ESSAYS ON THE MACROECONOMIC EFFECTS OF ENERGY PRICE SHOCKS

by

MARK ALAN MELICHAR

B.A., Hastings College, 2008

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

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Manhattan, Kansas

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Abstract

In the first chapter I study the effects of oil price shocks on economic activity at the U.S. state-level, an innovative feature of this dissertation. States which rely more heavily on manufacturing or tourism are more adversely affected by adverse oil price shocks, while states which are major energy producers either benefit or experience insignificant economic changes from historically large oil price increases. Additionally, oil price increases from 1986 to 2011 have not impacted state-level economies to the same degree as increases from 1976 to 1985. This discrepancy can be attributed to a fundamental change in the structure of the U.S. economy, for example, a declining manufacturing sector or an increase in the efficiency with which energy is used in the production process.

In the second chapter I explore the effects of alternative measures of energy price shocks on economic activity and examine the relative performance of these alternative measures in forecasting macroeconomic activity. The alternative energy prices I consider are: gasoline, diesel, natural gas, heating oil and electricity. I find that alternative measures of energy price shocks produce different patterns of impulse responses than oil price shocks. The overwhelming evidence indicates that alternative energy price models, excluding a model containing gasoline prices, outperforms the baseline model containing oil prices for many states, particularly at short-to-mid forecast horizons.

In the third chapter, which is coauthored with Lance Bachmeier, we determine whether accounting for oil price endogeneity is important when predicting state-level economic activity. We find that accounting for endogeneity matters for in-sample fit for most states. Specifically, in-sample fit would be improved by using a larger model which contains both regular oil price and endogenous oil price movements. However, we conclude that accounting for endogeneity is not important for out-of-sample forecast accuracy, and a simple model containing only the change in the price of oil produces equally accurate forecasts. Accounting for endogeneity is particularly important in an environment in which rising oil prices were caused by a growing global economy, such as in the years 2004-2007.

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Dedication

To my amazing wife, Halah.

Chapter 1 - U.S. State-Level Effects of Oil Price Shocks on Economic Activity: How the Oil Price-Macroeconomy Relationship Has Changed

Introduction

One of the important research questions in macroeconomics the past three decades has been identifying how and why oil prices affect the economy. Most empirical research has used measures of aggregate economic activity. However, the U.S. economy is very diverse, with different regions relying on different forms of economic activity, such as the Great Lakes depending on manufacturing and the Great Plains depending on agriculture. Consequently, there is much more variation in the responses of different states through time than there is using aggregate data. This cross-sectional variation can then be used to answer some of the important outstanding questions in the literature, such as the importance of oil price endogeneity and the weaker economic responses to more recent oil price shocks. To my knowledge, I am the first to analyze the macroeconomic response to oil price shocks for all 50 U.S. states. I find that, over the period 1976 to 2011, states which rely more heavily on manufacturing or tourism are more adversely affected economically, while states which rely more heavily on energy production benefit or experience small economic changes after historically large oil price shocks. Regression analysis reveals that the relative size of the manufacturing industry and the oil and natural gas extraction industry in each state are significant factors in determining the response after an oil price shock. These findings coincide with Davis and Haltiwanger (2001), Lee and Ni (2002), Hamilton (2009) and others, who find that durable goods industries, particularly automobiles, suffer the most in the months following an adverse oil price shock.

The period from the 1970s to the early 1980s was a time of rising oil prices, but after the collapse of the oil market in 1986 the market has experienced increased volatility. In addition, the high oil prices in the early period are thought to be a result of supply and speculative oil disruptions, and the high oil prices in the later period are thought to be a result of a growing global economy. Therefore, I examine the difference in economic responses between the two periods and find larger changes in both economic activity and unemployment during the early period. I show this can partly be explained by the declining importance of manufacturing as a share of GDP in many states over the last 35 years.

Kilian (2009) puts particular emphasis on the rising oil prices from 2002 to 2007, which can be thought of as a period of aggregate demand oil price shocks caused by a growing global economy. As a result, it is believed that rising oil prices during this period did not have detrimental effects on the U.S. economy. Consequently, I examine the economic response to aggregate demand oil price shocks in leading exporting states, but find sparse evidence of oil price shocks from 2002-2007 having positive economic effects.

I find evidence of asymmetric responses to oil price movements by using separate indexes containing only increases or decreases in the price of oil. In general, oil price increases have detrimental effects on economic activity, but oil price decreases do not have the same type of positive effect on economic activity. Future research examining the effects of oil price shocks should employ the separate indexes to get more accurate results.

Literature Review

For decades the relationship between energy prices and the macroeconomy has been studied in great detail, with Hamilton (1983) noting that all but one of the recessions in the U.S. between 1947 and 1981 have been preceded by oil price shocks. To check whether the oil price shocks are exogenous, Hamilton (1983) uses Granger-causality tests and finds that oil prices Granger-cause GNP and unemployment, but other macro variables such as price deflators, wages, or the money supply do not Granger-cause oil prices from 1948 to 1972. Therefore, it appears that oil price shocks play some role in explaining U.S. recessions. Mork (1989) investigates whether the correlation between oil prices and GNP continues to be strong post World War II with data up to 1988, which includes the collapse of the oil markets in 1985. He finds that the negative correlation of oil price increases and GNP persists through 1988, and that there appears to be asymmetric responses to oil price increases and decreases. In contrast, Hooker (1996) notes that the oil price macroeconomy relationship is considerably weaker in the OPEC period from 1973 to 1994 than it was from 1948 to 1973. Consequently, he concludes there was a structural break in 1973 between oil prices and macroeconomic variables such as GDP or unemployment. This structural break indicates that there has been a fundamental change in the transmission of oil price shocks to the economy. In response, Hamilton (1996) notes that many of the oil price increases post-1973 have been corrections to previous declines in oil prices, which the economy will respond to differently than typical oil price shocks. Thus, he suggests using the net oil price increase (NOPI), which only shows net increases in oil prices over a certain period of time, such as one year or three years. Using the NOPI and more recent data, the negative relationship between oil prices and output is still strong.

Valuable information can be gained from examining disaggregate or industry-level data. In a study explaining why oil shocks do not cause inflation, Bachmeier and Cha (2011) use disaggregate inflation data on consumer expenditures and find that variation across sectors provides information not found in the aggregate data. Similarly, in examining oil price shocks and industrial production, Herrera, Lagalo, and Wada (2010) suggest that their findings of asymmetric responses to oil price changes would be hidden by analysis using aggregate data.

There are many findings that show oil price shocks tend to have negative impacts on the economy, but there is not much in the way of explaining the transmission mechanism. Oil price shocks may directly impact production costs, which could lead to lower production and output levels. Davis and Haltiwanger (2001) document that employment declines the most in capital and energy intensive industries following an oil price shock. In addition, they find that oil price shocks generate bigger employment responses in durable goods industries. Lee and Ni (2002) find similar results showing that oil-intensive industries reduce supply in response to an oil price shock, and consumer durable industries such as household furniture, household appliances, and automobiles experience a decrease in demand due to an oil price shock. This finding is confirmed by Kilian (2007), who reports a one-year energy price elasticity for consumption expenditures of -0.47 for durable goods and -0.84 for vehicles during the period 1970 to 2006. Hamilton (2009) also concludes that declines in the automotive and related industries explain a great deal of past U.S. economic downturns. For example, if the motor vehicles and parts industry component of GDP had zero change during the oil price shocks of 1979-80 and 1990-91, then average GDP growth during those times would have been positive. Based on all of the previously cited papers that state the importance of the motor vehicle and parts industry following oil price shocks, one would expect to find that states with heavy reliance on this industry should have the largest deceases in economic activity following oil price shocks. Although durable goods consumption seems to explain a large portion of the economic response to oil price shocks, there are other avenues through which the economy is affected. Kilian

(2007) reports that energy price shocks adversely affect restaurant and lodging expenditures, as well as the sale of airline tickets. It would seem intuitive then that states which rely heavily on tourism would experience a decline in economic activity following an oil price shock. Fed chairman Ben Bernanke echoed many of the above findings when he stated that oil price shocks reduce household income and spending (Bernanke 2006).

Although oil price shocks typically seem to be a detriment to the economy, is it possible for oil price shocks to have positive effects? A handful of states are responsible for most of the energy production in the U.S., and when energy prices rise more revenue is generated in those states, and firms will expand production. Kilian (2007) examines one-year energy price elasticities for investment expenditures from 1970 to 2006 and finds a value of 1.39 and 2.13 for mining structures and mining and oil field machinery, respectively. Consequently, states with an economy that relies on energy production might experience higher economic activity in response to an oil price shock.

Another important consideration of the effect of oil price shocks is how they affect the consumer psyche and not just consumer income. Hamilton (2009) finds that energy price shocks that reduce disposable income by one percent decrease consumer sentiment by 15 percent. Clearly, rising oil prices will sour consumer confidence in the economy. Edelstein and Kilian (2009) address four ways that energy price shocks alter consumer spending: they reduce discretionary income, create uncertainty about future energy prices, increase precautionary savings, and via an operating cost effect cause complimentary goods to energy to be consumed in lower quantities. The authors use shocks to consumers' purchasing power driven by energy price fluctuations to quantify the effect of the purchasing power shock on various consumption categories. They find that durables, and motor vehicles in particular, have the largest decline in expenditures due to a purchasing power shock.

Until recently, the literature has assumed that oil price shocks were exogenous, usually stemming from supply disruptions abroad. Specifically, Hamilton (2009) examines the oil price shocks of 1973-74, 1978-79, 1980-81 and 1990-91 and finds that all four episodes experienced a substantial decrease in oil production, thus causing Hamilton to proclaim that previous oil price shocks were primarily caused by supply disruptions from exogenous geopolitical events. However, if oil prices are endogenous and influenced by global demand, then this would imply different implications for the effect on the macroeconomy. Kilian (2008) shows that many of the recent increases in oil prices were driven primarily by global demand, with exogenous supply disruptions accounting for only a small fraction of the increase in oil prices. Kilian (2009) decomposes oil price shocks into three categories: crude oil supply shocks, global aggregate demand shocks, and precautionary demand shocks. He then goes on to show that many of the oil price shocks in recent decades, especially the 2000's, have been driven primarily by global aggregate demand and precautionary shocks, which explains why recessions have not occurred after these episodes.

Data

Typically GNP or GDP is used to gauge economic activity in empirical studies involving energy price shocks, such as Hamilton (1983), Mork (1989), Hooker (1996), Hamilton (1996) and Kilian (2009). However, monthly GDP at the state level is only available starting in 1997. Therefore, the Coincident Economic Activity Index from the Federal Reserve Bank of Philadelphia is used instead from July 1979 to November 2010. According to the bank, the trend for each state's index is set to match the trend for gross state product. For robustness, state-level unemployment rates from the Bureau of Labor Statistics (BLS) are also employed from January 1976 to April 2011. To measure the monthly price of oil, I implement the Producer Price Index for Petroleum from the BLS. To ensure the data are stationary, standard transformations are used. More specifically, the first difference of the log level of the Coincident Economic Activity Index and the Producer Price Index for Petroleum are taken. Similarly, the first difference of the state-level unemployment rate is taken as well.

The three year NOPI, as discussed above, can be represented as:

$$Oil_t^{36} = max\{0, Oil_t - max\{Oil_{t-1}, \dots, Oil_{t-36}\}\}$$

where Oil_t is the log level of the Producer Price Index for Petroleum in period t. Since recent activity in oil markets has been relatively volatile compared to pre-OPEC, the NOPI might better capture price shocks to oil markets.

Lastly, various state-level statistics regarding industry shares of GDP are obtained from the U.S. Bureau of Economic Analysis (BEA), and yearly export figures are obtained from the International Trade Administration (ITA) from 1999 to 2010.

Methods

To begin, the following VAR model is estimated for the full sample via OLS:

$$Y_{i,t} = \alpha_1 + \sum_{j=1}^{k_i} \beta_{1j} Y_{i,t-j} + \sum_{j=1}^{k_i} \delta_{1j} Oil_{t-j} + \varepsilon_{y_{i,t}} \qquad (1)$$

$$Oil_t = \alpha_2 + \sum_{j=1}^{k_i} \beta_{2j} Y_{i,t-j} + \sum_{j=1}^{k_i} \delta_{2j} Oil_{t-j} + \varepsilon_{Oil_t} \qquad (2)$$

where $Y_{i,t}$ denotes the percentage change in the Coincident Economic Activity Index for state i at time t, Oil_t denotes the percentage change in the Producer Price Index for Petroleum, and k_i is the lag length selected for state i. For identification, I impose the assumption that Oil_t cannot contemporaneously affect $Y_{i,t}$. To examine the relationship between changes in oil prices and state-level unemployment, the following VAR model is estimated via OLS:

$$U_{i,t} = \alpha_1 + \sum_{j=1}^{k_i} \beta_{1j} U_{i,t-j} + \sum_{j=1}^{k_i} \delta_{1j} Oil_{t-j} + \varepsilon_{U_{i,t}} \qquad (3)$$

$$Oil_t = \alpha_2 + \sum_{j=1}^{k_i} \beta_{2j} U_{i,t-j} + \sum_{j=1}^{k_i} \delta_{2j} Oil_{t-j} + \varepsilon_{Oil_t} \qquad (4)$$

where $U_{i,t}$ denotes the percentage point change in the unemployment rate for state i at time t. As above, I impose the assumption that Oil_t cannot contemporaneously affect $U_{i,t}$.

To examine how states respond to oil price shocks, cumulative one-year impulse response functions (IRF) are calculated for each state, both for the Coincident Economic Activity Index and the state-level unemployment rate, in response to a one-standard deviation shock to the price of oil. 95% confidence bands are constructed using the wild bootstrap with 1,000 replications. I am then able to interpret the sign and magnitude of the response for each state, which allows for better understanding of the transmission of oil price shocks to economic activity. All of the previous equations are then re-estimated for the period July 1979 to December 1985 and January 1986 to November 2010 for the Coincident Economic Activity Index, and January 1976 to December 1985 and January 1986 to April 2011 for the unemployment rate to test for asymmetric responses to changes in the price of oil. In addition, all of the above equations, tests, and sub samples are re-estimated using the NOPI.

In order to understand the transmission of oil price shocks to economic activity and unemployment rates, impulse responses at 6 and 12 months for the full sample are regressed on various state-level statistics regarding industry shares. The estimation equation for the Coincident Economic Activity Index is:

$$IRF_{i,j}^{Y} = \beta_0 + \beta_1 Tourism_i + \beta_2 Manufacturing_i + \beta_3 OG_i + \beta_4 Ag_i + \varepsilon_{i,j} \quad (5)$$

where $IRF_{i,j}^{Y}$ is the impulse response j steps ahead to a standard oil price shock in state i, $Tourism_i$ is the average percentage of the Leisure & Hospitality industry as a share of GDP from 1976 to 2009 in state i, $Manufacturing_i$ is the average percentage of the manufacturing industry as a share of GDP from 1976 to 2009 in state i, OG_i is the average percentage of the oil and natural gas extraction industry as a share of GDP from 1976 to 2009 in state i, and Ag_i is the average percentage of the farming industry as a share of GDP from 1976 to 2009. Similarly, the estimation equation for state-level unemployment is:

$$IRF_{i,j}^{U} = \beta_0 + \beta_1 Tourism_i + \beta_2 Manufacturing_i + \beta_3 OG_i + \beta_4 Ag_i + \varepsilon_{i,j} \quad (6)$$

where $IRF_{i,j}^{U}$ is the impulse response j steps ahead to a standard oil price shock in state i and the other variables are the same as listed above. Equations (5) and (6) are then re-estimated using the impulse responses to a one-standard deviation NOPI shock.

Lastly, because of the large number of U.S. states, it is sometimes difficult to analyze the results. Therefore, the states are categorized by the largest industry as a share of GDP averaged over the full sample period. These classifications are only meant to simplify the interpretation of the impulse response functions by broadly grouping states by industry. The four industries considered are manufacturing, tourism, oil and natural gas extraction, and agriculture. The service sector is the dominant industry in the U.S., and uses little energy, so classifying all states as service sector would not be informative. It should be noted that in most states, the largest industry outside of the service sector is manufacturing, but states were only categorized as such if they exceeded the average manufacturing share of GDP for all 50 states. Therefore, if a state had below average manufacturing share of GDP, it is classified by its next largest industry share. For example, Florida's manufacturing share of GDP is below the national average, so it is classified as a tourism state because that is its next largest industry as a share of GDP. The classification for all 50 states can be seen in Table 1.1. States that appear in multiple industries without an asterisk do not have one dominant industry outside of manufacturing, such as California and Utah.

Table 1.1 Top Non-Service Industry by Share of State-Level GDP

Industry	State
Manufacturing	AL, AR*, CT, DE, GA, IL, IN, IA*, KS*, KY, ME, MA, MI, MN, MS, MO, NH, NC, OH, OR, PA, RI, SC, TN, VT*, WA, WI
Tourism	AZ, CA, FL, HI, MD, MT, NV, NJ, NY, UT, VA, VT*, WV
Oil & Natural Gas	AK, CO, LA, KS*, ND*, NM, OK, TX, UT, WV**, WY
Agriculture	AR*, CA, IA*, ID, KS*, MT, NE, ND*, SD, UT

* These states have above average GDP share in more than one industry, so they are listed in multiple categories. For example, Iowa has above average manufacturing share and agriculture share, so it is difficult to place it in one category.
** Technically, WV is not a top oil and natural gas producing state, but it does depend heavily on coal production, so it seems to make more sense grouping it with other energy producing states.

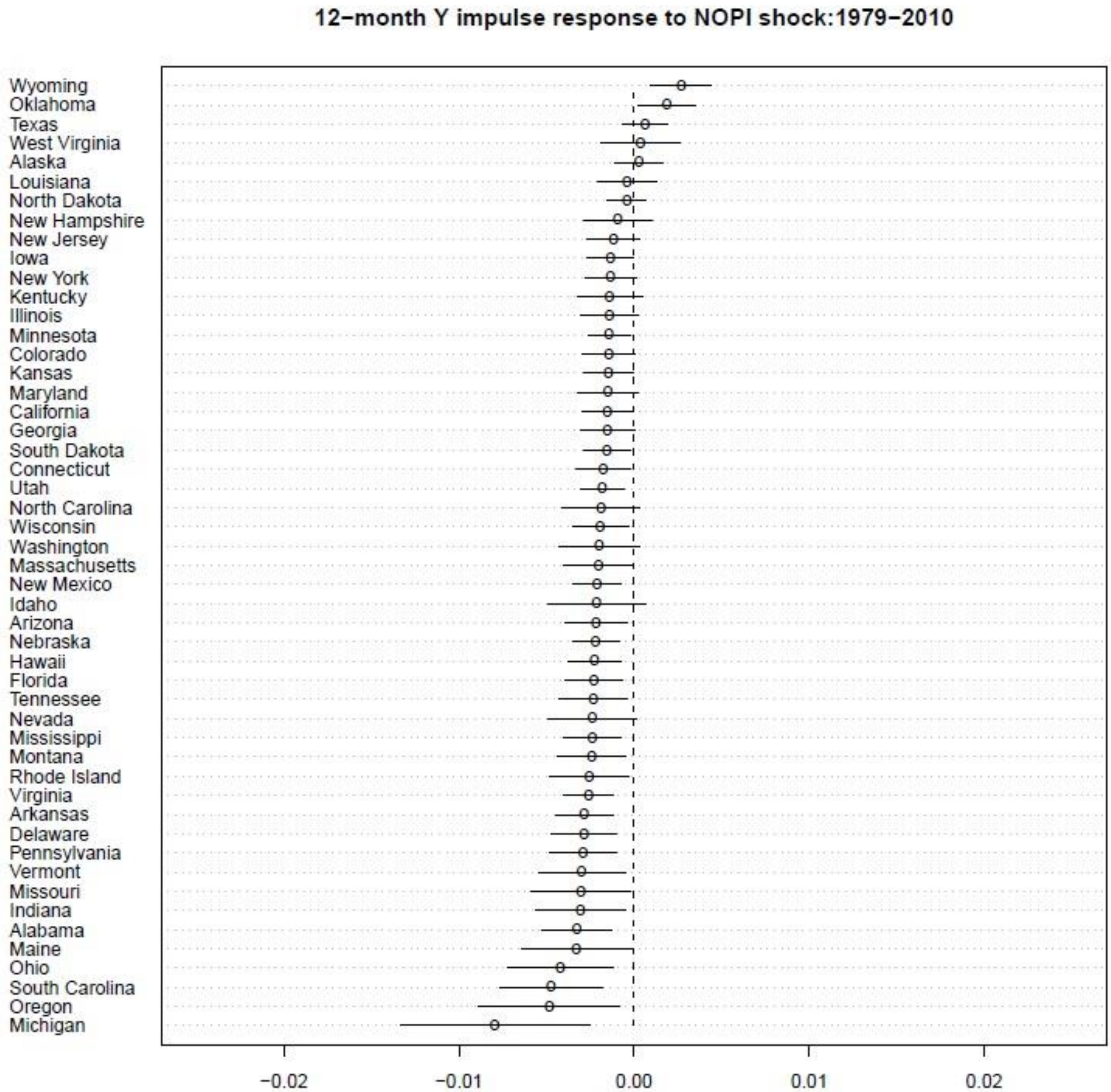
Results

When states experience a typical oil price shock, how do their economies respond? Is the response in each state positive or negative, and what is the magnitude of response? Answering these questions should help explain the transmission of oil price shocks through the economy and provide support for existing theories. Therefore, cumulative one-year IRFs are plotted as well as their respective upper and lower 95 percent confidence bands for both the coincident economic activity index and the unemployment rate. For the coincident economic activity index (Y) between 1979 and 2010, energy producing or refining states have positive responses and manufacturing and tourism states have negative responses to oil price shocks. However, the responses are not significantly different from zero. Using the relative size of each state's economy as a share of the total U.S. economy, a weighted effect on U.S. economic activity in response to an oil price shock between 1979 and 2010 is -0.01 percent. For the state-level unemployment rate (U) between 1976 and 2011, energy states experience a decrease in unemployment and manufacturing states experience an increase in unemployment one-year after an oil price shock, but the results are again insignificant. The weighted effect on the U.S. unemployment rate is a -0.01 percentage point change.

NOPI

In the OPEC period, fluctuations in the price of oil have been much more volatile than prior to the creation of OPEC. Consequently, Hamilton (1996) advocates the use of the NOPI when analyzing the oil price-macroeconomy relationship since the economy will respond differently to historically large price increases, than increases following price decreases. If this is true, then one should expect to see larger changes in economic activity and unemployment following a shock to the NOPI. The one-year cumulative impulse response to a standard deviation NOPI shock for the coincident economic activity index (Y) between 1979 and 2010 can be seen in Figure 1.1. Specifically, the dot for each state is the cumulative one-year impulse response and the line through each dot is the 95 percent confidence band. In addition, the percent change in economic activity is listed on the x-axis. For example, a value of -0.01 represents a one percent decrease in economic activity. Nearly all states see economic activity decline and by a larger magnitude for NOPI shocks compared to regular oil price shocks. Furthermore, out of the 15 most negative responses, all but two of them, Montana and Virginia, have above average manufacturing shares and are classified as such. The 15 most negative changes in economic activity range from -0.257 percent in Montana to -0.796 percent in Michigan. Looking at Figure 1.1, Michigan's negative response nearly doubles that of most other states. Michigan has long been known for manufacturing, most notably automobiles with the big three: GM, Ford and Chrysler. With Michigan's economy depending so heavily on durable goods such as automobiles, its large negative response in economic activity following a NOPI shock supports the findings of Davis and Haltiwanger (2001), Lee and Ni (2002), and Edelstein and Kilian (2009). The only states to experience no change or an increase in economic activity following a NOPI shock are some of the top energy producing states Wyoming, Oklahoma, Texas, West Virginia, and Alaska. Specifically, only Wyoming and Oklahoma experience increases in economic activity, and in fact Wyoming and Oklahoma have the highest percentage of

Figure 1.1 Economic Activity Impulse Response to NOPI Shock 1979-2010

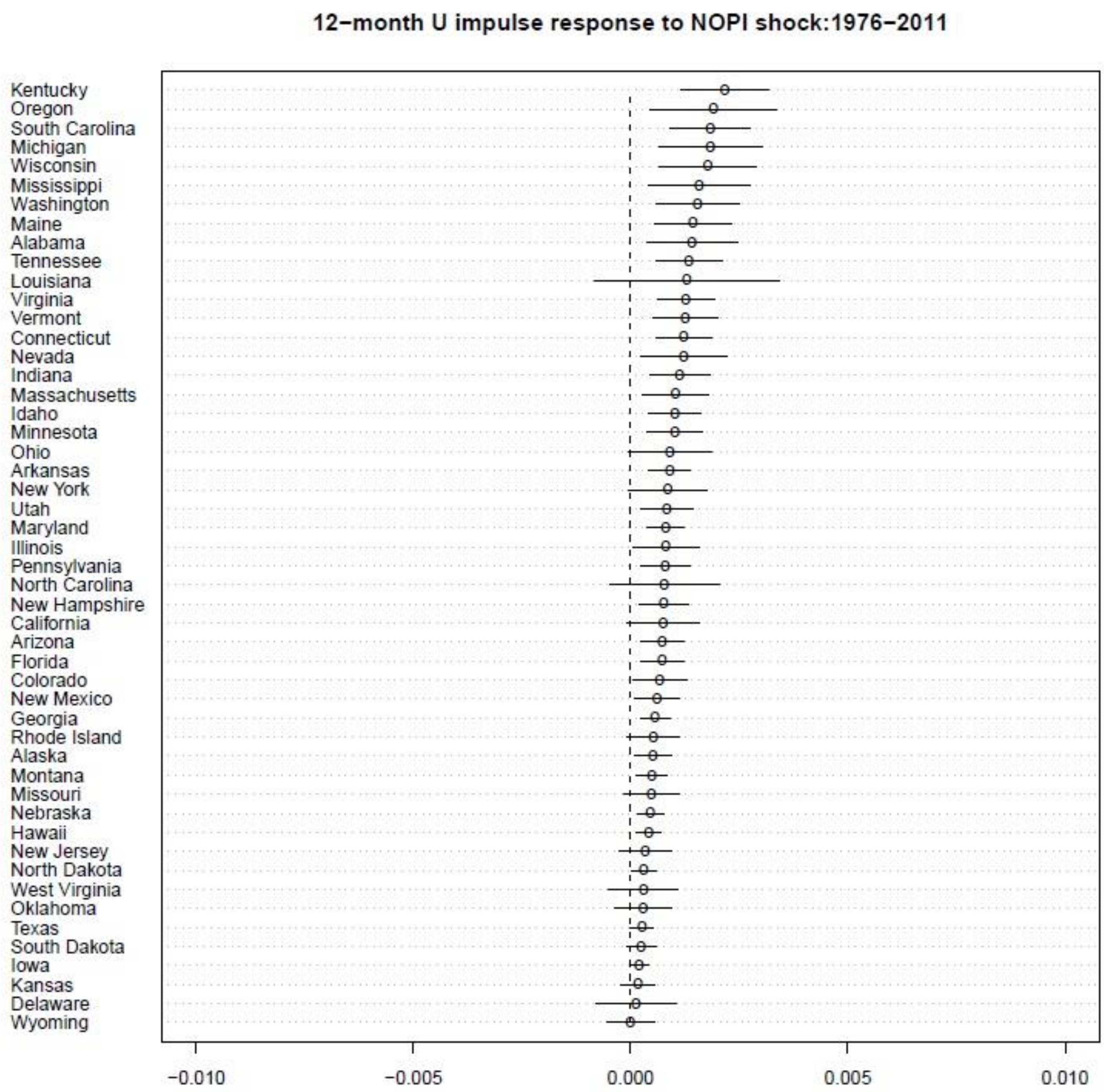


workers employed in the oil and natural gas extraction industry with 3.7 and 4.2, and the second and sixth highest share of GDP attributed to oil and natural gas extraction, respectively. Clearly their positive response in economic activity of 0.269 and 0.186 percent respectively is not unexpected.

The top five tourism states (Nevada, Hawaii, Vermont, Florida and Montana) all have responses that are in the 20 most negative, ranging from -0.23 to roughly -0.30 percent change in economic activity one year after a NOPI shock. These findings suggest that large increases in the price of oil may cause leisure travel to become too expensive for individuals and families and thus states that rely heavily on tourism suffer as a result of the higher oil prices. It is obvious that tourism and manufacturing states experience the largest declines in economic activity following a NOPI shock, but which states are relatively unaffected by these historically large increases to the price of oil? According to Figure 1.1, it appears that many agricultural states such as North Dakota, Iowa, Kansas, California and South Dakota, have very small negative responses in economic activity one year following a NOPI shock. According to the USDA economic research service in 2004, North Dakota, Iowa, Kansas, California and South Dakota ranked 20, 2, 7, 1, and 16 in agricultural output respectively. These results indicate that agricultural may be an industry that is more resilient to oil price shocks. It is widely known that during a recession or economic downturn, consumer spending on non-durable goods is much more stable than spending on durable goods. Therefore, spending on food is unlikely to change much after an oil price shock. In addition, if commodity prices move together, then an increase in oil prices might also coincide with an increase in agricultural commodity prices. As a result, many agricultural states may be partially insulated from the negative effects of an oil price shock. Lastly, the 12-month weighted effect on U.S. economic activity following a NOPI shock is roughly -0.20 percent change. Comparing this to the weighted effect from a typical oil price shock (-0.01 percent change), it is clear why Hamilton argues for the use of the NOPI when analyzing the effects of oil price increases on economic activity.

To see if the unemployment rate produces similar patterns, the one-year impulse response and 95 percent confidence bands to a standard NOPI shock for the state-level unemployment rate (U) between 1976 and 2011 can be seen in Figure 1.2. The values on the x-axis represent the percentage point change in the unemployment rate. For example, a value of 0.005 represents an increase in the unemployment rate of 0.5 percentage points. In general, the main patterns remain: manufacturing states experience the largest increase in unemployment rates while energy and agricultural states experience little to no increase in unemployment rates. The states that are most adversely affected are again top manufactures like Kentucky, Oregon, South Carolina, Michigan, Wisconsin and Mississippi.

Figure 1.2 Unemployment Impulse Response to NOPI Shock 1976-2011



At an aggregate level, the 12-month weighted effect on the U.S. unemployment rate is a 0.09 percentage point change.

From this analysis, it is clear that not all states are impacted in the same way following historically large oil price shocks. In general, states which rely on the oil and natural gas extraction industry experience no change or increases in economic activity following oil price shocks. Tourism states have significant decreases in economic activity, while manufacturing states are the most adversely affected by oil price shocks. These findings are important for the understanding of the transmission mechanism of oil price shocks to the macroeconomy, but a more rigorous approach is needed to verify the results.

Regression Analysis

Although clear patterns seem to emerge with manufacturing and tourism states being adversely affected by NOPI shocks, and energy states benefiting from NOPI shocks, it would be helpful to back up these findings via linear regression. Table 1.2 shows the results from equation (5), using the responses from shocks to the NOPI. The regression results from impulse responses

Table 1.2 Explaining the Economic Activity Response to NOPI Shock

	IRF_6^Y	IRF_{12}^Y
β_0	0.0000 (0.01)	-0.0001 (-2.15)
Tourism	-0.0013 (-1.18)	-0.0005 (-0.70)
Manufacturing	**-0.0013** (-2.72)	-0.0003 (-0.96)
OG	**0.0012** (2.21)	**0.0012** (3.70)
Ag	-0.0000 (-0.03)	0.0002 (0.30)
F-stat	6.52	6.49
p-value	0.00	0.00
Adj. R^2	0.31	0.31
Note: t-statistics are in parenthesis		

at 6 and 12 months following one-standard deviation NOPI shocks are found in columns 2 and 3, respectively, of Table 1.2. The coefficients on the variables represent the percentage change in impulse responses following a one percent increase in each respective industry share of GDP.

At an interval of six months, Manufacturing and Oil and Natural Gas extraction (OG) are statistically significant and both have the sign I expect. After a one-standard deviation shock to the NOPI, a state with a ten percent higher manufacturing industry as a share of GDP experiences a 1.3 percent decrease in economic activity. This finding is consistent with the IRFs in Figure 1.1 that show states like Michigan, South Carolina and Ohio having the largest declines in economic activity following a NOPI shock. Conversely, after a one-standard deviation shock to the NOPI, a state with a ten percent higher oil and natural gas extraction industry as a share of GDP experiences a 1.2 percent increase in economic activity. Since movements in the NOPI only show relatively large increases in the price of oil, the fact that oil and natural gas production is so important is intuitive. Large shocks to the price of oil will spur economic activity in those energy producing states. Based on the law of supply, when oil prices increase, there is an incentive for producers to expand production, which means more economic activity in those energy states. In addition, states are likely to receive higher tax revenue from the expanded oil production, which should have positive effects on the state's economy.

Table 1.3 shows the results from equation (6), using the responses from shocks to the NOPI. The coefficients on the variables in Table 1.3 represent the percentage point change in unemployment rate impulse responses following a one percent increase in each respective industry share of GDP. At an interval of six months, Manufacturing is statistically significant and has the expected sign. Specifically, a ten percent increase in the manufacturing industry as a share of GDP leads to an increase in the unemployment rate of 0.34 percentage points six months following a NOPI shock. At 12 months, Manufacturing is nearly statistically significant at the 5% level and has a similar value of 0.23 percentage points. Based on the findings of Table 1.3, after historically large oil price increases the only variable that statistically affects the change in the unemployment rate is the relative importance of the manufacturing industry. These findings give substance to the IRFs which show that states with a higher dependence on manufacturing have larger increases in unemployment rates following NOPI shocks.

Table 1.3 Explaining the Unemployment Response to NOPI Shock

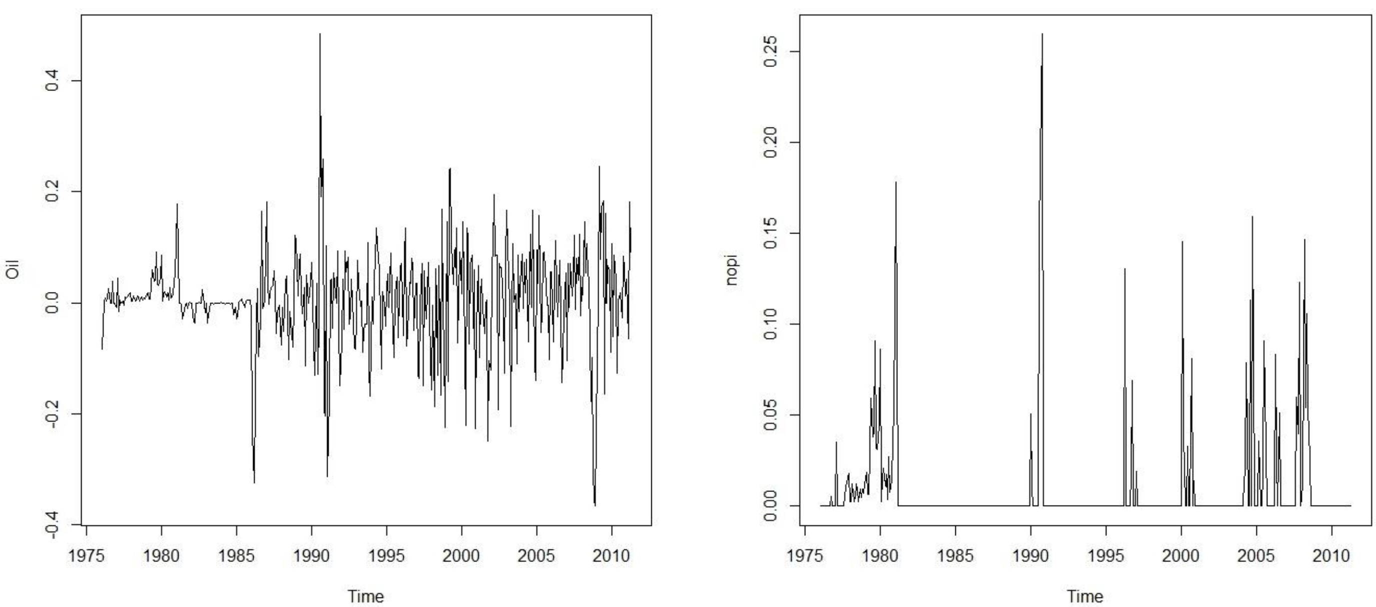
	IRF_6^U	IRF_{12}^U
β_0	0.0000 (0.97)	0.0000 (0.45)
Tourism	0.0005 (1.47)	0.0001 (0.16)
Manufacturing	**0.0003** (2.17)	**0.0002*** (1.75)
OG	-0.0002 (-1.25)	0.0000 (0.15)
Ag	-0.0002 (-0.46)	-0.0002 (-0.69)
F-stat	3.56	1.43
p-value	0.01	0.24
Adj. R^2	0.17	0.03
Note: t-statistics are in parenthesis		* = 10% Significance

Subsample Analysis

The late 1970s to mid-1980s primarily experienced increases in the price of oil, with large increases in 1979 and 1980 due to supply and oil-specific demand shocks, which can be thought of as precautionary demand for oil driven by uncertainty about future oil supply shortfalls (Figure 4: Kilian 2009). Therefore, the period from 1976 to 1985 provides a natural setting to examine the effects of an oil price shock caused by supply disruptions and fears of future oil shortages. The price of oil collapsed in early 1986 and has been quite volatile since, with many large increases and decreases in price. According to Figure 4 of Kilian (2009), much of the recent increase in oil prices since the early 2000s has been caused by increases in global economic activity, so the later period from 1986 to 2011 might provide a natural setting to examine the effects of an oil price shock caused by greater global demand for commodities, which indicate a healthy global marketplace. The percentage change in the price of oil and the NOPI are plotted over time in the left and right panel, respectively, of Figure 1.3.

In addition, the economic reaction to oil price movements between the two periods can be compared to test for asymmetric responses to oil price increases versus decreases, since the early period essentially only experienced increases in the price of oil while the later period was filled with equal amounts of price increases and decreases (see Figure 1.3). Finally, examining the responses to NOPI shocks between the two periods can show if the oil price-macroeconomy relationship has changed, and has less of an impact on economic activity and unemployment today than 20 to 30 years ago (see Figure 1.3). It should be noted that oil price shocks were slightly larger in magnitude during the later period. Therefore, in order to accurately compare results between the periods, the impulse responses for the later period are scaled down by using the same magnitude of shock that occurred in the early period.

Figure 1.3 Change in Oil Price (left panel) and NOPI (right panel) from 1976 to 2011



1976 to 1985

During a period of rising oil prices caused partly by supply disruptions and partly by fears of future oil shortages, how do changes in oil prices impact economic activity? To answer this, one-year impulse responses to a standard oil price shock for the coincident economic activity index (Y) between 1979 and 1985 are calculated. Oil producing states benefited and industrial states were adversely affected from the rise in oil prices in the late 1970s to mid-1980s and overall changes in economic activity were slightly larger than for the full sample period. However, the results are not significantly different from zero. Since most states had greater responses between 1979 and 1985, one would expect the cumulative effect on U.S. economic activity to be larger as well, which is evident with a value of -0.19 percent change. For the state-level unemployment rate (U) between 1976 and 1985, a similar pattern appears with nearly every state experiencing a rise in unemployment one-year after a typical oil price shock, especially manufacturing states. Once again though, the results are insignificant. At an aggregate level, the U.S. unemployment rate experienced a 0.07 percentage point increase one-year after a typical oil price shock.

1986 to 2011

After the collapse of oil prices in early 1986 and moving forward to the present day, what kind of effect do changes in oil prices have on economic activity? Does the volatility of the recent period change the results compared to the early period? Additionally, do the higher oil prices in the 2000s, caused by stronger global economic activity, mitigate the negative effects on the economy? For the coincident economic activity index (Y) between 1986 and 2010, the response to a standard oil price shock is very similar to that of the full sample period, both in magnitude and significance. Specifically, the results show that during the later period energy and agricultural states fared well in response to a typical oil price shock, while tourism and some manufacturing states did not. At an aggregate level, a one-standard deviation oil price shock increases economic activity by 0.02 percent. The one-year impulse response to a standard oil price shock for the state-level unemployment rate (U) between 1986 and 2011 also exhibits similar responses to that of the full sample period. For U.S. unemployment 12-months after a typical oil price shock, the rate decreases by 0.03 percentage points.

NOPI: 1976 to 1985

The one-year impulse response to a standard NOPI shock for the coincident economic activity index (Y) between 1979 and 1985 can be seen in Figure 1.4. The interpretation of Figure 1.4 is similar to that of Figure 1.1, with the percent change in economic activity listed on the x-axis. For example, a value of -0.01 represents a one percent decrease in economic activity. During this time of increasing oil prices, only energy states benefited while industrial hotbeds such as Indiana, Ohio and Michigan were damaged the most. The effects of oil price shocks during the early period were widespread, with 82 percent of states experiencing a decline in economic activity one-year after a NOPI shock. Consequently, the change in U.S. economic activity in response to a NOPI shock is -0.28 percent. It should be noted that some of the confidence bands are not statistically different from zero, but the top and bottom of Figure 1.4 tell a clear story of energy states benefiting and manufacturing states suffering as a result of historically large oil price shocks.

The one-year impulse response to a typical NOPI shock for the state-level unemployment rate (U) between 1976 and 1985 can be seen in Figure 1.5. The interpretation of Figure 1.5 is similar to that of Figure 1.2, with the values on the x-axis representing the percentage point change in the unemployment rate. For example, a value of 0.005 represents an increase in the unemployment rate of 0.5 percentage points. The results in Figure 1.5 are very similar to those above, with nearly every state having an adverse reaction to a NOPI shock except for a handful of states. In fact, 88 percent of states have higher unemployment rates one-year after a NOPI shock. As was the case above, some of the confidence bands are not statistically different from zero, but it is clear how states reacted to higher oil prices during the early period. One year following a typical NOPI shock, unemployment rises by 0.50 percentage points in Michigan and 0.37 percentage points in Wisconsin, with many other industrial states having similar responses. Similar to the regression analysis in Table 1.3, the oil and natural gas extraction and tourism industry are not significant in determining a state's change in unemployment following a typically NOPI shock. For example, Hawaii experiences no change in unemployment while Oklahoma experiences a slight increase. The weighted effect on the aggregate unemployment rate is an increase of 0.11 percentage points.

It seems evident that the historically large oil price increases during the early period had large and wide-spread detrimental effects on state-level economies. Whether this was because the U.S. economy was more reliant on oil in the production process or because this episode of higher oil prices was caused by supply and speculative disruptions cannot be inferred at this point but will be answered in the following sections.

Figure 1.4 Economic Activity Impulse Response to NOPI Shock 1979-1985

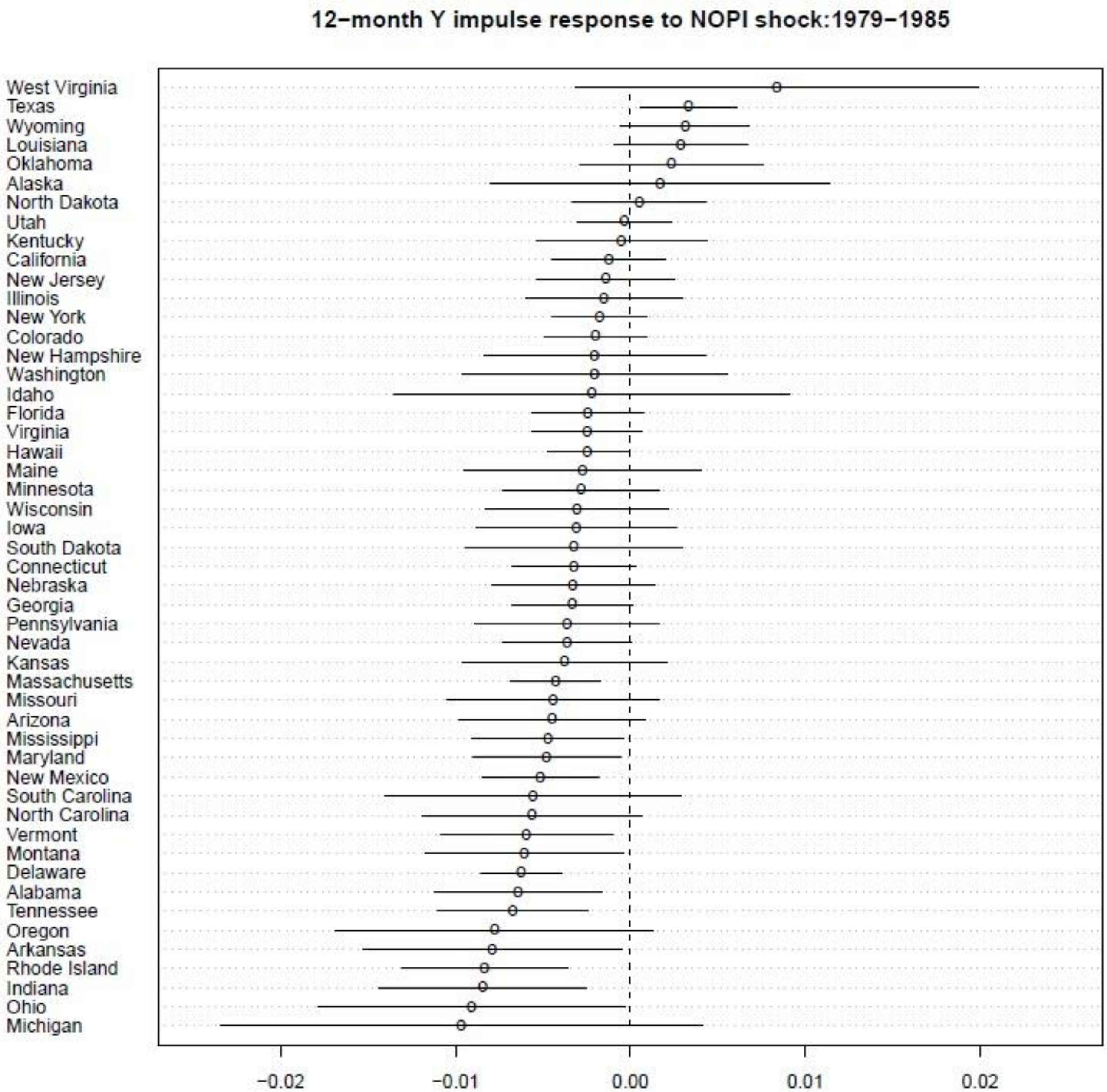
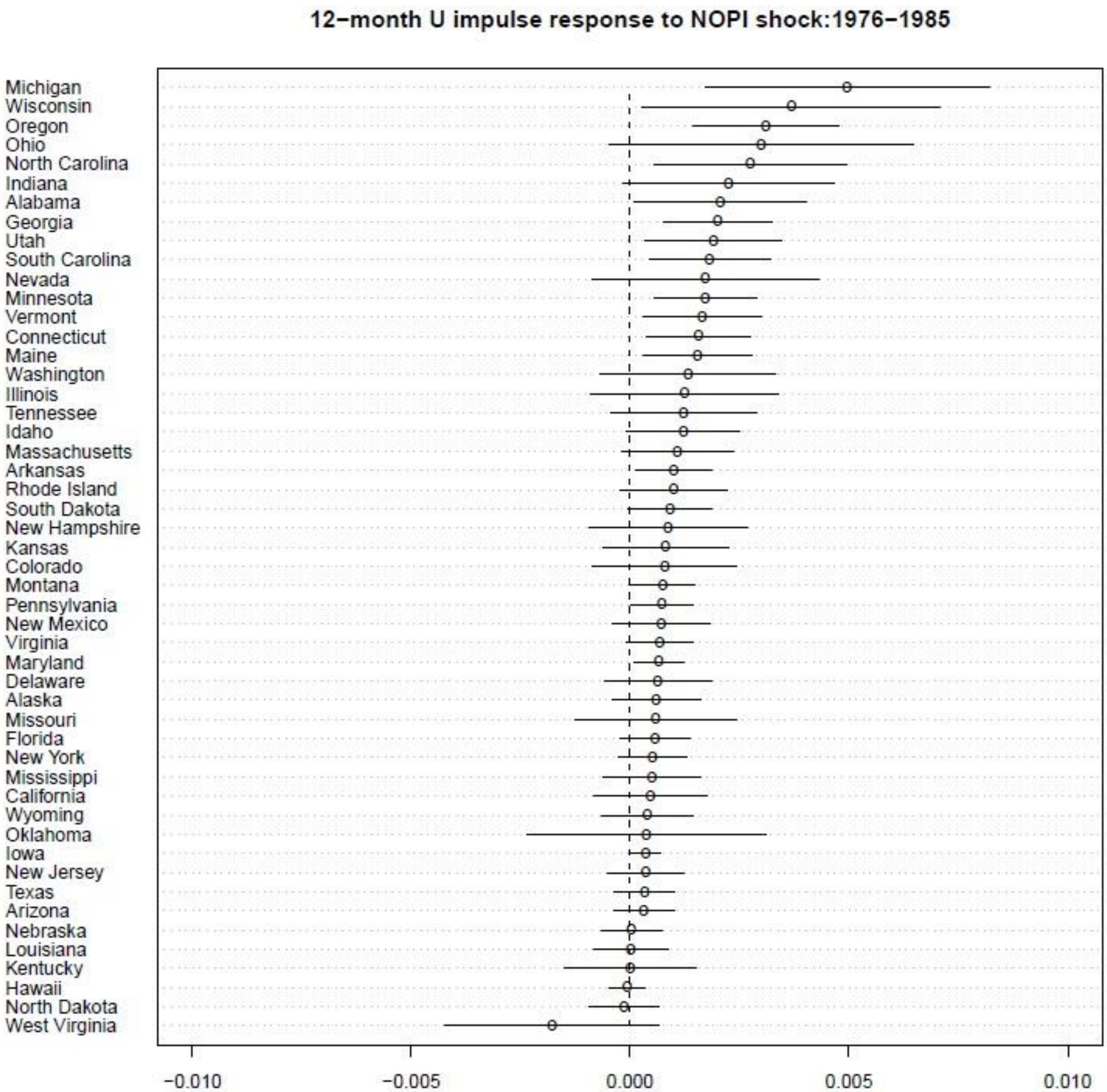


Figure 1.5 Unemployment Impulse Response to NOPI Shock 1976-1985



NOPI: 1986 to 2011

During the later period 1986 to 2010, how did state-level economic activity respond one-year after a typical shock to the NOPI? Figure 1.6, which can be interpreted in the same fashion as Figure 1.4, clearly shows that every state except Wyoming, Alaska and Texas experienced a decline in economic activity, while Ohio, Oregon, Maine, South Carolina and Michigan had the largest declines in economic activity. However, the magnitude of change is relatively small compared to the early period (Figure 1.4). What explains the smaller response during the later period? Evidence from Kilian (2009) suggests that the some of the oil price shocks in the later period were caused by a growing global economy, which would have some positive effects for the U.S. economy. Alternatively, it is possible that during the later period changes in economic activity were smaller because of a changing U.S. economy, which has shifted away from manufacturing and towards the service sector. The weighted effect of a one-standard deviation NOPI shock on U.S. economic activity during the later period is a decrease of 0.18 percent.

The one-year impulse response to a typical NOPI shock for the state-level unemployment rate (U) between 1986 and 2011 can be seen in Figure 1.7, which can be interpreted in the same fashion as Figure 1.5. Although many of the responses are not large in magnitude, nearly all of them show a rising unemployment rate, especially manufacturing states like Mississippi and Michigan. However, at the aggregate level, it is apparent that even historically large oil price increases from 1986 to 2011 do not have a significant impact on unemployment, with only a 0.08 percentage point increase. It is interesting to note that the handful of states in which unemployment rates are unchanged, are mostly agricultural or energy dependent; these two industries are the key to escaping the detrimental effects of relatively large increases to the price of oil.

Comparing the Early and Later Periods

When using the NOPI to examine the effects of oil price shocks, the transmission mechanism between the early and later periods are similar. Specifically, the states that had economic activity decline the most or unemployment rates rise the most were generally industrial, and the states that were unaffected or benefited generally depend on energy or agriculture more than the average state. One glaring difference between the two periods is the magnitude of response, with the early period exhibiting much larger responses in economic activity and unemployment rates. This implies that either the oil price-macroeconomy relationship is gradually becoming less important because of changing industries and technology, or that the early period suffered from oil price increases caused by supply and speculative disruptions, while the later period's oil price increase can be partly attributed to growing global aggregate demand.

Figure 1.6 Economic Activity Impulse Response to NOPI Shock 1986-2010

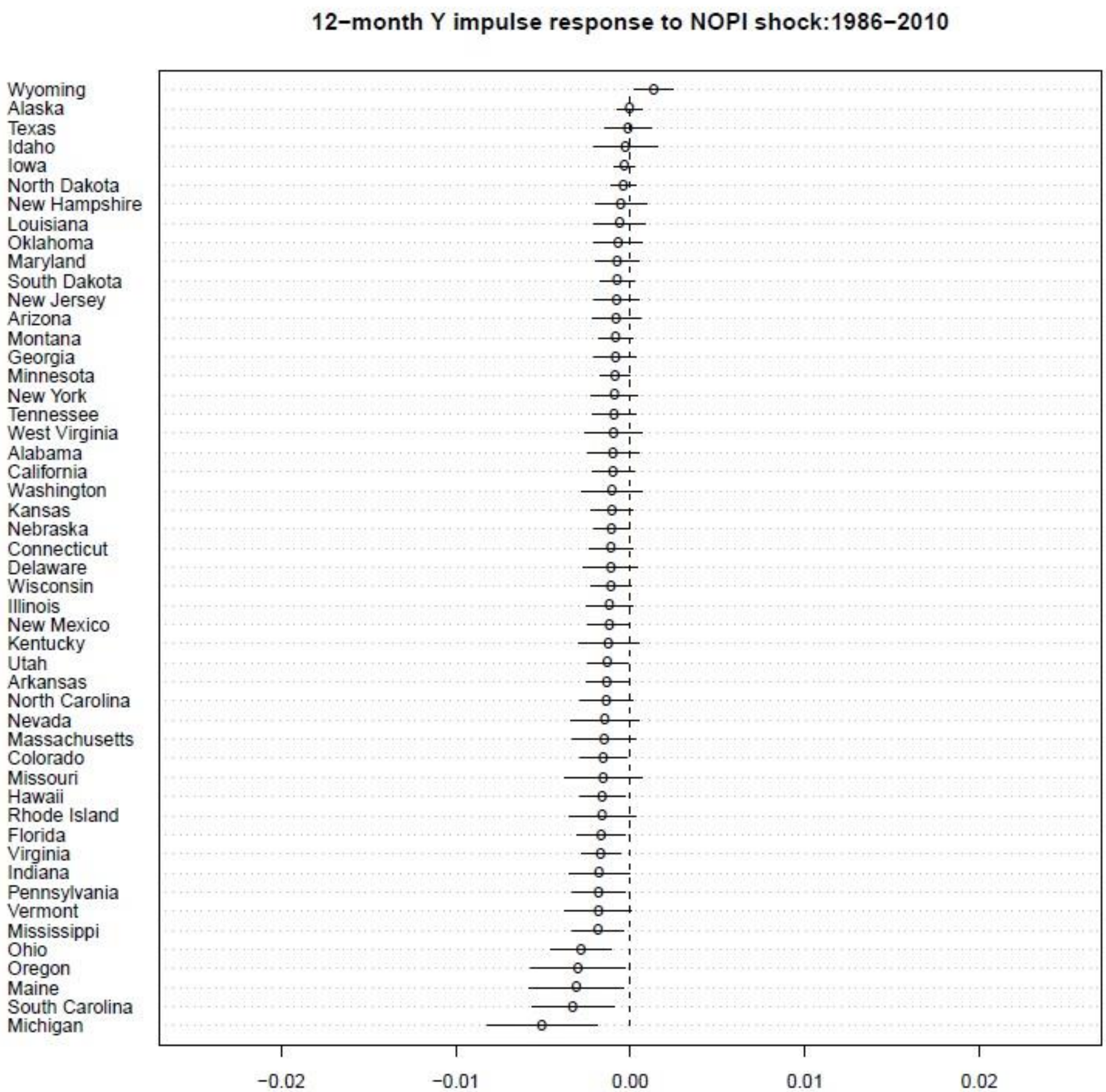
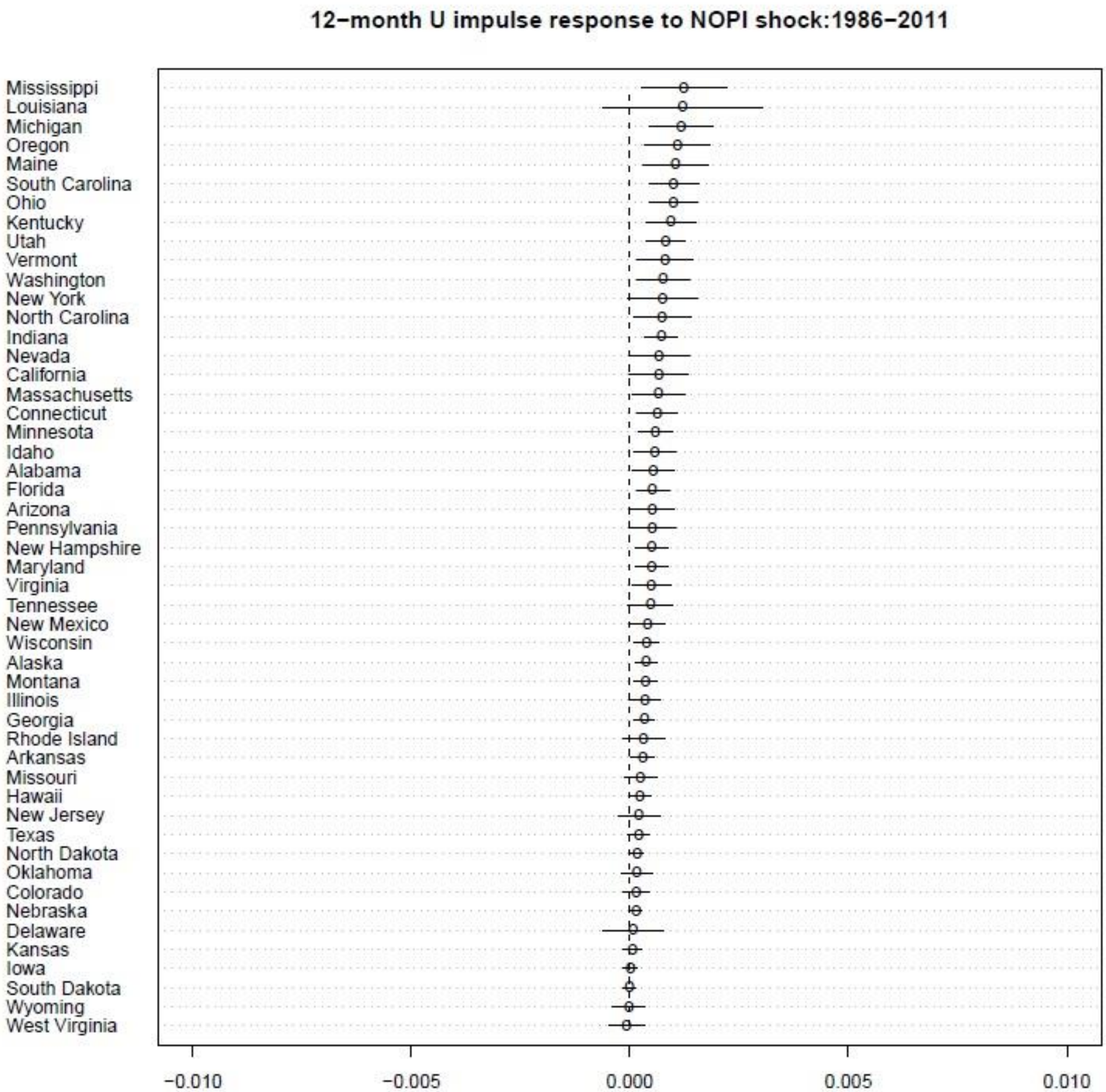


Figure 1.7 Unemployment Impulse Response to NOPI Shock 1986-2011



Explaining Smaller Economic Responses to Oil Price Shocks

There has been an overall decline in the relative importance of manufacturing in the U.S., both in employment and GDP shares, starting in the 1950s and accelerating in the 1970s. According to the Bureau of Economic Analysis, the manufacturing industry as a share of total U.S. GDP has gone from 22.7 percent in 1970 to 11.7 percent in 2010.[1] According to Davis and Haltiwanger (2001), Lee and Ni (2002), Kilian (2007), Edelstein and Kilian (2009), and Hamilton (2009), the durable goods industry, especially the automotive industry, is the most susceptible to the negative effects of oil price shocks. Consequently, the decline in manufacturing from the early to the later period should help explain why states are not as severely affected by oil price shocks as they once were. Another dramatic change during last 40 years has been the increase in energy efficiency, whether in production or consumption. However, the real question is how much is being spent on energy as a share of GDP, not necessarily how much energy is being consumed. Therefore, the importance of energy expenditures for each state, referred to as Energy Intensity (EI), is calculated as total energy expenditures as a percentage of state-level GDP between 1976 and 2010. State-level energy expenditures are available from the Energy Information Administration.[2]

The analysis between the early (1976-1985) and later (1986-2011) periods show that there has been a decline in the magnitude of response to a NOPI shock, both for the coincident economic activity index (Y) and the unemployment rate (U). To understand why the oil price-macroeconomy relationship has weakened, one can analyze how various industry shares of GDP and Energy Intensity (EI) have changed over the same period. Specifically, the following equation is estimated for the economic activity index (Y) and the unemployment rate (U):

$$\Delta IRF_i = \beta_0 + \beta_1 \Delta EI_i + \beta_2 \Delta Manuf_i + \beta_3 \Delta Tourism_i + \beta_4 \Delta OG_i + \beta_5 \Delta Ag_i + \varepsilon_i \quad (7)$$

where ΔIRF_i is the change in the cumulative 12-month impulse response to a NOPI shock for state i between 1976-1985 and 1986-2011, ΔEI_i is the change in energy intensity for state i between the two periods, $\Delta Manuf_i$ is the change in the percentage of GDP in the manufacturing industry for state i between the two periods, $\Delta Tourism_i$ is the change in the percentage of GDP in the tourism industry for state i between the two periods, ΔOG_i is the change in the percentage

[1] http://www.bea.gov/industry/gdpbyind_data.htm

[2] http://www.eia.gov/state/seds/seds-data-complete.cfm#full2

of GDP in the oil and natural gas extraction industry for state i between the two periods, and ΔAg_i is the change in the percentage of GDP in the agricultural industry for state i between the two periods.

Table 1.4 Explaining the Change in Response to NOPI Shocks for Economic Activity

	(1)	(2)	(3)	(4)	(5)	(6)
β_0	0.0011 (0.85)	-0.0009 (-1.61)	-0.0019 (-4.33)	-0.0025 (-5.64)	-0.0015 (-2.45)	0.0003 (0.13)
ΔEI	**-0.0652** (-2.49)					-0.0251 (-0.71)
$\Delta Manuf$		**-0.0228** (-2.45)				-0.0172 (-1.15)
$\Delta Tourism$			-0.0176 (-0.32)			-0.0022 (-0.04)
ΔOG				**0.0255** (3.13)		0.0080 (0.51)
ΔAg					-0.0339 (0.95)	-0.0438 (-1.03)
Adj. R^2	0.10	0.09	-0.02	0.15	0.00	0.12

First, how is the change in response to NOPI shocks for the economic activity index (Y) affected by changes in other variables? Table 1.4 contains the results from the estimation of equation (7), with column 6 containing all independent variables and columns 1-5 containing only one independent variable. The coefficients represent the percent change in the IRF due to a typical NOPI shock between the early and later period for a state with a one percent decline in the respective industry share of GDP. Examining the results in Table 1.4, it is evident that decreased energy expenditures as a share of state-level GDP has led to smaller economic responses to NOPI shocks in the later period, with a coefficient of -0.0652 for ΔEI. To give context to this coefficient, consider that the state with the largest decline in energy intensity experienced a 0.45 percent smaller decline in economic activity in response to a NOPI shock during the later period, while the state with the largest growth in energy intensity experienced a 0.21 percent larger decline in economic activity. In column (2), the decline in the manufacturing sector across the U.S. has played a role in the smaller economic response to oil price shocks between the early and later periods. The coefficient on $\Delta Manuf$ is -0.0228, indicating that states in which the manufacturing industry as a share of GDP declined between the two periods, experienced less of a decrease in economic activity one-year following a typical NOPI shock in the later period. The state with the largest decline in manufacturing experienced a 0.41 percent smaller decline in economic activity in response to a NOPI shock during the later period, while the state with the largest growth in manufacturing experienced a 0.12 percent larger decline in economic activity. Lastly, a general decline in the oil and natural gas extraction industry across the U.S. can help explain smaller economic responses to NOPI during the later period. Specifically, the coefficient on ΔOG is 0.0255, meaning that states which experienced a decline in the oil and natural gas extraction industry as a share of GDP between the two periods, experienced more of a decrease in economic activity one-year following a typical NOPI shock. Another way to explain this is that energy states experienced less of an increase in economic activity following oil price shocks. The state with the largest decline in oil and natural gas extraction experienced a 0.47 percent larger decline in economic activity in response to a NOPI shock during the later period.

Next, how is the change in response to NOPI shocks for the unemployment rate (U) affected by changes in other variables? The results of equation (7), with changes in the unemployment rate IRF between the periods as the dependent variable, are reported in Table 1.5, and can be interpreted in a similar fashion as Table 1.4. The results of Table 1.5 reveal the declining manufacturing and oil and natural gas extraction industry explain the smaller responses to oil shocks during the later period. However, Energy Intensity (EI) is insignificant in explaining the changing relationship. First, the coefficient on $\Delta Manuf$ is now positive with a value of 0.0063, but this is expected since Table 1.5 is dealing with changes in the unemployment rate. Again, to give some economic meaning to the results, the state with the largest decline in manufacturing as a share of GDP experienced a 0.11 percentage point smaller rise in unemployment in response to a NOPI shock during the later period, while the state with the highest growth in manufacturing experienced a 0.03 percentage point larger increase in unemployment. Second, the coefficient on ΔOG is -0.0075, which indicates that states with a declining oil and natural gas extraction industry experienced more of an increase in the unemployment rate in the later period. Specifically, the state with the most significant decline in

Table 1.5 Explaining the Change in Response to NOPI Shocks for Unemployment

	(1)	(2)	(3)	(4)	(5)	(6)
β_0	0.0001 (0.18)	0.0003 (1.56)	0.0006 (4.36)	0.0007 (4.95)	0.0006 (2.88)	0.0003 (0.43)
ΔEI	0.0127 (1.37)					-0.0028 (0.24)
$\Delta Manuf$		**0.0063** (2.15)				0.0070 (1.39)
$\Delta Tourism$			0.0186 (1.13)			0.0206 (1.18)
ΔOG				**-0.0075** (2.21)		-0.0020 (-0.34)
ΔAg					0.0011 (0.11)	0.0110 (0.86)
Adj. R^2	0.02	0.07	0.01	0.07	-0.02	0.05

oil and natural gas extraction experienced a 0.12 percentage point larger rise in unemployment in response to a NOPI shock during the later period.

The oil price-macroeconomy relationship has weakened during the last 40 years, which can be explained by the changing composition of the U.S. economy, namely the declining manufacturing and energy industry that has led to the U.S. economy being more resistant to oil price fluctuations. Interestingly, the United States is currently going through an energy boom in oil and natural gas extraction, which means future oil price shocks could lead to larger increases in economic activity for these energy states. Similarly, many manufacturing jobs are being brought back to the U.S. as cost advantages vanish in other countries and firms have access to cheap U.S. energy. Therefore, if there is a significant increase in the manufacturing industry as a share of GDP, the U.S. may experience magnitudes of response to large oil price shocks similar to the late 1970s and early 1980s. However, increased energy efficiency helps explain smaller responses to historically large oil price shocks during the later period when examining the economic activity index, so this may limit future responses to ever being as large as they were during the early period.

The Effects of Global Aggregate Demand Oil Shocks from 2002-2007

According to Kilian (2009), the rise in oil prices from 2002 to 2007 can be almost entirely explained by an increase in global economic activity, which is why he argued that there was no recession or economic downturn from 2002 to 2007. In addition, if high oil prices from 2002 to 2007 were caused by a strong global economy, then this might help explain the smaller economic responses that states experienced in the later period. To see if Kilian's theory holds true, the response in the coincident economic activity index and the unemployment rate are analyzed following oil price shocks from January 2002 to December 2007, particularly focusing on the leading exporting states (see Table 1.6).

Specifically, the following regressions are run to isolate the effects of NOPI shocks on economic activity and unemployment from January 2002 to December 2007:

$$Y_{i,t} = \alpha + \beta_1 NOPI_{t-1} + \cdots + \beta_{12} NOPI_{t-12} + \beta_{13} 2002 + \varepsilon_{i,t} \quad (8)$$

$$U_{i,t} = \alpha + \beta_1 NOPI_{t-1} + \cdots + \beta_{12} NOPI_{t-12} + \beta_{13} 2002 + \varepsilon_{i,t} \quad (9)$$

where $Y_{i,t}$ denotes the percentage change in the Coincident Economic Activity Index for state i at time t, $U_{i,t}$ denotes the percentage point change in the unemployment rate for state i at time t, $NOPI_{t-j}$ denotes the NOPI shocks at time t lagged $j = 1, \ldots, 12$ months, and 2002 is a dummy variable with values of 1 from January 2002 to December 2007 and zero otherwise. The NOPI coefficients from equations (8) and (9) are summed to obtain the one-year effect on economic activity and unemployment, respectively, following a one-standard deviation NOPI shock for the full sample period. The coefficient from the 2002 dummy is then added to reveal the effects of a NOPI shock during the 2002 to 2007 period.

For the economic activity index, there is little evidence of smaller responses to NOPI shocks from 2002 to 2007. Specifically, the average response across all 50 states for the full sample period and the 2002 - 2007 period is -0.2922 and -0.2919 percent change, respectively. The average response for the top ten exporting states for the full sample period and the 2002 - 2007 period is -0.3257 and -0.3260 percent change, respectively. During a period of rising oil prices caused by a growing global economy, the top exporting states actually experienced a larger decrease in economic activity. Compare this to the bottom ten exporting states, which experienced an average change for the full sample period and the 2002 - 2007 period of -0.1923 and -0.1898 percent, respectively. Unexpectedly, for the states which do not rely on the sale of goods and services to the global market, aggregate demand oil price shocks produced less negative economic responses.

Table 1.6 Top Ten Exporting States as a Percentage of GDP

State	Exports/GDP
Vermont	16.6%
Washington	14.7%
Texas	13.8%
Louisiana	13.7%
Michigan	10.2%
Kentucky	10.2%
South Carolina	9.5%
Oregon	9.3%
Alaska	8.9%
Indiana	8.5%

For the unemployment rate, there is also limited evidence of smaller responses to NOPI shocks from 2002 to 2007, both for exporting and non-exporting states. The average response across all 50 states for the full sample period and the 2002 - 2007 period is 0.1024 and 0.1017 percentage points, respectively. The average response for the top exporting states declined from 0.1285 to 0.1276 percentage points, and the average response for the bottom exporting states declined from 0.0793 to 0.0785 percentage points.

The magnitude of difference between the full sample period and the 2002-2007 period is very small and does not provide compelling evidence to explain the decline in the oil price-macroeconomy relationship post 1985. Therefore, to be certain that I am measuring true aggregate demand oil price shocks caused by a growing global economy, Kilian's (2009) endogenous aggregate demand oil shocks are constructed by using his methods discussed in Section II, pages 1058-1060. The index of real economic activity is available on Kilian's webpage[3], and global crude oil production is available from the U.S. Energy Information

[3] http://www-personal.umich.edu/~lkilian/reaupdate.txt

Administration. To be consistent with the rest of this chapter, the Producer Price Index for Petroleum is used as the measure of oil prices.

The following regression is run to isolate the effects of aggregate demand oil shocks on economic activity and unemployment from January 2002 to December 2007:

$$Y_{i,t} = \alpha + \beta_1 AD_{t-1} + \cdots + \beta_{12} AD_{t-12} + \beta_{13} 2002 + \varepsilon_{i,t} \quad (10)$$

$$U_{i,t} = \alpha + \beta_1 AD_{t-1} + \cdots + \beta_{12} AD_{t-12} + \beta_{13} 2002 + \varepsilon_{i,t} \quad (11)$$

where $Y_{i,t}$ denotes the percentage change in the Coincident Economic Activity Index for state i at time t, $U_{i,t}$ denotes the percentage point change in the unemployment rate for state i at time t, AD_{t-j} denotes the aggregate demand oil shocks at time t lagged $j = 1, \ldots, 12$ months, and 2002 is a dummy variable with values of 1 from January 2002 to December 2007 and zero otherwise. The results of equations (10) and (11) can be interpreted in the same fashion as equations (8) and (9), except the changes in economic activity and unemployment are in responses to a one-standard deviation aggregate demand oil price shock.

One year following an aggregate demand oil price shock, the average response across all 50 states for the full sample period and 2002 - 2007 period is 0.045 and -0.0812 percent change, respectively. These results are the opposite of what one would expect if the 2002 - 2007 period was a time of high oil prices caused by strong global economic growth. Furthermore, the top exporting states experienced an average response during the full period and 2002 - 2007 period of 0.0758 and -0.229 percent change, respectively. However, the bottom exporting states benefited from aggregate demand oil price shocks from 2002 - 2007. Specifically, the bottom ten exporting states experienced an average response during the full period and 2002 - 2007 period of 0.113 and 0.2895 percent change, respectively.

For the unemployment rate, there is some evidence of more beneficial responses to a typical aggregate demand oil price shock from 2002 to 2007, both for exporting and non-exporting states. The average response across all 50 states for the full sample period and the 2002 - 2007 period is -0.0112 and -0.0704 percentage points, respectively. In addition, the top ten exporting states experienced an average response during the full period and 2002 - 2007 period of -0.019 and -0.076 percentage points, respectively. Similarly, the bottom ten exporting states experienced an average response during the full period and 2002 - 2007 period of -0.016 and -0.10 percentage points, respectively. These results suggest that aggregate demand oil price shocks from 2002 - 2007 led to more beneficial outcomes for the average state, but it was the non-exporting states that benefited the most.

Overall, there is very limited evidence of global aggregate demand oil price shocks leading to beneficial outcomes, especially for the top exporting states. The results are stronger for the unemployment rate, both for NOPI and aggregate demand oil price shocks. Certainly, there is not compelling enough evidence that global aggregate demand oil price fluctuations from 2002 - 2007 can help explain smaller economic responses during the later period 1986 - 2011. Rather it was the declining manufacturing and oil and natural gas extraction industry, as well as an increase in energy efficiency, which led to smaller economic responses to oil price shocks during the later period.

Asymmetric Responses

When one compares the results of regular oil price shocks, which include both increases and decreases in price, with NOPI shocks, there is some evidence of asymmetric responses. However, the NOPI is a censored measure of oil price shocks, so a better way to test for the presence of asymmetry is to construct a net oil price decrease (NOPD) index. If the economy responds similarly to large decreases in the price of oil as it does to large increases, then the NOPD and NOPI should produce mirror results. The NOPD was constructed with the same techniques used for the NOPI, except I looked for the largest decreases in the price of oil. The three year NOPD can be represented as:

$$Oil_t^{36} = max\{0, min\{Oil_{t-1}, \ldots, Oil_{t-36}\} - Oil_t\}$$

Since there were hardly any major decreases in the price of oil prior to 1986, the asymmetric analysis is only carried out for the later period, 1986 to 2011.

Economic Activity Index

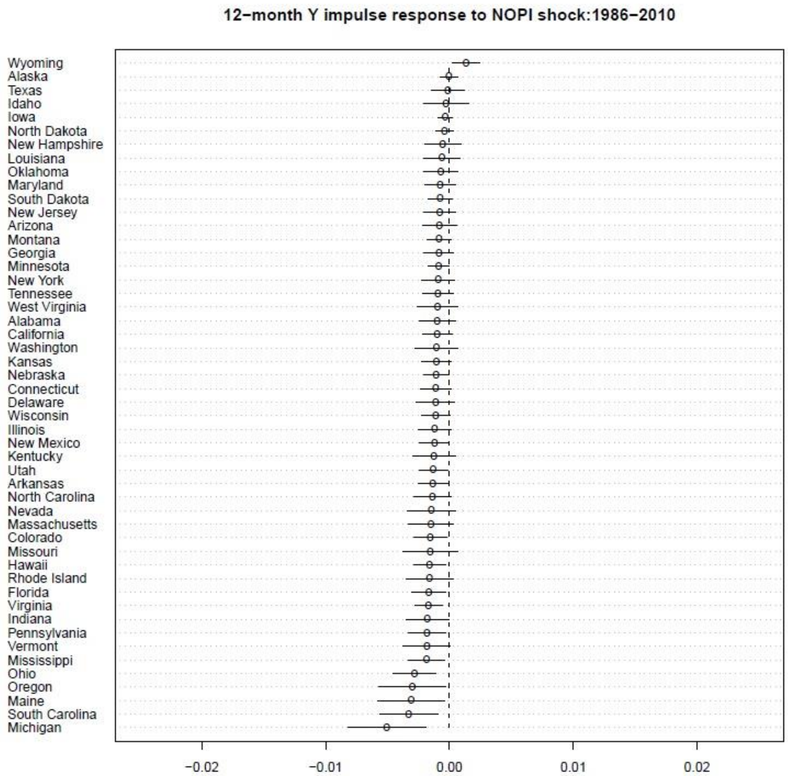
Comparing the one-year impulse response in the economic activity index (Y) for the NOPI and the NOPD between 1986 and 2010 reveals that there is strong evidence of asymmetric responses, seen in Figure 1.8. The top panel shows impulse responses to NOPI shocks and the bottom panel shows impulse responses to NOPD shocks. In response to a NOPI shock, nearly all of the states have a negative response, and if there is evidence of symmetry, then nearly all of the states should have a positive response to a NOPD shock. However, the bottom panel clearly shows otherwise, with about half of the states experiencing an increase and about half experiencing a decrease in economic activity. In addition to a different pattern of response, the magnitude of change is different as well. For example, Michigan's economic activity decreased by 0.51 percent in response to a typical NOPI shock, but increased by only 0.02 percent in response to a typical NOPD shock. Additionally, an energy state like Wyoming experienced an increase in economic activity of roughly 0.13 percent in response to a typical NOPI shock, but experienced a decrease in economic activity of roughly 0.44 percent in response to a typical NOPD shock.

Unemployment

Do changes in the unemployment rate show evidence of asymmetry? Examining the one-year impulse response in the state-level unemployment rate (U) for NOPI and NOPD shocks between 1986 and 2011, reveals that consumers and businesses respond differently to oil price increases and decreases. The top panel of Figure 1.9 shows impulse responses to NOPI shocks and the bottom panel shows impulse responses to NOPD shocks. It is obvious that nearly every state experienced higher unemployment rates in response to a NOPI shock, whereas not every state experienced lower unemployment rates in response to a NOPD shock. Furthermore, the magnitude of change is much smaller for the NOPD shock, with many states having no substantial increase or decrease in the unemployment rate.

After investigating both economic activity and unemployment rates, economic analysis involving energy prices and macro variables should not assume symmetric responses to price changes. Although energy price decreases may provide a boost in some regions of the country, these changes are not comparable to the negative effects felt by a vast majority of states following energy price increases. Future research should be clear on the meaning of price shock, as the response to increases and decreases are not the same.

Figure 1.8 Comparing NOPI and NOPD Responses for Economic Activity



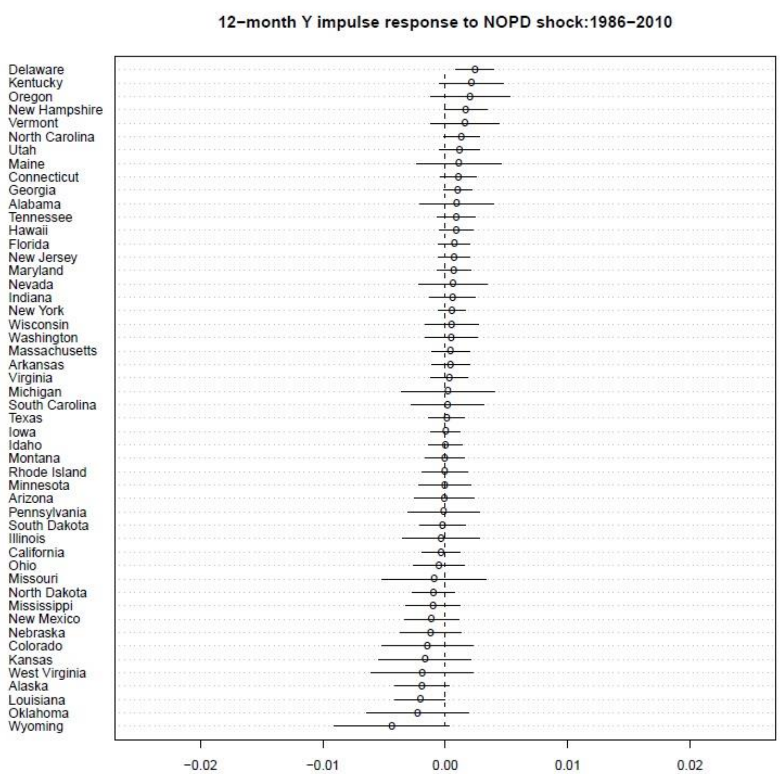
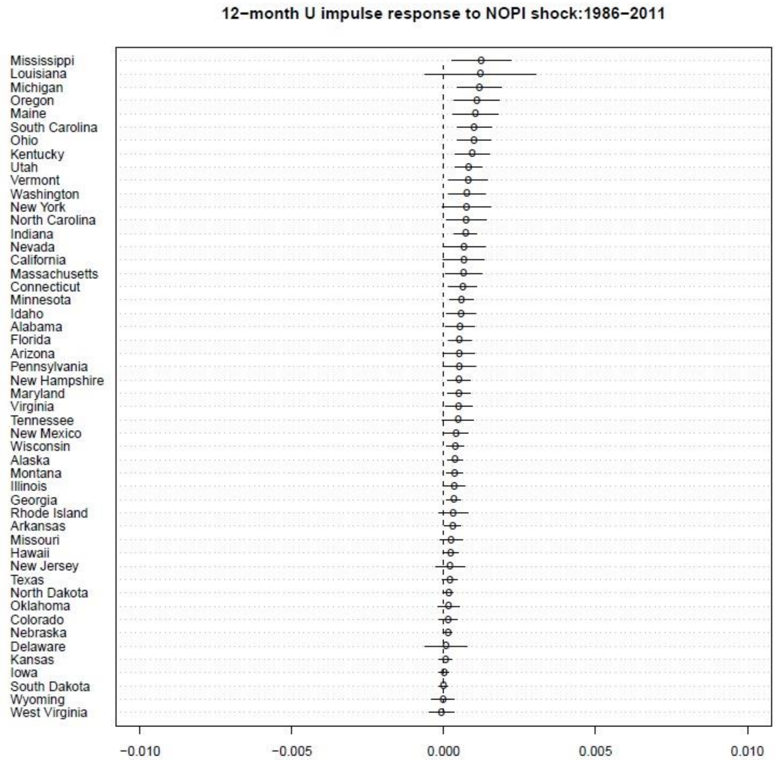
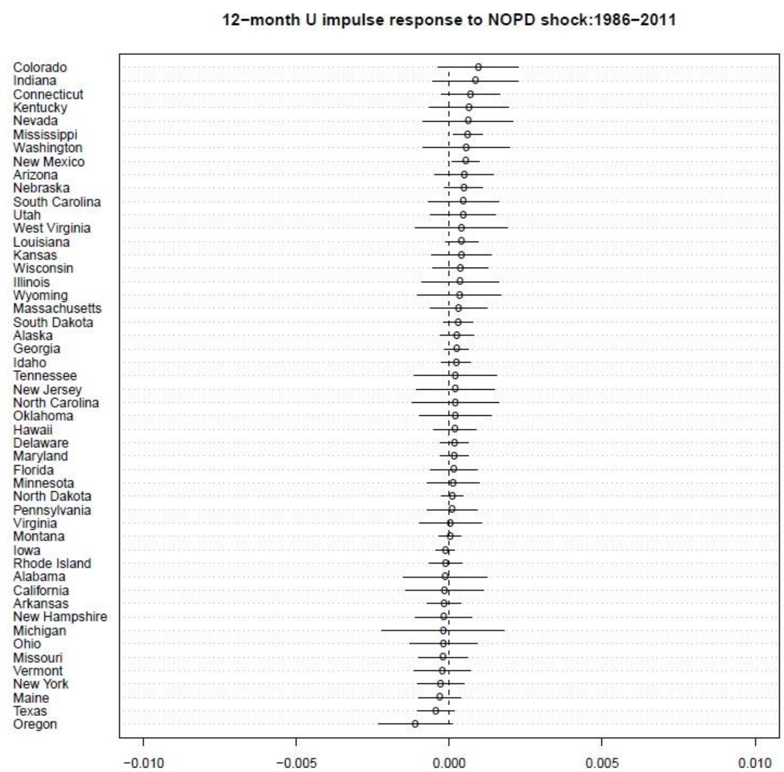


Figure 1.9 Comparing NOPI and NOPD Responses for Unemployment





Conclusion

Studying the oil price-macroeconomy relationship at the U.S. state-level allows for better understanding of how and why oil price shocks affect the economy. Specifically, I find detrimental effects for manufacturing states following a NOPI shock, while energy producing states benefit or are unaffected. As a robustness check, impulse responses are regressed on various state-level industry statistics, and the results indicate that higher industry shares of manufacturing and oil and natural gas extraction significantly affect the responses.

When the analysis is split into an early (1976-1985) and a later (1986-2011) period using the NOPI, the magnitude of change is much smaller in the later period when compared to the early period. Two possible explanations for these smaller responses are America's increased energy efficiency and the declining manufacturing industry. Regression analysis reveals that the state with the largest decline in the manufacturing industry between the early and later period had a 0.30 percent smaller decrease in economic activity and a 0.17 percentage point smaller increase in the unemployment rate as a result of a NOPI shock, while the state with the largest decline in energy intensity between the early and later period experienced a 0.45 percent smaller decrease in economic activity as a result of a NOPI shock. I find very limited evidence that global aggregate demand oil price fluctuations from 2002 - 2007 can help explain smaller economic responses during the later period 1986 - 2011. The reason the change in economic activity is smaller in response to oil price shocks between the two periods is not because of different types of oil prices shocks, but because of a fundamental shift in the U.S. economy.

I find evidence supporting asymmetric responses, both for economic activity and the unemployment rate, by comparing impulse responses to NOPI and NOPD shocks. In most cases, the pattern of response and the magnitude of change are quite different. Therefore, future studies analyzing the effects of oil price shocks, both positive and negative, should construct separate NOPI and NOPD series to truly understand how the economy responds.

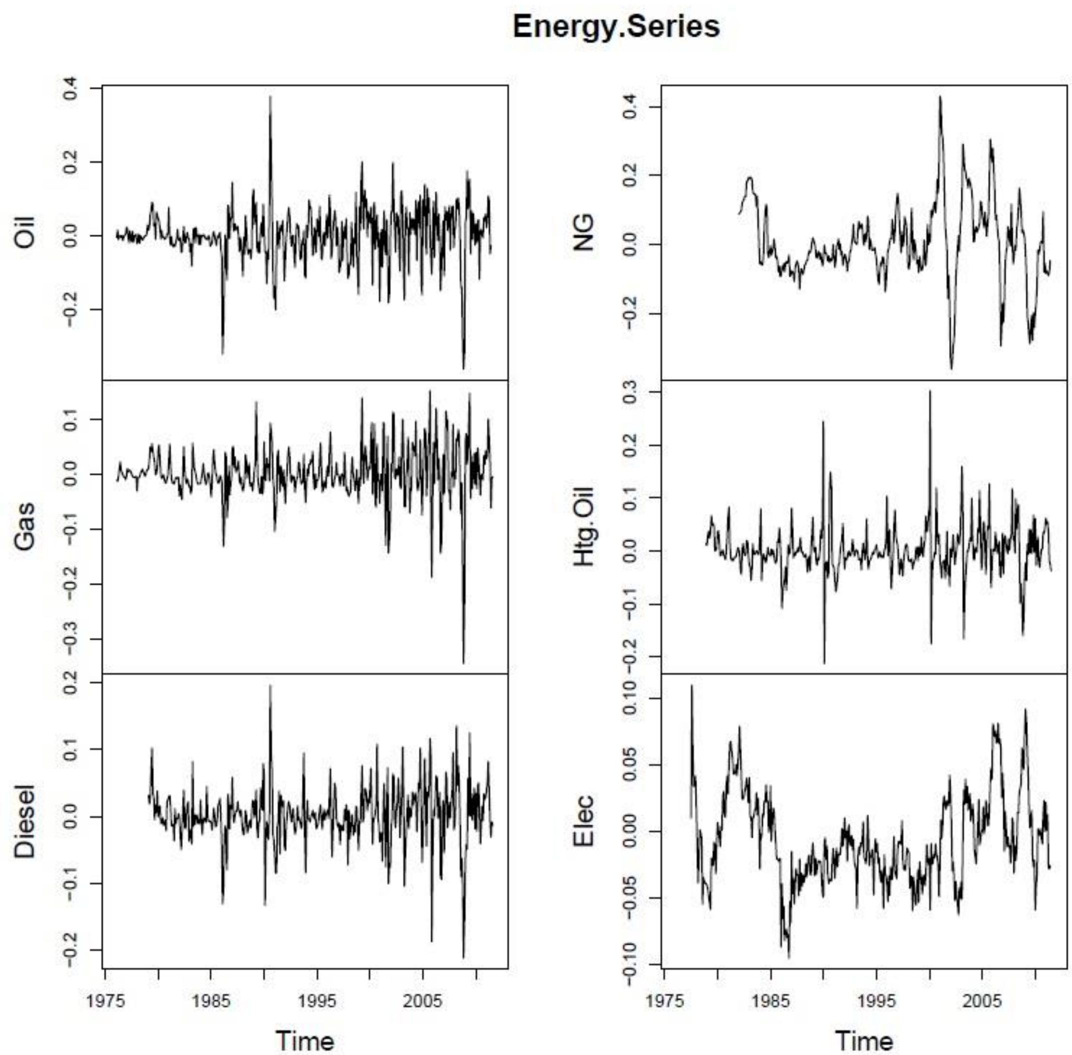
Chapter 2 - Energy Price Shocks and Economic Activity: Which Energy Price Series Should We Be Using?

Introduction

A considerable amount of literature has been devoted to understanding the effects of energy price shocks on economic activity. Energy price shocks are typically modeled as shocks to the price of oil and the effects of the shocks are frequently examined at the aggregate level. However, the United States is a very diverse country with very diverse economies in each state. For example, Nebraska's economy is much more dependent on agriculture than Massachusetts, which means each state might respond to various energy price shocks in its own way. In addition, energy price shocks other than oil may have varying effects on production or consumption decisions. Electricity and diesel price shocks may affect firms' production costs, but a shock to the price of gasoline is more likely to impact consumers on the demand side. Furthermore, weather differs significantly across the country, so it is possible that heating oil price shocks more directly impact states in the northeast than they do states in the southwest. In examining carbon emissions and urban development, Glaeser and Kahn (2010) find a negative correlation between the average January temperature and natural gas and heating oil consumption, and a positive correlation between average July temperature and electricity consumption. Therefore, conducting a study at the U.S. state-level that captures the effects of alternative energy price shocks on economic activity provides insight on how these price shocks affect the economy. Exploiting the considerable cross-sectional variation in state-level data allows us to better understand the transmission of energy price shocks to the macroeconomy. In this chapter, I estimate the magnitude and determine the sign of economic response to various forms of energy price shocks in each state, as well as how they differ by industry, climate, and other factors.

If alternative energy price shocks impact states differently, we should expect models with multiple energy prices to forecast economic activity better than models with only oil prices. This has implications for state-level forecasters who want to know how tax revenue, GDP, or unemployment will be affected by energy price shocks. Although many forms of energy such as gasoline and heating oil are derived from oil, and thus their prices are correlated, there are still large movements in alternative energy price series that are independent of movements in the oil market. For example, Kilian (2007) notes that Hurricanes Rita and Katrina in 2005 resulted in higher gasoline prices because of damaged refineries, but not higher oil prices. This suggests that from a consumer's point of view, gasoline prices may be more relevant than oil prices. Figure 2.1 plots the percentage change in the monthly energy price series of oil, gasoline, diesel, natural gas, heating oil and electricity.

Figure 2.1 Percentage Change in Energy Series



Although the gasoline and diesel series are similar to oil, it is clear some movements are independent of others. For example, the price of oil increased nearly 40 percent during the Gulf War, but gasoline prices only increased by about 10 percent. In addition, the natural gas and electricity series are very different than the oil-based series. In fact, Bachmeier and Griffin (2006) find that crude oil, coal and natural gas markets are only very weakly integrated, indicating that there is not one primary energy market.

Energy and movements in its price can affect the economy through many different channels. In 2009 the average U.S. consumer spent $6,110, or about 12.5 percent of total expenditures, on energy related items such as utilities, gasoline, motor oil, and public transportation.[4] With such a large portion of expenditures relating to energy, energy price shocks have a major impact on the typical U.S. family. It should also be noted that increases in energy or fuel prices tend to find their way into food prices, which accounted for about 13 percent of total expenditures in 2009. Since energy consumption is important for the average U.S. consumer, large and unexpected increases in energy prices could force consumers to make decisions on where to spend their income. As energy prices rise, consumers will reduce their consumption of energy; for instance, walking more and driving less, but empirical studies have found this to be limited. The majority of the population will still need to drive to work, heat their homes in the winter, and cool their homes in the summer. According to Hughes, Knittel, and Sperling (2008) the short-run price elasticity of gasoline demand from 2001 to 2006 ranged from -0.034 to -0.077, which means that in practice higher gasoline price increases cause energy to consume larger portions of family budgets. Consequently, large energy price shocks will force consumers to cut back on other purchases, possibly leading to a recession. The Labor and capital in the automobile industry will not be able to instantaneously move to other sectors of the economy, which will intensify the effects of an energy price shock (Hamilton 2008). Industries that are very energy intensive will also be negatively impacted by energy price shocks. Conversely, states that are producers of energy might benefit from a shock to energy prices and consequently see production and employment expand.

[4] U.S. Dept. of Labor, U.S. Bureau of Labor Statistics, Consumer Expenditures in 2009, Report 1029

Literature Review

It is my understanding that I am the first to study the macroeconomic effects of alternative energy price shocks to gasoline, diesel, natural gas, heating oil and electricity at the U.S. state-level. As a result, the literature surrounding these topics is limited. Currently, the literature focuses primarily on the macroeconomic effects of oil price shocks, but as it has already been noted, alternative energy series such as gasoline or natural gas do not always follow movements in the oil market, and vice versa. Kilian (2007) points out that oil is not the main source of energy consumed by either consumers or producers. Specifically, he notes that as of 2002, gasoline accounts for 48.7 percent of all energy used by consumers, compared with 12.3 percent for natural gas and 33.8 for electricity. For producers, electricity makes up 40.3 percent of energy usage, natural gas 14.5 percent, unleaded gasoline 14 percent, diesel fuel 11.4 percent and jet fuel 9.7 percent. Consequently, he notes that using these alternative energy price series in macroeconomic models may be more appropriate in certain situations.

A recent development in the literature is examining the role of high gas prices in explaining the financial crisis of 2007-08. Joe Cortright (2008) finds that in some major U.S. cities such as Chicago and Los Angeles, home prices in 2007 were likely to rise for zip codes closest to the city business district and fall for zip codes farther away from the city business district. In a working paper, Sexton, Wu and Zilberman (2012) take these findings a step further and formulate a theoretical model explaining how high gas prices in 2007-08 burst the housing bubble. Essentially, gas prices from 1986 to the early 2000s were below $2 per gallon in real 2001 dollars, which made suburban housing that requires long commute times affordable. Home ownership reached record levels in each year from 1994 to 2006, which was also the peak of subprime mortgages. Therefore, home ownership became an option for a new class of lower income individuals. When gas prices hit $4.15 per gallon in 2008, this caused suburban living to become unaffordable for some, causing foreclosure rates to rise and home values to fall. This is another example of how alternative energy prices, such as gasoline or diesel, may have more of a direct effect on the economy than oil prices. By studying the effects of alternative energy price shocks, this study adds to the energy price-macroeconomy literature.

Data

The Coincident Economic Activity Index from the Federal Reserve Bank of Philadelphia from July 1979 to June 2011 is used to measure economic activity at the state-level. According to the bank, the trend for each state's index is set to match the trend for each state's gross state product. For robustness, state-level unemployment rates from the Bureau of Labor Statistics (BLS) are also employed from January 1976 to June 2011.

Six different measures of energy prices are collected from the Energy Information Administration (EIA) Short-Term Energy Outlook from September 2011. The energy series end in June 2011 and include: imported crude oil prices (January 1976), motor gasoline retail prices (January 1976), on-highway diesel prices (January 1979), residential natural gas prices (January 1981), heating oil prices (November 1978) and residential electricity prices (July 1976). All of the energy series are deflated by the U.S. CPI for all urban consumers to create real energy price series. To ensure the data are stationary, standard transformations are used. More specifically, the first difference of the log level of the Coincident Economic Activity Index, oil price, gasoline price, diesel price and heating oil price are taken. Natural gas and electricity prices exhibited seasonality, so the seasonal difference of 12 months is applied to the log level of each series. Lastly, the first difference of the state-level unemployment rate is taken as well.

To help interpret the results, states are classified by their dominant industry. Annual industry shares of GDP are obtained from the U.S. Bureau of Economic Analysis (BEA) from 1976 to 2010.

Methods

To analyze the energy price-macroeconomy relationship, the following VAR model is estimated via OLS:

$$Y_{i,t} = \alpha_1 + \sum_{j=1}^{k_i} \beta_{1j} Y_{i,t-j} + \sum_{j=1}^{k_i} \delta_{1j} Energy_{z,t-j} + \varepsilon_{y_{i,t}} \qquad (1)$$

$$Energy_{z,t} = \alpha_2 + \sum_{j=1}^{k_i} \beta_{2j} Y_{i,t-j} + \sum_{j=1}^{k_i} \delta_{2j} Energy_{z,t-j} + \varepsilon_{Energy_{z,t}} \qquad (2)$$

where $Y_{i,t}$ denotes the percentage change in Economic Activity for state i at time t, $Energy_{z,t}$ denotes the percentage change in the price of energy series z at time t, and k_i is the lag length selected in state i. For identification, I impose the assumption that $Energy_{z,t}$ cannot contemporaneously affect $Y_{i,t}$. To examine the relationship between changes in energy prices and state-level unemployment, the following VAR model is estimated via OLS:

$$U_{i,t} = \alpha_1 + \sum_{j=1}^{k_i} \beta_{1j} U_{i,t-j} + \sum_{j=1}^{k_i} \delta_{1j} Energy_{z,t-j} + \varepsilon_{U_{i,t}} \qquad (3)$$

$$Energy_{z,t} = \alpha_2 + \sum_{j=1}^{k_i} \beta_{2j} U_{i,t-j} + \sum_{j=1}^{k_i} \delta_{2j} Energy_{z,t-j} + \varepsilon_{Energy_{z,t}} \qquad (4)$$

where $U_{i,t}$ denotes the percentage point change in the unemployment rate for state i at time t. As above, I impose the assumption that $Energy_{z,t}$ cannot contemporaneously affect $U_{i,t}$.

To examine how states respond to alternative energy price shocks, cumulative one-year impulse response functions (IRF) are calculated for each state, both for the Coincident Economic Activity Index and the state-level unemployment rate, in response to a two-standard deviation shock to the price of energy series z. In a working paper by Melichar (2013), one-standard deviation oil price shocks do not have statistically significant effects on economic activity, so two-standard deviation price shocks are used in this study. In addition, 95% confidence bands are constructed using the wild bootstrap with 1,000 replications. I am then able to interpret the sign and magnitude of the response for each state, which allows for better understanding of the transmission of energy price shocks to economic activity.

In order to decide which energy series help forecast economic activity best, both pseudo out-of-sample and in-sample tests are employed. Specifically, the Diebold-Mariano (DM) test compares the baseline model 1 with oil against models 2 through 6 with alternative energy series. All the models come from the VAR framework using equations (1) - (4). Forecasts are estimated recursively with a 75 percent hold-back sample. In other words, 75 percent of the data are used to estimate the VAR model, with the remaining 25 percent used for forecasting. The loss differential series for 3, 6 and 12 month-ahead forecasts can be represented by:

$$d_{i,t} = U_{1i,t} - U_{2i,t}$$

where $U_{1i,t}$ is the squared forecast error in state i at time t for model 1, and $U_{2i,t}$ is the squared forecast error in state i at time t for model 2. The null hypothesis of equal predictive power is tested by regressing $d_{i,t}$ on a constant, and using a t-test with HAC standard errors to determine if the mean of d is different from zero.

To test in-sample fit, the Davidson and MacKinnon J-test is employed. Similar to the DM test, the baseline model 1 is compared against models 2 through 6 using equations (1) - (4). The fitted values from the alternative energy price model are then included among the set of regressors for the baseline model to see if they improve fit and vice versa.

Results

To interpret the results from all 50 U.S. states, each state is classified according to the largest industry as a share of GDP in the full sample period. The four industries considered are manufacturing, tourism, oil and natural gas extraction, and agriculture. The service sector is the dominant industry in the U.S. and uses little energy, so classifying all states as service sector would not be informative. The classification of states can be viewed in Table 1.1.

Economic Activity Impulse Responses

Examining the impulse responses from energy price shocks allows for understanding of how and why they affect the macroeconomy. Additionally, the impulse responses from oil price shocks can be compared to those from alternative energy price shocks to see how they differ. Understanding which forms of energy matter the most for individual areas of the country improves our understanding of the energy price-macroeconomy relationship. Therefore, cumulative one-year impulse responses to energy price shocks are plotted, as well as their respective upper and lower 95 percent confidence bands. For all Figures 2.2 - 2.6, the percent change in economic activity is listed on the x-axis, meaning a value of -0.01 represents a one percent decrease in economic activity.

The one-year impulse response to a two-standard deviation oil price shock for the coincident economic activity index (Y) can be seen in Figure 2.2. There are three distinct groups of states in their response; ones that benefit, ones that do not experience much change, and ones that are hurt. For the most part, the states that benefit from oil price shocks are energy states like Wyoming, Oklahoma, West Virginia, Alaska, Kansas, Louisiana and Colorado. The states that have a negative response in economic activity to an oil price shock are mostly manufacturing states, with the exception of a few tourism states. All of the 15 most negative responses are either manufacturing states like Michigan, or tourism states like Nevada. It should be noted that many of the 95 percent confidence bands are not significantly different from zero, but the pattern of response is still clear.

Figure 2.2 Economic Activity Impulse Response to Oil Price Shock

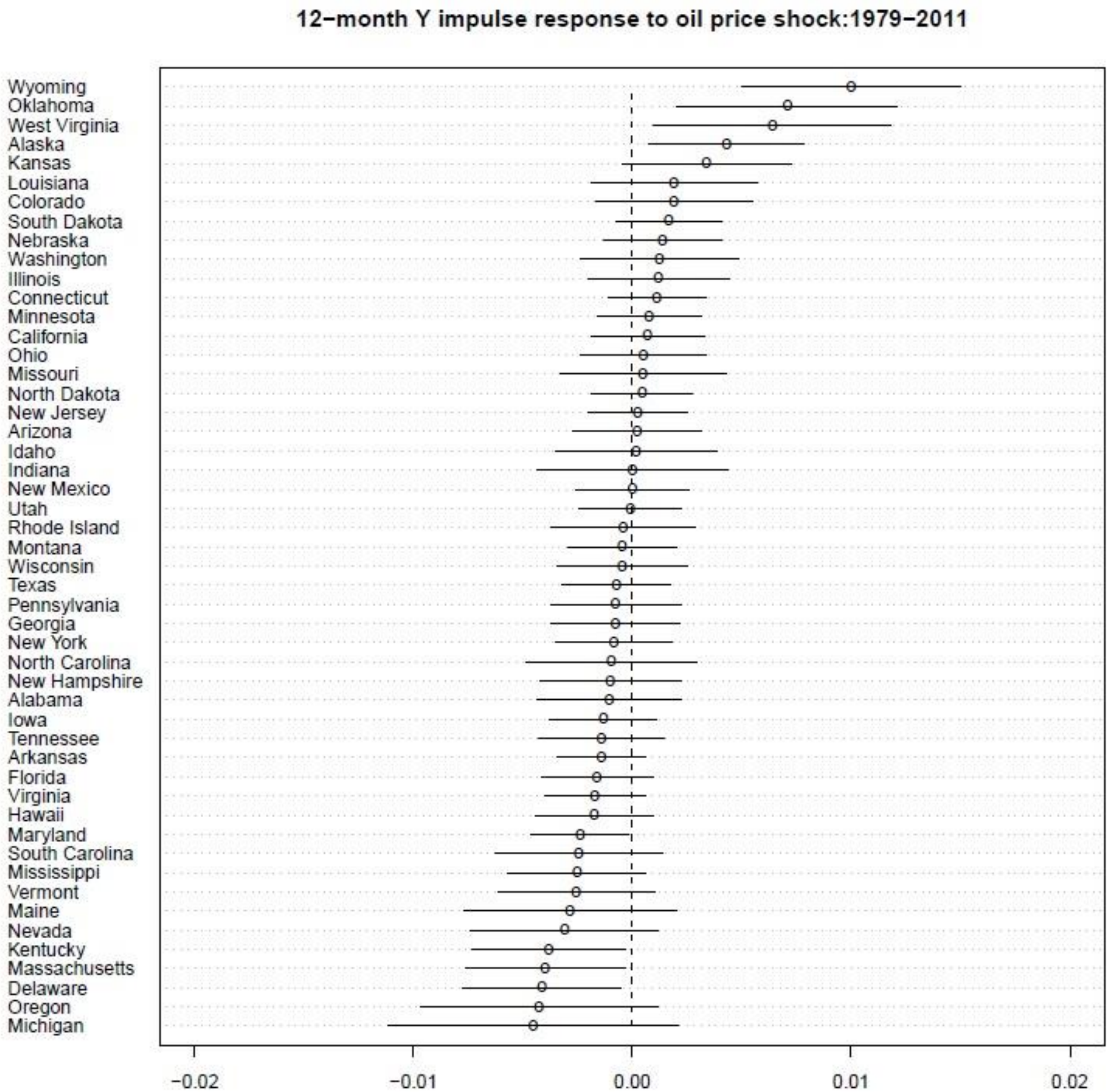
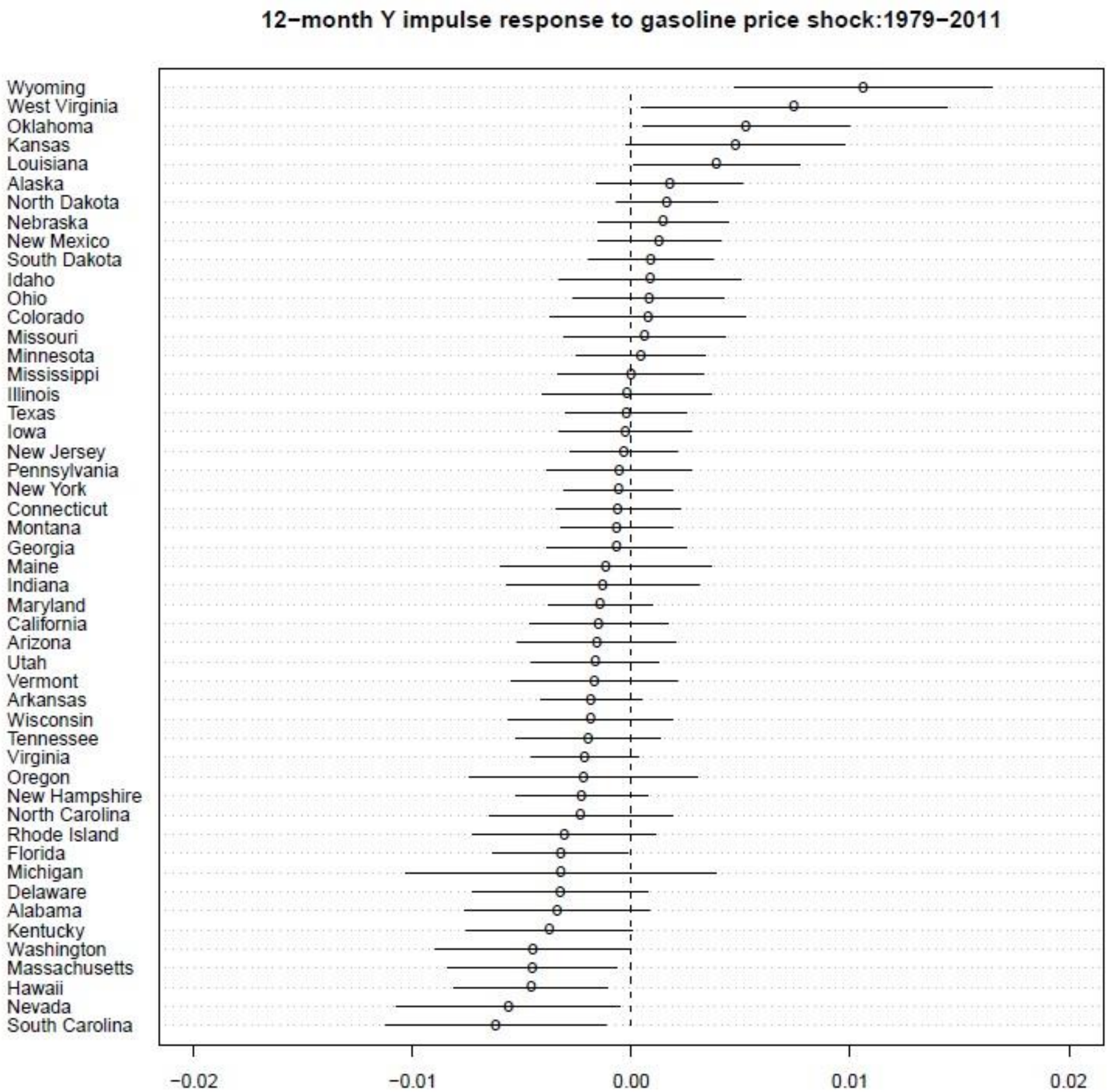


Figure 2.3 Economic Activity Impulse Response to Gasoline Price Shock



Next, Figure 2.3 shows the one-year impulse response to a two-standard deviation gasoline price shock for the coincident economic activity index (Y). The overall trends are the same when compared to Figure 2.2, but the top tourism states of Florida, Hawaii and Nevada have more negative responses. Therefore, based on the results of Figure 2.3 and the fact that higher gasoline prices have a more direct impact on consumer income than oil prices, using gasoline prices in macroeconomic models may be a better approach for tourism states. The effects of a diesel price shock are very similar to that of the gasoline price shocks shown in Figure 2.3, so they are omitted to conserve space.

Do higher natural gas prices have a different effect on economic activity than higher oil prices? It is evident from Figure 2.4, which shows the one-year impulse response to a two-standard deviation natural gas price shock, that the top energy states benefit less, especially Wyoming and Oklahoma. Furthermore, there is some evidence of rust-belt states being more negatively affected compared to oil price shocks, such as Michigan, Indiana, Minnesota, Ohio, Wisconsin and Illinois. Not only is natural gas important in the production process for these states, it is also important for consumers who use it to heat their homes in the winter. Therefore, since natural gas accounts for about 14.5 and 12.3 percent of energy usage by producers and consumers, respectively, this might help explain this region's negative response.

The effects of a two-standard deviation heating oil price shock price on economic activity are seen in Figure 2.5. The pattern of response is similar to an oil price shock, but New England states such as Massachusetts experience a larger decrease in economic activity. New England is a primary consumer of heating oil, so it is expected that these states are more adversely affected than others. Also, excluding Wyoming, the top energy states benefit less from a heating oil price shock compared to an oil price shock.

Lastly, Kilian (2007) notes that about 40 percent of energy usage by producers can be attributed to electricity. Figure 2.6 shows the one-year impulse response functions following a two-standard deviation electricity price shock for the coincident economic activity index (Y). One glaring difference between Figure 2.2 and Figure 2.6 is that higher electricity prices do not increase economic activity for U.S. states, except for Alaska. Furthermore, many Midwest states like Illinois, Nebraska, Minnesota, Iowa, Kansas and South Dakota have some of the most negative responses to electricity price shocks, whereas many of these states do not have a much of a decline following an electricity price shock, which is expected since electricity prices

Figure 2.4 Economic Activity Impulse Response to Natural Gas Price Shock

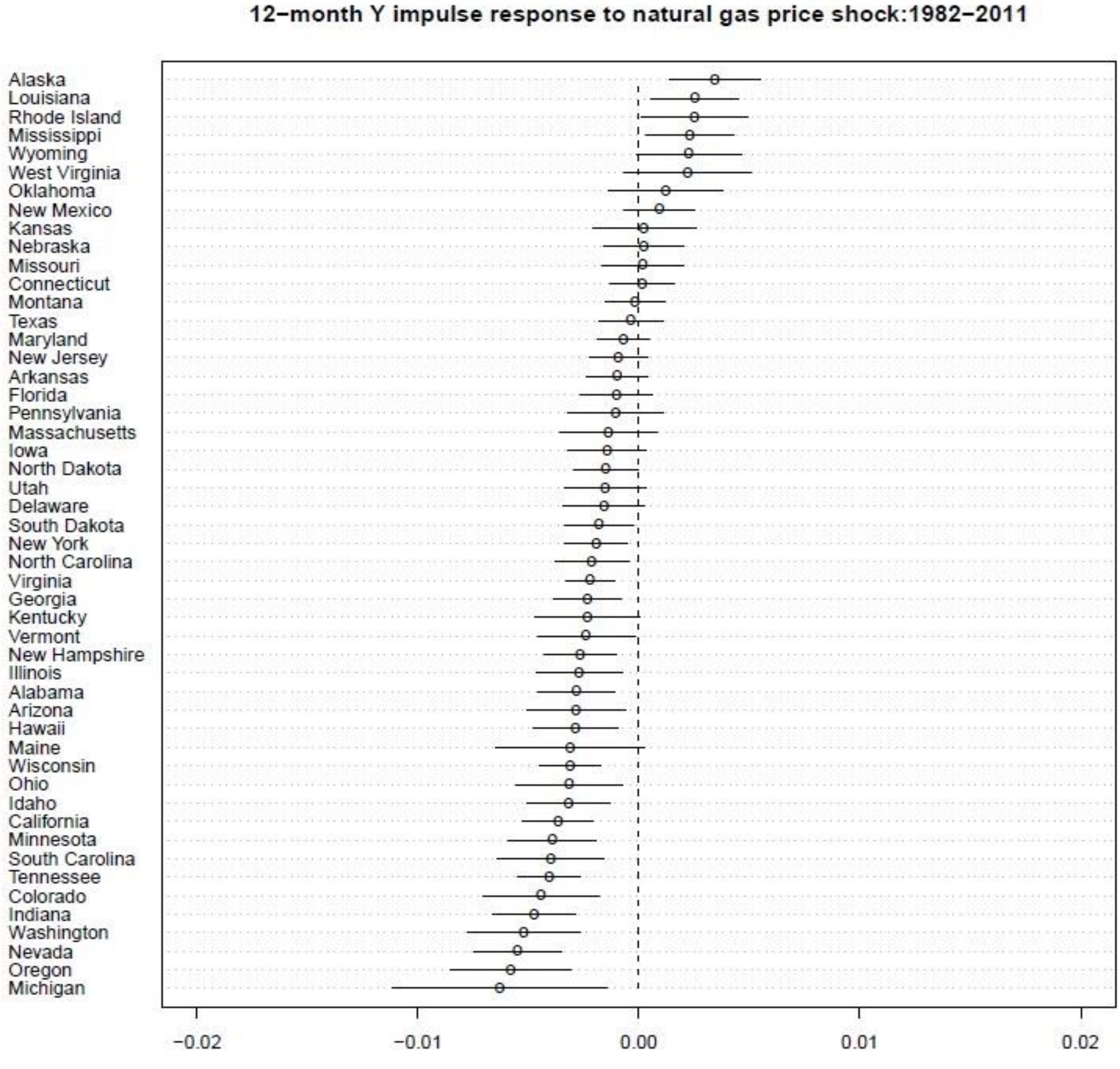


Figure 2.5 Economic Activity Impulse Response to Heating Oil Price Shock

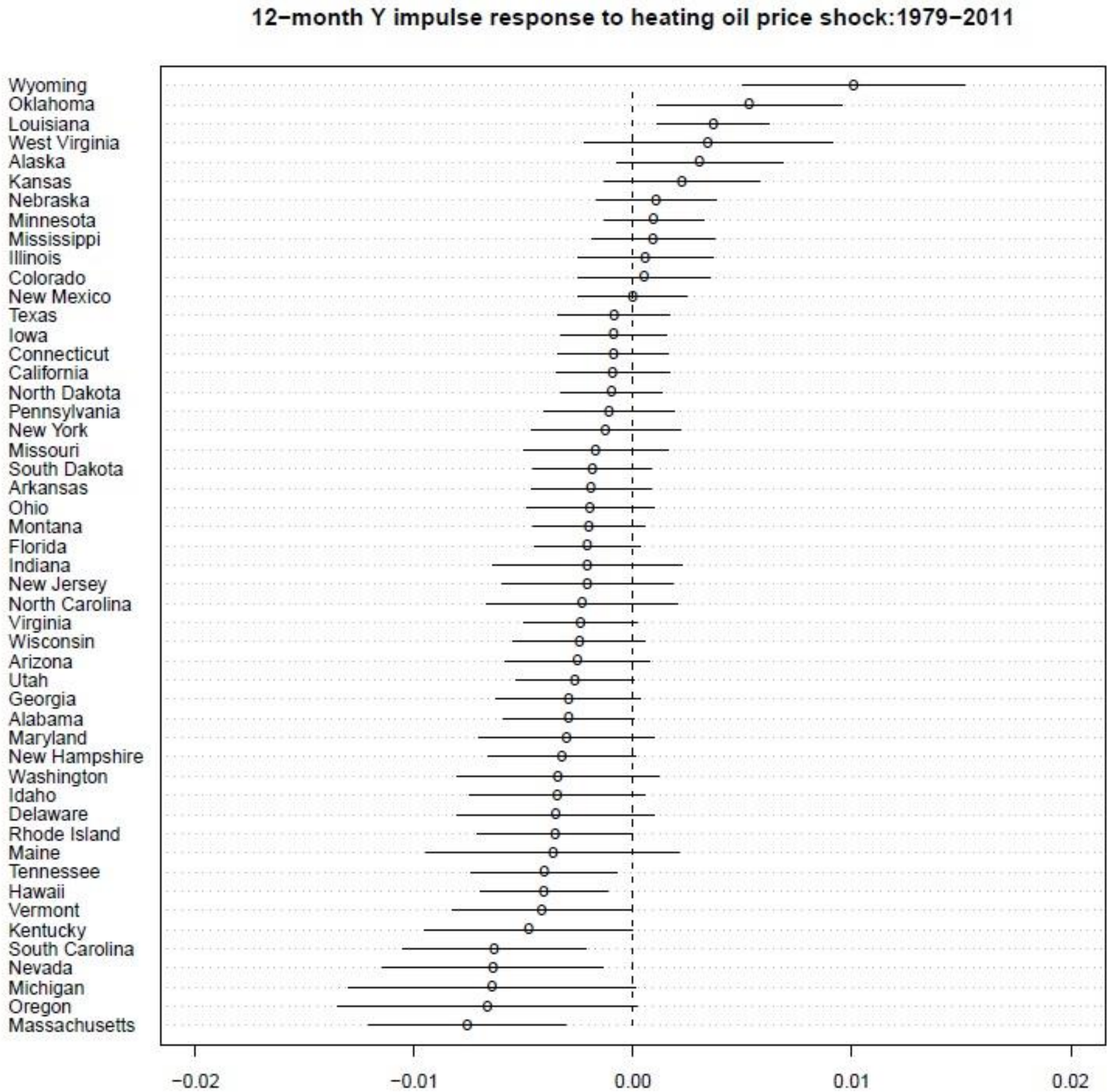
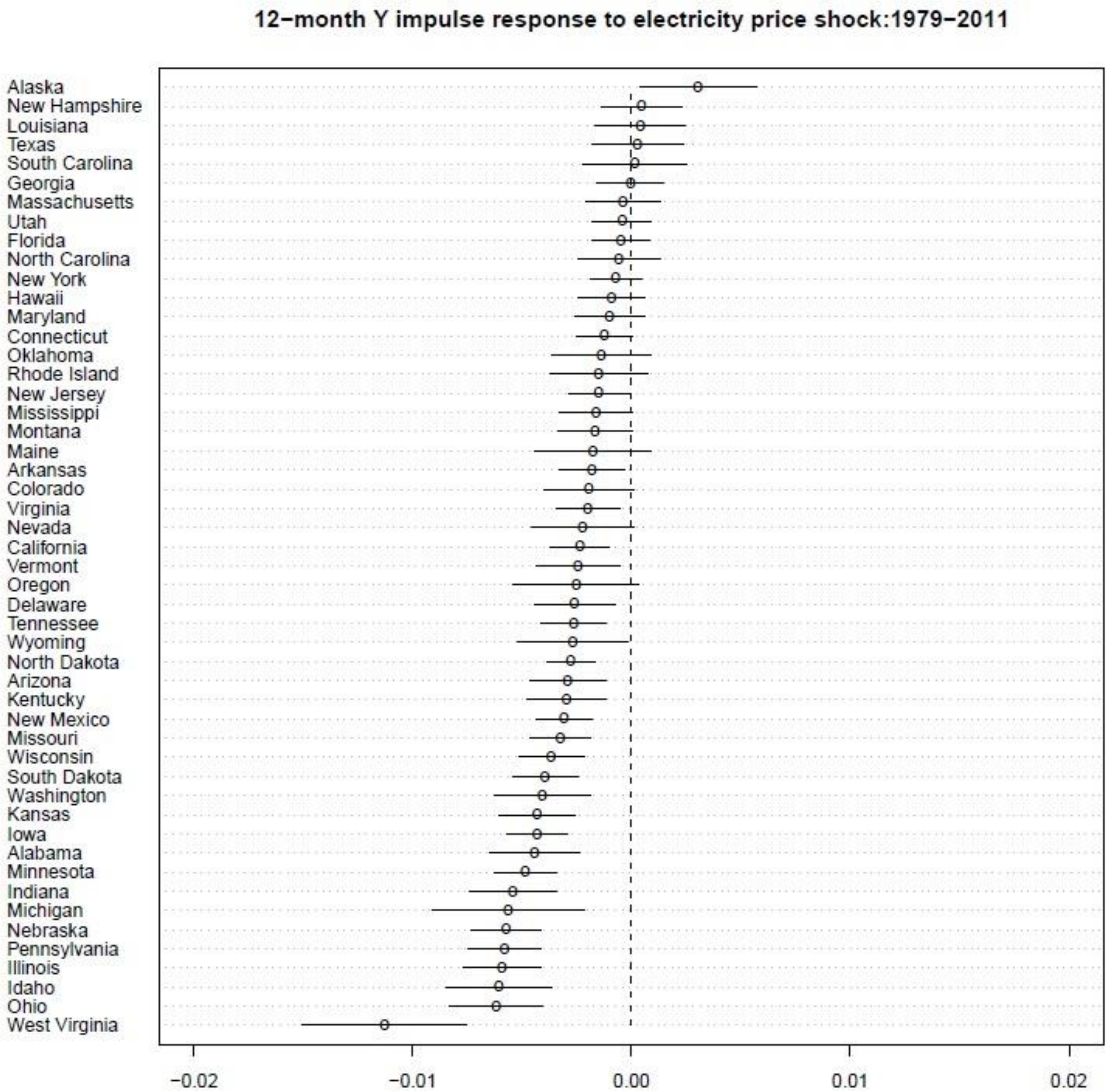


Figure 2.6 Economic Activity Impulse Response to Electricity Price Shock



do not directly impact the cost of vacations and travel. Interestingly, West Virginia experiences more than a one percent decrease in economic activity one year after a two-standard deviation electricity price shock. West Virginia has been one of the top steel producing states in the country, and since steel requires much electricity in production, this might explain its response. Illinois, Indiana, Ohio and Pennsylvania are also negatively impacted by electricity price shocks and all depend upon steel or other forms of manufacturing to sustain their economy.

Economic Activity Regression Analysis

A more rigorous approach to determine the effects of alternative energy price shocks on economic activity is represented in the equation below:

$$IRF{:}\,12_{i,z} = \beta_0 + \beta_1 Tourism_i + \beta_2 Manuf_i + \beta_3 OG_i + \beta_4 Ag_i + \varepsilon_{i,z} \quad (5)$$

where $IRF{:}\,12_{i,z}$ is the cumulative 12 month impulse response to a two standard deviation price shock to energy series z in state i, $Tourism_i$ is the average percentage of the Leisure & Hospitality industry as a share of GDP from 1976 to 2009 in state i, $Manuf_i$ is the average percentage of the manufacturing industry as a share of GDP from 1976 to 2009 in state i, OG_i is the average percentage of the oil and natural gas extraction industry as a share of GDP from 1976 to 2009 in state i, and Ag_i is the average percentage of the farming industry as a share of GDP from 1976 to 2009. The various permutations of equation (5) for all the energy series are available in Tables 2.1 – 2.6, with column (5) containing all of the independent variables. The coefficients on the variables represent the percentage change in cumulative impulse responses to a two standard deviation price shock to energy series z following a one percent increase in each respective industry share of GDP. The results from the various permutations of equation (5) confirm that the manufacturing and oil and natural gas extraction industry are the most important in determining a state's response to energy price shocks, but there are some instances where high industry shares in tourism or agriculture are important for energy shocks other than oil.

Table 2.1 contains the results of equation (5) for oil price shocks. Manufacturing and Oil and Natural Gas extraction (OG) are both statistically significant and have the expected sign. After a two standard deviation shock to the price of oil, a state with a one percent higher manufacturing share of GDP experiences a 1.5 percent decrease in economic activity. Conversely, increasing the oil and natural gas extraction industry share by one percent increases economic activity by 3.2 percent.

Table 2.1 Y: IRF Regressions for Oil Price Shocks

	(1)	(2)	(3)	(4)	(5)
β_0	0.000 (0.32)	0.002 (2.25)	-0.001 (-2.45)	-0.000 (-0.87)	0.001 (0.63)
$Tourism$	-0.019 (-1.18)				-0.023 (-1.53)
$Manuf$		**-0.015** (-2.59)			-0.009 (-1.40)
OG			**0.032** (5.00)		**0.026** (3.53)
Ag				0.014 (0.80)	0.009 (0.58)
Adj R^2	0.01	0.10	0.33	-0.01	0.35
Note: t-statistics are in parenthesis					

The results of the regression analysis for gasoline price shocks can be found in Table 2.2. The results are similar to those of Table 2.1, except the share of GDP in the tourism industry is significant at the ten percent level. Specifically, a state with a one percent higher tourism share of GDP experiences a 3.4 percent decrease in economic activity one year following a two standard deviation gasoline price shock. This result is consistent with Figure 2.3, which shows the top tourism states of Nevada, Hawaii and Florida exhibiting some the largest decreases in economic activity in response to gasoline price shocks. For top tourism states, economic forecasters may obtain more accurate results of the effects of energy price shocks on economic activity by using gasoline prices instead of oil prices.

Next, the results from the regression analysis involving diesel price shocks are available in Table 2.3. The results are very similar to that of gasoline price shocks, with higher shares of tourism and manufacturing leading to decreases in economic activity, and higher shares of oil and natural gas extraction leading to increases in economic activity.

Table 2.2 Y: IRF Regressions for Gasoline Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.001 (-0.38)	0.001 (1.20)	-0.001 (-3.62)	-0.001 (-2.12)	-0.000 (-0.38)
$Tourism$	**-0.034*** (-1.95)				**-0.031*** (-1.90)
$Manuf$		**-0.012*** (-1.88)			-0.005 (-0.71)
OG			**0.035** (4.97)		**0.032** (4.00)
Ag				0.028 (1.51)	0.024 (1.54)
Adj R^2	0.05	0.05	0.33	0.03	0.39
Note: t-statistics are in parenthesis					* = 10% Significance

Table 2.3 Y: IRF Regressions for Diesel Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.000 (-0.26)	0.002 (1.38)	-0.002 (-3.89)	-0.002 (-2.12)	0.000 (0.21)
$Tourism$	**-0.043** (-2.12)				**-0.046** (-2.44)
$Manuf$		**-0.017** (-2.17)			-0.011 (-1.32)
OG			**0.042** (5.04)		**0.035** (3.77)
Ag				0.029 (1.31)	0.021 (1.13)
Adj R^2	0.07	0.07	0.33	0.01	0.411
Note: t-statistics are in parenthesis					

Applying equation (5) to natural gas IRFs reveal similar patters to those above, but the reasoning behind them is less clear. Specifically, I am unsure why a state with a higher tourism share of GDP would experience a larger decrease in economic activity one year after a natural gas price shock. However, the sign of the coefficient for manufacturing and oil and natural gas extraction are expected, since industrial production is dependent upon natural gas and states extracting natural gas will benefit from higher prices. Specifically, one year following a two standard deviation natural gas price shock, a state with a one percent higher oil and natural gas extraction industry share of GDP experiences a 2.7 percent increase in economic activity. The results from the regression analysis involving natural gas IRFs can be found in Table 2.4.

Table 2.4 Y: IRF Regressions for Natural Gas Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.001 (-3.35)	0.000 (0.24)	-0.002 (-7.75)	-0.002 (-3.60)	-0.000 (-0.07)
$Tourism$	**-0.022*** (-1.72)				**-0.029** (-2.34)
$Manuf$		**-0.011** (-2.35)			-0.009 (-1.68)
OG			**0.027** (5.06)		**0.021** (3.43)
Ag				0.003 (0.18)	-0.004 (-0.33)
Adj R^2	0.04	0.08	0.33	-0.02	0.37

Note: t-statistics are in parenthesis * = 10% Significance

The results from the regression analysis involving heating oil price shocks can be seen in Table 2.5. The main points remain unchanged, with higher shares of manufacturing and oil and natural gas extraction leading to decreases and increases in economic activity one year following a large heating oil price shock, respectively.

Table 2.5 Y: IRF Regressions for Heating Oil Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.001 (-2.20)	0.001 (0.73)	-0.003 (-7.03)	-0.002 (-3.12)	-0.001 (-0.77)
$Tourism$	-0.030 (-1.66)				**-0.030*** (-1.88)
$Manuf$		**-0.015** (-2.30)			-0.006 (-0.97)
OG			**0.042** (6.25)		**0.037** (4.85)
Ag				0.016 (0.80)	0.011 (0.74)
Adj R^2	0.03	0.03	0.44	-0.01	0.46
Note: t-statistics are in parenthesis					* = 10% Significance

Table 2.6 contains the results of the regression analysis for electricity price shocks. A very interesting finding appears for states with higher shares of GDP in agriculture, which up to this point has been statistically insignificant in all regressions. However, one year after a two standard deviation electricity price shock, states with a one percent higher agriculture industry share of GDP experience a 2.5 percent decrease in economic activity. This finding is significant at the ten percent level and is consistent with Figure 2.6, which shows agricultural states like Iowa, Kansas, Idaho, Nebraska and South Dakota experiencing some of the largest decreases in economic activity following large electricity price shocks.

When examining the effects that various industry shares of GDP have on states' economic responses to energy price shocks, it is evident that the manufacturing and oil and natural gas extraction industry play the most important role in determining a state's response. However, higher shares of GDP in the tourism industry lead to significant decreases in economic activity following gasoline and diesel price shocks. This is an important finding that should be noted by state-level economists in tourism states. Lastly, electricity price shocks have a negative affect for states with higher industry shares in agriculture.

Table 2.6 Y: IRF Regressions for Electricity Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.003	-0.001	-0.003	-0.002	-0.001
	(-6.75)	(-1.01)	(-8.55)	(-4.16)	(-0.53)
$Tourism$	0.009				-0.002
	(0.64)				(-0.11)
$Manuf$		**-0.010**			-0.008
		(-2.04)			(-1.31)
OG			**0.016**		0.011
			(2.57)		(1.53)
Ag				**-0.025***	**-0.028**
				(-1.74)	(-1.96)
Adj R^2	-0.01	0.06	0.10	0.04	0.14
Note: t-statistics are in parenthesis				* = 10% Significance	

Unemployment Rate Impulse Responses

To see if the unemployment rate produces similar patterns, cumulative one-year impulse responses to energy price shocks are plotted, as well as their respective upper and lower 95 percent confidence bands. For all Figures 2.7 - 2.9, the percentage point change in the unemployment rate is listed on the x-axis, meaning a value of 0.005 represents an increase in the unemployment rate of 0.5 percentage points.

Figure 2.7 displays the response to an oil price shock, with familiar patterns of energy states benefiting and manufacturing states being hindered. Similar to economic activity, many of the 95 percent confidence bands for the unemployment rates are not significantly different from zero, but the pattern of response still sheds some light on the energy price-macroeconomy relationship. The responses to a gasoline price shock are very similar to that of Figure 2.7, so they are omitted to conserve space. However, tourism states of Nevada and Florida experience a greater increase in unemployment in response to a gasoline price shock. The impulse responses to a diesel price shock are similar to that of Figure 2.7, so they are omitted to conserve space as well.

One year after a two-standard deviation natural gas price shock, roughly half of states experience an increase in unemployment rates while half experience a decrease, which can be seen in Figure 2.8. However, the pattern of response, when grouped by industry, is less clear. Nevertheless, some patterns do appear, with certain top natural gas producing states such as Louisiana, New Mexico, Alaska and Wyoming, experiencing some of the largest declines in unemployment rates.

Figure 2.7 Unemployment Impulse Response to Oil Price Shock

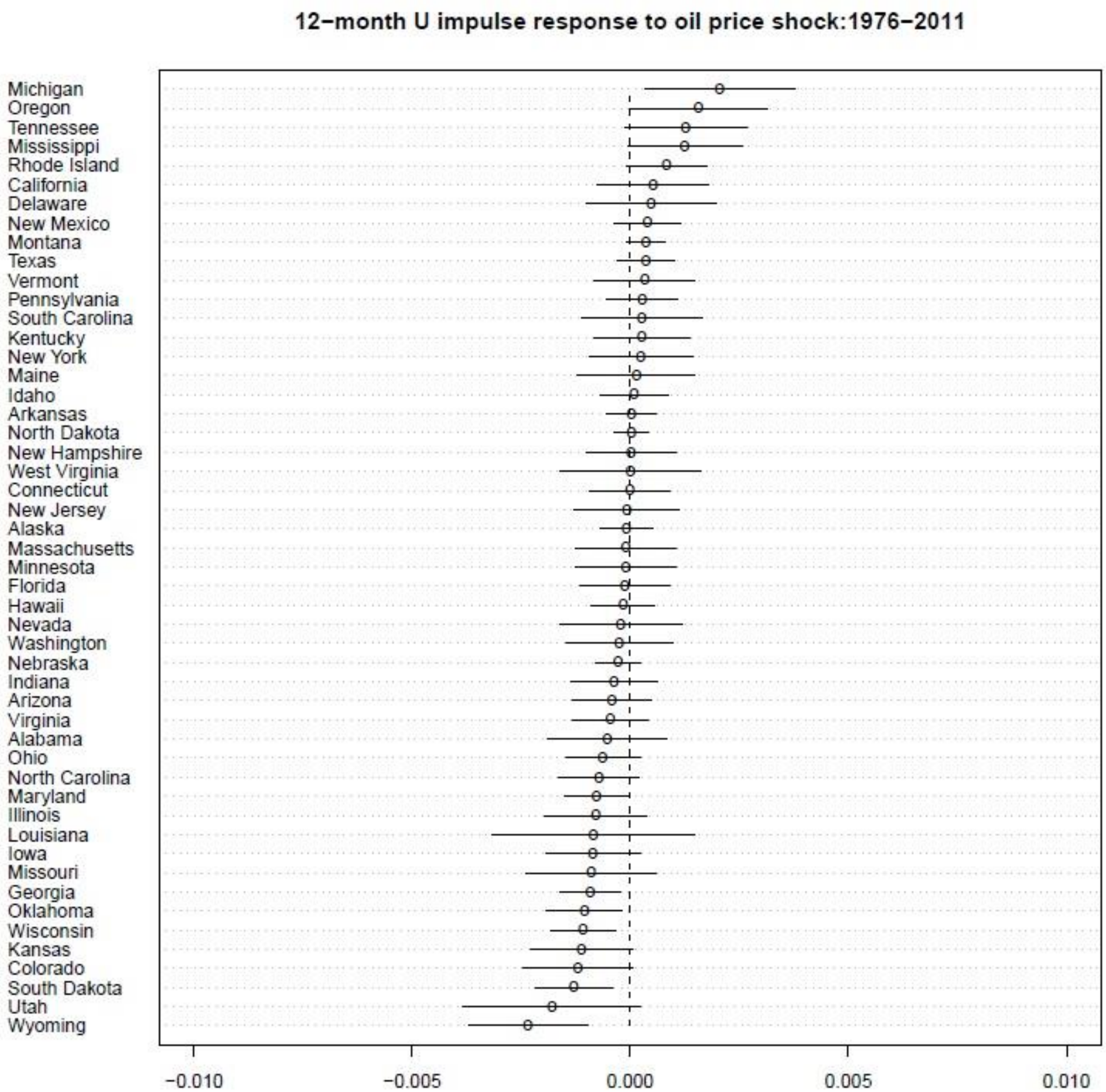


Figure 2.8 Unemployment Impulse Response to Natural Gas Price Shock

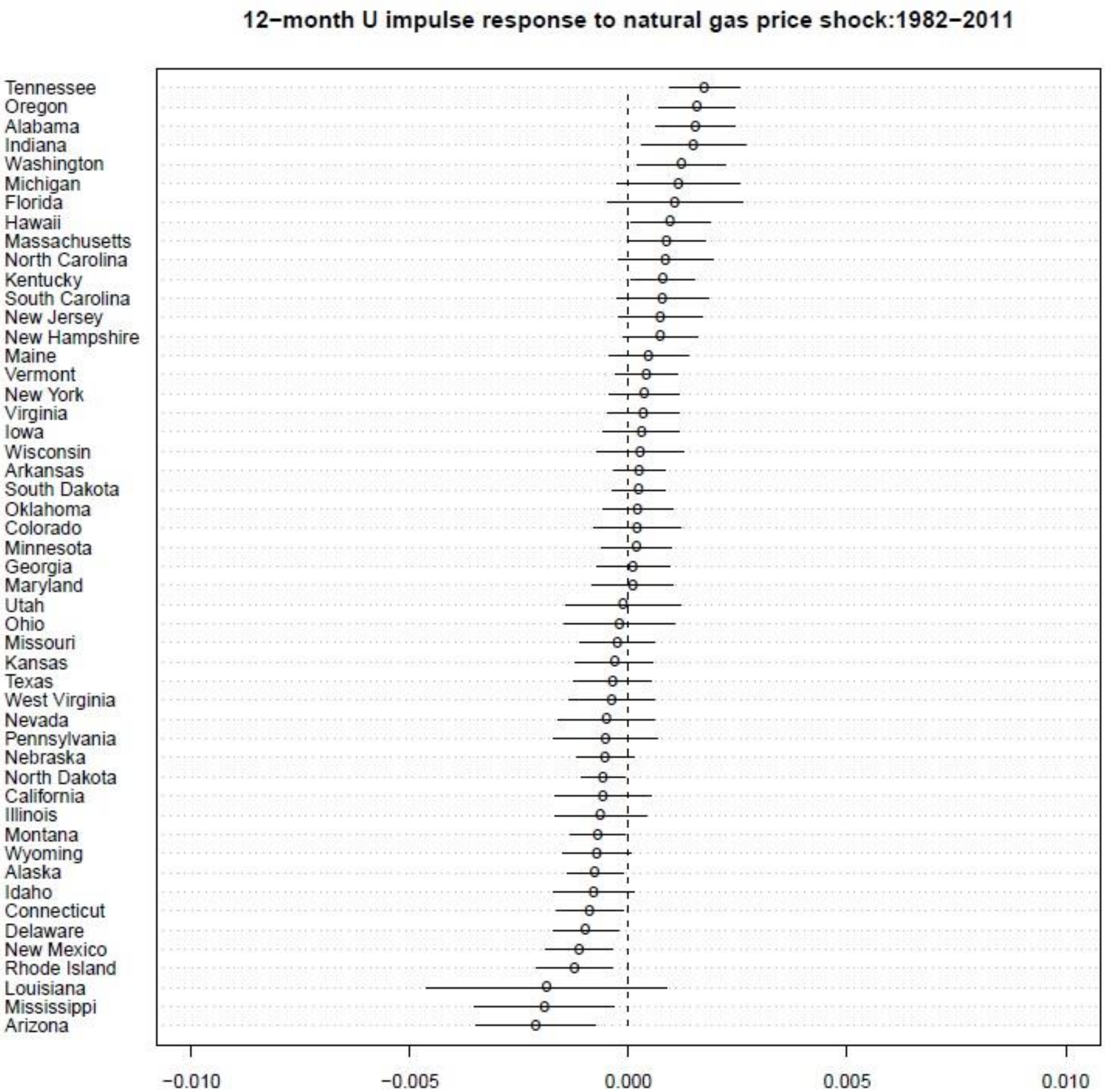
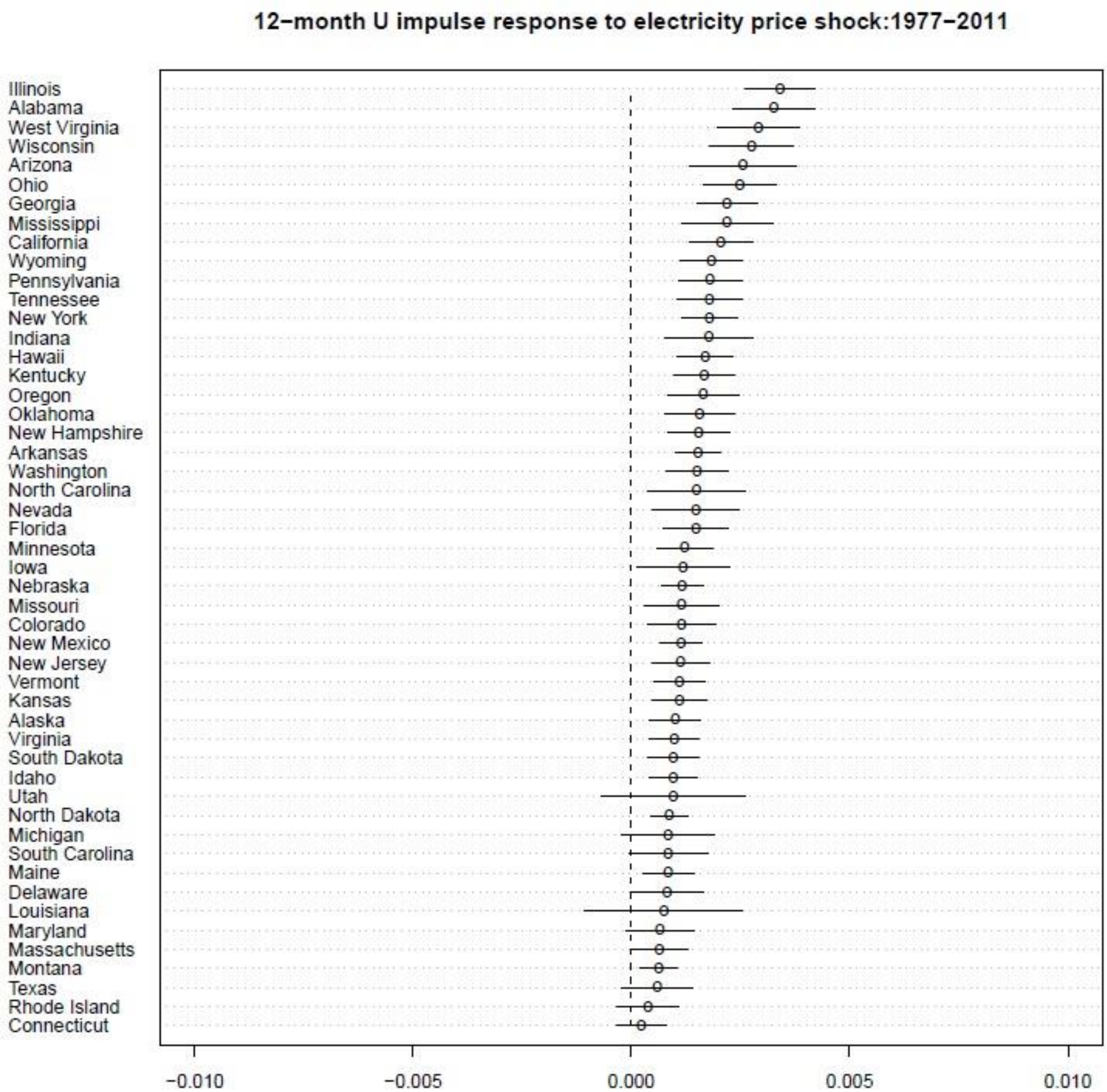


Figure 2.9 Unemployment Impulse Response to Electricity Price Shock



The way in which state-level unemployment rates respond to a heating oil price shock is similar to how they respond to an oil price shock, so they are omitted to conserve space. However, decreases are of smaller magnitude and increases are of larger magnitude. In addition, Vermont, Maryland and Delaware, all of which are states in the northeast that use heating oil, have much more of a detrimental response to a heating oil price shock than an oil price shock.

Lastly, electricity price shocks are painful for the entire country, which can be seen in Figure 2.9. As was the case for economic activity, traditional steel and manufacturing states of West Virginia, Illinois, Indiana, Ohio and Pennsylvania again have some of the least favorable responses.

In general, alternative energy price shocks like gasoline and diesel do not produce dramatically different economic responses than oil price shocks, except for a few tourism states. Energy series that are less closely tied to oil, such as natural gas and electricity, do produce different economic responses than oil. As a result of these different responses, and the fact that alternative energy series account for a large portion of energy consumption, it is possible that they may also help forecast economic activity or unemployment rates better than oil.

Unemployment Rate Regression Analysis

Tables 2.7 – 2.12 contain the results of the various permutations of equation (5) when applied to the unemployment rate and reveal the only industries that are significant in explaining a state's response to energy price shocks are manufacturing and oil and natural gas extraction. Table 2.7 shows the results for the regression analysis for oil price shocks, with a one percent increase in manufacturing share of GDP leading to a 0.3 percentage point increase in the unemployment rate one year following a two standard deviation oil price shock. Conversely, a one percent increase in the oil and natural gas extraction industry causes a 0.40 percentage point decrease in the unemployment rate.

Next, Tables 2.8 and 2.9 contain the results of equation (5) for gasoline and diesel price shocks, respectively. Again, manufacturing and oil and natural gas extraction have the expected sign, but tourism is not significant. Although the tourism industry was important in determining the response in economic activity, the same cannot be said for the unemployment rate.

Table 2.7 U: IRF Regressions for Oil Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	-0.000	-0.001	-0.000	-0.000	-0.000
	(-1.26)	(-2.24)	(-0.76)	(-0.42)	(-0.84)
$Tourism$	-0.000				0.002
	(0.02)				(0.29)
$Manuf$		**0.003***			0.002
		(1.79)			(1.00)
OG			**-0.004***		-0.003
			(-1.72)		(-0.96)
Ag				-0.004	-0.003
				(-0.87)	(-0.64)
Adj R^2	-0.02	0.04	0.04	-0.005	0.02
Note: t-statistics are in parenthesis * = 10% Significance					

Table 2.8 U: IRF Regressions for Gasoline Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	0.000	-0.000	0.000	0.000	0.000
	(0.37)	(-1.37)	(2.09)	(1.34)	(0.09)
$Tourism$	0.003				0.003
	(0.61)				(0.58)
$Manuf$		**0.003***			0.002
		(1.82)			(0.67)
OG			**-0.007**		**-0.006**
			(-3.09)		(-2.26)
Ag				-0.006	-0.005
				(-1.02)	(-0.90)
Adj R^2	-0.01	0.08	0.15	0.00	0.13
Note: t-statistics are in parenthesis * = 10% Significance					

Table 2.9 U: IRF Regressions for Diesel Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	0.000 (0.88)	-0.001 (-1.85)	0.000 (1.58)	0.000 (1.11)	-0.000 (-0.16)
$Tourism$	-0.003 (-0.53)				-0.002 (-0.24)
$Manuf$		**0.005** (2.28)			0.003 (0.98)
OG			**-0.006** (-2.26)		-0.005 (-1.48)
Ag				-0.005 (-0.86)	-0.005 (-0.75)
Adj R^2	-0.01	0.08	0.08	-0.01	0.07
Note: t-statistics are in parenthesis					

Table 2.10 U: IRF Regressions for Natural Gas Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	0.000 (0.26)	-0.001 (-2.25)	0.000 (1.19)	0.000 (0.50)	-0.000 (-0.46)
$Tourism$	-0.002 (-0.34)				-0.000 (-0.01)
$Manuf$		**0.005** (2.45)			0.003 (1.11)
OG			**-0.007** (-2.80)		**-0.005*** (-1.83)
Ag				-0.003 (-0.61)	-0.003 (-0.48)
Adj R^2	-0.02	0.09	0.12	-0.01	0.11
Note: t-statistics are in parenthesis * = 10% Significance					

Table 2.11 U: IRF Regressions for Heating Oil Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	0.001	-0.000	0.001	0.001	0.001
	(3.21)	(-0.79)	(5.07)	(3.75)	(1.21)
$Tourism$	-0.001				-0.002
	(-0.24)				(-0.35)
$Manuf$		**0.005**			0.001
		(2.39)			(0.59)
OG			**-0.008**		**-0.007**
			(-3.27)		(-2.60)
Ag				-0.009	-0.009
				(-1.56)	(-1.66)
Adj R^2	-0.02	0.09	0.17	0.03	0.19
Note: t-statistics are in parenthesis					

Table 2.12 U: IRF Regressions for Electricity Price Shock

	(1)	(2)	(3)	(4)	(5)
β_0	0.001	0.001	0.001	0.002	0.001
	(11.55)	(3.84)	(13.38)	(10.42)	(2.36)
$Tourism$	0.000				0.002
	(0.10)				(0.44)
$Manuf$		0.002			0.002
		(1.48)			(1.06)
OG			-0.002		-0.001
			(-0.98)		(-0.30)
Ag				-0.004	-0.003
				(-0.99)	(-0.67)
Adj R^2	-0.02	0.02	-0.00	-0.00	-0.02
Note: t-statistics are in parenthesis					

Table 2.10 and 2.11 show the results of the regression analysis for natural gas and heating oil price shocks, respectively. In both cases, the results are similar to those of oil, gasoline and diesel price shocks.

Finally, when equation (5) is applied for impulse responses to electricity price shocks, which can be seen in Table 2.12, none of the industries are statistically significant in determining a state's change in the unemployment rate.

In general, it is apparent from the regression analysis that states with higher industry shares in manufacturing and oil and natural gas extraction will experience increases and decreases in unemployment rates, respectively, following energy price shocks from all series except electricity.

Aggregate Level Impulse Responses

Although certain states or groups of states respond in distinct ways to various energy price shocks, these patterns may not filter through at an aggregate level. For example, Wyoming may have a large increase in economic activity following oil or diesel price shocks, but Wyoming's share of the U.S. economy is very small. Therefore, one-year impulse responses and 95 percent confidence bands are constructed at an aggregate level for each of the six energy series considered. It should be noted that Figure 2.10 shows the U.S. aggregate economic activity impulse response and not U.S. GDP, and has the percent change in economic activity on the x-axis. Interestingly, oil price shocks appear to have a negligible effect on U.S. economic activity, whereas gasoline price shocks have a statistically significant negative effect on economic activity. Specifically, one year following a two standard deviation gasoline price shock, U.S. economic activity decreases by 0.23 percent. Therefore, using alternative energy series such as gasoline or diesel may improve the modeling of the energy price-macroeconomy relationship. Also, electricity price shocks have a negative effect on the U.S. economy, which is expected based on the results of Figure 2.6, which showed a decline in economic activity for nearly every state.

Next, Figure 2.11 contains the U.S. unemployment rate one-year impulse responses for each of the six energy series, and has the percentage point change in the unemployment rate on the x-axis. Higher electricity prices lead to higher unemployment rates, but higher oil, gasoline and diesel prices lead to lower unemployment rates at an aggregate level. This finding of higher gasoline and diesel prices having a beneficial effect for the U.S. unemployment rate is curious, since the opposite is true for U.S. economic activity. It should be noted however, that the magnitude of change is small for all of the energy series. For example, the U.S. unemployment rate decreases by roughly 0.1 percentage points one-year after a two standard deviation gasoline price shock.

Figure 2.10 U.S. Economic Activity Impulse Response to Energy Price Shocks

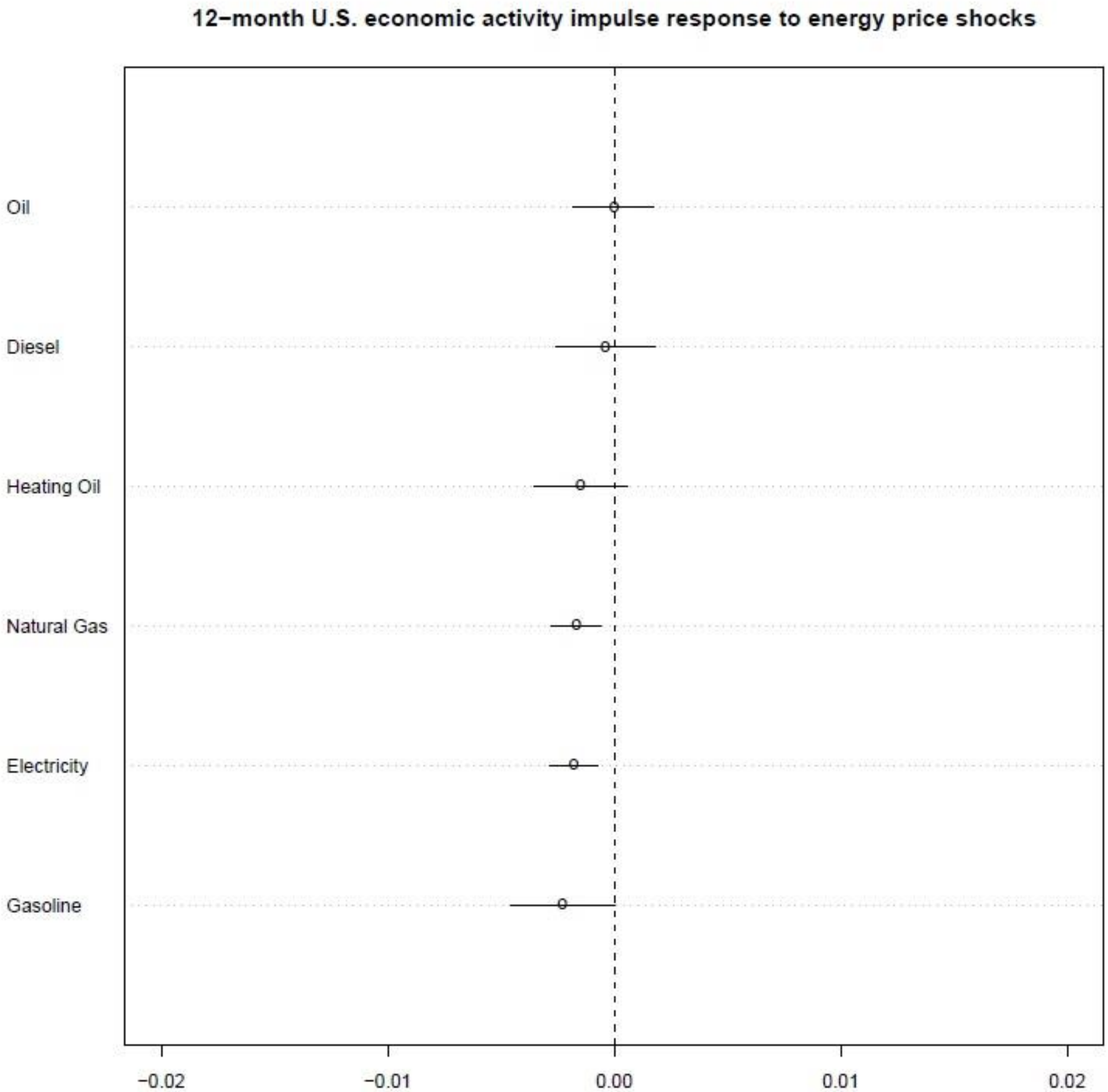
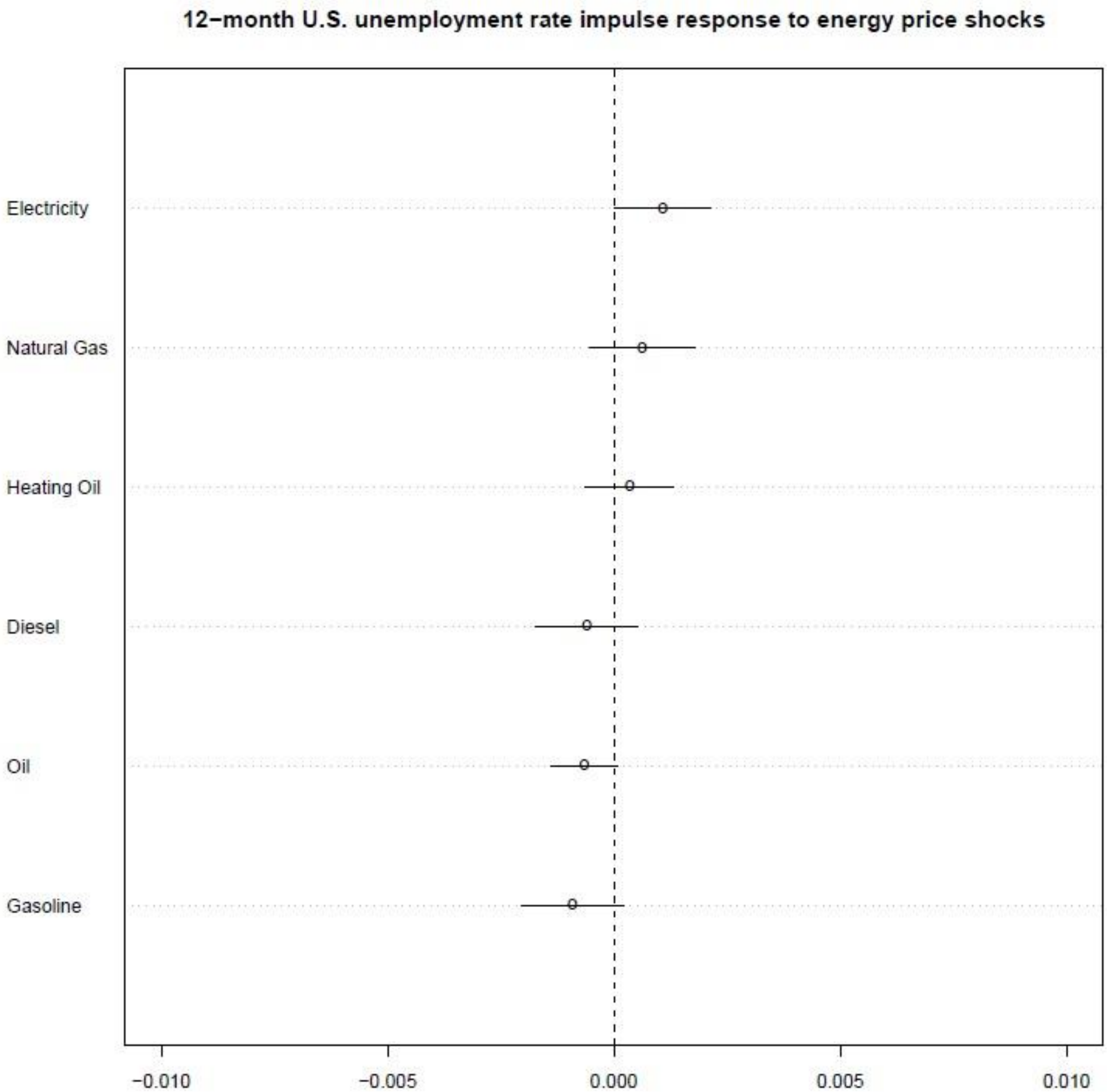


Figure 2.11 U.S. Unemployment Rate Impulse Response to Energy Price Shocks



Forecasting

DM Test

Can alternative energy series be used to improve forecasts of macroeconomic variables, either in the short or long run? The results from the DM test between oil and gasoline for the economic activity index at forecast horizons of 3, 6 and 12 months can be seen in Table 2.13. If a state is listed in the column for model 1, then the null hypothesis of equal forecast ability between the models is rejected, and model 1 provides forecasts with a smaller mean squared error. The opposite interpretation can be given to a state listed in the column for model 2 through 6, which are the alternative energy series models. In addition, a state with an asterisk rejects the null hypothesis at the ten percent level, as opposed to the traditional five percent level. The results from Table 2.13 indicate some evidence of model 1 producing better forecasts for energy states at longer forecast horizons. Also, there is some evidence of model 2 being preferred for a handful of manufacturing and tourism states.

Table 2.13 DM Test (Y) - Oil vs Gasoline

	1	**2**
h = 3	GA, OH*, SD	MA*
h = 6	NE*, OK	CA, MA*
h = 12	AK, OK*	DE*

Table 2.14 contains the results of the DM test for economic activity between oil and diesel. For a vast majority of states, there is no difference between model 1 and 3. It does appear, however, that tourism states of California, Florida and Montana produce better forecasts of economic activity with diesel, but Arizona does better with oil.

Table 2.14 DM Test (Y) - Oil vs Diesel

	1	**3**
h = 3	AZ	CA*, FL*
h = 6	SD	-
h = 12	NE	AR, MT

Next, Table 2.15 contains the results of the DM test for economic activity between oil and natural gas. There is no evidence of model 4, which is the alternative model with natural gas, producing better forecasts. Conversely, numerous energy states and a few agricultural states have better forecasts with model 1. Even though the IRFs exhibited a different pattern for natural gas price shocks, there is no evidence of this alternative energy series leading to improved out-of-sample forecasts. Table 2.16 contains the results of the DM test for economic activity between oil and heating oil and there is not a significant difference between the two. One state, Utah, consistently has more accurate forecasts when using model 5 however.

Table 2.15 DM Test (Y) - Oil vs Natural Gas

	1	**4**
h = 3	OK, WY	-
h = 6	AK*, OK*, WY	-
h = 12	AK, KS*, ME, MN, NE, SD, WY	-

Table 2.16 DM Test (Y) - Oil vs Heating Oil

	1	**5**
h = 3	WV	ME*, TN, UT, WI
h = 6	-	AL, UT
h = 12	CO*	UT

The results of the DM test between oil and electricity can be found in Table 2.17. Interestingly, there is no evidence of electricity producing better forecasts even though they account for almost half of energy usage by producers. Energy states improve fit with model 1 at all horizons, and agricultural and manufacturing states improve fit with model 1 at a long forecast horizon.

Table 2.17 DM Test (Y) - Oil vs Electricity

	1	6
h = 3	AK, MD*, NV, OK, WV, WY	-
h = 6	AK, OK, WV, WY	-
h = 12	AK, IA*, KS, LA, ME, MN, MS*, NE*, OH, PA, VT*, WV, WY	-

In general, there is not a great amount of difference between the baseline model and models 2 and 3 in terms of forecasting ability. Model 5 leads to better forecasts for only a handful of states, but the pattern of response is unclear. Lastly, for models 4 and 6, there is no evidence of better forecasts compared to the baseline model. When applying the DM test to unemployment rates, many of the same patterns appear. Therefore, the tables are omitted to conserve space, but they are available in Appendix A.

J Test

The J-test reveals whether alternative energy series lead to better in-sample fit. If a state is listed in the column for model 1, then the fitted values from the alternative model do not improve fit, and it can be concluded that model 1 produces the best fitting model. The opposite interpretation can be given to a state listed in the column for models 2 through 6, which are the alternative energy series models. In addition, it is possible that a better fit can be obtained by using a larger model with both oil and the alternative energy series. In this scenario, a state is listed in the column 'Both'. Lastly, a state with an asterisk is significant at the ten percent level, as opposed to the traditional five percent level.

First, the results from the J-test between oil and gasoline for the economic activity index at forecast horizons of 3, 6 and 12 months can be seen in Table 2.18. At a forecast horizon of 3 months, there is some evidence of model 2 or both models providing a better fit for energy states Oklahoma, West Virginia, Wyoming, Alaska and Texas. In general, the states that prefer model 1 at a forecast horizon of 3 months are either manufacturing or tourism states. As we transition to longer forecast horizons of 6 and 12 months, the usefulness of model 2 fades for energy states and many of them improve fit with model 1.

Table 2.18 J Test (Y) - Oil vs Gasoline

	1	2	Both
h = 3	AR*, AZ, HI, KY, MD, MI, ND, OH, OR, SC*	OK*, WV, WY	AK, TX
h = 6	AK, ID*, MD, MS*, NE*, OR, SC, WA, WY	NH, TN	OK, TX
h = 12	FL, IA*, MD, OR*, WY	MN	-

When model 3 is compared to model 1 in Table 2.19, it is immediately clear that diesel improves fit for many states, especially those with tourism as their dominant industry. This finding is especially true at a forecast horizon of 6 months, with Arizona, California, Florida, Hawaii, Utah and Vermont improving fit with model 3. In addition, many manufacturing states improve fit with model 3 and short-to-mid forecast horizons. There is limited evidence of model 1 improving fit, except for a handful of energy states. This finding of diesel producing better fitting models for manufacturing states, and especially tourism states, is an important finding for state-level forecasters.

Table 2.19 J Test (Y) - Oil vs Diesel

	1	3	Both
h = 3	AK*, ID*, ND, WA*	CA, DE*, IN*, LA*, MT, NH, OH*, OR, RI, TN, WV, WY	AR
h = 6	MN, OK*, WA	AZ, CA, FL*, GA*, HI, ID, IN, ME*, NH, OH* , SC, SD*, UT, VT*, WI	WY
h = 12	AR*, ID*, MD*, WA, WY	CA*, FL*, HI	-

Table 2.20 shows the results of the J-test between models 1 and 4. There is substantial evidence of model 4 improving fit, particularly at short-to-mid forecast horizons, for manufacturing and tourism states. However, the top two energy states of Oklahoma and

Wyoming improve fit with model 1 at these forecast horizons. It is clear at longer forecast horizons that the usefulness of model 4 diminishes and oil should be used in the energy price-macroeconomic models.

Table 2.20 J Test (Y) - Oil vs Natural Gas

	1	**4**	**Both**
h = 3	AR, IA*, MD, OK*, VT, WY	AL*, CA, ID*, IN*, KY, MI*, MN*, NV*, OH, PA, TN, TX*, UT, WA, WI	AK, AZ, HI, ME, ND, NE, SC
h = 6	AK, MD, ME, OK, WY	CA, HI, IN, KY, MN, NE*, OH*, PA, SD*, TN	SC
h = 12	AR*, AZ, HI*, IA*, KY*, MA*, MD, MN, MO*, RI, SC	NV*	-

Does heating oil, which is important for many cold-weather states in New England, produce better forecasts of economic activity than oil? It is evident from Table 2.21 that model 5 improves fit for numerous states, many of which are located in New England such as Massachusetts, New Hampshire, Maine, Rhode Island, and Vermont. In addition, other manufacturing and tourism states that are not located in New England, improve fit with model 5 as well. In fact, there are only a handful of states, most of whose dominant industry is energy, which improve fit with model 1. In the future, heating oil should be considered in energy price-macroeconomic models, except for selected energy states.

Finally, Table 2.22 shows the results of the J-test between models 1 and 6. As has been the case for many of the model comparisons, energy states of Alaska, North Dakota, Oklahoma, West Virginia and Wyoming improve fit with the baseline model containing oil prices. Conversely, there is some evidence of manufacturing states producing better fitting models with the alternative energy series of electricity or both oil and electricity, but only at short forecast horizons.

Table 2.21 J Test (Y) - Oil vs Heating Oil

	1	**5**	**Both**
h = 3	AK, ID, ND, NE*, NY*, WY	AL, AR, CA, CT, HI, IN, KY*, MA, MI, NH, NM*, NV*, OH, OR, SC, TN, VT	IA, WA
h = 6	AK*, MD, OK, WY	AL, AR, CA, GA, IN*, KY, MA, ME*, MI, NH*, NV, OH*, OR, RI*, SC, SD, TN, VT*, WA	HI
h = 12	AK*, ID, MD, OK*, WY	AR, CA, FL*, GA, HI, IA*, IL, MA*, ME*, MO*, NE, PA*, RI, SD*, TN*, VT*, WA, WI*	-

The findings of the J-test for economic activity indicate that energy states typically improve fit with the baseline model, but it is possible that model 2 or 3 improve fit at short-to-mid forecast horizons. In many instances, numerous manufacturing and tourism states have the best fit with alternative energy series, especially at shorter forecast horizons. Specifically, there is ample evidence of model 3 improving fit for tourism states, and model 5 improving fit for manufacturing and some states in New England.

Table 2.22 J Test (Y) - Oil vs Electricity

	1	**6**	**Both**
h = 3	AK, AZ, ME*, ND, OK*, OR, SC, WV*, WY	GA*, IL, IN*, KS, MI*, MN, NE, PA, WI*	AR, HI, IA, ID, KY, MD, OH
h = 6	AK, GA, HI*, ID, KY, MD, OH, OK, OR*, TN, WY	AR*, IA*, IL*, MN, NE	-
h = 12	AK, AR, FL, IA*, KY*, MA*, MD, NY, SC, WY*	MN*, MS*	ID

When applying the J-test to unemployment rates, the broad pattern of alternative models improving fit compared to the baseline model remains unchanged. The one alternative model that does not provide much benefit, either for economic activity or unemployment rates, is model 2. The results of the J-test for unemployment between oil and gasoline are found in Table 2.23 and show no meaningful difference between the models.

As was the case for economic activity, there is evidence of model 3 improving fit for numerous states, which can be seen in Table 2.24. At a forecast horizon of 3 months, model 3 is best for selected manufacturing states and even a top energy state of Wyoming. At a forecast horizon of 6 months, tourism states of Florida and Hawaii prefer model 3 as well. However, at longer forecast horizons there is no significant difference between the models.

Table 2.23 J-Test (U) - Oil vs Gasoline

	1	**2**	**Both**
h = 3	MT*, ND, NV*, RI*, WY*	FL, MN*, TX*, UT*, WV	-
h = 6	-	-	-
h = 12	KY, OR*, TN, WV*	-	DE

Table 2.24 J-Test (U) - Oil vs Diesel

	1	**3**	**Both**
h = 3	ID, OK	IN*, MI, OH*, OR, SC, VA*, VT, WY	-
h = 6	CO*, OK	FL, HI, MA*, MN, TN, WY	-
h = 12	MN*, OR*	NH*	AL

The results of the J-test between models 1 and 4 for the unemployment rate are found in Table 2.25. Model 1 improves fit for only a few states, many of which whose dominant industry is energy. The model including natural gas improves fit for many manufacturing states, which is an important input in the production process. As noted by Kilian (2007), natural gas accounts for 14.5 percent of energy used by producers. Another possible explanation for the states that prefer model 4 is that many of them have relatively cold winters and use more natural gas as a result.

Table 2.25 J-Test (U) - Oil vs Natural Gas

	1	4	Both
h = 3	IL, RI, WY	AL*, IN, MA*, MD*, ME*, MT*, NH, PA, SC, TN*, VA*, VT	AZ
h = 6	WY	AZ, IN, MA*, MI*, NH, PA, SD*	-
h = 12	CO*, MN, OR, WV*	ND, NH, OH*, PA*	-

Table 2.26 J-Test (U) - Oil vs Heating Oil

	1	5	Both
h = 3	CO*, NE, RI*, WV, WY*	CA*, IN*, MD, MN*, NC*, ND, OR*, SC, VT	OK
h = 6	OK, UT, WV*	FL, MD*, SC, SD*, TN, WI	MN
h = 12	MN*, OR	AZ, FL, MA, NH, NY, RI*, VT*	NC

Table 2.26 contains the results of the J-test between the baseline model and model 5, which includes heating oil. The findings are very similar to that of Table 2.25, with more states improving fit with the alternative energy series. The last J-test comparison is between model 1 and model 6, which can be found in Table 2.27. Interestingly, at a forecast horizon of 3 and 6 months, either model 6 or both models improve fit for energy states of Alaska, Oklahoma, North Dakota and Wyoming. At these short-to-mid forecast horizons, there is very limited evidence of the baseline model providing the best fit. However, at longer forecast horizons the usefulness of model 6 declines.

All of the alternative models, except model 2, outperform the baseline model containing oil, especially at short-to-mid forecast horizons. These findings are consistent with those of the J-test for economic activity, and should be considered moving forward in the energy price-macroeconomy literature.

Table 2.27 J Test (U) - Oil vs Electricity

	1	**6**	**Both**
h = 3	FL, OR, RI, WV	AK*, GA*, HI, IA, ID*, IL*, MA*, MS, MT, NE, OH, OK, PA, SC	ND, WY
h = 6	-	AR*, FL, GA*, IA, MS*, MT, ND*, OK	WY
h = 12	IN*, KY*, MN, OH, OR, WV	LA, MT*, NH, OK*	-

Conclusion

Individuals and businesses consume many different forms of energy, such as gasoline, natural gas and electricity. However, the energy price-macroeconomy literature widely uses the price of crude oil to model energy price shocks, even though Bachmeier and Griffin (2006) find that oil and alternative energy markets are only very weakly integrated. Therefore, I explore whether alternative energy price shocks impact the economy differently and produce better forecasts of economic activity than oil price shocks.

I discover that alternative energy series produce different patterns of impulse responses than the oil price series. Specifically, gasoline and diesel price shocks have more of a negative impact on tourism states than oil price shocks. Fewer states benefit from natural gas price shocks and industrial, Midwest states are hurt more compared to oil price shocks. States in New England, which are the preeminent users of heating oil, have a more negative response to heating oil price shocks. All of the energy price shocks produce both positive and negative responses across the U.S., except for electricity price shocks, which produce negative responses for nearly every state. Furthermore, numerous agricultural states are more negatively impacted by electricity price shocks compared to oil price shocks. Also, traditional steel and manufacturing states have a more detrimental response to electricity price shocks than oil price shocks, which is expected since electricity is an important input in the production process.

The results of the pseudo out-of-sample DM test reveal that in most scenarios, there is no significant difference between oil and the alternative energy series when forecasting economic activity. However, a handful of energy states produce better forecasts with the baseline model containing oil, while some tourism states produce better forecasts with the alternative models containing either gasoline or diesel.

The results of the in-sample J-test reveal that energy states typically improve fit with the baseline model, but it is possible that model 2 or 3 improve fit at short-to-mid forecast horizons. In many instances, numerous manufacturing and tourism states have the best fit with alternative energy series. Specifically, there is ample evidence of model 3 improving fit for tourism states, and model 5 improving fit for manufacturing states and some states in New England. The overwhelming evidence of the J-test indicates that alternative energy price models, excluding model 2, exceed the baseline model for many states, particularly at short-to-mid forecast horizons. However, the results clash with those from the DM test, which indicate limited evidence of alternative energy price series producing superior forecasts. Therefore, it is possible that alternative energy price series improve fit in-sample, but do not lead to better fit out-of-sample. Lastly, the results when using unemployment rates are similar, but the patterns are weaker.

This paper is the first to explore the effects of alternative energy price shocks on economic activity and whether they yield better forecasts of economic activity. My results showcase the importance of examining these alternative series, which produce different patterns of response following price shocks, and lead to improved fit for numerous states when compared to the baseline model containing oil. There is not one primary energy market and the price of oil is not a good proxy for many of the alternative energy prices. Therefore, implementing models with alternative energy prices should lead to a more accurate modeling of the energy price-macroeconomy relationship.

Chapter 3 - How Important is Oil Price Endogeneity?

Introduction

A very large literature has estimated the effect of oil price shocks on economic activity.[5] Until recently, it was common to treat oil price movements as if they were exogenous, in the sense that they were not driven by changes in the macroeconomy. Kilian (2009) cast doubt on the reasonableness of the assumption of exogenous oil price movements. He estimated a structural VAR model with shocks to the supply of oil, world economic activity, and the precautionary demand for oil,[6] and found that the response of the economy to a higher oil price is heavily dependent on the underlying reason for the change. A shock to world economic activity causes the price of oil and US GDP to rise. In contrast, a shock to the precautionary demand for oil causes the price of oil to rise but GDP to fall. In his words (page 1061), a thought experiment asking what happens to the macroeconomy after an unanticipated movement in the price of oil is "not well defined".

This essay attempts to quantify the importance of modeling the price of oil as an endogenous variable when the goal is to predict output. Little work has been done to show the implications in practical forecasting exercises of modeling oil price endogeneity. There are two reasons that explicitly modeling feedback from output to the price of oil may not lead to better forecasts of output, in spite of the impulse response functions reported in Kilian (2009). First, while a model with endogenous oil prices is more realistic, modeling feedback from output to the price of oil comes at the cost of having to estimate more parameters. Second, the mere presence of oil price endogeneity is not sufficient to justify the use of such a model for predicting output. If most oil price movements represent only a single structural shock, or if the relative variances of the different shocks that affect the price of oil are constant over the sample, a model with endogenous oil prices will offer no advantages over a model with exogenous oil prices.[7]

This essay uses state-level data on economic activity to compare the performance of models with feedback from output to the price of oil against models that treat the price of oil as

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[5] See Hamilton (2009) for a literature review.

[6] Precautionary oil demand shocks arise from the uncertainty about shortfalls of expected supply relative to expected demand.

[7] A related discussion is found in Kilian (2009, page 1068).

exogenous. There is much variation across the fifty US states in terms of industrial mix, reliance on exporting industries, and comovement with the world economy. By evaluating the predictive power of models with endogenous oil prices for all fifty states, we can gain a better understanding of the transmission of oil shocks to the economy. There may be patterns in the results that help us to understand when it is important to model oil price endogeneity, and when it is not.

We also do the analysis on different subsamples. The large fluctuations in oil prices in some time periods, such as 1979-1980, 1985-1986, and 1990-1991, are widely believed to be due to events that directly affected the oil market.[8] In other time periods, such as 2004-2009, it is believed that oil price changes were driven to a large extent by the world economy. A priori, there is no reason to expect models with endogenous oil prices to provide better predictions if most oil price fluctuations are due to oil market shocks.

Data and Models

Data

State-level economic activity is measured by using both the Coincident Economic Activity Index from the Federal Reserve Bank of Philadelphia from July 1979 to October 2011, and unemployment rates from the Bureau of Labor Statistics (BLS) from January 1976 to October 2011. According to the Federal Reserve Bank, the trend for each state's index is set to match the trend for gross state product. To ensure the data are stationary, standard transformations are used. More specifically, the first difference of the log level of the Coincident Economic Activity Index and the first difference of the state-level unemployment rate are taken. Consistent with Kilian (2009) measure of the price of oil, we use the Refiner Acquisition Cost of Crude Oil (RAC) from the Energy Information Administration (EIA) deflated by U.S. CPI from the Bureau of Labor Statistics (BLS) from January 1974 to December 2011 in log levels.

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[8] Kilian (2009) finds large "precautionary oil demand" shocks in these time periods, but that distinction is not important for the purposes of this paper, because we are evaluating the predictive power of endogenous oil price movements.

We also implement a three year Net Oil Price Increase (NOPI) index based off of the work of Hamilton (1996). Specifically, the three year NOPI from January 1977 to December 2011 can be represented as:

$$Oil_t^{36} = max\{0, Oil_t - max\{Oil_{t-1}, \ldots, Oil_{t-36}\}\}$$

where Oil_t is the log level of the deflated RAC series in period t.

In order to capture the exogenous and endogenous oil price shocks, we use the Real Economic Activity (REA) index from January 1976 to Decemeber 2011, which is available on Lutz Kilian's webpage[9], and world crude oil production data from January 1973 to October 2011 from the EIA. The first difference of the log level of the world crude oil production data is taken to ensure stationarity.

Models

The baseline forecasting model takes the form:

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j oil_{t-j} + \nu_{i,t} \quad (1)$$

where $x_{i,t}$ is economic activity in state i at time t, as measured by either the Coincident Economic Activity Index or the unemployment rate, oil_t is the percentage change in RAC from time $t-1$ to time t, and ρ is the lag length chosen by the Akaike information criteria (AIC). Equation (1) can be viewed as an equation from a bivariate VAR model of the macroeconomy and the price of oil. We use equation (1) as the baseline because all of the regressors are known at time t, and the price of oil is observed without a lag, making it suitable for real-time forecasting.

Although some authors have used linear VAR models, many other authors, building on the work of Hamilton (1996), have substituted the net oil price increase (NOPI) for Δoil. We consider a variation of equation (1) where the percentage change in the price of oil is replaced by NOPI:

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j nopi_{t-j} + \nu_{i,t} \qquad (2)$$

[9] http://www-personal.umich.edu/~lkilian/

where $nopi_t$ is constructed as described above. The model with $nopi$ as a regressor allows for a nonlinear response of output to oil shocks, but still treat the price of oil as predetermined. In order for us to conclude that explicitly modeling oil price endogeneity leads to better forecasts, we require that a model with endogenous oil prices fit better than each of equation (1) – (2).

We now turn to the models with endogenous oil prices. The first model decomposes the change in the price of oil into a component that is due to fluctuations in economic activity and a component that is due to other shocks.[10] To remove the endogenous component of oil prices, we run the regressions:

$$oil_t = \alpha + \sum_{j=1}^{\rho} \beta_j oil_{t-j} + \sum_{j=1}^{\rho} \gamma_j REA_{t-j} + \varepsilon_{ot}$$

where REA is Kilian's index of real economic activity at time t. From these regressions, the exogenous oil shock is the residual, ε_{ot}, which enters the model as:

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \, \widehat{\varepsilon_{ot}} + \nu_{i,t} \qquad (3)$$

It is important to emphasize that there is no a priori reason to believe that forecasts of output in any particular state will benefit from removing the endogenous oil price component. Oil prices have been shown to respond to changes in world output, which implies that oil price endogeneity is not an issue for forecasts of state economies that are weakly correlated with world output.

The second model follows Kilian (2009) in allowing for three shocks, an aggregate demand shock that affects the demand for oil, and two oil market shocks, one to the supply of oil, and one to the precautionary demand for oil. We estimate the reduced form VAR model:

$$prod_t = \alpha_1 + \sum_{j=1}^{\rho} \beta_j prod_{t-j} + \sum_{j=1}^{\rho} \gamma_j REA_{t-j} + \sum_{j=1}^{\rho} \delta_j oil_{t-j} + e_{pt}$$

[10] Kilian (2009) allows for both “oil supply shocks” and “precautionary demand shocks”. What we call the “oil market shock” here includes both of Kilian's shocks. Both the oil supply shock and the precautionary demand shock should have similar implications for state-level output, as both represent an increase in the price of oil that is not a response to output. We consider the two shocks separately below.

$$REA_t = \alpha_1 + \sum_{j=1}^{\rho} \beta_j prod_{t-j} + \sum_{j=1}^{\rho} \gamma_j REA_{t-j} + \sum_{j=1}^{\rho} \delta_j oil_{t-j} + e_{rt}$$

$$oil_t = \alpha_1 + \sum_{j=1}^{\rho} \beta_j prod_{t-j} + \sum_{j=1}^{\rho} \gamma_j REA_{t-j} + \sum_{j=1}^{\rho} \delta_j oil_{t-j} + e_{ot}$$

where $prod$ is the percentage change in world crude oil production. Using a recursive ordering for identification, following Kilian (2009), we compute the three shocks. The oil supply shock, $\varepsilon_t^{oil\ supply}$, is equal to the residual of the equation for $prod_t$. The aggregate demand shock, $\varepsilon_t^{aggregate\ demand}$, is the residual from a regression of e_{rt} on e_{pt}. The oil specific demand shock, $\varepsilon_t^{oil\ demand}$, is the residual from a regression of e_{ot} on e_{rt} and e_{pt}.

The three identified shocks are then used as predictors:

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ supply} + \nu_{i,t} \qquad (4)$$

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{aggregate\ demand} + \nu_{i,t} \qquad (5)$$

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ demand} + \nu_{i,t} \qquad (6)$$

The final model in our comparison is:

$$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ supply} + \sum_{j=1}^{\rho} \delta_j \varepsilon_t^{aggregate\ demand}$$

$$+ \sum_{j=1}^{\rho} \omega_j \varepsilon_t^{oil\ demand} + \nu_{i,t} \qquad (7)$$

which is a larger model containing all of the endogenous oil price shocks. All models and whether they account for endogeneity are represented in Table 3.1.

Table 3.1 List of Models

Model	Estimation Equation	Endogeneity (Yes/No)
M1	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j oil_{t-j}$	No
M2	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j nopi_{t-j}$	No
M3	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \widehat{\varepsilon_{ot}} + \nu_{i,t}$	Yes
M4	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ supply} + \nu_{i,t}$	Yes
M5	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{aggregate\ demand} + \nu_{i,t}$	Yes
M6	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ demand} + \nu_{i,t}$	Yes
M7	$x_{i,t} = \alpha + \sum_{j=1}^{\rho} \beta_j x_{i,t-j} + \sum_{j=1}^{\rho} \gamma_j \varepsilon_t^{oil\ supply} + \sum_{j=1}^{\rho} \delta_j \varepsilon_t^{aggregate\ demand} + \sum_{j=1}^{\rho} \omega_j \varepsilon_t^{oil\ demand} + \nu_{i,t}$	Yes

Results

Selection of Models

The first step is to select the models for comparison. For each state, the model that does not allow for endogenous oil prices is the one out of M1 and M2 that has the lowest associated Akaike information criteria (AIC) value, while the model that allows for endogenous oil prices is the one out of M3 through M7 with the lowest AIC value. The AIC for all models is reported in Table 3.2, with the selected models in boldface. For a majority of states, the model with NOPI shocks was selected over the model with the change in the price of oil. Among the models that allow the price of oil to be endogenous, M7, which includes the aggregate demand, oil supply, and precautionary oil demand shocks, is never selected. The additional parameter estimation error from the larger model is never offset with a sufficiently large improvement in the fit. We note that the AIC is a criterion that is biased toward the selection of large models.[11] In the vast majority of cases, the model selected is M5, which uses only the aggregate demand shock.[12]

J-test

The J-test is a test of the null hypothesis that nothing is lost by ignoring the variables in model M_A when one is working with model M_O. Assume the regressors in M_O are x_O and the regressors in M_A are x_A. Davidson and MacKinnon (1981) recommended the following strategy:

1. Estimate the model M_A. Get the fitted values of that model. Call the fitted values $\widehat{y_M}$.
2. Estimate model M_O by regressing on x_O and $\widehat{y_M}$.
3. Do a t-test of the null hypothesis that the coefficient on $\widehat{y_M}$ is zero. If you reject, conclude that the variables in x_A belong in M_O.

For our analysis, we do two J-tests. The first sets the null model M_O to be the model that does not have endogenous oil prices and the alternative model M_A to be the model that allows the price of oil to be endogenous. The second switches M_O and M_A. A rejection of the null hypothesis for the first comparison implies that allowing for endogeneity improves the fit of the output model for a particular state. A rejection for the second comparison implies that something is lost by accounting for only some oil price movements.

The J-test results for each state are presented in Table 3.3. Column 2 is the test statistic for the null hypothesis that the model with endogeneity contributes nothing to the model without endogeneity. Column 3 is the test statistic for the converse. For most states, we reject both null hypotheses. The most basic interpretation of these results is that it is important to account for the behavior of oil prices when modeling state-level output. The rejection of both null hypotheses for most states would not happen if there was not a strong relationship between the price of oil and output. In addition, there are significant benefits to decomposing oil price movements into oil supply shocks and oil demand shocks. It is necessary to use a joint model of oil price

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[11] Andrews (1999) has shown that the AIC asymptotically overselects the number of regressors.

[12] Using only the aggregate demand shock is not the same as using an index of world output for prediction. The aggregate demand shock is an identified VAR shock that requires data on the price and production of oil. M3 uses only the index of world output and is selected in only two cases.

Table 3.2 AIC for All Models

	M1	M2	M3	M4	M5	M6	M7
AK	**-4105.4**	-4100.8	-4051.1	-4104.2	**-4107.7**	-4105.7	4104.9
AL	-4156.7	**-4157.5**	-4102.9	-4155.8	**-4159**	-4154.4	-4156.5
AR	**-5669.4**	-5668.6	-5595.8	-5667	-5668.9	**-5669.6**	-5654.9
AZ	-4031.1	**-4031.3**	-3981.3	-4030.6	-4028.4	**-4031**	-4021.8
CA	-4344.8	**-4350.4**	-4291.3	-4343.3	-4342.4	**-4343.4**	-4334.3
CO	**-3884.1**	-3880.8	-3827.3	-3879.7	**-3883.8**	-3879.7	-3877.4
CT	-4961.7	**-4972.9**	-4901.2	-4961.4	**-4967.4**	-4961.2	-4956.3
DE	-4954.5	**-4956.3**	-4908.8	**-4956.6**	-4953.3	-4954.5	-4952.1
FL	-4606	**-4609.6**	-4539.5	**-4604**	-4604	-4603	-4601.2
GA	-5292	**-5293.9**	-5227.2	**-5297**	-5296.1	-5291.9	-5292.9
HI	-4230.5	**-4231.3**	-4171.1	**-4232.4**	-4223.7	-4226.9	-4224
IA	-4219.8	**-4222.6**	-4165.9	-4220.5	**-4227.4**	-4217.4	-4224.5
ID	**-5198**	-5197.4	-5149.3	-5190.9	-5187.1	**-5191.8**	-5185.8
IL	-4148.5	**-4150.4**	-4110.2	-4150.5	**-4161.6**	-4146	-4151.9
IN	-4672.1	**-4675.2**	-4621.5	-4668.2	**-4673.7**	-4669.1	-4663.2
KS	**-3833**	-3831.6	-3787.9	-3830	**-3845.2**	-3828.6	-3832.4
KY	-5267.9	**-5275.6**	-5214.1	**-5272**	-5265.3	-5266.8	-5264.7
LA	-3402.5	**-3409**	-3357.4	-3399.2	**-3410.6**	-3401.3	-3401.6
MA	-4066.8	**-4076.7**	-4013.6	-4066.5	**-4068.7**	-4066.3	-4061
MD	**-5543.6**	-5541.9	-5479.1	-5540.1	**-5543.7**	-5542.1	-5535.2
ME	-3662.8	**-3672.4**	-3611.7	-3664.2	**-3665.3**	-3662.8	-3659
MI	-4303	**-4306.4**	-4255.5	-4296.5	**-4304.2**	-4303.9	-4293.8
MN	**-3807.2**	-3802.6	-3752.7	-3801	**-3803.5**	-3799.9	-3795.3
MO	-4403.8	**-4411.2**	-4351.6	-4403.2	**-4414.1**	-4403.9	-4404.6
MS	-3775	**-3787.8**	-3720.3	-3772.6	**-3777.3**	-3772.1	-3771.3
MT	**-4478.2**	-4472.5	-4424.2	-4470.7	-4471.8	**-4472.9**	-4466.7
NC	-4987.4	**-4989.7**	-4926.8	-4988	**-4989.3**	-4987.3	-4981
ND	-4982.9	**-4984.7**	-4925.8	-4977.9	-4980.4	**-4981.8**	-4977.1
NE	**-3909.1**	-3907	-3870.8	-3909.1	**-3912.2**	-3902.8	-3905.5
NH	-5470.1	**-5471.6**	-5402.2	-5473.6	**-5475.2**	-5470.8	-5464.1
NJ	-5263.5	**-5266.8**	-5212	**-5266.1**	-5263.8	-5263	-5255
NM	-4345.1	**-4349.1**	-4294.5	-4347.7	**-4350.1**	-4345.1	-4347.6
NV	**-4922**	-4918.5	-4860.4	**-4915.2**	-4912.5	-4914.3	-4905.1
NY	-5517.8	**-5522.3**	-5459.1	-5514.4	-5515	**-5520.3**	-5508.9
OH	-4243.7	**-4253.5**	-4215.8	-4243.3	**-4249**	-4241.1	-4240.3
OK	-3883.4	**-3883.5**	-3829.6	-3883.4	**-3885.8**	-3884.4	-3883
OR	**-4784.1**	-4780.1	-4733.5	-4776.9	**-4786.2**	-4774.9	-4777
PA	-3888.6	**-3894.8**	-3839.4	-3886.2	**-3892.1**	-3887.8	-3878.8
RI	-3981.1	**-3990.5**	-3929.1	-3981.6	**-3981.7**	-3981	-3974.6
SC	-4099.7	**-4102.2**	-4048.3	-4094.1	**-4099**	-4098.6	-4091.3
SD	**-3931.9**	-3930	-3891.9	-3928.4	**-3930.6**	-3929.2	-3928.5
TN	-5225.1	**-5227**	-5157.9	**-5229.9**	-5227.7	-5222	-5226.3
TX	**-5707.4**	-5706.3	-5637.9	-5713.3	**-5716.4**	-5708.1	-5709.9
UT	-4929	**-4933.9**	-4867.3	**-4927.7**	-4926.6	-4926.6	-4924.2
VA	-5100	**-5105.4**	-5036.3	-5097	-5097.7	**-5099.4**	-5095.3
VT	-4043.3	**-4049.8**	-3996.1	-4044.8	**-4048.8**	-4045.2	-4044.4
WA	**-4061.8**	-4059.6	-4016.6	-4054.4	-4058	**-4059.4**	-4053.8
WI	-5188.7	**-5190**	-5135.1	-5187.8	**-5190.2**	-5183.3	-5180.3
WV	**-3342.4**	-3333	-3302.1	-3336.5	-3336	**-3337.8**	-3335
WY	**-3636.6**	-3624.4	-3579.8	-3625	**-3633.3**	-3628.5	-3630.9

movements and world output as in Kilian (2009) in order to make full use of the information in oil prices. We reject for most states the null hypothesis that a model with only oil demand shocks is sufficient for predicting output, suggesting the price of oil has value for predicting output beyond the aggregate demand shock.

The results in Table 3.3 do not provide any information about the economic significance of the differences in the models. To capture that, we look at two measures of the effect on forecasts. First, we report the mean absolute difference of (in-sample) predictions of the two models. Second, we do out-of-sample forecast comparisons for the period 1996-2011 to see if one of the models would have systematically produced forecasts that were more accurate than the other. We test for significance of the difference in mean squared forecast error (MSE) using the Diebold and Mariano (1995, DM) test.

Figure 3.1 is a plot of the mean absolute difference in (in-sample) predictions of output for the two models, for each state. There is much variation across states. For some, like Arkansas, Maryland, Texas and New Hampshire, there are almost no differences in the predictions of the two models. In other states, like Vermont, Wyoming and Louisiana, they are very different. In the case of Louisiana, the two predictions differ, on average, by more than half a percentage point.

In Table 3.4 are the ratios of MSE for the two models and associated DM statistics at forecast horizons of h = 1, 3, and 12 months. Suppose you have a vector e_1 of forecast errors from model 1 and a vector e_2 of forecast errors from model 2. The loss differential series is defined by $d_t = e_{1t} - e_{2t}$. The DM test is a test of the null hypothesis that the two models produce equally accurate forecasts. It can be implemented by estimating the regression:

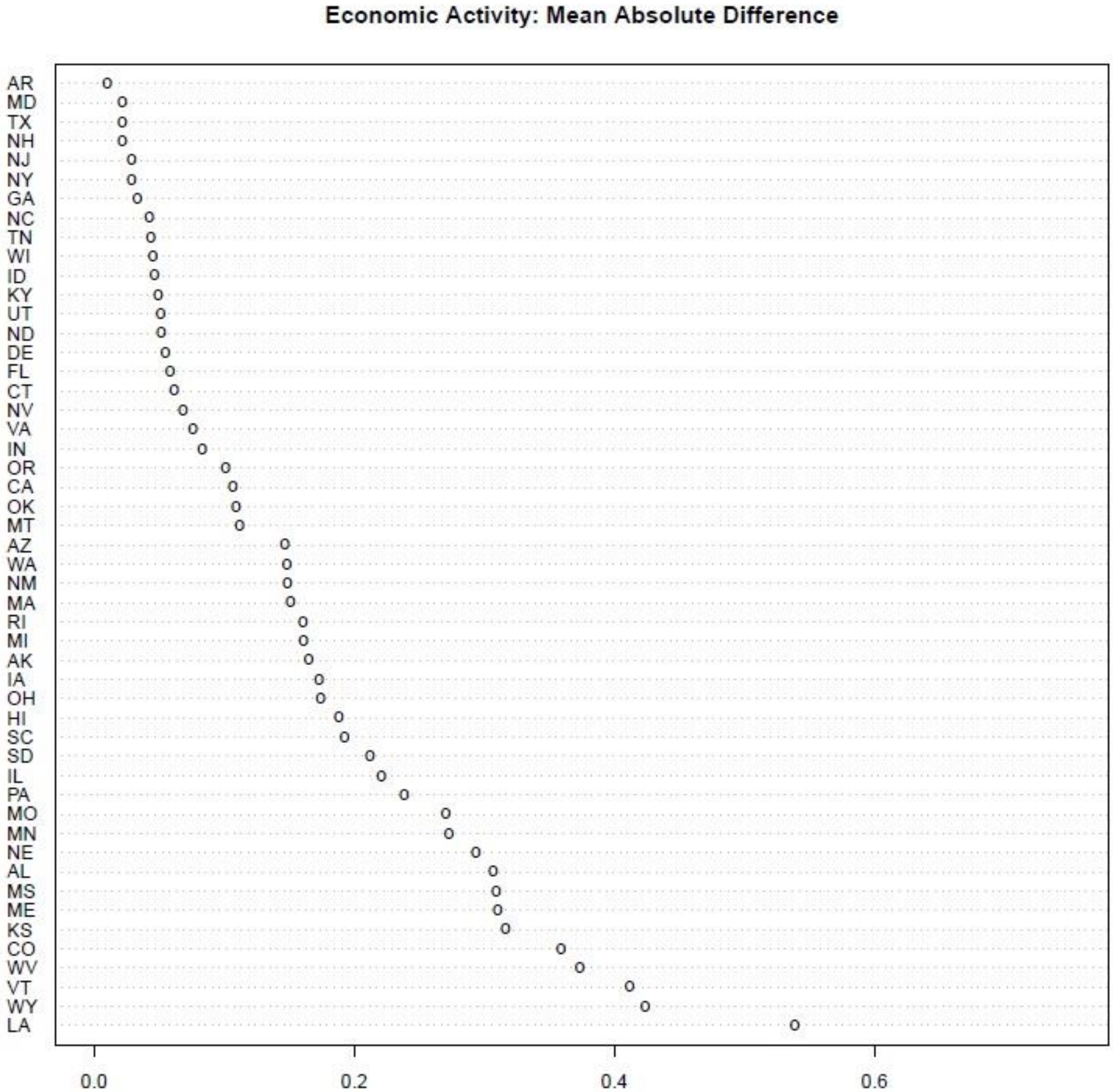
$$d_t = \alpha + \varepsilon_t$$

and testing $H_o\colon \alpha = 0$. Because the models are nonnested, that hypothesis can be tested using the Newey-West t-statistic for $\hat{\alpha}$ (West 1996).

Table 3.3 Economic Activity: J-test

State	Adding Endogeneity	Adding Oil
AK	2.33	2.16
AL	1.13	4.44
AR	1.79	0.64
AZ	2.36	2
CA	1.32	3.52
CO	3.89	2.05
CT	2.1	4.09
DE	3.04	3.21
FL	1.23	2.86
GA	2.55	2.23
HI	4.29	4.19
IA	2.96	3.45
ID	0.76	3.38
IL	3.87	2.51
IN	2.19	2.44
KS	1.99	1.27
KY	2.54	4.45
LA	2.23	1.07
MA	1.49	3.97
MD	2.76	1.91
ME	2.27	3.25
MI	2.88	3.74
MN	2.13	2.22
MO	2.99	3.7
MS	2.2	1.92
MT	2.08	2.84
NC	1.78	2.63
ND	2.18	2.44
NE	3.01	2.44
NH	2.61	1.83
NJ	1.98	1.65
NM	2.81	2.47
NV	1.42	2.79
NY	2.75	3.26
OH	3.45	2.97
OK	1.57	0.39
OR	3.83	2.96
PA	1.87	3.75
RI	1.08	3.49
SC	2.21	3.65
SD	1.37	1.9
TN	2.98	3.46
TX	3.6	1.34
UT	2.6	7.48
VA	1.25	5.3
VT	6.72	4.1
WA	1.38	2.05
WI	2.38	3.13
WV	0.85	1.9
WY	2.82	2.85

Figure 3.1 Economic Activity: Mean Absolute Difference



It is clear from Table 3.4 that the difference in forecast performance of two models is not statistically significant for most states. In fact, over all three horizons, we reject the null hypothesis of equal predictive ability 5% of the time - exactly what we should expect under the null hypothesis of equal forecast accuracy. For almost all states and forecast horizons, the mean squared forecast error of the two models are within 10% of one another. Overall, from an out-of-sample forecasting perspective, it is hard to argue for one model over the other. You do not lose anything by complicating the model to accommodate feedback from output to the price of oil, but at the same time, you do not gain anything.

This appears to conflict with the results of the J-tests reported in Table 3.3.[13] Yet it is consistent with other results in the forecasting literature. Improving out-of-sample forecasts is much more difficult than improving in-sample fit, due to parameter estimation error, structural instability, and model misspecification. In-sample and out-of-sample predictability tests are distinct methods of model evaluation (see e.g. Inoue and Kilian (2005) and Campbell and Thompson (2008)). It is not uncommon for significant in-sample predictability to not translate into improved out-of-sample forecasts.

Tables 3.5 and 3.6 and Figure 3.2 repeat the analysis substituting the unemployment rate for the economic activity index. The results are similar to those for output. In most cases, the J-test rejects for both models. There is much variation in the mean absolute difference of the model predictions. The difference is close to zero in several states but greater than 0.7 percentage points for Louisiana and Utah. The out-of-sample forecasts have similar MSE and rarely does the DM test reject the null of equal predictive ability.

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[13] Technically, that is not true. The J-test is analogous to a test for forecast encompassing (Fair and Shiller 1990).

Table 3.4 Economic Activity: OOS Forecast Evaluation

	h=1		h=3		h=12	
State	MSE Ratio	DM Statistic	MSE Ratio	DM Statistic	MSE Ratio	DM Statistic
AK	1.01	0.24	1.15	1.17	0.98	-0.38
AL	1.03	0.81	1.03	0.47	0.95	-1.58
AR	1.02	0.65	1.1	1.31	0.96	-0.38
AZ	0.92	-1.28	0.97	-0.41	0.95	-0.59
CA	1.03	0.61	1.03	0.49	0.93	-1.81
CO	1.05	0.68	1.15	1.07	0.95	-1.27
CT	1.01	0.2	1.09	0.92	0.96	-1.52
DE	1.4	2.57	1.03	0.66	1.03	0.92
FL	0.98	-0.49	1	-0.12	0.91	-1.47
GA	0.99	-0.2	0.96	-1.33	0.96	-1.78
HI	1	0.27	1	0.04	0.95	-1.28
IA	1.03	3.07	1	-0.13	1	0.03
ID	1.04	0.92	1.01	0.24	1	0.13
IL	1.1	1.61	1.12	1.44	0.99	-0.14
IN	1.1	0.94	1.13	0.94	0.93	-2.2
KS	1.04	0.37	1.05	0.41	1.03	1.25
KY	1.01	0.13	1.04	0.34	0.99	-0.86
LA	0.94	-0.99	0.95	-1.19	1.01	0.21
MA	0.98	-0.47	0.99	-0.16	0.92	-2.59
MD	1	0.02	1.03	0.68	1.03	1.5
ME	1.07	0.77	1.18	1.14	1.03	1.3
MI	1.03	0.79	1.13	1.43	1.03	1.12
MN	1.11	1.45	1.17	1.57	1.03	0.61
MO	1.05	0.72	1.04	0.49	1.02	1.04
MS	0.96	-1.01	0.99	-0.52	1	-0.05
MT	1.02	0.77	0.95	-1.11	0.91	-1.59
NC	1.02	0.23	1.11	0.85	0.97	-1.67
ND	1.05	1.46	1.2	2.03	1.05	1.12
NE	1.06	0.99	1.09	0.9	1.06	1.72
NH	1.01	0.27	1.09	1.55	0.95	-1.99
NJ	1.02	0.3	1.08	0.96	0.99	-0.38
NM	0.97	-0.63	0.97	-0.5	1.02	0.56
NV	1.01	0.19	0.95	-0.76	0.9	-0.69
NY	1.04	0.71	1.24	2.18	0.93	-1.74
OH	1.02	0.26	1.09	0.76	0.96	-0.18
OK	1.05	0.62	1.05	0.6	1.03	0.15
OR	1.06	1.07	1.02	0.33	0.95	-0.54
PA	0.94	-0.91	0.98	-0.25	0.83	-2.14
RI	0.99	-0.53	0.99	-0.45	0.91	-1.85
SC	1.1	1.73	1.12	1.53	0.97	-0.79
SD	1.05	0.55	1.11	1.03	1.02	1.47
TN	1.14	1.44	1.17	1.38	0.96	-1.29
TX	1.04	1.18	1.04	0.67	0.97	-0.21
UT	1.06	0.5	0.93	-1.26	0.94	-0.77
VA	1	-0.05	1.09	0.81	0.92	-1.53
VT	1.13	1.4	1.25	1.3	1.09	1.18
WA	1.12	1.28	1.2	1.61	0.92	-1.3
WI	0.72	-1.78	0.94	-0.5	0.86	-1.62
WV	0.97	-0.77	0.94	-0.87	0.86	-0.61
WY	1.04	0.78	0.94	-0.54	0.99	-0.03

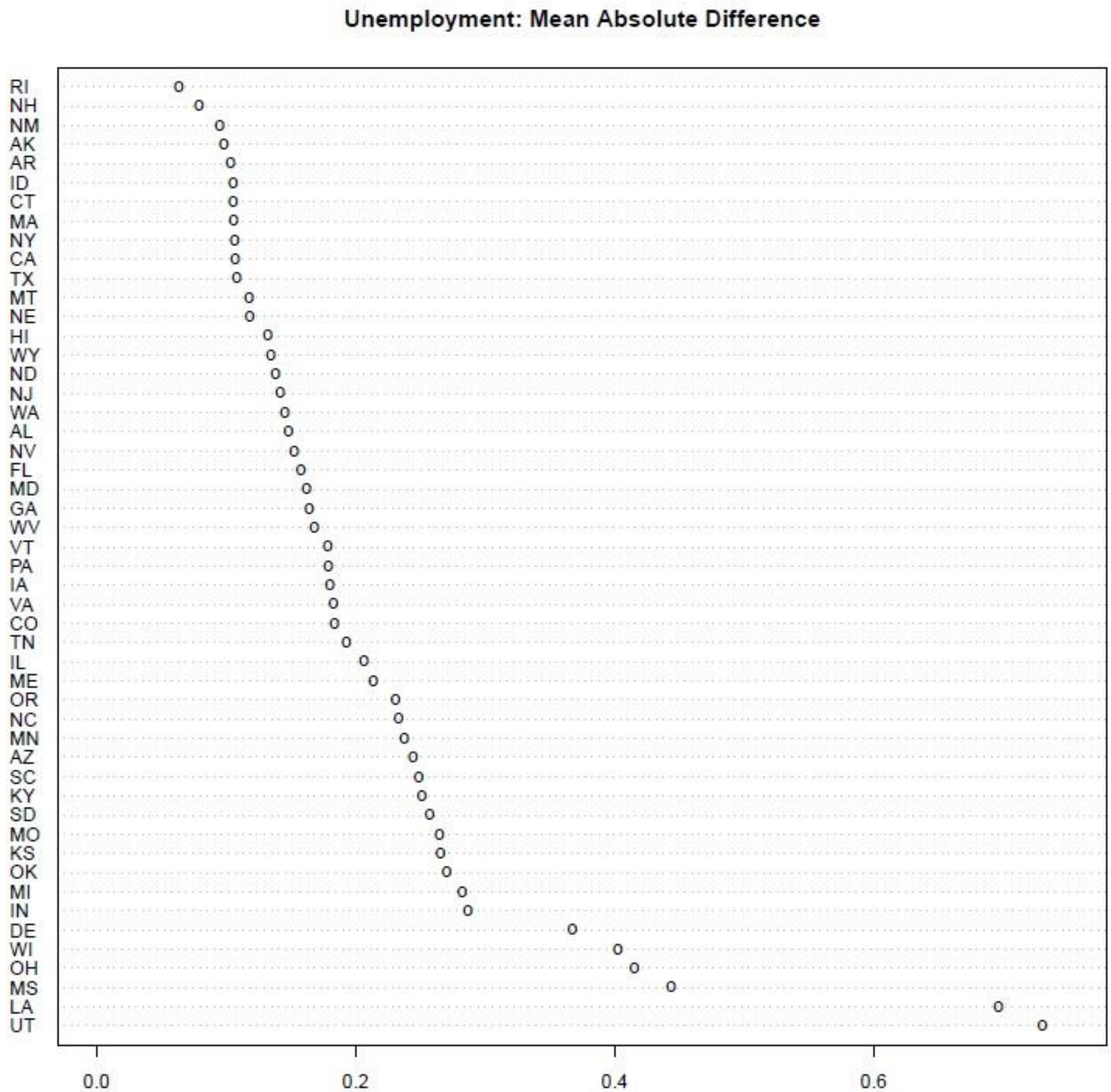
Table 3.5 Unemployment: J-test

State	Adding Endogeneity	Adding Oil
AK	2.03	3.12
AL	2.54	4.02
AR	1.63	2.02
AZ	0.94	1.31
CA	2.11	2.06
CO	4.83	2.47
CT	1.93	3.88
DE	1.24	1.32
FL	2.29	2.68
GA	1.42	2.55
HI	2.86	1.94
IA	1.79	2.24
ID	2.44	2.73
IL	5.22	1.47
IN	2.26	2.54
KS	1.95	0.75
KY	4.19	5.88
LA	0.72	1.21
MA	2.80	4.10
MD	2.70	1.95
ME	2.06	5.37
MI	3.34	2.95
MN	3.05	1.02
MO	2.29	0.95
MS	1.86	1.51
MT	3.42	1.25
NC	3.06	2.87
ND	3.94	2.89
NE	3.80	0.97
NH	1.51	2.77
NJ	3.74	1.85
NM	2.55	2.54
NV	4.01	2.83
NY	1.84	2.65
OH	1.77	2.89
OK	4.42	5.34
OR	7.28	4.83
PA	1.88	2.96
RI	1.72	2.05
SC	5.68	1.90
SD	2.18	1.30
TN	3.66	2.59
TX	2.31	1.43
UT	1.94	1.37
VA	3.98	2.59
VT	3.10	3.49
WA	3.03	1.47
WI	3.68	1.74
WV	2.90	3.26
WY	2.80	2.12

Table 3.6 Unemployment: OOS Forecast Evaluation

	h=1		h=3		h=12	
State	**MSE Ratio**	**DM Statistic**	**MSE Ratio**	**DM Statistic**	**MSE Ratio**	**DM Statistic**
AK	1.01	0.24	1.15	1.17	0.98	-0.38
AL	1.03	0.81	1.03	0.47	0.95	-1.58
AR	1.02	0.65	1.1	1.31	0.96	-0.38
AZ	0.92	-1.28	0.97	-0.41	0.95	-0.59
CA	1.03	0.61	1.03	0.49	0.93	-1.81
CO	1.05	0.68	1.15	1.07	0.95	-1.27
CT	1.01	0.2	1.09	0.92	0.96	-1.52
DE	1.4	2.57	1.03	0.66	1.03	0.92
FL	0.98	-0.49	1	-0.12	0.91	-1.47
GA	0.99	-0.2	0.96	-1.33	0.96	-1.78
HI	1	0.27	1	0.04	0.95	-1.28
IA	1.03	3.07	1	-0.13	1	0.03
ID	1.04	0.92	1.01	0.24	1	0.13
IL	1.1	1.61	1.12	1.44	0.99	-0.14
IN	1.1	0.94	1.13	0.94	0.93	-2.2
KS	1.04	0.37	1.05	0.41	1.03	1.25
KY	1.01	0.13	1.04	0.34	0.99	-0.86
LA	0.94	-0.99	0.95	-1.19	1.01	0.21
MA	0.98	-0.47	0.99	-0.16	0.92	-2.59
MD	1	0.02	1.03	0.68	1.03	1.5
ME	1.07	0.77	1.18	1.14	1.03	1.3
MI	1.03	0.79	1.13	1.43	1.03	1.12
MN	1.11	1.45	1.17	1.57	1.03	0.61
MO	1.05	0.72	1.04	0.49	1.02	1.04
MS	0.96	-1.01	0.99	-0.52	1	-0.05
MT	1.02	0.77	0.95	-1.11	0.91	-1.59
NC	1.02	0.23	1.11	0.85	0.97	-1.67
ND	1.05	1.46	1.2	2.03	1.05	1.12
NE	1.06	0.99	1.09	0.9	1.06	1.72
NH	1.01	0.27	1.09	1.55	0.95	-1.99
NJ	1.02	0.3	1.08	0.96	0.99	-0.38
NM	0.97	-0.63	0.97	-0.5	1.02	0.56
NV	1.01	0.19	0.95	-0.76	0.9	-0.69
NY	1.04	0.71	1.24	2.18	0.93	-1.74
OH	1.02	0.26	1.09	0.76	0.96	-0.18
OK	1.05	0.62	1.05	0.6	1.03	0.15
OR	1.06	1.07	1.02	0.33	0.95	-0.54
PA	0.94	-0.91	0.98	-0.25	0.83	-2.14
RI	0.99	-0.53	0.99	-0.45	0.91	-1.85
SC	1.1	1.73	1.12	1.53	0.97	-0.79
SD	1.05	0.55	1.11	1.03	1.02	1.47
TN	1.14	1.44	1.17	1.38	0.96	-1.29
TX	1.04	1.18	1.04	0.67	0.97	-0.21
UT	1.06	0.5	0.93	-1.26	0.94	-0.77
VA	1	-0.05	1.09	0.81	0.92	-1.53
VT	1.13	1.4	1.25	1.3	1.09	1.18
WA	1.12	1.28	1.2	1.61	0.92	-1.3
WI	0.72	-1.78	0.94	-0.5	0.86	-1.62
WV	0.97	-0.77	0.94	-0.87	0.86	-0.61
WY	1.04	0.78	0.94	-0.54	0.99	-0.03

Figure 3.2 Unemployment: Mean Absolute Difference



Subsample Analysis

It is implausible that oil price endogeneity is equally important for all observations. There is likely to be little benefit from accounting for endogeneity in times when oil price movements are the result of shocks to the supply of oil, as in 1979. Working with the full sample may hide the importance of global aggregate demand shocks during time periods such as 2004-2009. This section redoes the analysis for two periods. One is a group of oil market shocks that includes all observations from the years 1979-1980 (overthrow of the Shah in Iran), 1985-1986 (the breakdown of the OPEC cartel and its aftermath), and 1990-1991 (first Gulf War). The other is a period of global aggregate demand shocks from 2004-2009.[14]

Table 3.7 shows J-test results for the two subsamples. As expected, the J-test finds that the model with exogenous oil price shocks is important in periods with large oil market shocks. The J-test statistics in column 3 are larger than 1.96 for nearly all states, and in many cases, much larger. On the other hand, for the 2004-2009 period, the null hypothesis that the model with endogenous oil prices contributes nothing is rejected for almost all states. Many of the J-test statistics for that comparison (column 4) are much larger than 1.96. This supports the notion that the decision of whether or not one should account for endogeneity depends on the economic environment at that time.

In Figure 3.3 and 3.4 are plots of the mean absolute differences of predictions for the two models over the two time periods. Unlike the case for the full subsample, there are large differences in predictions for most states over the two time periods, particularly for the 2004-2009 period which can be thought of as oil price shocks caused by a growing global economy. The decision to model oil price endogeneity matters much more in these two periods than for the rest of the sample.

[14] Kilian (2009, p. 1066) emphasizes the importance of identifying the causes of specific oil price movements.

Table 3.7 Subsample J-test

	Supply Shocks		2004-2009	
State	Adding Endogeneity	Adding Oil	Adding Endogeneity	Adding Oil
AK	2.30	2.48	0.86	3.27
AL	0.23	4.87	0.72	7.29
AR	3.99	2.14	3.28	5.14
AZ	3.51	5.06	3.59	1.97
CA	1.86	2.32	3.19	2.48
CO	2.88	1.37	2.65	1.71
CT	0.59	4.24	4.42	3.90
DE	1.92	0.84	3.48	2.44
FL	1.01	7.58	3.98	2.30
GA	1.62	0.92	5.56	2.31
HI	2.15	6.70	3.56	2.76
IA	1.13	1.64	4.36	1.65
ID	1.77	3.48	2.27	2.82
IL	4.35	1.30	4.82	2.48
IN	3.01	1.10	2.31	1.81
KS	0.49	1.91	2.10	2.46
KY	2.78	5.11	4.49	5.45
LA	2.91	1.52	1.93	1.20
MA	1.95	3.19	1.51	2.48
MD	1.97	4.34	2.57	1.60
ME	3.81	2.49	1.94	4.00
MI	1.97	2.59	2.31	2.83
MN	2.97	7.45	9.90	3.57
MO	1.54	2.80	3.35	1.89
MS	0.99	1.88	2.21	2.15
MT	0.71	0.82	1.42	2.59
NC	2.31	1.30	3.17	1.29
ND	3.64	2.03	3.49	1.35
NE	2.34	1.75	3.49	2.39
NH	2.33	5.02	4.29	2.61
NJ	2.89	1.58	2.29	2.18
NM	6.65	2.32	2.91	2.60
NV	2.83	1.91	1.97	2.89
NY	4.67	6.37	3.17	1.31
OH	2.03	1.93	1.39	2.43
OK	4.18	-0.17	1.42	0.39
OR	1.43	0.98	7.11	2.15
PA	1.65	2.07	2.54	2.15
RI	1.19	3.10	3.44	2.01
SC	2.63	2.32	6.40	2.26
SD	1.86	1.27	2.22	1.87
TN	1.31	2.09	2.30	1.49
TX	1.88	2.81	5.08	1.08
UT	2.82	3.18	1.81	2.58
VA	1.76	3.72	3.33	2.15
VT	2.26	5.99	4.25	5.14
WA	5.45	1.50	3.02	3.50
WI	0.69	4.19	4.57	2.93
WV	2.52	2.63	3.64	0.54
WY	4.07	2.71	2.97	6.83

Figure 3.3 Subsample Supply Shocks: Mean Absolute Difference

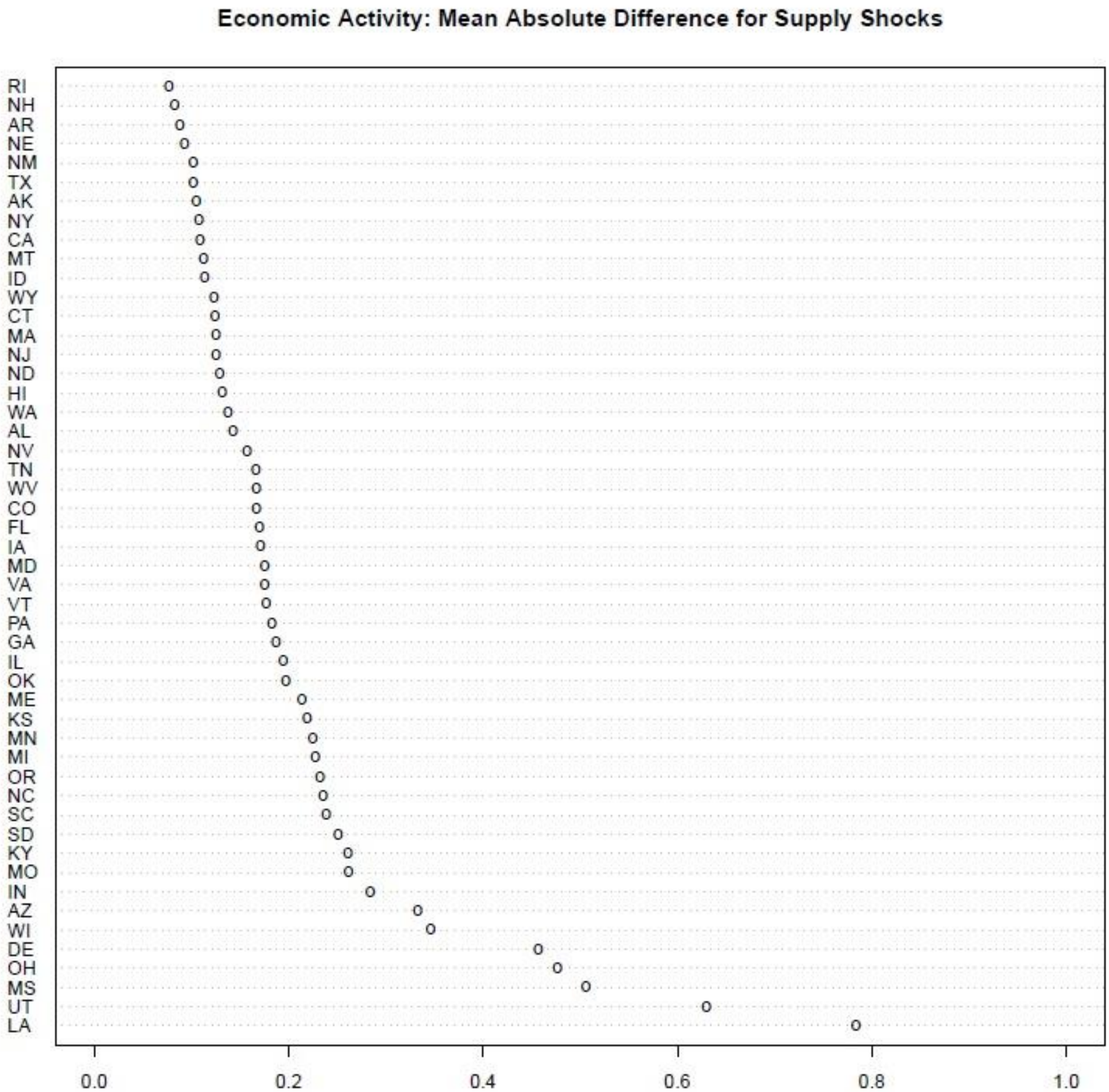
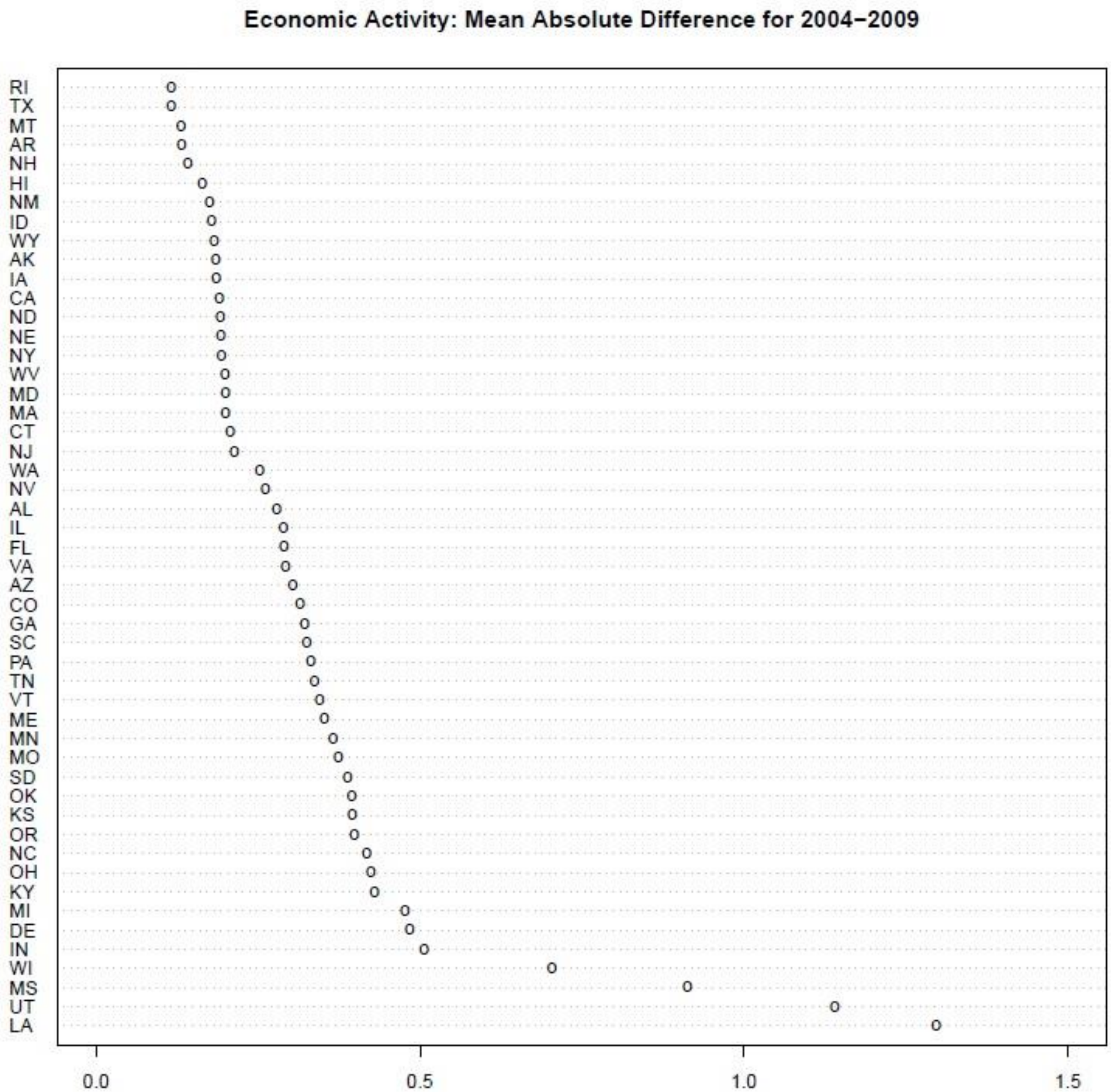


Figure 3.4 Subsample 2004-2009: Mean Absolute Difference



Conclusion

This essay has evaluated the performance of models of state-level output that explicitly model the feedback from output to the price of oil. The results are heavily dependent on the choice of in-sample fit versus out-of-sample forecast accuracy as the relevant metric. In terms of in-sample fit, and consistent with Kilian (2009), we conclude that it is better in most cases to construct a more complicated model of output that decomposes oil price movements into world aggregate demand, oil supply, and oil market shocks. On the other hand, when the models are judged on the basis of out-of-sample forecast accuracy, there is rarely an advantage to using the more complicated model - a simple model that includes only the change in the price of oil delivers forecasts that are just as accurate.

A subsample analysis looked at the predictions of state-level output in periods with large oil market shocks and large aggregate demand shocks. In line with expectations, we found that the oil price change is a valuable predictor in the first subsample, and the endogenous oil movement is a valuable predictor in the second subsample.

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Appendix A - Chapter 2

Unemployment DM Tests

Table A.1 DM Test (U) - Oil vs Gasoline

	1	2
h = 3	WI	MA*
h = 6	-	MA, ND
h = 12	-	GA*, MA*, NY*

Table A.2 DM Test (U) - Oil vs Diesel

	1	3
h = 3	NJ, WV	-
h = 6	NJ*, WA, WV	ID*
h = 12	HI*, IA	IL

Table A.3 DM Test (U) - Oil vs Natural Gas

	1	4
h = 3	CA*, DE, GA*, ID*, MO*, NV, PA, SD*	-
h = 6	AR, DE, GA, HI, ID*, IN, MT*, NC*, NV*, PA	MA*
h = 12	AR, GA, MO*, OH, PA, TX*, WV	-

Table A.4 DM Test (U) - Oil vs Heating Oil

	1	**5**
h = 3	DE, NY*, WV*, WY*	SC*
h = 6	DE, MT, OK, WY	TN*
h = 12	MD, ME, RI	AK*, IA*, MA*, NV*

Table A.5 DM Test (U) - Oil vs Electricity

	1	**6**
h = 3	AZ, CA, DE, GA*, NC, OK, WV*	-
h = 6	AZ, CA*, CO, DE, GA, IN, MO, NC, NY, OK, PA*	-
h = 12	GA, KS, TX, WA	-