)	(0.00824)	(0.0169)
treatmentbust	0.0307	0.00905	0.00458	-0.00333
	(0.0277)	(0.00838)	(0.00791)	(0.0162)
treatmentpost	0.0200	0.00481	0.00382	0.00643
	(0.0285)	(0.00865)	(0.00816)	(0.0167)
Q2	0.196***	0.0336***	0.0346***	0.0321***
	(0.0113)	(0.00342)	(0.00323)	(0.00662)
Q3	0.0739***	0.00228	-0.00445	0.0127*
	(0.0114)	(0.00344)	(0.00325)	(0.00665)
Q4	0.00414	0.0231***	-0.00308	0.0147**
	(0.0114)	(0.00345)	(0.00325)	(0.00667)
malepop100	0.00593	-0.000945	0.000418	0.00562
	(0.00951)	(0.00288)	(0.00272)	(0.00557)
femalepop100	-0.00118	0.00167	0.00137	-0.00196
	(0.00889)	(0.00269)	(0.00254)	(0.00521)
unemployed100	-0.00576**	-0.000617	-0.00216***	-0.00689***
	(0.00233)	(0.000705)	(0.000665)	(0.00136)
_cons	-0.468*	-0.0759	-0.154**	-0.313**
	(0.254)	(0.0769)	(0.0725)	(0.149)
N	1236	1236	1236	1236
R^2	0.291	0.132	0.181	0.070

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 and Table 6 report the results of examining the changes in the growth rate of average weekly wage and total wages in each sector, respectively. The growth rate of average weekly wages in each sector is not statistically different between coal counties and non-coal counties across any period. This shows that the coal boom and bust had no effect on the average wage of workers in the construction, retail, service and manufacturing industries during this period. Further, the only coefficient that yielded significance for a time period dummy is in the service industry. However, this result is barely significant at the 10% level and does not relate to spillover effects since it's for non-coal counties. The driving factor for average weekly wages appears to seasonal changes since Q2, Q3 and Q4 are all significant at the 1% level. This makes sense after looking at the graphs for wages in each sector, which all clearly show seasonal fluctuations. These graphs are found in the data appendix.

Similar to average weekly wage, total wages for each sector do not indicate any spillover effects from the coal industry. The only indication of potential spillover effects is in the manufacturing industry. During the bust, the growth rate for total wages in the manufacturing industry was 4.14 percentage-points less in coal counties relative to non-coal counties. However, this coefficient is hardly significant at the 10% level and does not follow any of the results in previous models. Therefore, its quality in explaining spillover effects in the manufacturing industry should be scrutinized.

Table 5

Spillover Effects for Average Weekly Wage by Sector, 2006-2011

	(1) Construction	(2) Retail Trade	(3) Service	(4) Manufacturing
boom	-0.00516	0.00491	0.00837*	0.00688
	(0.0130)	(0.00557)	(0.00500)	(0.0102)
bust	-0.0192	-0.00434	0.00275	0.00344
	(0.0195)	(0.00835)	(0.00750)	(0.0153)
post	-0.0116	0.00205	0.00523	0.00941
	(0.0163)	(0.00694)	(0.00624)	(0.0127)
treatmentboom	0.0320	0.00501	-0.00782	0.0232
	(0.0281)	(0.0120)	(0.0108)	(0.0220)
treatmentbust	0.00902	-0.00593	-0.00812	-0.0336
	(0.0270)	(0.0115)	(0.0103)	(0.0211)
treatmentpost	-0.00680	0.00266	0.00131	0.0196
	(0.0278)	(0.0119)	(0.0107)	(0.0218)
Q2	0.233***	0.0857***	0.0832***	0.115***
	(0.0110)	(0.00470)	(0.00422)	(0.00862)
Q3	0.191***	0.0711***	0.0839***	0.0874***
	(0.0111)	(0.00473)	(0.00425)	(0.00867)
Q4	0.233***	0.108***	0.150***	0.172***
	(0.0111)	(0.00474)	(0.00426)	(0.00869)
malepop100	0.00236	0.00220	0.00677*	0.00932
	(0.00926)	(0.00396)	(0.00356)	(0.00726)
femalepop100	-0.00295	-0.00291	-0.00671**	-0.00839
	(0.00866)	(0.00370)	(0.00333)	(0.00679)
unemployed100	0.00134	0.000836	-0.000274	0.000299
	(0.00227)	(0.000968)	(0.000870)	(0.00178)
_cons	-0.106	-0.00132	-0.0735	-0.178
	(0.247)	(0.106)	(0.0949)	(0.194)
N	1236	1236	1236	1236
R^2	0.352	0.349	0.539	0.284

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6

Spillover Effects for Total Wages by Sector, 2006-2011

	(1) Construction	(2) Retail Trade	(3) Service	(4) Manufacturing
boom	-0.0201	-0.00343	0.00129	-0.00176
	(0.0199)	(0.00586)	(0.00552)	(0.0117)
bust	-0.0350	-0.0142	0.00679	0.0166
	(0.0299)	(0.00879)	(0.00827)	(0.0176)
post	0.00809	-0.00340	0.0131*	0.0447***
	(0.0249)	(0.00731)	(0.00688)	(0.0146)
treatmentboom	0.0497	0.00651	0.00172	0.0286
	(0.0430)	(0.0126)	(0.0119)	(0.0253)
treatmentbust	0.0446	0.00404	-0.00390	-0.0414*
	(0.0413)	(0.0121)	(0.0114)	(0.0242)
treatmentpost	0.00706	0.00877	0.00286	0.0262
	(0.0426)	(0.0125)	(0.0118)	(0.0250)
Q2	0.499***	0.129***	0.133***	0.139***
	(0.0168)	(0.00495)	(0.00466)	(0.00989)
Q3	0.367***	0.0903***	0.101***	0.0994***
	(0.0169)	(0.00498)	(0.00468)	(0.00994)
Q4	0.333***	0.129***	0.156***	0.181***
	(0.0170)	(0.00499)	(0.00470)	(0.00997)
malepop100	0.00825	0.00178	0.00800**	0.0150*
	(0.0142)	(0.00417)	(0.00392)	(0.00833)
femalepop100	-0.00483	-0.00196	-0.00616*	-0.0108
	(0.0133)	(0.00390)	(0.00367)	(0.00779)
unemployed100	-0.00301	0.000311	-0.00251***	-0.00558***
	(0.00347)	(0.00102)	(0.000960)	(0.00204)
_cons	-0.585	-0.0643	-0.236**	-0.461**
	(0.378)	(0.111)	(0.105)	(0.222)
N	1236	1236	1236	1236
R^2	0.471	0.457	0.549	0.293

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Discussion:

While my results indicate a significant increase and decrease in coal employment data during the boom and bust, it appears this only affected the service industry. This contradicts many of the previous literature that found spillover effects across different sectors from long-terms changes in energy markets. However, it is hard to compare my findings against others because very few papers examined short-term shocks or changes in the coal industry. Most of these papers looked at the changes in the natural gas industry. Further, only a few papers examined the spillover effects on employment data, whereas others used different economic measures. Therefore, my results, while small, fill a void in the literature since it quantifies the industry spillover effects of a short-term energy shock.

My first model examining spillover effects suggested that employment and total wages across all industries grew at a quicker rate for coal counties during the boom. This follows Black et al. (2005) who found significant differences for employment, total wages and earnings per working between coal and non-coal counties when using employment data for all industries. However, he did not include variables for changes in population and unemployment, which are even more pertinent considering the long-term scope of his data.

While my results for spillover effects in specific sectors yield little significance, the difference between coal and non-coal counties in the growth rate for service employment is important. The fact that the service industry was the only sector to show a significant short-term spillover effect makes sense intuitively. The increase in coal employment during the boom would inevitable create windfalls for local businesses as there are more people engaging the service industry. This increase in the local economy would cause the service industry to respond by hiring more employees.

However, when looking specifically at the retail-trade industry, which is included in the service industry dataset, it yields no significant spillover effects. Therefore, the spillover effects in the service industry must be driven by another sub-section. Intuitively, I believe it may be caused by the food and accommodation industry since restaurants can more easily hire temporary workers than retail stores in response to an increase in patrons. I would have liked to include employment data on specifically the food and accommodation industry in my model, but as stated earlier, the little data available would have forced me to drop too many observations.

For the other industries, I believe the shock in the coal industry were too short-lived to affect them due to lagged effects. The construction industry will not be as affected by short-term changes in employment like the service industry. While people will immediately engage local restaurants and stores, demand for new buildings and homes require a long-term change. Therefore, since the number of employed people increased and then decreased in only a two-year time period, it could not have created a sustained demand to stimulate construction.

The manufacturing industry will not be as affected by changes in the local employment since its goods are traded to other communities. Therefore, an increase in coal employment would only affect the manufacturing industry if its workers quit and became coal miners. However, this seems unlikely to me as the conditions in coal mines are generally more dangerous than manufacturing jobs. Further, the only incentive for manufacturing employees to shift to coal mining would be an increase in coal wages. My results showed that during the boom and bust there was no significant change in coal weekly wages. Therefore, the manufacturing workers would have little incentive to switch

since there was not an increase in coal wages. This is evident in there being no significant difference in manufacturing employment between coal and non-coal counties.

Further, if other industries did not have to compete with higher wages from the coal industry during the boom, it would not cause them to change their wages. Therefore, my paper may also highlight the importance of changes in wages on spillover effects rather than changes in employment. While total wages in the coal industry increased during the boom, equally large increases in employment most likely caused this change.

Conclusion:

In this study, I found that the increase in coal employment during the 2008 boom is associated with higher growth rates for employment in the service industry in coal producing counties relative to non-coal producing counties. While the effects are modest, it is integral to quantify the spillover effects of a short-term labor and resource shock. Further studies should use this finding and apply it to other short-term labor shocks in a specific industry. Further examination for this topic would be to explore different sectors in addition to the four industries I used in this paper. If more data becomes available, I would suggest trying to further probe the service industry and examine more specific sectors to see what's driving the significant difference in service employment between coal counties and non-coal counties.

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