Journal of Finance and Economics
Volume 10, No. 1 (2018), 1-25
ISSN 2291-4951 E-ISSN 2291-496X
Published by Science and Education Centre of North America

Oil Price Shocks: Bank Size and Firm Size Effects

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Received: January 3, 2018 Accepted: March 24, 2018 Online Published: July 15, 2018

DOI: 10.12735/jfe.v10n1p1 URL: https://doi.org/10.12735/jfe.v10n1p1

Abstract

This paper uses regional variation to study the propagation of oil price shocks from vector autoregressions. Using data from the lower 48 states, we find strong and distinct asymmetrical patterns in the impulse responses of personal income and housing prices from an oil price shock. Specifically, impulse responses are amplified or dampened depending on the size distributions of banks and firms within a state. More importantly, the small bank and small firm size effects normally associated with the propagation of monetary policy shocks, are shown to propagate oil price shocks. Overall, our results are indicative of multiple transmission channels.

JEL Classifications: R11, Q43, E52, G21

Keywords: Oil price shock; transmission; regional; small bank; small firm; monetary policy

1. Introduction

Regional economic theory, supported by empirical research, indicates that not all regions within the United States respond the same way to macroeconomic shocks. Regional variation can amplify or dampen shocks and have the potential to explain the cross-sectional dispersion observed in economic activity across the country. The purpose of this paper is to gain a better understanding of the transmission mechanisms behind oil price shocks by identifying the local factors that account for different regional economic responses. The rich diversity across the states, combined with the volatility in oil prices in recent years, makes this area of research topical.

Bernanke, Gertler, and Watson (1997) contend that although oil price shocks may have instigated many of the U.S. recessions since World War II, it was actually the Federal Reserve's policy reaction to the shocks

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How to cite this paper: Smoluk, B. (2018). Oil price shocks: Bank size and firm size effects. *Journal of Finance and Economics*, *10*(1), 1-25. https://doi.org/10.12735/jfe.v10n1p1

that accounts for most of the economic downturns. When the U.S. experienced a positive oil shock, the Federal Reserve followed by raising interest rates to mitigate the shock's inflationary potential and economic activity fells thereby reducing oil demand. These arguments suggest that when examining the transmission mechanisms for oil price shocks, monetary policy variables should be included endogenously in the system. The ideas put forth by Bernanke *et al.* (1997) are not without critics. Hamilton and Herrera (2004), for example, argue that oil shocks are the primary source of most of U.S. recessions and that the Federal Reserve played a much smaller role.

We conduct our study on the lower 48 states with national and state data from 1991 to 2015. Macroeconomic data include crude oil prices, the federal funds rate, and the consumer price index. The state variables employed are per capita personal income and residential housing price indexes. Our procedure involves three steps. First, we estimate VARs using macroeconomic and state variables. Second, we estimate personal income and housing price impulse responses from an oil price shock for each state, when appropriate. Third, we regress the impulse responses onto state characteristics. Borrowing ideas developed in the monetary policy literature, our primary interest lies in the estimated slope coefficients for bank size and firm size. From these estimates, we can determine which characteristics dampen, propagate, or have no effect on personal income and housing prices after an oil price shock. The value to employing a regional VAR is that it allows for different state reactions to oil price as well as monetary policy shocks. Different states have different demand and supply exposures to oil prices. On the demand side, northern states might react more negatively to an oil price increase than southern states. On the supply side, oil producing states such as Texas, Oklahoma, Louisiana, and Wyoming might see personal income increase when oil prices increase.

This paper enriches a vast body of economic research by examining the transmission mechanisms of oil price shocks within a framework typically used to analyze monetary policy transmission. Our contributions to the literature are several. First, we find distinct patterns in both personal income and housing price impulse responses depending on the size distributions of banks and firms across the lower 48 states. Second, the distinct differences and patterns in the way personal income and housing prices respond to oil price shocks conditional on entity size suggests multiple channels are at work in the transmission processes. Lastly, we conduct simultaneous monetary policy and oil price shocks and find that the addition of a monetary policy shock changes the response patterns across the states very little compared to an oil price shock alone.[1]

Carlino and DeFina (1998) developed the primary framework used in our paper, connecting monetary policy and regional variation. With nearly two decades of additional research at our disposal, however, we refine their methodology, expand the model's predictive capacity, and augment the dataset in the following ways. First, we recast their VAR to handle oil price shocks, instead of just federal funds rate shocks. Second, Carlino and DeFina (1998) only estimate their VARs in first differences, losing some of the information embedded in the levels of the data. Sims (1980) and Sims, Stock, and Watson (1990) warn about the hazards of transforming nonstationary data in VARs.[2] We estimate VARs in first-differences and also in levels and show consistent patterns across both estimation methods. Third, we expand and partition the data to include banks from each asset size quartile, and firms in various size categories from less than 20 employees up to 500 or more. Lastly, we add state housing prices to the VAR.

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[1] This finding is not necessarily inconsistent with Bernanke *et al.* (1997) who examine the efficacy of monetary policy on a macro level. Our approach focuses on regional characteristics that may influence shocks; it does not speak to macroeconomic effectiveness of monetary policy.

[2] Indeed, unit root tests are notorious for suffering from low power, and estimating an unknown cointegrating mechanism is subject to misspecification error, see for example Cochrane (1991) and Campbell and Perron (1991). On page 136 of Sims *et al.* (1990), "This work shows that the common practice of attempting to transform models to stationary form by differencing or cointegration operators whenever it appears likely the data are integrated is in many cases unnecessary."

We regress the impulse responses from these shocks onto state-level data and focus on how the presence of small and large banks, as well as small and large firms, impact personal income and housing prices after an oil price shock.[3] Small banks and small firms, often constrained in their ability to adjust to shocks, are expected to propagate the negative effects of a positive oil price shock. Thus, the higher the presence of small entities within a state, the more sensitive their economies will be, indicating a larger decline in personal income and housing prices from an oil price shock. The presence of large banks and firms, on the other hand, are expected either to dampen the negative effects of an oil shock or show no relationship as these entities are flexible enough to adjust to the changes and mitigate the economic impact.

While some of our findings are consistent with our expectations, others surprised us. For example, as expected, we find personal income falls typically across the states in response to a positive oil price shock and the slope estimates within the various size categories for small banks and small firms are positive.[4] This indicates *within* the various small-bank (75 percentile or less) and small-firm categories, larger banks and larger firms dampen the negative effect on personal income of a positive oil price shock. This was expected. On the other hand, we were surprised by the negative slope estimates for larger banks *within* the large bank size category. This indicates that the largest banks within the largest-bank size category propagate or worsen the decline in personal income in response to an oil price shock. Housing price impulse responses are typically negative across the states after a positive oil price shock, as expected. However, surprisingly, the slope estimates for larger firms within the large-firm size category (500 or more employees) are negative. In other words, larger firms in the larger-firm size category are associated with larger drops in housing prices.

Our findings are robust to a number of different tests. For example, we address concerns about possible outliers by removing states from the sample with a high amount of gross state product related to oil and gas extraction, by estimating the results with a federal funds rate that is adjusted for the zero lower bound, and by estimating the VAR in first differences and levels. Regardless of these checks, the patterns among personal income and housing prices across the states, as they relate to the distribution of bank size and firm size presented, remain unchanged.

The remainder of this paper unfolds as follows: section 2 reviews the relevant literature on monetary shocks, oil price shocks, transmission channels, and asymmetric responses to oil price shocks. Section 3 presents our VAR model that incorporates oil prices, federal funds rate, consumer prices, and personal income. Section 4 reviews our expectations and presents empirical findings that incorporate a variety of robustness tests. Section 5 concludes the paper.

2. Literature Review

Among the many channels proposed in the literature for the transmission of monetary policy, we begin our review by focusing on three: the balance sheet channel, the bank lending channel, and the working capital channel. Although these channels are relevant for all banks and firms, regardless of size, the literature often discusses them in the context of small banks and small firms. Most explanations of monetary policy efficacy rely on frictions or rigidities to magnify and propagate shocks. Smaller entities are a natural place to look. We next discuss the oil price shocks literature. The literature review on oil price shocks is brief, as there is very little work relating oil price shocks to bank size and firm size. Consequently, we relate the frictions and

[3] Less than 500 employees is a widely used standard for defining a small firm according to the Small Business Association (SBA). Bank size data is highly skewed. We define small banks as those within the 75th percentile.

[4] While the results of Carlino and DeFina (1998) are not directly comparable, as their paper focuses solely on monetary policy shocks, they are interesting. Contrary to their expectations, the authors find no evidence that the concentration of small banks in states leads to propagation in personal income. Furthermore, they find that the concentration of small banks actually leads to less sensitive personal income responses.

rigidities found in the small bank and small firm monetary shock literature to oil price shocks. Finally, while regional variation is a broad concept, with a seemingly endless number of dimensions, we narrow the discussion to a few characteristics commonly found in the regional economic literature.

2.1. Monetary Policy Transmission

The balance sheet channel describes a process where the value of a firm's balance sheet, and hence its net worth, adjusts to changes in interest rates caused by a shift in monetary policy, as in Gertler (1992), Bernanke, Gertler, and Gilchrist (1996), and Peek and Rosengren (2013). There are two reinforcing phenomena that account for the change in firm net worth and we'll discuss both of them in terms of a contractionary monetary policy. First, a contractionary policy leads to higher interest rates and a decline in the present value of firm future cash flow causing net worth to shrink. In an economy with asymmetric information, firm net worth is a proxy for collateral value suggesting the ability to obtain financing is negatively affected. Second, a monetary contraction leading to higher interest rates dampens economic activity and reduces economic spending leading to lower cash flow.

Changes in monetary policy also influence the economy via the bank lending channel as discussed in Kashyap, Stein, and Wilcox (1993), Bernanke and Gertler (1995), and more recently in Peek and Rosengren (2013). The bank lending channel focuses on the supply of overall credit available in the economy. When the Federal Reserve decreases the money supply through open market sales of securities, it drains reserves from the banking system. A loss in reserves ultimately causes a decline in checking and savings deposits. To the extent that banks cannot make up these lost deposits through more expensive time deposits, such as CDs, the supply of overall loanable funds decreases causing bank-dependent borrowers to reduce output as they are unable to finance their recent pace of business activity. If, on the other hand, banks are able to raise additional funds by way of more expensive time deposits, the increased cost of borrowing ultimately reduces the amount banks lend. This can be represented as an inward shift in the supply of loanable funds. Regardless of the funding situation of the bank, the bank lending channel predicts higher interest rates and less lending due to changes in banks' funding sources.

The working capital channel suggests that because firms borrow the cost of production and then use sales proceeds to pay off loans, they are vulnerable to a rise in interest rates, see Barth III and Ramey (2002), Ravenna and Walsh (2006), Christiano, Trabandt, and Walentin (2010). The effect is magnified by a contractionary monetary policy shock that reduces sales and causes an accumulation of inventory costs. Production is then reduced causing the economy to contract.

The theory behind these channels is independent of entity size. However, a number of researchers argue that because small banks and small firms are subject to constraints, which magnify the frictions associated with the channels, small entities have the potential to magnify shocks. Gertler and Gilchrist (1993, 1994) claim that small firms are especially prone to a contraction in monetary policy. Higher interest rate increase carrying costs, and in response, small firms quickly reduce inventory levels thereby lowering their financing needs to support it. At the same time, consistent with Kashyap and Stein (1995), cash flows, net of higher interest expense, are reduced for loan-dependent firms further deteriorating the balance sheet. These affects can be represented as an inward shift in the demand curve for loanable funds. Consistent with these ideas, Gertler and Gilchrist (1994) find that loans to small manufacturing firms quickly drop after a contractionary monetary shock.

For a bank with a flexible capital structure, a contractionary monetary shock drains its reserves, which in turn, causes the bank to realign its funding sources away from high-reserve deposits to low-reserve funding sources such as large CDs or commercial paper, without friction. Thus, outstanding and potential new loans are relatively insulated from the policy shock. However, smaller banks are prone to liquidity frictions that make it difficult for them to freely adjust to monetary shocks. According to Kashyap and Stein (2000) and Stein (2002) small banks do not have easy access to these alternative sources of funds. Small banks, as a result of information asymmetries and possibly diseconomies of scale, are unable access the capital markets and their loan portfolios are likely to shrink. A contraction in monetary policy, therefore, leads to a contraction in lending by smaller banks and less economic activity.

Kashyap, Lamont, and Stein (1994) argue that small businesses account for much of the decline in economic activity following a Federal Reserve tightening and that there are a number of reasons for the contraction. First, small firms are highly reliant on bank loans. Second, small firms are often highly specialized and operate in narrow markets. Their inventory and equipment are idiosyncratic resulting in illiquid collateral that limits their access to credit. Lastly, there are higher agency costs that are associated with monitoring small idiosyncratic firms. Higher agency costs coupled with higher interest rates from a monetary contraction, substantially raises the cost of borrowing and reduces loan demand. In response to a tightening in monetary policy, small businesses are likely to reduce their dependence on external financing by shrinking inventory levels as discussed in Gertler and Gilchrist (1993, 1994). Inventory reductions lead to a slowdown in production, hours worked, employment, and ultimately worker income, especially for regions with a significant proportion of small businesses.

Berger, Miller, Petersen, Rajan, and Stein (2005) examine bank organizational structure as it relates to both bank and firm size. They find that small firms, which often do not have audited financial statements, and in some cases, no financial statements at all, are more likely to conduct business with small banks on a more personal level. Such small firms maintain only "soft information," rather than more reliable "hard information" such as financial statements. The authors argue that large hierarchy-driven banks have a difficult time processing and relaying soft information up the chain of command for loan approval. Small banks, on the other hand, are relatively hierarchically flat with the president often responsible for extending loans. Berger *et al*. (2005) find that these small bank and small firm relations are maintained over relatively short physical distances where frequent monitoring in conjunction with relationship-building is continual. The high fixed-costs associated with establishing a close relationship built around soft financial information tends to make long term, rather than short term, relationships more profitable.

Monetary policy shocks do not necessarily occur in isolation to other shocks and in some cases they may be a reaction to a stock market shock or even an oil price shock. Given the Federal Reserve's mandate of full employment and stable prices, an oil price shock could induce the Federal Reserve to react by attempting to offset the consequences. Bernanke *et al.* (1997) examine the monetary responses to oil price shocks over several decades and find that most of the negative impact on economic activity coming from an oil price increase is actually the result of the Federal Reserve's response to counteract the oil shock. In other words, they claim that it is the combination of oil price shocks and the ensuing contractionary monetary policy response that accounts for the large negative impact that many others suggest is coming from oil price shocks alone.

2.2. Oil Shock Transmission

Interestingly, to the best of our knowledge, the small bank and small firm effects which are prevalent in the monetary policy research are not directly addressed in the oil shock transmission literature.

Kilian (2008, 2014) and Brown and Yucel (2002) conduct extensive literature reviews of oil price shocks and there is no mention of a small bank or a small firm effect. Nevertheless, there are allusions in the literature even if they are macroeconomically oriented, that may shed light on the subject. For instance, Bernanke (1983) discusses the possibility that the uncertainty following an oil shock could cause firms to postpone investment decisions. We can extend this line of reasoning one step further and suggest that since small firms are less flexible and face more constraints, they may react by reducing investment more than large firms. If small firms tend to conduct business with small banks, as in Berger *et al*. (2005), then small firms and small banks have the potential to propagate oil price shocks. In a similar vein, Bernanke *et al.* (1996) suggest that credit market imperfections resulting from information asymmetries and agency costs may accelerate shocks by increasing the possibility of financial distress and bankruptcy. As a consequence, the higher probability of loan default causes banks to reduce lending, thereby squeezing businesses and propagating shocks. Again, since small banks and small firms often face the brunt of these market imperfections, a larger proportion of small banks and small firms within a state more are likely to propagate shocks.

Oil price shocks lead to widespread economic uncertainty as oil is ubiquitous. Firms, knowing that consumers tend to reduce consumption and increase savings in response to an oil price shock, will tend to reduce inventory levels consistent with Gertler and Gilchrist (1993, 1994). Inventory is often financed with bank loans. Small firms, especially ones with limited financial documentation according to Berger *et al.* (2005), tend to conduct business with small banks. While monetary shocks and oil price shocks are different, the underlying sources for the amplification mechanisms might be similar. Could the sources be coming from small banks and small firms?

2.3. Multifaceted Asymmetric Responses

An interesting and contentious area of research is the potentially asymmetric economic effects of oil price changes. The asymmetry appears multifaceted, and therefore, has the possibility of being driven by multiple channels. There has been a long held believe that positive oil price shocks are associated with subsequent significant economic downturns while similarly-sized negative oil price shocks do not generate economic upswings of the same magnitude (see, e.g., Hamilton 1988; Mork 1989). One source of the asymmetry comes potentially from the Federal Reserve. The Federal Reserve has been much more concerned about the negative economic consequences of a positive oil price shock than a negative one, and has reacted accordingly, thereby introducing asymmetry into the markets. Kilian and Vigfusson (2011) address the issues and difficulties that arise when modeling asymmetries in oil prices and contend that a VAR model that incorporates censored oil price inputs designed to focus on price increases, is likely misspecified. They find with a correctly specified VAR, the impulse responses are roughly equal in magnitude for a positive or negative oil price shock.

Our paper takes a step towards identifying additional other potential sources of asymmetry using regional firm size and bank size distributions and relating them to changes in personal income brought about by oil price shocks. We control for regional industry mix, and consistent the arguments of Kilian and Vigfusson (2011), we avoid censored oil price data, and allow the data to suggest the dynamics of oil price shocks with unconstrained impulse responses. One potential downside in our analysis is not differentiating supply and demand shocks for oil, but with state-level analysis that level of identification presents difficulties.

3. The Base Model and Data

In the first step of our modeling process we estimate a VAR for each state. Equations 1 through 4 show the VAR for each state *i*:

$$FF_t = c_{1,i} + \sum_{s=1}^{12} FF_{t-s} + \sum_{s=1}^{12} \Delta Y_{i,t-s} + \sum_{s=1}^{12} \Delta Oil_{t-s} + \sum_{s=1}^{12} \Delta CPI_{t-s} + trend + e_{i,t} \tag{1}$$

$$\Delta Oil_t = c_{2,i} + \sum_{s=1}^{12} FF_{t-s} + \sum_{s=1}^{12} \Delta Y_{i,t-s} + \sum_{s=1}^{12} \Delta Oil_{t-s} + \sum_{s=1}^{12} \Delta CPI_{t-s} + trend + e_{i,t} \tag{2}$$

$$\Delta CPI_t = c_{3,i} + \sum_{s=1}^{12} FF_{t-s} + \sum_{s=1}^{12} \Delta Y_{i,t-s} + \sum_{s=1}^{12} \Delta Oil_{t-s} + \sum_{s=1}^{12} \Delta CPI_{t-s} + trend + e_{i,t} \tag{3}$$

The equation for state personal income takes the form:[5]

$$\Delta Y_{i,t} = c_{4,i} + \sum_{s=1}^{12} FF_{t-s} + \sum_{s=1}^{12} \Delta Y_{i,t-s} + \sum_{s=1}^{12} \Delta Oil_{t-s} + \sum_{s=1}^{12} \Delta CPI_{t-s} + trend + e_{i,t} \quad (4)$$

where *FF* denotes actual federal funds rate, Δ indicates the first-difference of the natural log variables, Y_i denotes state *i*'s log real per capita personal income, *Oil* denotes the log real price of crude oil, and *CPI* denotes the log Consumer Price Index excluding food and energy. We include crude oil prices as an endogenous variable consistent with the arguments put forth by Bodenstein, Guerrieri, and Kilian (2012). Each equation for a particular state has identical regressors, and therefore, is estimated by OLS without loss of efficiency, see Judge, Hill, Griffiths, Lutkepohl, and Lee (1988). Each stochastic variable is lagged 12 months.[6] The sources for our dataset, as well as bank and firm size percentiles, are presented in the Data Appendix.

Using the personal income impulse responses for all 48 states from a positive one standard deviation oil price shock, we run a regression for each combination of bank size and firm size along with other (conditioning) regional variables. We are especially interested in the results for smaller banks and smaller firms and whether they show evidence of amplifying personal income after a shock. Our literature review indicates that these entities are likely to experience more information asymmetry, constraints, and frictions in attempting to adjust to shocks, and therefore, are our main interest. We sort banks into four quartiles based on total assets with cutoffs determined at the national level (lower 48 states). By partitioning the entire size distribution we are better able to compare and contrast the results based on bank size. For all banks within a state that fall into a particular asset quartile, we compute the percentage of loans within the state associated with these banks. Thus, there are 48 loan-based data points, one for each state in each quartile. These data represent our bank size variable. Because the overall size distribution is highly skewed, banks in the first three quartiles are considered smaller banks. Bank size data comes from the FDIC. Firm size is measured using the percentage of employment within a state for firms with 20 or less employees, 20-99 employees, 100-499 employees, and 500 or more employees. Financial institutions and insurance firms are excluded from the firm size data. Firms with less than 500 employees are typically considered "small" by the Small Business Association and we adopt their definition. See the Data Appendix Table.

4. Materials and Methods

4.1. Economic Expectations and Estimation Methods

We expect a positive oil shock will lead to a decline in personal income growth. Therefore, all regressions of personal income growth impulse responses onto bank and firm size variables should reveal negative

[5] Our VARs estimated in first-differences exclude the housing price equation. State housing price indices are available quarterly and we linearly interpolate intra-quarter months (see the Data appendix). First differencing linearly interpolated level data on housing prices would severely bias the data and, therefore, are excluded from the first difference VARs.

[6] The VARs for each state are symmetric and equal. They are estimated in the spirit of Sims (1980) who contends that "any variable which appears on the right-hand side of one of these equations belongs in principle on the right-hand side of all of them." While some may argue that a single asymmetric VAR system might be acceptable, the argument runs head on into problems with multiple VAR systems. Given that we have 48, five-variable VAR systems with monthly data, it is important to keep the sample size equal for each variable and each state, otherwise some VARs would begin at different points in time and capture different dynamics making inference questionable across states and the variables. We ran several lag length information criteria tests, AIC, BIC, and SBC and experimented with various symmetric lag lengths keeping in mind we have monthly data with the potential for seasonal effects. In an attempt to balance the need to capture the dynamics of the systems and mitigate the possibility of misspecification error, we settled on 12 lags. We did estimate more parsimonious symmetric models across the states, but the results did not alter our conclusions presented in this paper.

intercepts. Figure 1 shows the drop (averaged across the 48 states) in personal income growth responses forecast 36 months out from a positive oil price shock. The responses level off after about four months, with a small blip around 11 months out and remains steady further in the forecast. Within any smaller size category, we expect positive slope estimates on bank size and firm size. In other words, given the constraints faced by small banks and small firms, a positive oil price shock is likely to propagate (cause a larger decline in) personal income growth in states with smaller entities. For large banks and firms, we expect negative intercepts and zero slope estimates suggesting no relationship between size and an oil price shock.

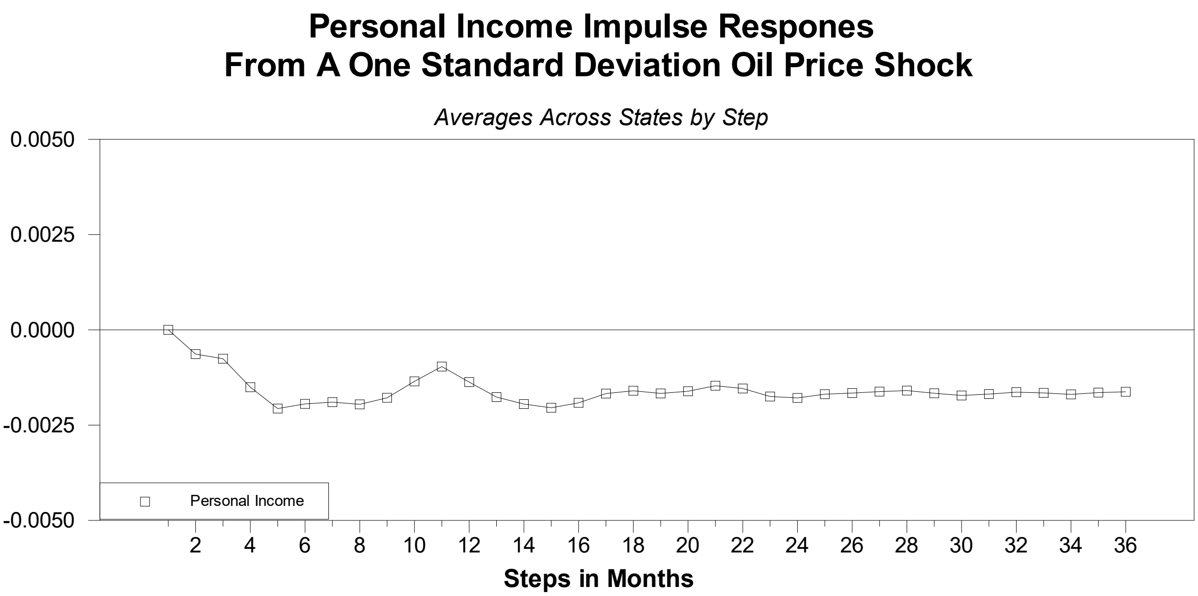

Figure 1. Average impulse responses across the lower 48 states for a one standard deviation oil price shock, forecasted 36 months out. First-differenced VAR.

Also included in our oil price shock impulse regressions are several industry mix variables such as the percentage of gross state product (GSP) devoted to the oil and gas extraction sector and the transportation sector. The personal income impulse responses for states with a large component of production devoted to oil and gas extraction should be more sensitive (positive slope estimate) to an oil price shock than states with little resources employed in oil and gas extraction. The transportation sector represents the business of moving goods and people. A significant component of its cost, directly or indirectly, derives from oil consumption. We expect the impulse responses of states with a large share of GSP devoted to transportation to be more sensitive (positive slope estimate) to an oil price shock. Because of the often counter-cyclical behavior of government expenditures, the expected sign on government size variable is expected to be negative for an oil shock.

4.2. Results

Table 1 presents detailed results using personal income growth impulse responses at the 6-month, 12-month, 24-month, and 36-month forecast steps regressed onto a constant and various state characteristics that have the potential to propagate or dampen oil price shocks. The VAR order is oil prices, federal funds rate, personal income, and the consumer price index, excluding food and energy. In the top left panel, reflecting very small banks and firms, the intercepts are negative as expected and the signs on both bank size and firm size slope coefficients are positive and statistically significant across the horizons, as hypothesized. We employ heteroskedastic-robust standard errors and define significance at the 5 percent level or better throughout the paper. Thus, smaller banks (second quartile) and the smaller firms (20-99 employees), tend to propagate the decline in the growth rate of personal income due to an oil price shock. In other words, for states with banks and firms in these size categories, the growth rate of personal income responses increases with bank and firm size. The coefficients on oil and gas extraction are positive and statistically significant, as hypothesized, while the percentage of state GDP devoted to transportation and government are typically insignificant. The adjusted R^2s range from 0.50 to 0.615 indicating that regional variables used explain over 50 percent of the shock variability. The forecast error variance decomposition indicates that approximately 15-17 percent of the variation in the growth rate of state personal income, on average, is driven by oil price shocks.

Table 1. Linear regression of personal income impulse responses from a one standard deviation positive oil shock onto state characteristics

	Banks in the 25-50th Percentile and Firms with 20-99 Employees				Banks in the 50-75th Percentile and Firms with 20-99 Employees			
Months	6	12	24	36	6	12	24	36
Intercept	-0.005	-0.007	-0.007	-0.008	-0.006	-0.008	-0.008	-0.008
	(-3.122)	(-2.555)	(-3.953)	(-3.450)	(-3.326)	(-2.706)	(-4.229)	(-3.655)
Bank size	0.687	0.869	0.791	0.860	0.209	0.063	0.124	0.108
	(2.206)	(2.708)	(2.423)	(2.624)	(0.928)	(0.193)	(0.468)	(0.362)
Firm size	0.024	0.038	0.033	0.038	0.026	0.041	0.036	0.041
	(2.617)	(2.319)	(3.220)	(2.964)	(2.757)	(2.449)	(3.435)	(3.141)
Oil & gas extract	0.019	0.030	0.031	0.029	0.019	0.032	0.033	0.031
	(2.873)	(4.030)	(5.721)	(4.517)	(2.816)	(4.145)	(5.652)	(4.608)
Transport	-0.004	-0.002	-0.006	-0.006	0.005	0.014	0.007	0.009
	(-0.335)	(-0.119)	(-0.459)	(-0.410)	(0.449)	(0.669)	(0.533)	(0.539)
Govt size	-0.008	-0.008	-0.005	-0.006	-0.009	-0.008	-0.005	-0.006
	(-2.324)	(-1.441)	(-1.050)	(-1.099)	(-2.537)	(-1.485)	(-1.096)	(-1.121)
Adjusted R^2	0.503	0.526	0.615	0.568	0.474	0.500	0.589	0.539
FEVD in %	15.948	17.228	17.118	17.112	15.948	17.228	17.118	17.112
	Banks in the 25-50th Percentile and Firms with 100-499 Employees				Banks in the 50-75th Percentile and Firms with 100-499 Employees			
Intercept	-0.004	-0.005	-0.004	-0.005	-0.005	-0.006	-0.005	-0.005
	(-1.580)	(-1.300)	(-1.461)	(-1.415)	(-1.721)	(-1.434)	(-1.616)	(-1.561)
Bank size	0.779	1.060	0.989	1.069	0.278	0.185	0.236	0.231
	(2.574)	(3.163)	(2.874)	(3.143)	(1.309)	(0.614)	(0.936)	(0.829)
Firm size	0.019	0.024	0.017	0.021	0.021	0.028	0.020	0.024
	(1.059)	(0.987)	(0.824)	(0.925)	(1.155)	(1.083)	(0.939)	(1.030)
Oil & gas extract	0.023	0.037	0.037	0.036	0.024	0.040	0.039	0.038
	(4.903)	(7.218)	(9.674)	(8.118)	(4.564)	(6.791)	(9.281)	(7.821)
Transport	-0.003	-0.002	-0.007	-0.007	0.007	0.017	0.008	0.011
	(-0.184)	(-0.076)	(-0.425)	(-0.349)	(0.553)	(0.637)	(0.464)	(0.497)
Govt size	-0.006	-0.004	-0.001	-0.002	-0.006	-0.004	-0.002	-0.002
	(-1.896)	(-0.811)	(-0.319)	(-0.379)	(-2.128)	(-0.794)	(-0.368)	(-0.401)
Adjusted R^2	0.453	0.449	0.526	0.472	0.421	0.412	0.489	0.431
FEVD in %	15.948	17.228	17.118	17.112	15.948	17.228	17.118	17.112

Notes: Impulse responses for personal income at 6, 12, 24, and 36 steps (months) out. The VAR order is oil prices, federal funds rate, personal income, and the consumer price index, excluding food and energy. *Bank size* denotes the proportion of loans held by banks in a state with assets in the indicated bank size quartile; *Firm size* denotes the proportion of employment in a state working for businesses with the indicated number of employees, excluding finance and insurance; *govt size* denotes the proportion of gross state product associated with the government sector. The same underlying VAR is employed throughout this table. *FEVD in %* denotes impulse response forecast error variance decomposition percentages averaged over the lower 48 states based on *t*-statistics are in parentheses and are based on heteroskedastic-adjusted standard errors.

Table 2. Dual shocks exclude high-oil producing states

	Bank ≤ 25th			Bank 25-50th			Bank 50- 75th			Bank 75-100th		
	12	24	36	12	24	36	12	24	36	12	24	36
Bank size	2.66	2.06	2.34	0.97	0.81	0.90	0.14	0.17	0.17	-0.27	-0.23	-0.26
	(2.76)	(3.83)	(3.34)	(2.75)	(2.75)	(2.78)	(0.58)	(0.72)	(0.67)	(-2.42)	(-2.18)	(-2.26)
Firm size < 20	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(1.71)	(1.88)	(1.89)	(2.02)	(2.14)	(2.19)	(1.90)	(2.02)	(2.07)	(1.82)	(1.91)	(1.97)
Adjusted R^2	0.55	0.62	0.57	0.47	0.56	0.50	0.42	0.52	0.46	0.45	0.55	0.48
FEVD in %	17.23	17.12	17.11	17.23	17.12	17.11	17.23	17.12	17.11	17.23	17.12	17.11
Bank size	2.31	1.75	1.97	0.84	0.70	0.77	0.11	0.14	0.13	-0.23	-0.20	-0.21
	(3.04)	(3.87)	(3.56)	(2.85)	(2.54)	(2.64)	(0.44)	(0.63)	(0.54)	(-2.24)	(-1.92)	(-1.99)
Firm size 20-99	0.03	0.03	0.03	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.03	0.04
	(2.24)	(2.99)	(2.91)	(2.30)	(3.21)	(3.00)	(2.27)	(3.21)	(2.98)	(2.20)	(3.06)	(2.87)
Adjusted R^2	0.60	0.66	0.63	0.53	0.62	0.58	0.50	0.60	0.55	0.52	0.61	0.57
Bank size	2.71	2.17	2.43	1.03	0.88	0.96	0.26	0.28	0.29	-0.31	-0.28	-0.30
	(3.04)	(3.94)	(3.62)	(2.92)	(2.88)	(2.99)	(1.24)	(1.36)	(1.35)	(-2.77)	(-2.60)	(-2.73)
Firm size 100-499	0.02	0.01	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02
	(1.00)	(0.78)	(0.92)	(1.05)	(0.89)	(1.00)	(1.07)	(0.93)	(1.03)	(1.05)	(0.90)	(1.01)
Adjusted R^2	0.56	0.61	0.57	0.47	0.55	0.49	0.43	0.51	0.45	0.46	0.54	0.49
Bank size	2.34	1.75	1.99	0.91	0.75	0.83	0.17	0.19	0.19	-0.25	-0.22	-0.24
	(2.87)	(3.70)	(3.37)	(2.90)	(2.81)	(2.90)	(0.74)	(0.91)	(0.86)	(-2.46)	(-2.21)	(-2.31)
Firm size 500+	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.51)	(-3.29)	(-3.18)	(-2.56)	(-3.60)	(-3.31)	(-2.50)	(-3.52)	(-3.24)	(-2.46)	(-3.42)	(-3.17)
Adjusted R^2	0.60	0.67	0.63	0.54	0.64	0.58	0.50	0.61	0.55	0.52	0.63	0.57

Notes: Impulse responses for personal income are forecasted 12, 24 and 36 steps (months) out based on one standard deviation shock on oil prices and the federal funds rate. Included in the regressions, but not shown, are estimated coefficients for a constant and the percentage of a state's gross product in oil and gas extraction. Bank ≤ 25th, Bank 25-50th, Bank 50-75th, and Bank 75-100th denote the percentage of loans in FDIC covered banks in a state for banks with assets in the 25th, 20-50th, 50-75th, 75-100th percentiles, respectively. *Firm size* denotes either the percentage of employment in a state for firms with less than 20 employees, 20-99 employees, 100-499 employees, or 500 employees or more. Since we maintain the same underlying VAR, the *FEVD in %* remains unchanged across and down the table. VAR order is oil prices first differenced, federal funds rate, personal income first differenced, and consumer price index excluding food and energy first differenced. *t*-statistics are in parentheses and are based on heteroskedastic-adjusted standard errors.

Interestingly, on the upper right side of the table for banks in the next higher quartile (50-75th percentile), bank size slope coefficients are all statistically insignificant (zero). This suggests that bank size, within the second quartile, does not appear related to oil price shocks. Firm size slope coefficients, however, are positive and significant. In the lower left quadrant, the results for small banks (second quartile) and larger firms (100-499 employees) indicate that the smaller banks within this quartile tend to propagate oil shocks, but the firms within this employment category do not based on the statistical significance of the coefficients. The adjusted R^2s are a bit lower in the bottom panels. The slope coefficients in the lower right panel indicate that the of size of banks within the third quartile and the size of firms within the 100-499 employment category are not related to the responses of personal income growth rates from an oil price shock.

Some of the lower 48 states have substantial oil extraction sectors and despite the use of an oil and gas extraction conditioning variable in the regressions, these states still might skew our results. Consequently, as a robustness check we exclude from our panels the four states with the largest percentage of gross state product devoted to oil and gas extraction over our sample period: Louisiana, Oklahoma, Texas, and Wyoming and add bank and firm size categories. The results are not shown due to space constraints as they are not unlike the results shown in Table 1.

Following the arguments of Bernanke *et al.* (1997), we conduct a simultaneous or dual shock to the state VARs: a one standard deviation positive federal funds shock and a one standard deviation positive oil price shock on all the lower 48 states. Regression results for the dual shock are shown in Table 2 with the intercepts and conditioning variables excluded because of space limitations. Table 2 results are not much different from Table 1 in terms of statistical significance and coefficient sizes indicating monetary policy shocks had little impact on our impulse responses in relationship to bank size and firm size. Another way of interpreting these results is that federal funds shock had little additional impact and that the two shocks appear not to have significant synergistic effects.

4.3. Robustness Tests

The preceding analysis establishes benchmark results relating oil price shocks to personal income, a proxy for output at the state level. As such, the analysis is more directly comparable to the VAR literature on oil prices and monetary policy, e.g., Bernanke *et al.* (1997), Hamilton and Herrera (2004), and Kilian and Lewis (2011). In the analysis that follows, we perform several robustness tests, one of which shows that our results survive the inclusion of housing prices to the model. Using the VAR shown above, we add a housing price equation and we estimate impulse responses.[7] Figure 2 shows the average (across the states) impulse responses for personal income and housing prices. Both averages decline, have a tendency to peak around 11 months out, then decline. Housing prices seem to trend upward towards the end, while personal income seems to be leveling off at 36 months. The VAR order is oil prices, federal funds rate, personal income, housing prices, and the consumer price index, excluding food and energy.

[7] We ran unit root tests on the residuals, with a trend and 6 lags, on each of the five variables for each state and all results rejected the null hypothesis of a unit root with each *t*-test statistic estimated to be greater than 5.46 (housing price residual for Washington state is 5.468) in absolute value, strongly suggesting stationarity. The Engle-Granger asymptotic critical value at the five percent level for four *I(1)* variables (oil prices, CPI, personal income, and housing prices) and no trend is 4.10 in absolute value.

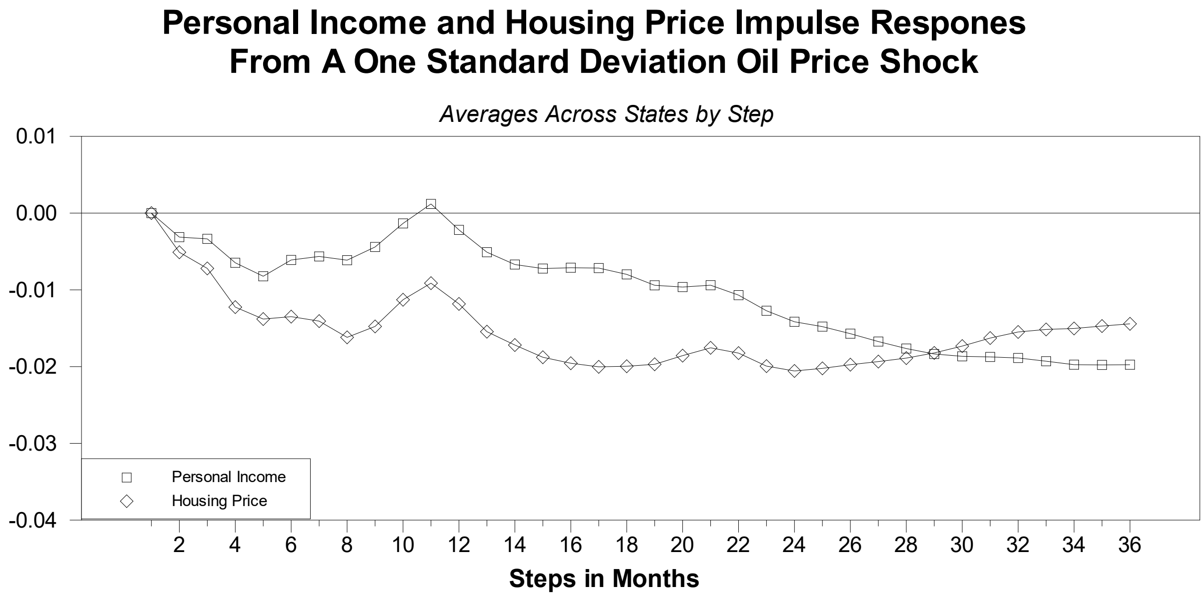

Figure 2. Average impulse responses across the lower 48 states for a one standard deviation oil price shock, forecasted 36 months out. levels VAR

Table 3 shows the full regression results (includes the same three state conditioning variables as in Table 1) for a positive one standard deviation oil price shock for select bank and firm sizes. In the top left panel for personal income, the signs on both slope coefficients on bank size and firm size early in the forecasts are positive and statistically significant, as hypothesized, at the 5 percent level or better. These results indicate that within these relatively small bank and firm size categories, there is a positive relationship between personal income responses, oil price shocks, and entity size. The presence of small banks and firms in these size categories is associated with a larger drop in personal income. Interestingly, on the right side of the table for housing prices, bank size coefficients are all *negative* and statistically significant.[8] This suggests the presence of larger banks within this size quartile propagate or exacerbate the housing price decline after an oil shock. This is a surprise as we expected a positive and significant slope in this relatively small-bank quartile. Furthermore, as the percentage of gross state product devoted to oil and gas extraction increases, conditioned on bank and firm size, the larger the impulse responses from personal income and housing prices as can be seen from the positive and significant coefficients. The adjusted R^2s on personal income are substantially larger than those on housing prices early in the forecast horizon.

The bottom panel of Table 3 shows regression results for larger banks and larger firms. Interestingly, the slope coefficients on bank size for the personal income impulses on the left are not significant, and on the right, firm size estimates are not significant for housing price impulses. Table 4 shows more results for an oil price shock for impulses at the 16-month horizon with all four bank asset size quartiles and four firm size categories. There are strong observable patterns for the bank size and firm-size coefficient estimates throughout the table. For example, signs on the bank size coefficients are opposite for the two types of responses throughout the table and tend to flip in the last two columns. Firm size slope estimates on personal income and housing responses tend to be positive, but turn insignificant or negative as firms get larger going down the table. The consistent personal income sign flip-pattern moving from smaller to the largest banks is puzzling as we expected the largest banks in largest bank size category to mitigate shocks, not propagate

[8] We reviewed the data for multicollinearity and did not find correlation coefficients large enough to explain the flip in signs from an econometric standpoint.

them, as can be seen with significant negative slope signs. Large banks have less financial and operating constraints and therefore should be able to adjust to oil price shocks in a way that does not affect local lending and economic activity.

Table 3. Linear regression of impulse responses from a one standard deviation oil price positive shock onto state characteristics

	Bank ≤ 25th		Bank 25-50th		Bank 50- 75th		Bank 75-100th	
	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response
Intercept	-0.024	-0.023	-0.031	-0.020	-0.033	-0.019	-0.011	-0.061
	(-2.938)	(-2.342)	(-3.974)	(-2.115)	(-4.141)	(-2.033)	(-0.675)	(-3.621)
Bank size	19.846	-18.055	7.334	-11.564	0.919	-5.784	-1.936	3.954
	(3.227)	(-3.117)	(2.274)	(-2.705)	(0.373)	(-2.162)	(-1.590)	(2.587)
Firm size <20	0.048	0.112	0.072	0.096	0.079	0.099	0.073	0.105
	(1.845)	(2.461)	(2.343)	(2.127)	(2.275)	(2.045)	(2.061)	(2.242)
Adjusted R^2	0.487	0.256	0.399	0.268	0.346	0.245	0.377	0.271
FEVD in %	21.894	33.858	21.894	33.858	21.894	33.858	21.894	33.858
Intercept	-0.036	-0.057	-0.049	-0.044	-0.054	-0.039	-0.034	-0.089
	(-2.453)	(-3.214)	(-3.243)	(-2.700)	(-3.540)	(-2.292)	(-1.366)	(-3.693)
Bank size	18.017	-23.521	6.349	-12.883	0.778	-5.808	-1.644	4.293
	(2.917)	(-4.105)	(1.829)	(-2.977)	(0.322)	(-2.188)	(-1.273)	(2.795)
Firm size 20-99	0.115	0.306	0.181	0.240	0.203	0.216	0.183	0.248
	(1.586)	(2.952)	(2.212)	(2.435)	(2.441)	(2.108)	(2.131)	(2.420)
Adjusted R^2	0.495	0.311	0.429	0.303	0.391	0.263	0.413	0.301
Intercept	-0.034	-0.019	-0.044	-0.015	-0.049	-0.010	-0.026	-0.050
	(-2.070)	(-0.996)	(-2.446)	(-0.895)	(-2.679)	(-0.593)	(-1.082)	(-2.234)
Bank size	19.354	-15.588	6.914	-11.056	1.302	-5.01	-1.959	3.509
	(3.162)	(-2.203)	(2.172)	(-2.501)	(0.581)	(-1.771)	(-1.729)	(2.216)
Firm size 100-499	0.114	0.084	0.162	0.065	0.185	0.036	0.168	0.059
	(1.368)	(0.752)	(1.684)	(0.630)	(1.877)	(0.354)	(1.729)	(0.563)
Adjusted R^2	0.493	0.203	0.407	0.226	0.363	0.197	0.393	0.219
Intercept	0.003	0.040	0.010	0.030	0.012	0.028	0.026	-0.012
	(0.313)	(1.922)	(-0.870)	(1.534)	(0.989)	(1.395)	(1.814)	(-0.550)
Bank size	16.673	-25.257	6.143	-12.876	0.851	-5.658	-1.575	4.273
	(2.715)	(-4.321)	(1.863)	(-3.102)	(0.374)	(-2.182)	(-1.286)	(2.879)
Firm size 500+	-0.046	-0.106	-0.067	-0.079	-0.073	-0.073	-0.068	-0.081
	(-2.249)	(-2.860)	(-3.005)	(-2.334)	(-3.274)	(-2.023)	(-2.902)	(-2.273)
Adjusted R^2	0.512	0.336	0.461	0.314	0.425	0.270	0.445	0.311

Notes: Impulse responses for personal income and housing prices are forecasted 16 steps (months) out. Included in the regressions are state characteristics such as the percentage of a state's gross product in *oil & gas extraction*, *transportation*, and *government size*. Bank ≤ 25th, Bank 25-50th, Bank 50-75th, and Bank 75-100th denote the percentage of loans in FDIC covered banks in a state for banks with assets in the 25^{th}, $20\text{-}50^{th}$, $50\text{-}75^{th}$, $75\text{-}100^{th}$ percentiles, respectively. *Firm size* denotes either the percentage of employment in a state for firms with less than 20 employees, 20-99 employees, 100-499 employees, and 500 employees or more. The same underlying VAR is employed throughout this table. *t*-statistics are in parentheses and are based on heteroskedastic-adjusted standard errors. Data in levels.

Table 4. Linear regression of impulse responses from a one standard deviation positive oil shock onto state characteristics

	Banks in the $25\text{-}50^{th}$ Percentile and Firms with 20-99 Employees							
	Personal Income Response				Housing Price Response			
Months	6	12	24	36	6	12	24	36
Intercept	-0.021	-0.034	-0.071	-0.079	-0.008	-0.020	-0.073	-0.088
	(-3.337)	(-3.095)	(-2.923)	(-3.054)	(-0.813)	(-1.537)	(-2.645)	(-2.276)
Bank size	4.371	5.918	5.098	0.689	-4.340	-9.405	-17.886	-27.694
	(2.362)	(2.394)	(0.976)	(0.132)	(-2.373)	(-3.307)	(-2.696)	(-3.269)
Firm size	0.089	0.143	0.224	0.237	-0.019	0.162	0.388	0.399
	(2.199)	(2.274)	(1.697)	(1.673)	(-0.365)	(2.030)	(2.390)	(1.799)
Oil & gas extract	0.109	0.137	0.020	-0.027	0.148	0.130	0.212	0.146
	(4.369)	(4.405)	(0.248)	(-0.376)	(5.899)	(3.421)	(3.300)	(1.815)
Transport	-0.09	-0.036	0.123	0.133	0.018	-0.298	-0.485	-0.319
	(-1.358)	(-0.385)	(0.694)	(0.700)	(0.261)	(-3.277)	(-1.958)	(-1.017)
Govt size	-0.008	0.026	0.081	0.101	-0.017	-0.062	0.049	0.192
	(-0.486)	(0.847)	(1.611)	(2.108)	(-0.571)	(-1.126)	(0.503)	(1.381)
Adjusted R^2	0.500	0.478	0.173	0.095	0.225	0.316	0.278	0.208
FEVD in %	20.229	19.761	27.114	37.129	20.229	19.761	27.114	37.129
	Banks in the $50\text{-}75^{th}$ Percentile and Firms with 100-499 Employees							
Intercept	-0.026	-0.034	-0.081	-0.093	-0.011	0.000	-0.020	-0.057
	(-3.812)	(-2.706)	(-2.963)	(-3.406)	(-0.988)	(0.007)	(-0.672)	(-1.374)
Bank size	1.494	1.702	-0.823	-2.265	-2.832	-4.186	-6.234	-12.635
	(1.231)	(0.980)	(-0.261)	(-0.733)	(-2.431)	(-2.088)	(-1.364)	(-2.307)
Firm size	0.121	0.148	0.298	0.347	0.004	0.047	0.067	0.241
	(2.731)	(2.045)	(1.972)	(2.221)	(0.062)	(0.692)	(0.393)	(1.049)
Oil & gas extract	0.133	0.175	0.088	0.039	0.148	0.158	0.269	0.214
	(5.083)	(4.948)	(1.266)	(0.633)	(6.021)	(3.233)	(3.025)	(1.919)
Transport	-0.014	0.072	0.300	0.261	-0.003	-0.382	-0.69	-0.545
	(-0.263)	(0.717)	(1.576)	(1.324)	(-0.041)	(-3.980)	(-2.826)	(-1.858)
Govt size	-0.001	0.04	0.116	0.139	-0.010	-0.029	0.111	0.273
	(-0.050)	(1.282)	(2.355)	(2.984)	(-0.341)	(-0.563)	(1.192)	(2.111)
Adjusted R^2	0.474	0.415	0.179	0.172	0.232	0.243	0.165	0.151
FEVD in %	20.229	19.761	27.114	37.129	20.229	19.761	27.114	37.129

Notes: Impulse responses for personal income and housing prices at 6, 12, 24, and 36 steps (months) out. The VAR order is oil prices, federal funds rate, personal income, housing prices, and the consumer price index, excluding food and energy. *Bank size* denotes the proportion loans held by banks in a state with assets in the indicated bank size quartile; *Firm size* denotes the proportion of employment in a state working for businesses with the indicated number of employees, excluding finance and insurance; *govt size* denotes the proportion of gross state product associated with the government sector. The same underlying VAR is employed throughout this table. *FEVD in %* denotes impulse response forecast error variance decomposition percentages averaged over the lower 48 states based on *t*-statistics are in parentheses and are based on heteroskedastic-adjusted standard errors. Data in levels.

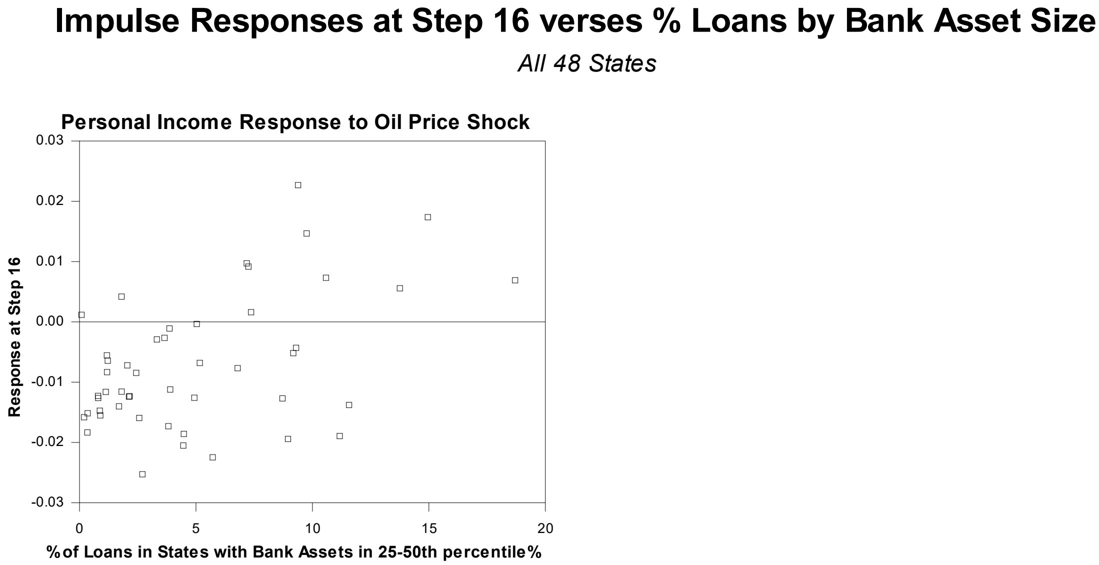

Figure 3. Personal income impulse responses for each state by bank size. The fitted line in each graph is estimated by ordinary least squares

The relationships between the slope sign estimates, shock amplification, and dampening, discussed above, are hard to visualize working just with tables of data. A more intuitive grasp of relationships may be obtained from Figures 3 through 6. In these figures, the distribution of the 48-state impulse responses for selected columns and rows of Table 4 are presented and unconditional OLS fitted lines are superimposed. The x-axis of each graph in Figure 3 represents the percentage of loans within each state from banks classified in that asset quartile. The y-axis represents the personal income response at step (month) 16 for each of the lower 48 states. The intercepts are consistent with the average drop in personal income and housing prices after a shock as shown in Figure 2. The slopes of the fitted lines are consistent with the signs of the coefficient estimates shown in the appropriate column or row of Table 4.[9]

An important observation to note in both graphs of Figure 3 is that 11 states' personal income (Delaware, Iowa, Kansas, Louisiana, Montana, Nevada, North Dakota, Oklahoma, South Dakota, West Virginia, and Wyoming) respond *positively* to a positive oil price shock. Interestingly, while Oklahoma and Wyoming, and to a lesser degree North Dakota, have an above average percentage of their gross state products devoted to oil and gas production, we are unable to identify other relevant common traits amongst these states to

[9] The data used in the figures span an entire column or row in Table 4. The OLS fitted lines shown in Figures 3 through 6 are based on unconditional estimates as there are no other regional variables employed in the estimation. The intercept and slope estimates in the tables, however, are conditional on the estimated coefficients on the other regional variables included in the regressions. We view the overall consistency between the conditional and unconditional intercept and slope estimates as a form of robustness check. The other conditioning variables are not affecting our conclusions concerning bank size and firm size.

explain the positive responses.[10] The upward sloping line, starting below zero, in Figure 3 for the smaller bank quartile (25-50th) indicates the personal income of states with a lower percentage of loans within these banks are more sensitive to the negative impact of an oil price shock. The positive slopes are consistent with the estimates 7.334, 6.349, 6.914, and 6.143 found in the third column in Table 4.

The downward sloping line for the largest bank category indicates the personal income of states with a high percentage of loans within large banks are, on average, more negatively impacted by an oil price shock. Again, we expected a flat slope, indistinguishable from zero, for the largest bank category. The slope is consistent, however, with the negative coefficient estimates -1.936, -1.644, -1,959, and -1.575 in the second to last column of Table 4.

Impulse Responses at Step 16 verses % Loans by Bank Asset Size

All 48 States

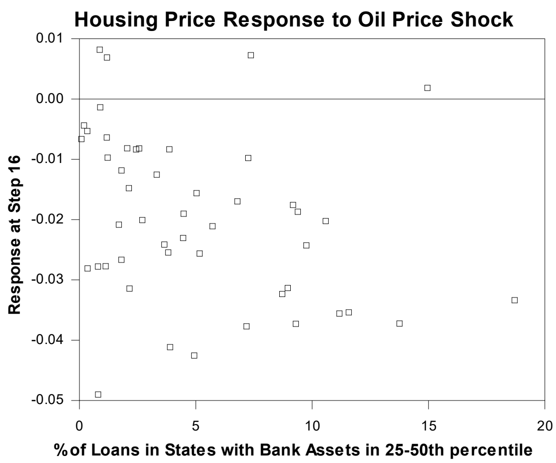

Figure 4. Housing price impulse responses for each state by bank size. The fitted line in each graph is estimated by ordinary least squares

Overall, both graphs in Figure 3 indicate the personal income of states with a disproportionate amount of small and large banks (the tails of each state's bank asset size distribution) tend to fall more in response to an oil price shock. Based on Table 4, there is a much harder to detect, or in some cases no apparent, relation between the personal income of states and the percentage of loans from banks in the 50-75th percentile (figure not shown). Overall, the results in Table 4 indicate personal income and housing prices respond differently to monetary policy shocks and oil price shocks. The clear bank size and firm size patterns suggest that there are multiple channels at work that impact personal income and housing prices differently.

Roughly, the way to interpret Figure 3 (and those below) is to look at the observations close to the zero line as small responses to shocks and those responses further away from the zero line as indicating larger shocks, although care must be taken in that statistical significance is not delineated in the figures. The estimated responses and their statistical significance are shown in the tables. Thus, the tables and the figures complement each other. For example, in Figure 4, the negative intercept combined with the downward sloping line in the

[10] The level and form of agricultural output in these states may play a role in the positive relationship detected, but as we explain further below, we examined the percentage of GSP devoted to agriculture in our work and were unconvinced of its explanatory ability. It might be the case that the type of agricultural output, not just the overall level of output, matters to our analysis. A decomposition of agricultural output might help explain some of these results and is a potential avenue of future research.

small bank quartile (25-50th) indicates that housing prices are more sensitive to an oil price shock for larger banks within this size category. These lines are consistent with the negative slope estimates found in the Table 4 presenting regression results, -11.564, -12.883, -11.056, and -12.876. Only four states (California, New Mexico, Nevada, and Wyoming) respond with positive impulses for housing prices. On the right, the negative intercept and the upward sloping line for the largest banks in the large bank quartile indicates the housing prices of states with largest banks have a smaller reaction to an oil price shock as expected. Again the results are supported by the positive bank size coefficient estimates in Table 4, the last column.

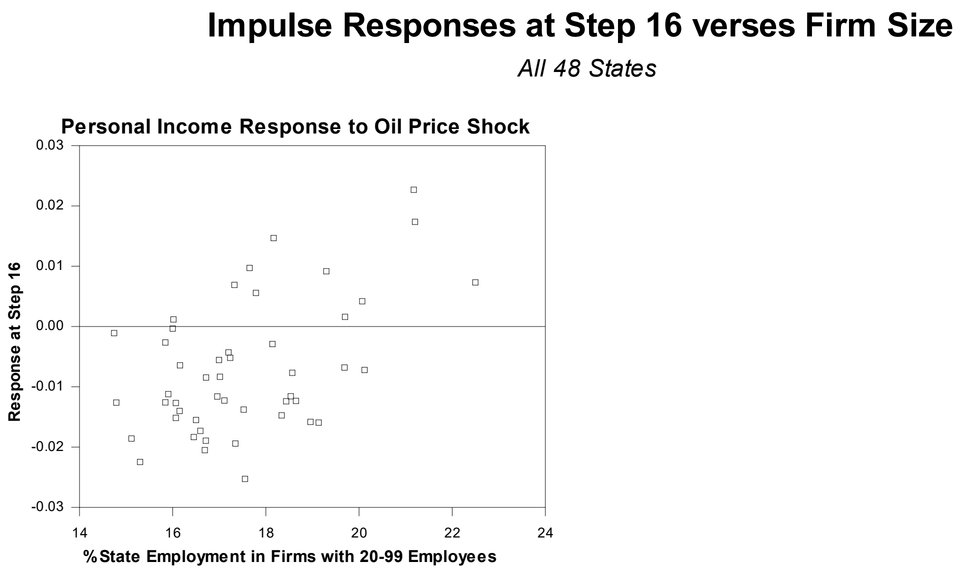

Figure 5. Personal income impulse responses for each state by firm size. The fitted line in each graph is estimated by ordinary least squares

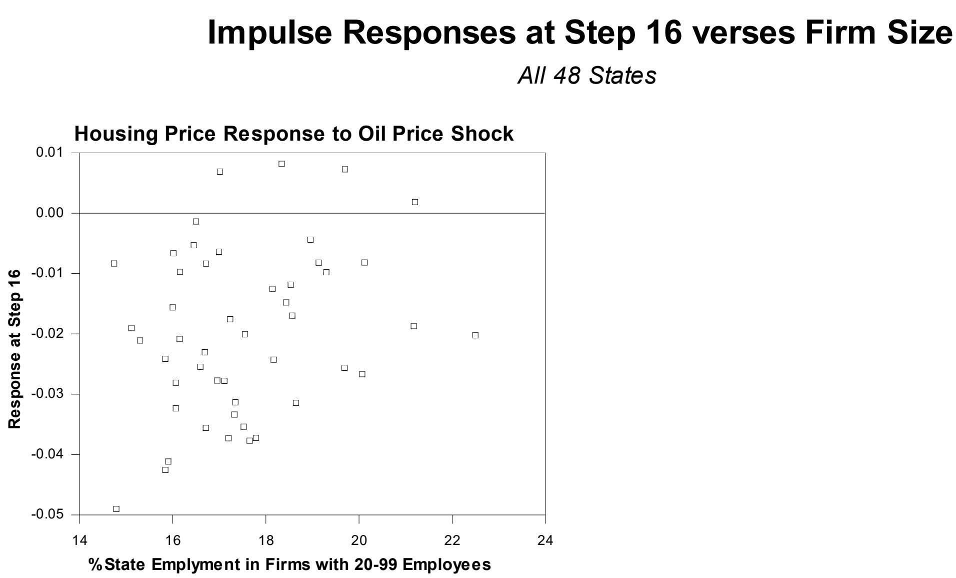

Figure 6. Housing price impulse responses for each state by firm size. The fitted line in each graph is estimated by ordinary least squares

In Figure 5 on the left, given the negative intercept and positive slope, the personal income of states with a lower percentage of state employment from smaller firms (20-99 employees) are more negatively sensitive to an oil price shock. The personal income of states with a high percentage of state employment from large firms (500 or more employees) amplify the drop from an oil price shock, based on the negative slope noted on the right side of Figure 5. In Figure 6 the housing prices of states with a low percentage of state employment within small firms (20-99 employees) are more sensitive to, in other words propagate the negative effects of an oil price shock. Surprisingly, the housing prices of states with a high percentage of state employ from large firms (500 or more employees) are more negatively sensitive to an oil price shock. The signs of the intercept and slope coefficient shown in Table 4 are consistent with the fitted lines in Figures 5 and 6.

Table 5. Dual shocks

	Bank ≤ 25th		Bank 25-50th		Bank 50- 75th		Bank 75-100th	
	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response	Personal Income Response	Housing Price Response
Intercept	-0.003	-0.048	-0.005	-0045	-0.005	-0.048	0.015	-0.095
	(-0.499)	(-3.082)	(-0.822)	(-2.837)	(-0.731)	(-2.929)	(1.087)	(-5.600)
Bank size	15.213	-21.816	6.431	-13.882	1.783	-7.767	-1.949	4.792
	(2.713)	(-4.783)	(1.997)	(-3.945)	(0.846)	(-3.222)	(-1.740)	(3.958)
Firm size < 20	0.020	0.118	0.036	0.105	0.039	0.119	0.031	0.121
	(0.574)	(2.290)	(1.048)	(1.982)	(1.066)	(2.004)	(0.868)	(2.198)
Adjusted R^2	0.480	0.254	0.410	0.263	0.359	0.222	0.396	0.263
FEVD	21.894	33.858	21.894	33.858	21.894	33.858	21.894	33.858
Intercept	-0.019	-0.079	-0.025	-0.068	-0.026	-0.066	-0.008	-0.118
	(-1.433)	(-3.623)	(-1.806)	(-3.022)	(-1.866)	(-2.770)	(-0.421)	(-4.920)
Bank size	13.351	-25.232	5.752	-14.421	1.564	-7.241	-1.683	4.821
	(2.568)	(-5.384)	(1.811)	(-4.020)	(0.777)	(-2.951)	(-1.543)	(3.909)
Firm size 20-99	0.116	0.322	0.159	0.256	0.173	0.240	0.157	0.269
	(1.450)	(3.182)	(1.821)	(2.484)	(1.895)	(2.131)	(1.750)	(2.502)
Adjusted R^2	0.506	0.311	0.460	0.294	0.419	0.233	0.446	0.287
Intercept	-0.023	-0.029	-0.027	-0.024	-0.028	-0.020	-0.007	-0.063
	(-2.414)	(-1.345)	(-2.380)	(-1.154)	(-2.361)	(-0.963)	-(0.553)	(-3.005)
Bank size	13.693	-18.484	6.292	-12.561	2.421	-6.276	-1.998	4.007
	(2.898)	(-3.306)	(2.167)	(-3.430)	(1.334)	(-2.263)	(-2.033)	(3.046)
Firm size 100-499	0.191	0.002	0.225	-0.037	0.240	-0.068	0.229	-0.044
	(2.569)	(0.012)	(2.488)	(-0.288)	(2.463)	(-0.532)	(2.491)	(-0.338)
Adjusted R^2	0.544	0.192	0.496	0.214	0.458	0.166	0.489	0.200
Intercept	0.019	0.025	0.026	0.015	0.028	0.012	0.043	-0.031
	(1.614)	(1.436)	(2.021)	(0.897)	(2.133)	(-0.684)	(2.785)	(-1.732)
Bank size	13.274	-25.278	5.915	-14.201	1.679	-7.145	-1.730	4.760
	(2.502)	(-5.470)	(1.941)	(-4.217)	(0.887)	(-2.952)	(-1.662)	(4.001)
Firm size 500+	-0.041	-0.112	-0.054	-0.090	-0.058	-0.086	-0.053	-0.094
	(-1.732)	(-2.654)	(-2.147)	(-2.161)	(-2.222)	(-1.961)	(-2.067)	(-2.173)
Adjusted R^2	0.515	0.339	0.471	0.315	0.429	0.255	0.457	0.309

Notes: Impulse responses for personal income and housing prices are forecasted 16 steps (months) out. Linear regression of impulse responses from a one standard deviation oil price shock and 50-basis point federal funds shock onto state characteristics all 48 states. Regressions include a bank size and firm size variable with estimated coefficient estimates shown above. Included in the regressors are the state characteristics such as the proportion of gross state product associated with durable goods manufacturing and the percentage of a state's gross product in oil and gas extraction. Bank ≤ 25th, Bank 25-50th, Bank 50-75th, and Bank 75-100th denote the percentage of loans in FDIC covered banks in a state for banks with assets in the 25th, 20-50th, 50-75th, 75-100th percentiles, respectively. *Firm size* denotes either the percentage of employment in a state for firms with less than 20 employees, 20-99 employees, 100-499 employees, and 500 employees or more. Since we maintain the same underlying VAR the *FEVD in %* remains unchanged across and down the table. *t*-statistics are in parentheses and are based on heteroskedastic-adjusted standard errors.

We conducted dual one standard deviation positive oil price shocks and 50-basis point positive federal funds shocks and report the results in Table 5. Like the dual shock results with first-differenced data, the results are not much different than from an oil price shock alone. Thus, the impact of the federal funds shock on the levels of personal income and housing prices are relatively small. As an additional test, we excluded from our sample the four states with the largest percentage of gross state product devoted to oil and gas extraction over our sample period: Louisiana, Oklahoma, Texas, and Wyoming as a robustness check. The results are not shown due to space constraints, however, the same bank size pattern for personal income shown in Table 4 appears: smaller bank (50th percentile) coefficients are positive and significant, but fade and turn negative as banks become larger right across the columns. In addition, firm size coefficient estimates tend to be positive and significant, then fade and become negative and significant for firms with 500 or more employees.

The Federal Reserve, near the middle of our sample period, began employing an aggressive monetary policy that is characterized by a historically low federal funds target rate that approached zero (the zero lower bound). Despite the zero lower bound, the Federal Reserve continued to aggressively conduct monetary policy. As a robustness check, we employ an alternative measure of the federal funds rate in our VAR based on the Taylor Rule that incorporates suggestions from Bernanke (2015) concerning its estimation. Taylor (1993) proposed the following rule for setting the nominal federal funds rate: *i* = *real rate* + *inflation* + 0.5(*inflation* - 2) + 0.5(*output gap*), where inflation is based on the last 4-quarter rise in the GDP deflator, 2% is the target inflation rate, and the output gap reflects the difference between the actual real GDP and the real GDP potential from the Congressional Budget Office. The rule incorporates Taylor's principle that the nominal federal funds rate should not just keep up with the inflation rate with a coefficient equal to 1.0, but should include an additional premium based on the difference between actual and target inflation to elevate the funds rate to dampen a robust economy. Bernanke (2015) suggests modifying the Taylor rule by replacing the 0.5 coefficient associated with the output gap with 1.0. Bernanke states "*In my experience, the FOMC paid closer attention to variants of the Taylor rule that include the higher output gap coefficient.*" Employing Bernanke's suggestion concerning the size of the output gap coefficient, we splice onto the actual federal funds rate the Taylor-rule-based rate from September 2008 to the fourth quarter 2015. We chose September 2008 as that date was the beginning of the Federal Reserve's extraordinary effort to stabilize the economy in the face of a zero lower bound on the federal funds rate. We re-estimated Table 4 using the Taylor-rule adjusted federal funds rate with no meaningful difference compared to the results previously shown.[11]

Over the course of this research project, we considered many potential variables that might explain our results. For example, we examined other sectors of the economy such as the percentage of GSP devoted to natural resources and mining, utilities, agriculture, F.I.R.E. (finance, insurance, and real estate),

[11] Due to space constraints, the results are not shown. We also estimated the Taylor equation using a variety of other plausible coefficients and substituted them in the VAR with no significant difference in the regional regression results compared to those shown in this paper.

construction, and the size of government vs. private industry within each state. Based on the results, plausibility, and for ease of comparison to other papers in this line of research (e.g., Carlino & DeFina, 1998), we choose and presented the explanatory variables as shown in this paper based on our judgement. While these components of industry mix are not uncommon in this line of research, we did explore other variables often found in regional economic and agglomeration work such as population density, highway-miles per state, and state credit ratings. Population density is a familiar variable in regional economic studies and has the potential to influence our results, but given its nature of being deeply interwoven into the fabric of any state economy, disentangling its multitude of direct and indirect effects could be the subject of another paper that complements our work. Highway-miles, especially when combined with population density, within a state is an interesting variable as it has the potential to influence our results. Our initial attempt at relating highway-miles to our results was not very insightful, but nevertheless it has the possibility illuminating our results within a well-crafted model. However, developing a convincing framework involving highway miles would, again, involve another paper that could be seen as complementing our work here. State credit ratings, seems like a less obvious variable for this line of research until one realizes that poor credit ratings signify a state operating under financial constraints and we know from the literature review above that small firms and banks feel the hardships of constraints to varying degrees. Again, developing a framework to relate state credit ratings to our results would involve another paper that deals with the knotty issue of endogeneity between ratings and state personal income. Thus, there are potential avenues for further research in identifying the asymmetric causes of the results presented in this paper.

4.4. Discussion

Some of the findings reported in this paper were surprising and on the surface counterintuitive. Recent research along the lines of bank size anomalies might shed light on our asymmetric results. For example, Gandhi and Lustig (2015) find large and significant differences in the returns of bank stocks depending on how the banks are sorted according to size. In their paper, bank size is shown to be correlated with capitalization levels as measured by the capital to asset ratio and that size measures are highly procyclical. This cyclicality appears to play a role in large banks' ability to manage shock risk over time. Buch and Prieto (2014) find differences in the behavior of banks depending on the degree of capitalization and size. Specifically, they find that bank loans and capital are cointegrated and that large banks are able to adjust to shocks faster than smaller bank in the short run. Another plausible explanation is that banks may be adjusting their loan mix in response to shocks. Thus, any adjustments over the business cycle, including portfolio shifts, may ultimately influence housing prices and even the personal income of local communities.

It is important to note that while the statistical evidence in this paper indicates that small banks and small firms tend to amplify and propagate oil price shocks, the economic significance of the smallest banks (assets in the 25th percentile) within each state appears slight. We show, however, that somewhat larger, yet still relatively small banks, also support our conclusions so that the totality of the economic impact cannot be overlooked.

5. Conclusion

The lower 48 states provide a rich data set for examining the regional differences in the effects of oil price shocks. We explore these data with VARs and their impulse responses, to gain a better understanding of how regional variation influences the propagation of shocks. We examine the model in levels and first differences, with and without high oil producing states. The main results indicate strong and consistent patterns between personal income and housing price impulse responses and bank size and firm size, some of which surprised us. Highlights of our findings, organized by personal income and housing price responses, are as follows.

1) Our slope estimates indicate the personal income responses across the states from an oil price shock are positively related to bank size for smaller banks, below the 50th percentile. This indicates that smaller banks propagate oil price shocks as they are associated with more negative personal income responses. For the largest banks, with assets in the 75-100th percentile, the slope estimates are negative indicating the largest banks in the largest bank size quartile also propagate the negative effect of an oil price shock through personal income. This finding surprised us as we expected the presence of large banks to dampen the negative effects of an oil shock as they are less constrained in their ability to adapt compared to smaller banks.

2) Housing price impulse responses are strongly related to our measures of bank size and firm size based on slope estimates, but mostly in unexpected ways. Specifically, housing price impulse responses are negatively related to bank size for smaller banks (in each of the three lower asset quartiles) across the states. It suggests the presence of larger banks below the 75th percentile in assets propagate the negative effects of oil price shock through housing prices. This is surprising as we expected the presence of smaller banks in these size categories to propagate oil shocks. Further evidence shows housing price impulse responses, and the presence of larger firms within the largest firm size category (500 or more employees), are negatively related. Thus, states with the largest employment share from the largest firms are associated with a larger decline in housing prices after a shock. This finding also surprised us as we expected the relatively high degree of flexibility associated with large firms to bear no, or possibly a positive, relationship to shocks. The housing prices of states with a heavy presence of smaller firms are positively related to oil price shocks as expected. This indicates that states with a smaller share of employment coming from small firms are associated with a larger drop in housing prices.

Our contribution to the literature is that oil price shocks are propagated or dampened across the states depending on the distributions of bank size and firm size. The differences in the responses that we note in personal income and housing prices may help identify or at least provide interesting clues into the underlying dynamics. A complete explanation of these findings appears complex as there seems to be multiple channels at work. Network dynamics has the potential help identify these multiple channels. Can these results provide a link in explaining the asymmetric behavior resulting from oil prices shock as discussed in Balke, Brown, and Yucel (2002)? We look forward to gaining deeper insights into these issues in future research.

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Data Appendix

State personal income data are from the Bureau of Economic Analysis. State housing price indexes are published by the Federal Housing Finance Agency and represent a national single-family housing price index based on data from Fannie Mae and Freddie Mac for repeat sales and refinancings on the same property using purchase price. The federal funds rates are from the Federal Reserve St. Louis FRED website and are monthly averages. Spot crude oil prices are from the U.S. Energy Information Administration for Brent. Real potential GDP data, used to compute the output gap in the Taylor rule, are from the Congressional Budget Office. State population figures were obtained from the Bureau of Economic Analysis. State square miles are from the U.S. Geological Survey website. Firm size is categorized by the number of employees. The percentage of employment within each of these categorizes within a state data are computed from the U.S. Census Bureau's website, Statistics of U.S. Business. Data by firm size is averaged over the follow census periods: 1992, 1998, 2003, 2012, and 2015. Firm size data excludes employment from financial institutions and insurance companies. Bank size data by state comes from the FDIC website, Statistics on Depository Institutions. It captures all bank branches within a state that take deposits. State data reflects the loans and assets associated with branches located within the state. Thus, if a large money center bank had a single deposit-accepting branch in a state, only the loans and assets that are associated with that branch are included in the state statistics when determining bank size. Bank size statistics reflect the percentage of loans associated with banks with assets at the indicated percentiles, derived from the lower 48 states data, within the state. These data are averaged by state and by year from 1992 to 2015. Gross state product industry data such as durable goods manufacturing is relative to the state's private industry gross state product. The government size variable is a percentage all industries, private and public, using gross state product data. The classification is NAICS, averaged from 1997-2014. The consumer price index, All Items, from the Bureau of Labor Statistics, is used as the price deflator. See Data Appendix Table below.

Data Appendix Table. Firm and bank size distributions by state averages 1992-2015

State	Percentage Employment By Number Employees per firm				Percentage of Loans By Bank Assets Percentiles			
	<20	29-99	100-499	500+	<25%	25-50%	50-75%	75-100%
Alabama	0.183	0.175	0.141	0.502	0.006	0.024	0.050	0.920
Arkansas	0.167	0.159	0.204	0.471	0.013	0.036	0.074	0.876
Arizona	0.193	0.167	0.134	0.506	0.025	0.087	0.214	0.674
California	0.193	0.194	0.146	0.467	0.001	0.009	0.024	0.966
Colorado	0.208	0.184	0.132	0.476	0.035	0.090	0.152	0.723
Connecticut	0.192	0.181	0.148	0.480	0.002	0.009	0.046	0.943
Delaware	0.184	0.181	0.132	0.503	0.000	0.001	0.003	0.999
Florida	0.197	0.157	0.122	0.524	0.008	0.039	0.108	0.846
Georgia	0.171	0.160	0.126	0.543	0.009	0.045	0.089	0.857
Idaho	0.255	0.206	0.131	0.409	0.016	0.052	0.161	0.771
Illinois	0.172	0.178	0.147	0.502	0.019	0.038	0.090	0.853
Indiana	0.171	0.174	0.150	0.505	0.011	0.045	0.118	0.826
Iowa	0.193	0.186	0.155	0.466	0.083	0.187	0.251	0.479
Kansas	0.195	0.188	0.158	0.459	0.091	0.138	0.175	0.597
Kentucky	0.181	0.175	0.144	0.500	0.029	0.112	0.215	0.645
Louisiana	0.191	0.202	0.154	0.453	0.016	0.073	0.137	0.774
Maine	0.243	0.197	0.164	0.396	0.007	0.022	0.060	0.911
Maryland	0.191	0.193	0.154	0.463	0.010	0.033	0.141	0.815
Massachusetts	0.175	0.175	0.153	0.498	0.003	0.017	0.075	0.904
Michigan	0.187	0.184	0.150	0.479	0.008	0.027	0.093	0.873
Minnesota	0.175	0.187	0.160	0.478	0.075	0.116	0.175	0.634
Mississippi	0.191	0.165	0.136	0.507	0.013	0.039	0.127	0.822
Missouri	0.181	0.183	0.139	0.498	0.036	0.092	0.142	0.731
Montana	0.323	0.236	0.146	0.295	0.081	0.106	0.135	0.679
Nebraska	0.201	0.185	0.140	0.474	0.083	0.093	0.150	0.674
New Hamp	0.152	0.154	0.129	0.565	0.002	0.008	0.013	0.977
New Jersey	0.212	0.195	0.145	0.447	0.002	0.018	0.138	0.842
New Mexico	0.201	0.182	0.143	0.474	0.002	0.012	0.045	0.941

Nevada	0.225	0.206	0.149	0.419	0.019	0.074	0.183	0.726
New York	0.205	0.180	0.155	0.460	0.001	0.003	0.012	0.984
North Carolina	0.181	0.169	0.135	0.515	0.001	0.003	0.012	0.984
North Dakota	0.236	0.224	0.175	0.364	0.077	0.094	0.106	0.723
Ohio	0.168	0.180	0.151	0.501	0.004	0.011	0.022	0.963
Oklahoma	0.208	0.191	0.146	0.455	0.053	0.098	0.175	0.674
Oregon	0.232	0.201	0.151	0.416	0.007	0.026	0.066	0.901
Pennsylvania	0.178	0.180	0.150	0.491	0.004	0.012	0.045	0.940
Rhode Island	0.215	0.203	0.168	0.415	0.001	0.002	0.009	0.988
South Carolina	0.185	0.166	0.130	0.520	0.014	0.049	0.116	0.821
South Dakota	0.250	0.218	0.173	0.358	0.014	0.018	0.021	0.948
Tennessee	0.161	0.161	0.135	0.543	0.011	0.057	0.125	0.808
Texas	0.172	0.169	0.136	0.523	0.020	0.050	0.091	0.839
Utah	0.182	0.180	0.132	0.506	0.005	0.008	0.020	0.967
Vermont	0.262	0.210	0.164	0.364	0.006	0.021	0.180	0.793
Virginia	0.183	0.171	0.142	0.504	0.002	0.012	0.046	0.939
Washington	0.221	0.194	0.144	0.441	0.008	0.021	0.044	0.927
West Virginia	0.212	0.184	0.144	0.460	0.018	0.072	0.212	0.698
Wisconsin	0.184	0.197	0.165	0.454	0.023	0.068	0.140	0.768
Wyoming	0.311	0.220	0.139	0.330	0.056	0.150	0.286	0.509
Average	0.201	0.186	0.147	0.466	0.021	0.050	0.107	0.822

See data descriptions in Data Appendix.