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The Shale Oil Boom and the U.S. Economy: Spillovers and Time-Varying Effects*

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We analyze if the transmission of oil price shocks on the U.S. economy has changed as a result of the shale oil boom. To do so we allow for spillovers at the state level, as well as aggregate country level effects. We identify and quantify these spillovers using a factor-augmented vector autoregressive (VAR) model, allowing for time-varying changes. In contrast to previous results, we find considerable changes in the way oil price shocks are transmitted: there are now positive spillovers to non-oil investment, employment and production in many U.S. states from an increase in the oil price - effects that were not present before the shale oil boom.

JEL-codes: C11, C55, E32, E42, Q43

Keywords: Shale oil boom, FAVAR model, Time-varying changes, Geographical dispersion

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1 Introduction

In view of the volatile oil prices experienced over the past decades, understanding the factors underlying oil price movements and the impact on economic activity has been important.[1] When oil prices fell by more than 70% between 2014 and 2016, a natural question therefore quickly rose as to what extent the massive fall in oil prices would now stimulate U.S. economic growth. After all, such a decline should be good news to both consumers and producers in an oil importing country. Little evidence, however, has been found to back up such claims. In fact, according to an IMF Survey (March 2016), cheap oil doesn't seem to have given a boost to U.S. real economic activity.

Why didn't growth in the U.S. pick up following the lower oil price? One obvious suggestion is that the U.S. has dramatically reduced its dependence on petroleum imports as its own production of oil has surged. Throughout the 2000s, horizontal drilling and hydraulic fracturing led to a massive boost in the production of oil from shale rock deep underground. The U.S. eventually produced more oil than it imported, becoming by 2015 a net oil exporter. Thus, when oil prices fell, U.S. oil producers were instead hurt, affecting the overall economy negatively.

Recent studies analyzing whether the shale boom has fundamentally changed the way oil price shocks are being transmitted to the U.S. economy have, however, not found any evidence of such effects. In particular, Baumeister and Kilian (2016) analyze the effects of the massive oil price decrease on the U.S. economy using simple regressions, and conclude that while real investments in the oil sector have declined, private real consumption and non-oil related business investments have been positively stimulated by the oil price decline, offsetting the negative drawback from the oil sector. Thus, according to Baumeister and Kilian (2016), the U.S. still responds to the oil price shocks as a net oil importer: when oil prices rise, GDP falls, and vice versa.

We challenge this claim on two grounds. First, we believe that transitioning from a net oil importer to a significant net oil exporter does not happen by itself. Such a transition requires capital, technology, labor, skills, and, most importantly, learning by doing (LBD) over a prolonged period of time. In fact, the seed of the shale gas boom was planted already in the 1970s when the U.S. government decided to fund R&D programs and provide tax credits to enterprises interested in developing unconventional natural gas. Still, it was not before the private entrepreneurship of Mitchell Energy, who experimented with new techniques for drilling shale in the early 2000s, i.e., combining horizontal drilling

[1] A higher oil price will typically increase the cost of producing domestic output, while demand for other goods and services declines as consumers have less money to spend, see Hamilton (1983) for a seminal paper and e.g. Hamilton (2009), Kilian (2009), Edelstein and Kilian (2009), Peersman and Robays (2012), Cashin et al. (2014), Aastveit (2014) and Aastveit et al. (2015) for more recent studies.

with hydraulic fracturing, that the process escalated and the natural gas boom spread to oil.[2] Hence, when analysing the effects of the recent oil price drop on the U.S. economy, allowing for changing dynamics related to the shale oil boom seems imperative.

Second, during such a transition process, there may be productivity spillovers between the oil-related and non-oil related industries. To the extent that these spillovers are important, it could imply wider benefits for the economy, cf. Bjørnland and Thorsrud (2016) and Bjørnland et al. (2018) for applications to resource rich countries such as Australia and Norway. Thus, allowing for spillovers between various industries seems important when analyzing the wider impact of a resource boom such as that experienced in the U.S.[3] In fact, claims for local spillovers are already being backed up by a recent branch of literature using primarily cross-section or panel data, see, e.g., Weber (2012), Allcott and Keniston (2018), Feyrer et al. (2017), and Gilje et al. (2016) among others. Applied to regional data in resource abundant U.S. states, these studies consistently find that energy booms benefit local non-oil employment, wages and production.

Common to these recent (panel) data studies, however, is the fact that they focus on activity at the local level in resource abundant U.S. states. Hence, while accounting for instantaneous spillovers in certain geographical areas, little is known about the dynamic effects on the aggregate macroeconomy. Our hypothesis is that the oil boom has had positive spillovers to many different industries across the U.S., and that these spillovers have changed over time. For this purpose, we need a time-series framework that also allows for geographical dispersion. Previous times series studies addressing this issue, have typically been aggregate and focus on only a few macroeconomic variables. Furthermore, most often they rely on time-invariant regressions. Thus, their maintaining assumption is that the effect of an oil price shock has not changed over time, and that the role of the oil sector is of little importance when analysing the dynamic effects of oil prices on the U.S. economy.

We address all of these shortcomings. In particular, we analyse the effect of an oil price shock on the U.S. economy taking into account spillovers from oil to various industries and employment across the U.S. states, while also allowing these dynamics to vary over time. In so doing, we investigate whether the effects of oil price shocks on the U.S. economy

[2] Natural gas from shale could now be economically produced, which led to dramatic increase in natural gas production, and consequently lower prices of natural gas in the U.S. In 2009, when oil prices were relatively high, firms began to experiment with shale technology to extract oil. Several firms were successful in adopting shale technology in oil basins and production of shale oil increased significantly (see Wang and Krupnick (2013) for the review of history of shale gas development in the United States).

[3] In particular, technological developments in drilling and fracking have unlocked huge reserves that lie trapped in shale rock, which again have had major implications for the economic development locally in the resource abundant states in the U.S.

have changed during the last two decades. For this purpose we specify and estimate a time-varying parameter (TVP) factor-augmented VAR (FAVAR) model with stochastic volatility, see e.g. Korobilis (2013), Bernanke et al. (2005), Primiceri (2005) for seminal contributions.

We combine several approaches already developed in the literature, but in a separate manner. First, we relate to a large literature that analyses the effect of oil price changes on the U.S. economy, see e.g. Hamilton (2009), Kilian (2009), Edelstein and Kilian (2009), Peersman and Robays (2012), Cashin et al. (2014), Aastveit (2014) and Aastveit et al. (2015) among many others. However, in contrast to these papers which analyze the effect of oil price shocks on the U.S. economy in the period when the country was a net oil importer, we explicitly include the oil sector into the analysis to allow for changing dynamics due to the shale oil boom. For this purpose, we use a FAVAR model with a large data set and time varying changes.

Second, we relate to a branch of the literature that has documented important differences in the transmission channels of oil price shocks to disaggregate industries, see e.g. Bresnahan and Ramey (1993), Davis and Haltiwanger (2001), Lee and Ni (2002) and Herrera (2018). However, while these papers have primarily studied how the negative effects of an oil price shock are transmitted to industries when the U.S was an oil importer, our focus is to unravel potential heterogeneous effects due to the shale oil boom, at both the industry level and across U.S. states.

Third, we relate to the recent literature using panel data studies that have consistently found that energy booms benefit non-oil employment at the local level in many resource abundant U.S. states, c.f. Weber (2012), Allcott and Keniston (2018), Feyrer et al. (2017), and Gilje et al. (2016) among others. In contrast to these papers, however, we focus on the geographical dispersion of the oil price shocks across U.S. states, allowing also for time varying changes.

The TVP FAVAR model is particularly useful when it comes to answering our research questions. First, it allows us to distinguish between different types of shocks affecting the oil market. Second, we are able to simultaneously estimate direct and indirect spillovers between the different sectors of the economy. Third, we can estimate responses to a large number of variables that is not possible with standard multivariate time series techniques due to the curse of dimensionality. Lastly, we are able to take into account the time variation and investigate how the effects of shocks have changed over time. To the best of our knowledge this is the first paper that jointly models the interaction between the oil market and the U.S. economy in a large data environment, allowing for time-varying changes during the fracking revolution.

We find substantial changes in the way an oil price shock is transmitted to the U.S.

economy. In contrast to previous studies, our analysis suggests that after the emergence of the shale oil boom, an increase in the oil price has now positive spillovers to the aggregate U.S. economy, effects that were not present before. In particular, we find non-oil nonresidential business investments, as well as non-oil employment in both oil-producing and manufacturing-intensive states to increase following an oil price rise. What's more, there are positive spillovers to real personal income, and, to some extent, to personal consumption. Hence, the U.S. responses to an oil price shock now more resembles those of an oil exporter rather than those of an oil importer. Assuming symmetric effects, our results imply that an oil price decline will have negative effects on the U.S. economy. This explains the puzzle that has preoccupied IMF recently: namely why the U.S. economy did not experience a boom following the steep decline in oil prices between 2014 and 2016. The answer is simply that the U.S. has increased its reliance of oil, not as a consumer, but by becoming the world's largest oil producer. Going forward, economic policy needs to take into account that the transmission of an oil price shock has changed with the shale oil boom. An oil price increase may now actually be good news for U.S. economic activity.

The remainder of the paper is structured as follows. Section 2 describes a framework for analysing spillovers of oil in an resource rich economy while Section 3 describes the TVP FAVAR model and the dataset. Empirical results are discussed in Section 4, focusing on, among others, the effects of an oil price shock on various industries, the general macroeconomy and geographical dispersion of shocks to state level employment. In Section 5 we analyse robustness while Section 6 concludes.

2 The shale oil boom - A blessing or a curse?

The history of the petroleum industry in the United States goes back to the early 19th century. Petroleum became a major industry following the discovery of oil at Oil Creek, Pennsylvania in 1859, and for much of the 19th and 20th centuries, the U.S. was the largest oil producing country in the world. However, after production peaked in 1970, the U.S. has experienced decades of production decline. Over time, the country has become increasingly dependent on oil, and in 1973, the U.S. government banned firms from exporting oil.

The empirical oil-macroeconomic literature, which took off after the seminal contribution of Hamilton (1983), has typically analyzed the effect of oil price shocks on the U.S. economy in the period when the country was a net oil importer. In line with this, scholars have also found that the U.S. economy responds negatively to an oil price shock that increases oil prices, as both consumers and producers have to pay more for the imported

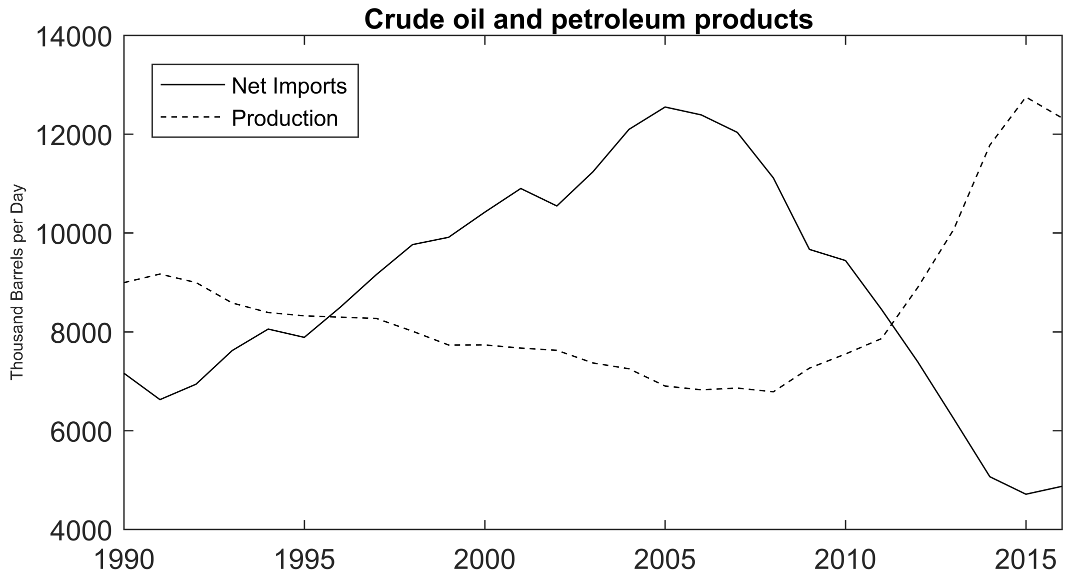


Figure 1: US: Net import of petroleum and crude oil vs. crude oil production

energy products and for the complementary products to energy; again, see, for instance, Hamilton (2009) and Kilian (2009) among many others.

The shale oil boom may have changed this relationship. By 2013 the U.S. was producing more oil than it imported for the first time in two decades, and by 2015 had surpassed Russia and Saudi Arabia to become the worlds biggest producer of oil and gas. By the end of that year, the export ban was lifted, and the U.S. became a net oil exporter. Figure 1 illustrates the transition. It shows how net imports of crude oil have plummeted from 2005/06 as the shale oil boom sparked a strong recovery in the production of crude oil.

In line with this increased production, the oil-producing industry has also grown, with potential spillovers to other industries. The spillovers can, of course, be of any form, crowding in or crowding out other industries. In particular, traditional theories suggest that energy booms often lead to a 'crowding out' of other tradable industries, such as manufacturing. The idea is that gains from the boom largely accrue to the profitable sectors servicing the resource industry, while the rest of the country, including traditional manufacturing, suffers adverse effects from increased wage costs, an appreciated exchange rate, and a lack of competitiveness as a result of the boom. In the literature, such a phenomenon is commonly referred to as Dutch disease, based on similar experiences in the Netherlands in the 1960s, see e.g. Corden and Neary (1982) and Corden (1984) for influential early contributions.

Traditional theories of Dutch disease, however, do not account for productivity spillovers and learning by doing (LBD) between the booming resource sector and other non-resource sectors. Instead, they emphasise that labour would be transferred from strong to weak

LBD sectors, and therefore reduce overall growth, see e.g. van Wijnbergen (1984), Krugman (1987) and Sachs and Warner (1995), Gylfason et al. (1999) and Torvik (2001) among others. Recently, some studies have shown that oil endowment may not necessary be a curse, but can instead be an engine for growth. For instance, Bjørnland et al. (2018) have shown that by developing a dynamic three sector model that incorporates the productivity dynamics from the spending as well as the resource movement effect, the conclusions proffered by earlier models of LBD and the Dutch disease are altered dramatically. In particular, the resource movement effect implies that the growth effects of natural resources are likely to be positive, reversing previous growth results in the literature. The wider benefits for the economy are particularly evident when taking account of productivity 'spillovers' and 'learning-by-doing' between industries, as has also been shown empirically for the resource rich countries Australia and Norway, see Bjørnland and Thorsrud (2016) and Bjørnland et al. (2018).

That the shale oil boom has had implications for economic growth at the local level in the oil rich U.S. states has, as mentioned in the introduction, been documented in some recent papers. In particular, Allcott and Keniston (2018) examine county-level data to investigate the local spillover effects of boom-bust cycles in natural resource production, Weber (2012) examines county level direct effect of drilling, Maniloff and Mastromonaco (2015) study the effect of the number of wells on local economies, Fetzer (2014) estimates the effect of any drilling activity after 2007 on economic outcomes at the local level, while Feyrer et al. (2017) measure the effect of new oil and gas production on income and employment at the county and regional level. Despite different methods, measures of oil and gas activity, areas of study, and time frames, these studies consistently find that energy booms benefit local or regional employment in the resource rich states in the U.S.[4]

However, little, if anything, is known about the spillovers of the shale boom to employment outside the oil rich states, and ultimately, to the aggregate U.S. economy. In particular, to what extent will a resource boom[5] stimulate investment, production, employment, and wages beyond those at the local level in the energy rich states? If there is LBD between industries, one should expect some positive spillovers for the wider economy. However, are these positive spillovers sufficiently strong so as to offset any negative effects from the reduced purchasing power off the consumers? According to Baumeister and Kilian (2016), the answer to this question is no. They find no spillovers from oil-

[4]In addition, Gilje et al. (2016) analyze in a recent study the effect of shale oil development on asset prices. Using the shale oil discovery announcement as their measure of technology innovation the authors find that in the period from 2012 to 2014 these technology shocks explain a significant component of cross-sectional and time series variation in both asset prices and employment growth.

[5]A resource boom takes the form of either a new oil discovery, a more productive oil field or higher real oil prices, see Corden (1984).

related investment to non-oil related investment. In fact, they argue that the recent U.S. economy's response to oil price changes has not been fundamentally different from that observed after the oil price decline in 1986.

We re-address this question, focusing in particular on the potential spillovers from the oil industry to other industries, and the extent to which these spillovers have changed the transmission of oil price shocks to the U.S. economy. To do so, we specify a model that can account for (i) heterogeneous responses in employment to the oil price shocks across U.S. states; (ii) spillovers between industries; and (iii) time-varying responses. We now turn to describe the econometric model in detail.

3 Modeling Framework

Many recent papers, including those cited above, have used SVAR models to study the effects of oil price shocks on the aggregate U.S. economy. As we want to consider the role of the oil industry for the dispersion of oil price shocks to economic activity, we augment the standard VAR model with estimated factors that reflect information from both oil and non-oil variables. To that end, we specify a factor-augmented vector autoregressive (FAVAR) model that includes four factors. The factors will be driven by shocks that have the potential to affect all sectors of the U.S. economy. First, we include a measure of global activity and the real price of oil as two separate factors in the model. These are included to capture, respectively, international business cycle conditions and developments in the oil market that are relevant for the U.S. economy. This allows us in turn to identify two global shocks: a global activity shock and an oil price shock, both of which can affect the real oil price, though with potentially very different macroeconomic implications.

Second, to take into account the fact that there may be heterogeneous responses to the oil price across U.S. industries, we estimate two separate latent factors for the U.S. economy. The inclusion of latent factors also enables us to simultaneously estimate direct and indirect spillovers between different industries and states in the U.S. The simultaneous spillovers between different sectors at different geographical levels can not be captured by including only observable variables in a small panel of data and have therefore not been taken into account in previous studies.[6] While we do not impose any identifying restrictions on these factors, we do see that the four factors capture different aspects of the U.S. economy related to oil and non-oil, see Section 3.4.

Finally, the factors are used in a time-varying parameter (TVP) Vector Autoregressive model with both time-varying coefficients and time-varying variance covariance matrix of

[6] As was shown by Aastveit (2014), the response of macroeconomic variables to different oil price shocks can be considerably different when one jointly models the interaction among endogenous variables.

innovations. By allowing coefficients in the VAR augmented with factors to vary over time we account for possible non-linearities or time variations between the oil price and the U.S. economy. To account for possible heteroscedasticity of the structural shocks and nonlinearities in the simultaneous relations among the variables we allow for multivariate stochastic volatility.[7] All together, this framework allows us to investigate if the transmissions of oil price shocks have changed over time.

On a final note, we have chosen to use a TVP approach to capture smooth changes in the transmission of shocks, which are important for our setting. In particular, we believe that going from a net oil importer to net oil exporter takes time and is therefore well approximated with the TVP approach, rather than a model framework that allows for discrete breaks.

3.1 Data

To accommodate the effects of oil price shocks on the U.S. economy, we include a broad range of domestic macroeconomic indicators as observable variables (reported in Appendix A - Table 2). Among others, we include consumer and producer prices, investment series, stock prices, personal income, various IP series, consumption, and the short term interest rates. To account for local effects we also include employment series in 50 states of the U.S, and distinguish between oil-related and non-oil employment series.

For the two observable global factors, we use a factor that captures global demand proposed by Chiaie et al. (2017). The global factor is strongly related to the measure of economic activity and has homogeneous effects on all commodity markets. Hence, we believe it is well suited as a proxy for global demand. Still, we analyse extensive robustness to our choice of variable in Section 5 by, among others, using an estimate of industrial production for the OECD - plus other major emerging countries - published by OECD Main Economic Indicators and extended from November 2011 by Baumeister and Hamilton (2018). See also Hamilton (2018a) for justification. For the real oil price, we follow Lee and Ni (2002) and Herrera (2018), among many others, and use the U.S. Refineries Acquisition Cost deflated by CPI. Again we analyze robustness to our choice of the real oil price in Section 5, using among other the WTI.

In sum, this gives us a panel of 107 domestic and international quarterly series, covering a sample period from 1990Q1 to 2016Q4. All the series were initially transformed to induce stationarity and demeaned, while the series used to extract factors was also standardized.

[7] As was documented by Baumeister and Peersman (2013a) and Baumeister and Peersman (2013b), there have been changes in elasticities in the oil market in recent decades.

3.2 The time-varying FAVAR Model

Our framework builds on the FAVAR model, first proposed by Stock and Watson (2005) and Bernanke et al. (2005). Technically, the developed and employed model is most closely related to the set-up used in Korobilis (2013). In particular, we use a two-step estimator and replace the factors by the first principal components obtained from the singular value decomposition of the data matrix, and consequently treat them as observables. These factors are then used in a time-varying VAR model with both time-varying coefficients and time-varying variance covariance matrix of innovations, see Primiceri (2005).

Still, we deviate from Korobilis (2013) in several important ways. First, while Korobilis (2013) uses a framework based on Bernanke et al. (2005) and Belviso and Milani (2006) to identify the factors, we follow Boivin and Giannoni (2007) since it is well suited to use with quarterly data.[8] Second, to keep our model as parsimonious as possible, we do not allow for stochastic volatility in the factor analysis regression. Finally, we stick to the standard convention in the literature and model the random walk evolution of the VAR parameters as in Primiceri (2005).

Now, let F_t be a $m \times 1$ vector of common factors assumed to drive the dynamics of the economy. In our application, F_t contains both observable factors y_t of dimension $l \times 1$ and unobservable latent factors, f_t of dimension $k \times 1$, such that $F_t = \begin{pmatrix} y_t \\ f_t \end{pmatrix}$ and $l + k = m$. The latent factors are extracted from a larger dataset X_t of dimension $n \times 1$, and assumed to summarize additional information not captured by the observable factors. We assume that X_t can be described by an approximate dynamic factor model given by

$$X_t = \Lambda F_t + e_t, \tag{1}$$

where Λ is $n \times m$ matrix of factor loadings and $e_t \sim \mathcal{N}(0, R)$, is $n \times 1$ vector of errors assumed to be uncorrelated with the factors F_t and mutually uncorrelated. The joint dynamics of the factors F_t are given by the following transition equation:

$$F_t = c_t + b_{1t} F_{t-1} + ... + b_{pt} F_{t-p} + u_t, \tag{2}$$

where c_t is an $m \times 1$ vector of time-varying intercepts; b_{jt} are $m \times m$ matrices for $j = 1, .., p$ of time-varying coefficients; u_t is an unconditionally heteroskedastic disturbance term that is normally distributed with zero mean and time-varying covariance matrix Ω_t. According to the literature on efficiently parametrizing large covariance matrices, Primiceri (2005),

[8] While Bernanke et al. (2005) and Belviso and Milani (2006) perform a transformation of the principal components exploiting the different behavior of "slow moving" and "fast moving" variables, the same identification scheme would be not be suitable for quarterly data series as most of these series would respond as "fast moving" to oil price shocks within a quarter.

we decompose Ω_t in the following way:

$$\Omega_t = A_t^{-1}\Sigma_t\Sigma_t^{'}(A_t^{-1}), \tag{3}$$

where Σ_t is a diagonal matrix that contains the stochastic volatilities and A_t is a unit lower triangular matrix with ones on the main diagonal that models the contemporaneous interactions among the variables in (2):

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{m1,t} & \cdots & a_{m(m-1),t} & 1 \end{bmatrix} \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{m,t} \end{bmatrix} \tag{4}$$

It follows that

$$F_t = b_{1t}F_{t-1} + ... + b_{pt}F_{t-p} + A_t^{-1}\Sigma_t\varepsilon_t. \tag{5}$$

We follow the standard convention and assume that model's time-varying parameters and stochastic volatilities follow random walk processes. Let $B_t = (vec(c_t)^{'}, vec(b_{1t})^{'}, ..., vec(b_{pt})^{'})^{'}$ be the vector of all R.H.S. coefficients in (5), $\alpha_t = (a_{j1,t}^{'}, ..., a_{j(j-1)}^{'})^{'}$ for $j = 1, ..., m$ be the vector of nonzero and nonone elements of the matrix A_t, and $\sigma_t = (\sigma_{1,t}^{'}, ..., \sigma_{m,t}^{'})^{'}$ be the vector containing the diagonal elements of Σ_t .The dynamics of the three processes are specified as follows:

$$\begin{aligned} B_t &= B_{t-1} + \eta_t^B \\ \alpha_t &= \alpha_{t-1} + \eta_t^\alpha \\ log\sigma_t &= log\sigma_{t-1} + \eta_t^\sigma \end{aligned} \tag{6}$$

We assume that innovations in the model are jointly normally distributed with the following assumptions on the variance covariance matrices:

$$Var\left(\begin{bmatrix} e_t \\ \varepsilon_t \\ \eta_t^B \\ \eta_t^\alpha \\ \eta_t^\sigma \end{bmatrix}\right) = \begin{bmatrix} R & 0 & 0 & 0 & 0 \\ 0 & I_m & 0 & 0 & 0 \\ 0 & 0 & Q & 0 & 0 \\ 0 & 0 & 0 & S & 0 \\ 0 & 0 & 0 & 0 & W \end{bmatrix} \tag{7}$$

where I_m is an m-dimensional identity matrix.

Following Primiceri (2005), we postulate a block-diagonal structure for S, with blocks corresponding to parameters belonging to separate equations. Thus, the shocks to the coefficients of the contemporaneous relations among variables in (5) are assumed to be correlated within equations, but uncorrelated across equations.

3.3 Identification

As motivated above, we estimate a model with four factors, $m = 4$, and with associated shocks that have the potential to affect all sectors of the U.S. economy. The first two 'foreign' factors represent global activity and the real price of oil, and are treated as observables. The two latent factors capture different parts og the domestic activity in the U.S. and are inferred from data.

Starting with the foreign factors, we can identify two structural shocks: a global demand shock and an oil price shock. Specifically, we identify a global activity shock and an oil price shock in a recursive manner, ordering oil prices after global activity in the VAR. Thus we follow the usual assumption from the models of commodity markets, and restrict global activity to respond to oil price disturbances with a lag, see e.g., Hamilton (2009). In turn, any unexpected news regarding global activity is assumed to affect oil price contemporaneously, see e.g., Kilian (2009) and Aastveit et al. (2015).[9]

Turning to the domestic economy, we assume domestic structural shocks can have no contemporaneous effects on global variables (i.e., within the quarter), including the oil price. Hence, the oil price is predetermined with respect to the domestic U.S. variables, in line with findings of Kilian and Vega (2011). Still, one could argue that as the U.S. has gained in importance as an oil producer, news about the U.S. oil activity may have an immediate impact on oil prices. However, we believe the assumption is reasonable, as the cost to the U.S. refiners has closely followed, with few exceptions, the prices of WTI and the Brent Blend crude oil, both of which are traded globally. Furthermore, during most of the period we are analysing, the U.S. oil producers have not been able to export their crude oil export. Still, as the U.S. is a part of the global activity measure (being a large open economy), a shock that originates in the U.S. can therefore affect the real price of oil contemporaneously via the global activity measure.

Finally, note that all observable variables in the vector X_t may respond to all shocks on impact inasmuch as they are contemporaneously related to the factors through the loading matrix, Λ.

[9] In contrast to these papers, and to keep our empirical model as parsimonious as possible, we do not explicitly identify a global oil supply shock, but assume the oil price shock captures all supply side developments as well as speculation etc. However, we believe this is reasonable. As shown in Kilian (2009) and a range of subsequent papers, supply shocks explain a trivial fraction of the total variance in the price of oil, and do not account for a large fraction of the variation in real activity either (at least in the sample used here).

3.4 Estimation and interpretations of the factors

Our model is estimated using a computationally simple two-step estimation method, see Korobilis (2013) and Stock and Watson (2005). In the first step, we estimate the space spanned by the factors using the approach advocated by Boivin and Giannoni (2007), to ensure that the estimated latent factors, f_t, will recover dimensions of the common dynamics not already captured by the observable variables, y_t. Once we have estimated the factors, we treat them as observables, before moving to the second step in which we estimate the time-varying parameters in (5).

In the estimation, we use 4 lags ($p = 4$) for the VAR.[10] A more detailed description of the estimation strategy and prior specification is provided in Appendix B. In Appendix C we provide justification of convergence of the Markov Chain Monte Carlo Algorithm.

The system is estimated using two observable and two latent factors in the vector F_t ($l = 2$, $k = 2$). These four factors explain roughly 60 percent of the variation in X_t. Adding one additional factor increases the variance explained by a modest 5 percent. Even using 8 factors, the variance has only increased to 70 percent.

Before going into the details of the empirical results, we interpret the factors somewhat. As discussed above, the four factors are included to capture different aspects of relevance to the U.S. economy. While the two observable factors are easily interpretable insofar as they capture global activity and the oil price, the two latent factors are unobservable, estimated using the whole dataset for the U.S.

Tables 3 and 4 in Appendix A shed some light on the latent factors by displaying correlations between each factor and some of the series. We focus here on the series that display a correlation coefficient above 0.5 with either of the factors. We note from Table 3 that the first factor turns out to be a good proxy for real non-oil activity in the U.S, as it captures most of the movements in non-farm employment in non-oil states and some key macroeconomic aggregates. Still, the factor has also a small positive correlation with some oil related series. The second factor can be interpreted as an oil activity factor as it follows very closely the movements in oil-related employment and oil investments, and has a small negative correlation with employment in non-oil states, see Table 4. Finally, as we can see from Figure 10 in Appendix A, the factors seem to fit data quite well, even though all the series in our dataset load on these factors.

[10] Hamilton and Herrera (2004) show that a too restrictive lag length can produce misleading results regarding the effects of oil market shocks on the macro economy, while increasing the lag length to over one year has negligible effects.

4 Empirical Results

The aim of this paper is to analyze if the transmission of oil price shocks on the U.S. economy has changed as a result of the shale oil boom. To that end, we focus on the effects of an oil price shock that is normalized to increase oil prices, using impulse responses and variance decompositions. As we will allow for time-varying changes, we report two types of impulse responses. We report median impulse responses at different dates: 2001:Q1, 2004:Q1, 2007:Q1, 2011:Q1, 2013:Q1, 2014:Q1, and 2015:Q1. These dates are chosen arbitrarily and are not crucial for our conclusion. In addition, we also report the impulse responses after 4 quarters over all periods. In so doing we emphasize the maximum effect of an oil price shock, which typically occurs after about three to four quarters according to Hamilton (2008), Herrera and Pesavento (2009), Clark and Terry (2010), Peersman and Robays (2012) and Herrera (2018), at various points in time. However, our conclusions are robust for alternative horizons.

Finally, note that all estimated responses have been accumulated and are shown in levels. To ensure that we compare an equal sized shock over time, we normalize the dynamic effects of exogenous oil price shock to a 1 percent increase in the oil price on impact (for all the calculated responses).[11]

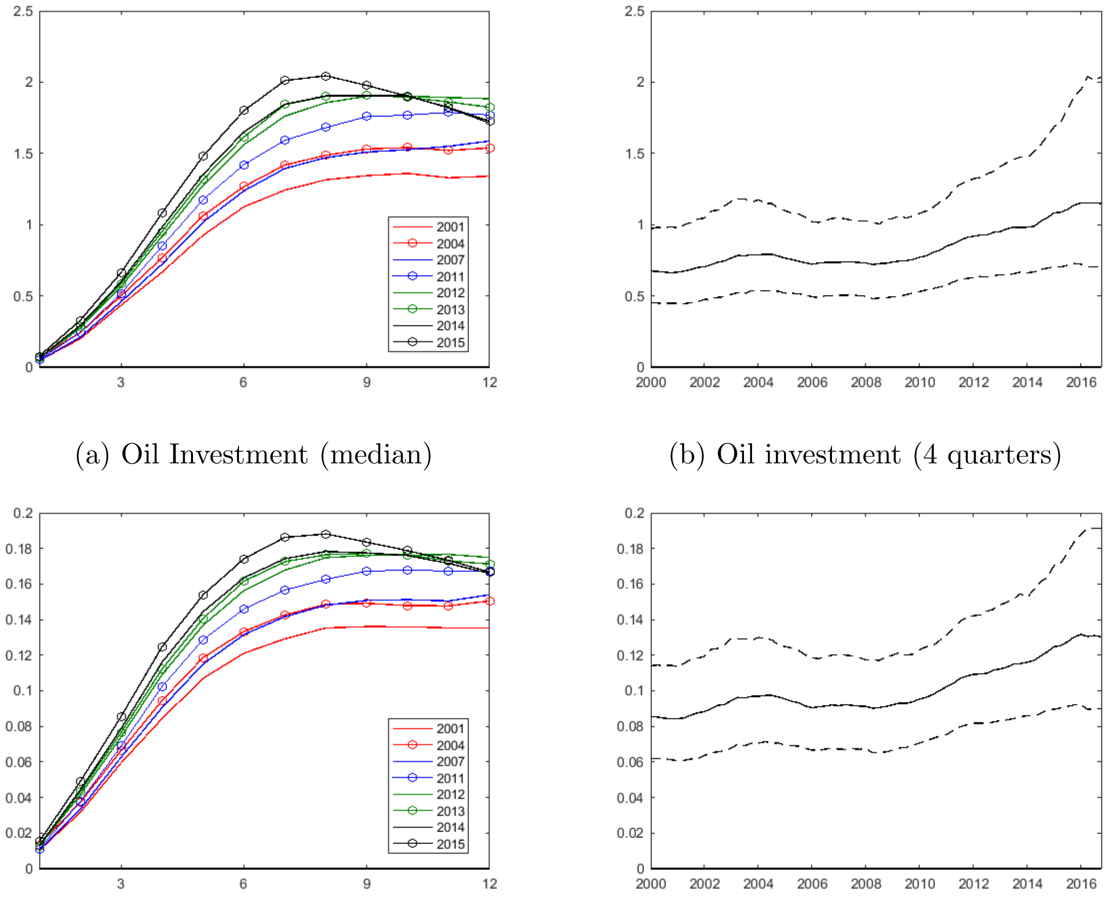
4.1 Oil price shocks and resource boom

We start by examining the impact of the oil price shock on aggregate activity in the oil-producing sector, see Figure 2. To the extent that higher oil prices also generate a resource boom in the U.S. economy, we should expect to see investment and production in the oil sector increase. And we do, cf. Figure 2. The figure reports impulse responses of oil investment and mining to an oil price shock. In the left column, we focus on median responses at different time intervals, while the right column displays responses after four quarters.

Clearly, an oil price increase creates a boom in the oil sector, by gradually increasing investment and mining activity. These effects are in line with our expectations: a higher oil price makes it more profitable for firms operating in the oil sector to produce, and stimulates their investments and activity.[12] We also note that the (maximum) effect has drifted slightly up over time. That is, for an equally sized increase in oil prices, oil investment and mining activity increase slightly more now than before.

[11] A common way to report impulse responses is to examine one standard deviation shock. However, in the models where volatility changes over time, one standard deviation shock corresponds to a different-sized shock at each point in time. Therefore, we normalize the impact effects of the shock over time.

[12] This is consistent with Bjørnland et al. (2017) that shows shale (unconventional) oil producers to be more price responsive than conventional oil producers following an oil price increase.



(a) Oil Investment (median) (b) Oil investment (4 quarters)

(c) Mining (median) (d) Mining (4 quarters)

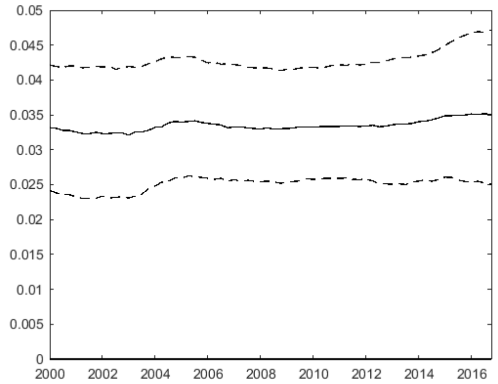
Figure 2: The effect of an oil price shock: Impulse responses for the resource sector: oil-investment and mining. Left column: Posterior median of impulse responses. Right column: Impulse responses after 4 quarters with 16-th and 84-th percentiles

Hence, we conclude that higher oil prices generate a resource boom in the U.S. economy, and even more so now, than prior to the shale boom.

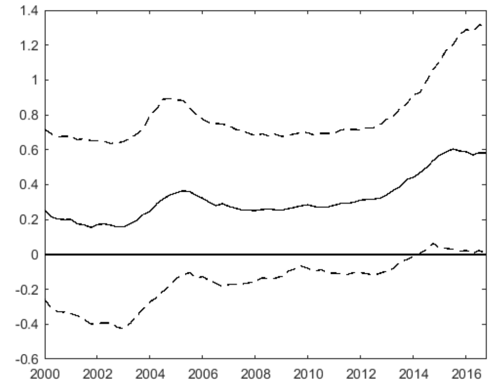
4.2 Aggregate macro effects

Having established that an oil price shock leads to a resource boom, we turn to examine the effects on the aggregate macroeconomy. In particular, Figure 3 presents the responses of an oil price shock after four quarters to some key nominal macro variables: CPI, interest rates, dollar exchange rates, and SP500, while in Figure 4 we examine the responses in some key real variables; investment, income, and consumption.

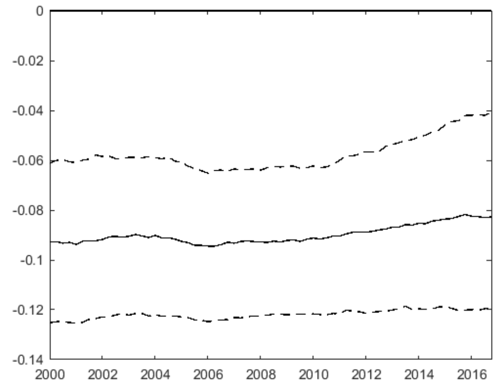
We first note that an oil price increase is strongly associated with an increase in consumer prices (CPI). This effect is significant during the whole sample and is in line



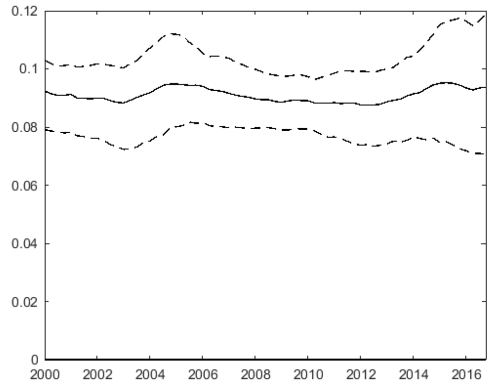
(a) CPI



(b) Interest rate



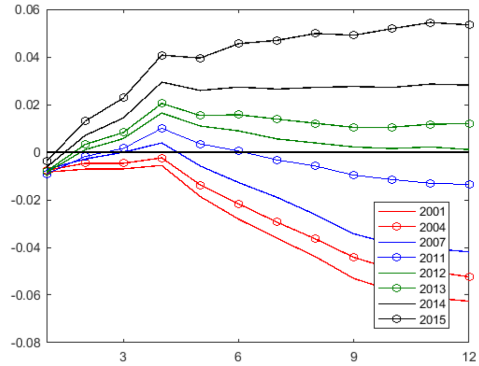
(c) Exchange rate



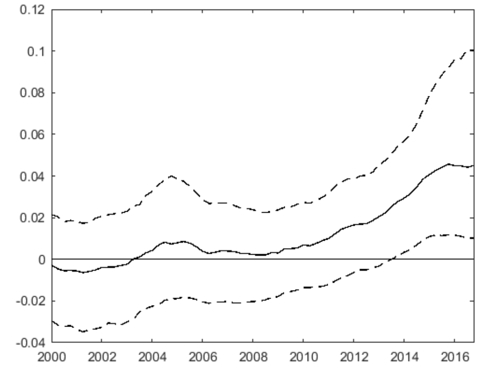
(d) Stock prices (S&P 500)

Figure 3: The effect of an oil price shock: Impulse responses for selected nominal variables in the U.S. economy with 16-th and 84-th percentiles. All responses are reported after 4 quarters, except the response in the stock price that is displayed after 1 quarter

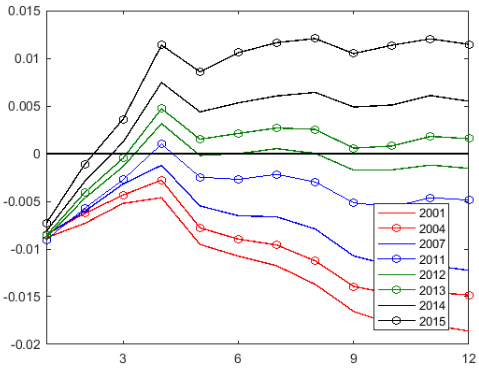
with our expectations and previous findings in the literature (c.f., Hamilton and Herrera (2004)): higher oil prices lead to higher cost for firms, hence prices rise. We also note that the effect on consumer prices shows little time variation. Second, we find that the interest rate also increases after an oil price shock, but the response is only significant at the end of the sample. Hence, with higher oil prices and higher activity in the oil sector, the central bank responds by tightening policy, and significantly more so now than before. The fact that monetary policy has responded more contractionary to increased oil prices over time could also have contributed the more stable responses in prices noted above. Third, the exchange rate depreciates following an oil price shock. This is consistent with many previous studies where it is noted that, since 2000, there has been a negative relationship between the oil price and U.S. dollar, see e.g. Fratzscher et al. (2014). Still, we find that the negative relationship has declined somewhat over time. Finally, we find



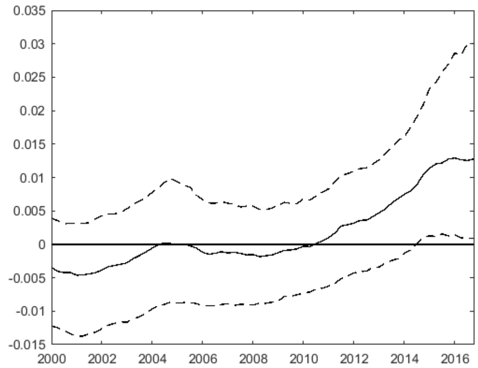
(a) Investment (median)



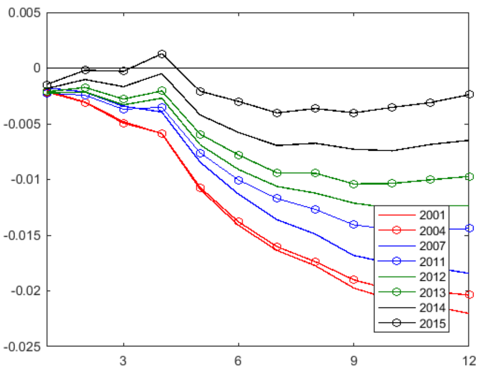
(b) Investment (4 quarters)



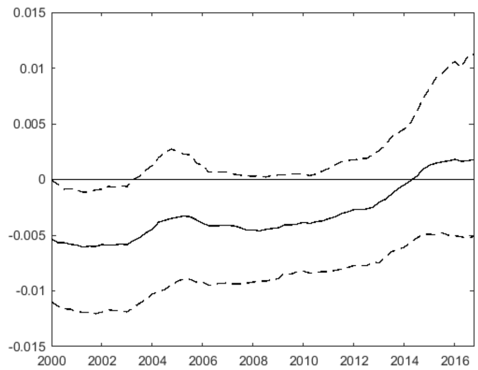
(c) Income (median)



(d) Income (4 quarters)



(e) Consumption (median)



(f) Consumption (4 quarters)

Figure 4: The effect of an oil price shock: Impulse responses for selected real variables of the U.S. economy. Left column: posterior median of impulse responses. Right column: impulse responses after 4 quarters with 16-th and 84-th percentiles

that stock prices increase on impact[13] following an oil price shock. This is very different from the findings in Kilian and Park (2000) using a sample ending in 2006, but well in

[13]Note that the responses for stock prices are reported on impact, as the effect dies quickly out, as expected.

line with more recent studies such as Fratzscher et al. (2014) and Mohaddes and Pesaran (2017).

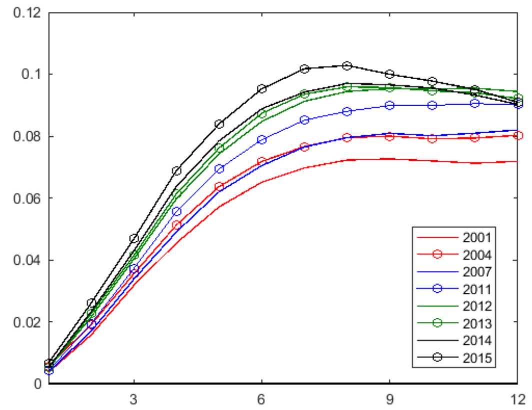
As for the (non-oil) real macro variables, Figure 4 presents the median impulse responses (left column) and the responses after four quarters (right column) to non-residential investment, real personal income, and real private consumption. In contrast to the nominal variables, that did not show much evidence of time-variation, we now observe large time variation for the real variables. First, we find that non-residential (non-oil related) investment has responded systematically more positively to an oil price shock throughout the 2000s, and the effect is significantly positive from 2012/2013, cf. Figure 4. Hence, while non-oil investment in the U.S. economy previously fell when oil prices rose, it is now picking up. This is a new finding in the literature.

Second, for an oil importing country, higher oil prices typically mean lower purchasing power and potentially also lower demand for goods and services, as prices increase, c.f. the results above. This is manifested in lower income and consumption throughout the first part of the sample, see Figure 4. However, from 2012 and onward, real personal income starts to drift upward following an oil price shock. The response in consumption has also gradually changed, and consumption is no longer responding significantly negatively following an oil price shock.

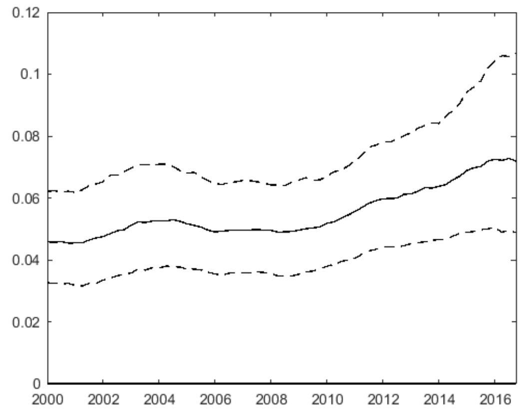
Taken together, these results are consistent with U.S. now behaving more like a net oil exporter. Following an oil price increase, activity in the oil sector increases, and then there are spillovers to non-oil aggregate investment and income, which also now increase with the U.S. resource boom. While these results may be consistent with what has been documented at the local level in oil rich states recently, c.f., Feyrer et al. (2017) and Allcott and Keniston (2018), these are new results for the aggregate U.S. economy. Importantly, it means that higher oil prices are no longer bad news for the U.S. economy. Hence, and oil price decline such as that experienced between 2014 and 2016, may not be beneficial either.

4.3 Disaggregate industry effects

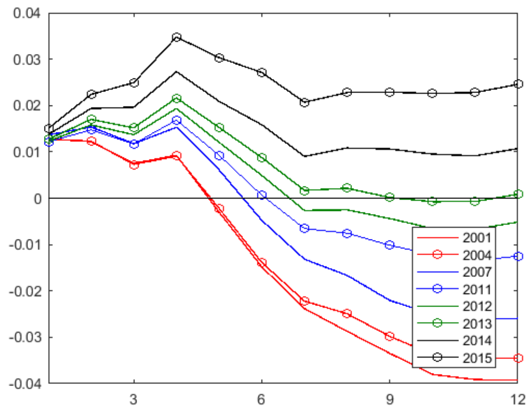
Having seen that there are positive effects on the aggregate U.S. economy arising from an oil price shock that increases oil prices, Figure 5 examines in more detail the response in various industry groups. Not surprisingly, we find that the effect of higher oil prices on energy materials is significantly positive, and shows little time variation over the sample. Hence, production of energy materials increases with the oil boom. More interestingly, however, we observe a strong upward drift in the impulse responses for business supplies and manufacturing, which respond significantly positively to an oil price shock, from approximately 2010. Hence, there are now some positive spillovers from the increased



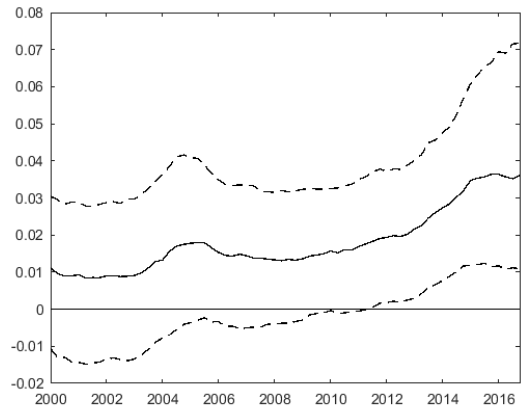
(a) Energy materials (Median)



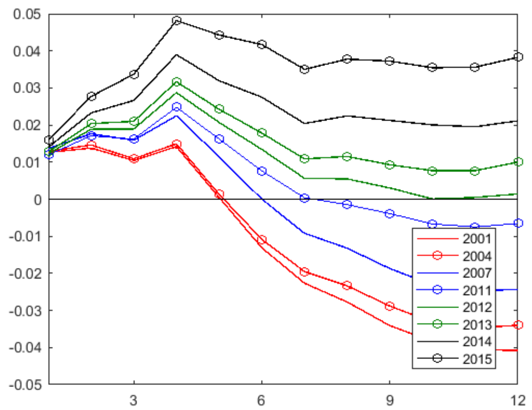
(b) Energy materials (4 quarters)



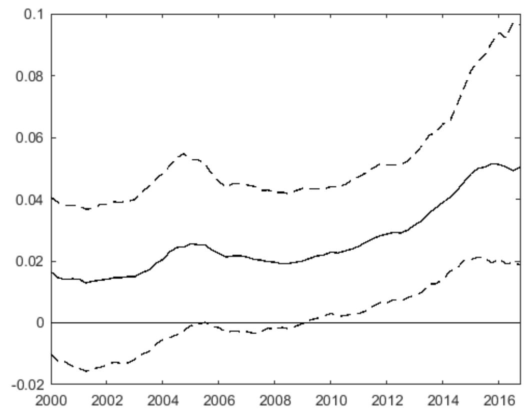
(c) Business supplies (Median)



(d) Business supplies (4 quarters)



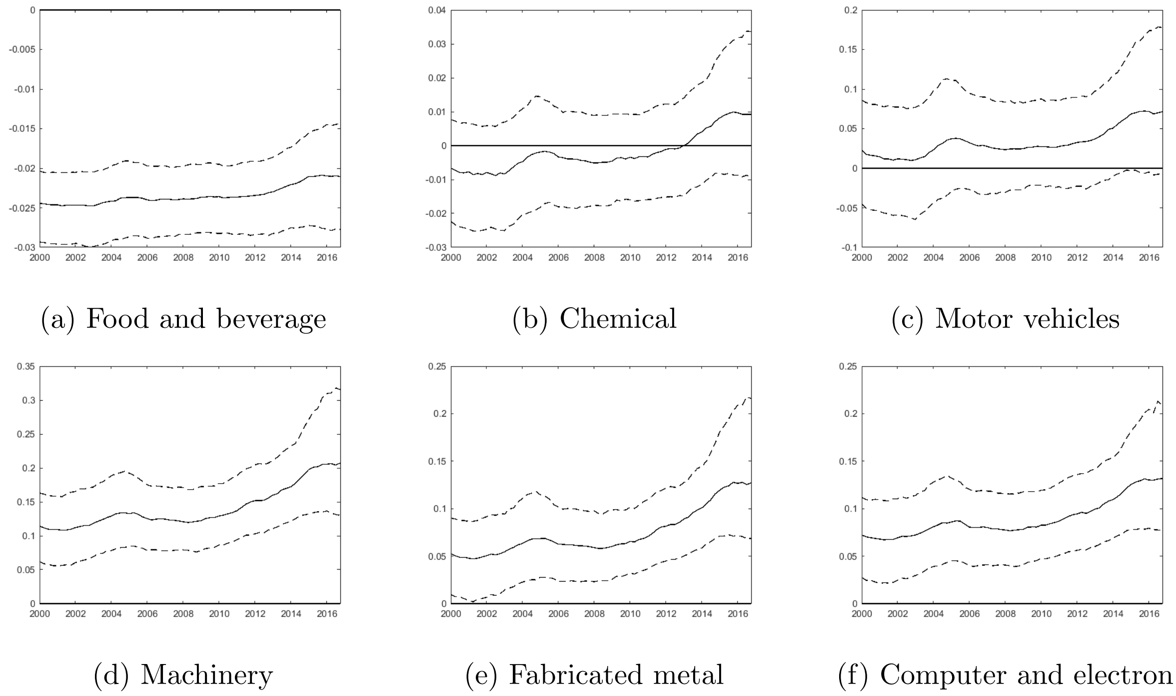
(e) Manufacturing (Median)



(f) Manufacturing (4 quarters)

Figure 5: The effect of an oil price shock: Impulse responses for Industrial Production series divided according to Market Groups. Responses are reported after 4 quarters with 16-th and 84-th percentiles

activity in the oil industry to manufacturing production and business supplies, effects



(a) Food and beverage

(b) Chemical

(c) Motor vehicles

(d) Machinery

(e) Fabricated metal

(f) Computer and electron

Figure 6: The effect of an oil price shock: Impulse responses for Manufacturing series at a disaggregate level. Responses are reported after 4 quarters with 16-th and 84-th percentiles

that were not present before.

Still, we observe some heterogeneity among manufacturing industries when we dig deeper. Investigating subgroups of manufacturing production in Figure 6, we find that some industry groups do still respond negatively, or insignificantly, to the higher oil price. These are typically energy-intensive in production, i.e., food, beverage and tobacco products, motor vehicles, and chemical products. Increased energy prices imply higher consumer prices and therefore reduced demand and production of consumer goods (such as food, beverage, and tobacco products).[14] Several other studies have found similar results, see e.g. Bresnahan and Ramey (1993), Davis and Haltiwanger (2001), Lee and Ni (2002), Herrera (2018). Yet, there are industry groups that respond gradually more positively throughout the period. These are, in particular: machinery, fabricated metal products and computer and electronic products, again see Figure 6. These industries are more closely related to the shale boom and may have benefited from increased demand and spillovers from the resource boom as oil prices increased.

Thus, we suggest that a gradual shift has taken place. More industries are now re-

[14] We also find that petroleum and coal production declines temporarily with the oil boom, which could relate to the fact that downstream oil and gas industries, such as refining and petrochemicals, typically benefit from falling energy prices, not vice versa, see e.g. Herrera (2018) and Brown and Yücel (2013) for further discussions.

sponding by increasing investment and activity when oil prices increase. This suggests why, on average, manufacturing has benefited from higher oil prices during the shale boom, cf. Figure 5. That is, allowing for spillovers between industries, we have found that the oil industry can be an engine for growth.

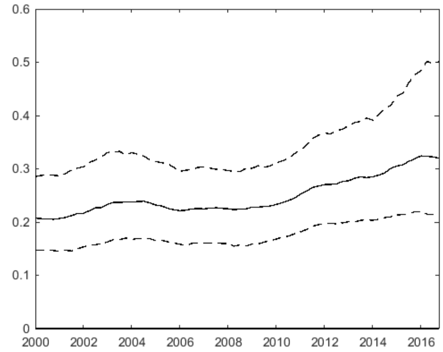
4.4 State level effects - employment

So far we have focused on aggregate macro responses and disaggregate industry responses for the U.S. taken as a whole. We now turn to investigate the response in employment at the state level. We focus on employment as an important part of a resource boom is the movement of labour into the energy producing sector, see Corden (1984) for theory. Furthermore, there is some recent empirical evidence of local spillovers to employment in the oil rich states, see Allcott and Keniston (2018) and Feyrer et al. (2017) using cross section data.

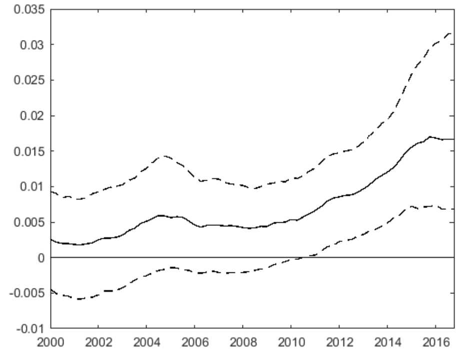
We first investigate the responses in oil related employment and non-farm employment in the oil rich states in Figure 7. Thereafter we investigate non-farm employment in non-oil states in Figure 8. We display in the upper row responses to non-oil employment in states with large manufacturing sectors, and in the lower row, responses to employment in states where manufacturing is small, and not among the main industries. Detailed responses for all other states can be found in Appendix D.

For all the oil-rich states, we find oil-related employment to respond significantly positively during the whole period, and there is little evidence of time variation. Hence, as expected, employment in mining and oil-related industries rise with higher oil prices, and has done so over the whole sample. More interestingly, turning to non-oil employment, there is now clear evidence of time variation. In particular, for some oil rich states, non-oil employment is now increasing with the higher oil prices, see for instance Texas and Oklahoma. In fact, we find significant positive effects on non-oil employment for the 9 biggest oil-producing states. For California, however, the response is not significant positive. These results are consistent with the literature using cross-section data and which suggests the existence of positive spillovers from oil activity on local employment see e.g., Feyrer et al. (2017). The findings are also consistent with the results we have seen at the aggregate level, indicating a geographical dispersion of oil related shocks to non-oil sectors within resource abundant states.

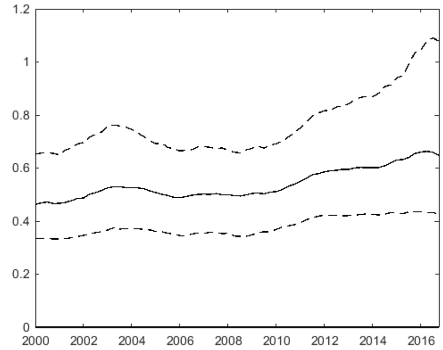
Turning to the states that do not produce oil, there is evidence that also here non-farm employment has gradually responded more positively to an oil shock over the period, see Figure 8. As it turns out, we find significant positive effects on employment in states where a high proportion of their manufacturing sector relates to the oil industry, see for instance Iowa, Illinois and Pennsylvania. These are states where the main industries are



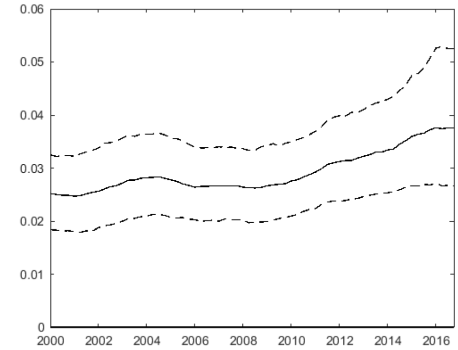
(a) Texas: Oil employment



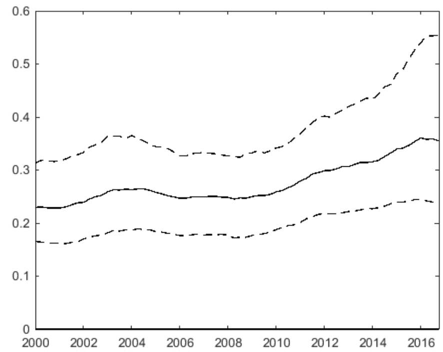
(b) Texas: Non-oil employment



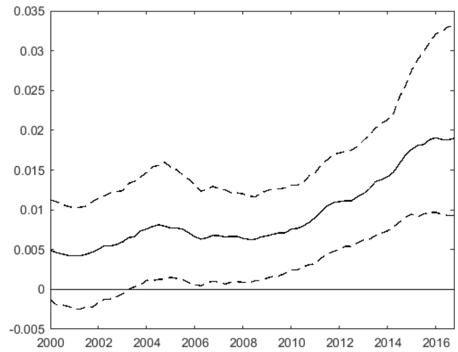
(c) North Dakota: Oil employment



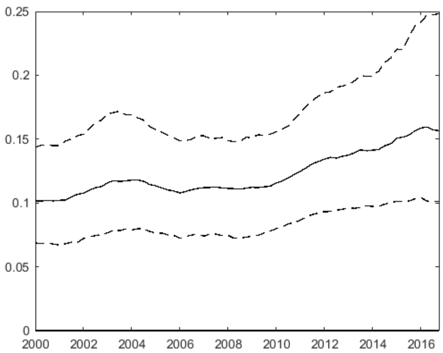
(d) North Dakota: Non-oil employment



(e) Oklahoma: Oil employment



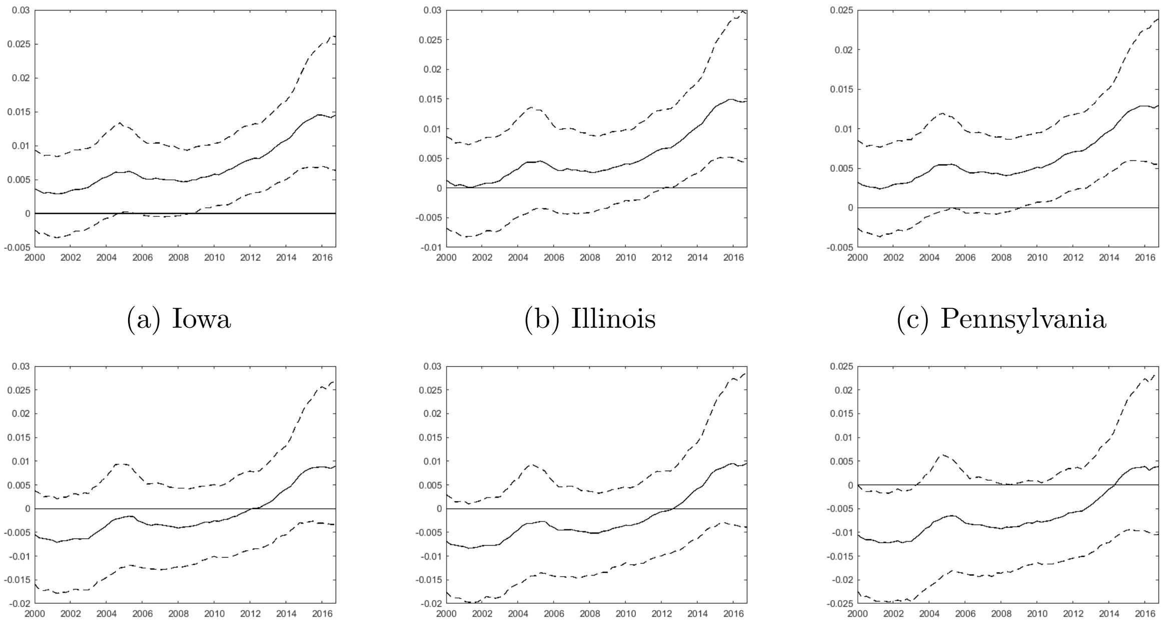
(f) Oklahoma: Non-oil employment



(g) Alaska: Oil employment

(h) Alaska: Non-oil employment

Figure 7: The effect of an oil price shock: Posterior median of impulse responses for employment series in oil-producing states



(a) Iowa (b) Illinois (c) Pennsylvania

(d) Tennessee (e) South Carolina (f) Florida

Figure 8: The effect of an oil price shock: Posterior median of impulse responses for employment in some (non-oil) U.S. states. Upper row: states with a high Manufacturing share in employment, Lower row: states with a low manufacturing share in employment

machinery, fabricated metal products, computer and electronic products, and primary metals. On the other hand, in states with energy-intensive manufacturing production, i.e., the motor vehicle industry, as well as states which have important production of chemical products, petroleum and coal products and production of food, beverages, and tobacco, the effect is still negative or insignificant, see for instance Tennessee, South Carolina, and Florida.

Our results may seem surprising. As alluded to above, the manufacturing sector is a traded goods sector, and, according to the standard Dutch disease literature (e.g. Corden (1984)), we would expect to see a contraction of the traded goods sector and expansion of the non-traded sectors (due to a spending effect). Instead, we find opposite results: The higher oil price generates a resource boom, which again leads to increased demand for output from the manufacturing sector and increased demand for labour. There is also learning by doing spillovers during the shale oil boom, affecting all sectors of the U.S. economy. For instance, as the development of new technology for drilling shale and hydraulic fracturing demands complicated technical solutions, this could in itself generate positive knowledge externalities that benefit many sectors. This is consistent with recent theoretical contributions such as Allcott and Keniston (2018) and Bjørnland et al. (2018).

How important are these effects? The variance decomposition in Table 1 confirms that the oil price shocks explain an important share of the variation in non-oil employment

Table 1: *Employment variance decomposition*

	State	2001Q1	2011Q1	2015Q1
Oil states	Alaska	0.50	0.43	0.60
	North Dakota	0.50	0.43	0.58
	Wyoming	0.44	0.38	0.53
	Oklahoma	0.23	0.27	0.47
	Texas	0.16	0.21	0.42
	California	0.12	0.11	0.21
Non-oil states	Iowa	0.13	0.17	0.40
	Pennsylvania	0.13	0.17	0.39
	Illinois	0.11	0.13	0.32
	South Carolina	0.14	0.13	0.23
	Tennessee	0.11	0.10	0.19
	Florida	0.15	0.11	0.16

Note: Variance decomposition of (no-oil) non-farm employment after 4 quarters explained by oil price shocks

in most oil rich states and in many non-oil states, and the effect has also increased over time. For instance, by 2015, oil price shocks explained 50 - 60 percent of the variation in non-oil employment after four quarters in oil-producing Alaska, North Dakota and Wyoming. The effect is somewhat smaller in the other oil-producing states, and lowest in California, where oil price shocks explain around 20 percent of the variation in non-oil employment. For the non-oil states, the effect is largest in Iowa, Pennsylvania and Illinois, where oil price shocks explain 30-40 percent of the variation in non-oil employment, while for Florida, oil price shocks explain around 15 percent of the variation in employment.

4.5 Geographical dispersion

So far we have seen that there are positive spillovers from the resource boom to employment across the U.S. states. How does this tally with the location of various industries? To discuss this issue we illustrate geographical dispersion of shocks in Figure 9. That is, each U.S. state is colored according to (i) the significance of the oil price shocks on non-oil employment in that state, see Section 4.4, and (ii) the main types of industries in the relevant state, c.f. NAM (2015) for source. To that end, we let grey refer to the oil-rich states where employment responds significantly positively to an oil price shock;

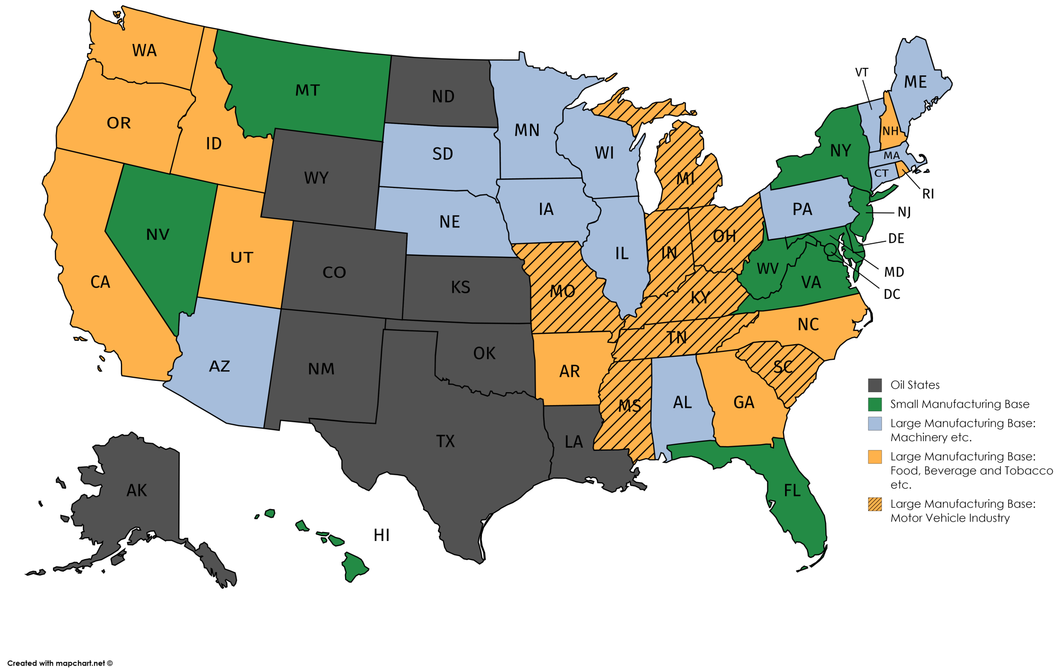


Figure 9: U.S. States and geographical dispersion of oil price shocks. Grey and blue refer, respectively, to oil-rich states and states with a large manufacturing base, and where employment responds significantly positively to an oil price shock; orange represents states with a large manufacturing base and where employment responds negatively or insignificantly to the same shock, while green reflects states with a small manufacturing base and where the effect on employment from an oil price shock is small/insignificant. See the main text for additional explanations.

blue refers to non-oil states with a large manufacturing base (more than 6 percent of the total output in the state) and where employment also responds significantly positive to an oil price shock; orange represents states with an equally large manufacturing base but where employment responds negatively or insignificantly, while green reflects states with a small manufacturing base, and where the effect on employment is small/insignificant.

We have four main findings. First, Figure 9 shows that the positive and significant effects of an oil price shock on non-oil employment in the nine biggest oil producing states (coloured grey) are located in the middle of the U.S., all part of the shale oil boom. Second, the non-oil states that observe an important positive effect on employment (coloured blue) have industries that includes some of machinery, fabricated metal products, aerospace equipment, computer and electronic products, and primary metals as the three most important industries. These industries are typically closely connected to the energy boom and are also primarily located close to the oil producing states or in the north east. Third, the negative/insignificant effects are found in states that have an important manufacturing base that is typically energy-intensive in production, i.e., the motor vehicle industry (coloured orange with stripes), chemical products, petroleum and coal products, food, beverages and tobacco products, and wood products industries (orange colour). These states are either located to the far west, or to the far east, as well as within the 'Rust Belt' (mainly motor vehicle industries). Finally, there are a few states with insignificant but small effects, randomly spread out across the U.S. These are the states with a small manufacturing base (smaller than 6 percent).

We conclude that while there are heterogeneous effects to an oil price shock across the U.S. states, the majority of the U.S. states are now behaving more procyclically with the U.S. oil boom (states coloured grey, blue and green).

5 Robustness

To account for changes in the transmission of an oil price shock to the U.S. economy, we use a time-varying parameters FAVAR model with stochastic volatility. Here we analyze robustness of our choices along several dimensions. First, to what extent are the results driven by the use of time-varying parameters? To illustrate this we estimate a constant parameter parameter model over two different samples, 1990-2006 and 2000-2016. Doing so we still find evidence of changing coefficients, see Figures 13 and 14 in Appendix E. Hence, the results of changing responses are not driven by our choice of model. Having said that, using a simple split sample framework is sensitive to the subjectively chosen break date, and may under or overestimate the true coefficients if there is variation within each sub-sample, as the analysis in Section 4 clearly suggests. To capture such behavior, one needs a flexible model allowing for time-variation, as the one we have applied here.

Second, one concern about our framework is whether the changes in the impulse responses relate to the changes in the size of shock rather than to changes in the propagation mechanisms. To address this issue, we estimate our model with constant coefficients and a drifting variance covariance matrix, suggesting that the time variation comes only from the size of the shocks. Doing so, one can no longer find any evidence for significant changes in the way U.S. economy responded to an oil price shock over the last 16 years, see Appendix F. We therefore conclude that it is the change in mechanisms that is driving the changes in the impulse responses, although the size of oil price shocks also matters.[15]

Third, we justify our prior specification in Appendix G. There, we also report a sensitivity analysis showing that our results are robust to a set of alternative prior choices.

Finally, as is well known in the literature, the choice of data included in the FAVAR

[15]We also estimate a model with time varying factor loadings. However we do not gain any additional information from this extension and the main results (not shown here) remain unchanged.

model may be crucial for the results. In our benchmark model we are using a relative large dataset that includes, among other items, employment for all U.S. states in addition to a bunch of industrial production series. Many of these series could be seen as more of the same type of data, which could have perverse effects, as shown by Boivin and Ng (2006). Furthermore, there are alternative global variables we could include. To deal with this we do a series of changes: (i) We replace our two global variables with alternative data series. In particular, we use GDP for OECD countries instead of our original measure of global activity and the West Texas Intermediate (WTI) deflated by CPI instead of the real oil price. Results are robust to these changes. (ii) We exclude all the employment series at the state level, but include instead a few aggregate employment series divided by industry type. This does not change our main results. (iii) We also test for robustness by excluding the Manufacturing sub-industries series, and we try adding the shadow Federal Funds rate, see Wu and Xia (2016). This latter change is motivated by a concern that the focusing on the Federal rate underestimates the stimulative effect of the unconventional monetary policies conducted in this period. Results are robust to these changes as well. Appendix H illustrates robustness to a combination of all these changes to the data for some selected variables.

6 Conclusion

It is widely accepted that the unprecedented expansion of the U.S. shale oil sector has been a major contributor to oil investment since 2010. In this paper, we demonstrate that the shale oil boom has not only impacted oil investment, but has also changed the way oil price shocks are transmitted to aggregate investment, employment and various industries across the U.S. To capture these effects, we have estimated a factor-augmented vector autoregression (FAVAR) model with time-varying coefficients and stochastic volatility. Our framework allows us to study the effects of oil price shocks on a large number of U.S. macroeconomic variables and analyze the time variation in these effects. To the best of our knowledge this is the first paper that jointly models the interaction between the oil market and the U.S. economy in a large data environment.

In contrast to previous studies, we find substantial changes in the way an oil price shock is transmitted to the U.S. economy. In particular, we find both oil and the non-oil nonresidential business investments, as well as production and employment in oil-producing and manufacturing-intensive states to pick up following an oil price increase. What's more, there are positive spillovers to real personal income. Hence, this explains why the U.S. did not experience a boom following the steep decline in oil prices between 2014 and 2016. The answer is simply that the country has increased its reliance of oil, not as a consumer, but by becoming the world's largest oil producer. Going forward, economic policy needs to take into account that the transmission of an oil price shock has changed with the shale oil boom. An oil price increase may now actually be good news for economic activity in the U.S.

References

Aastveit, K. A. (2014). Oil Price Shocks in a Data-Rich Environment. *Energy Economics 45*, 268–279.

Aastveit, K. A., H. C. Bjørnland, and L. A. Thorsrud (2015). What Drives Oil Prices? Emerging Versus Developed Economies. *Journal of Applied Econometrics 30*(7), 1013–1028.

Allcott, H. and D. Keniston (2018). Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America. *Review of Economic Studies 85*(2), 596–731.

Baumeister, C. and J. D. Hamilton (2018). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *Working paper, UCSD*.

Baumeister, C. and L. Kilian (2016). Lower Oil Prices and the U.S. Economy: Is This Time Different? *Brookings Papers on Economic Activity*, 287–357.

Baumeister, C. and G. Peersman (2013a). The Role of Time-Varying Price Elasticities in Accounting for Volatility Changes in the Crude Oil Market. *Journal of Applied Econometrics 28*(7), 1087–1109.

Baumeister, C. and G. Peersman (2013b). Time-Varying Effects of Oil Supply Shocks on the US Economy. *American Economic Journal: Macroeconomics 5*(4), 1–28.

Belviso, F. and F. Milani (2006). Structural Factor-Augmented VARs (SFAVARs) and the Effects of Monetary Policy. *The B.E. Journal of Macroeconomics 6*(3).

Bernanke, B. S., J. Boivin, and P. Eliasz (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics 120*(1), 387–422.

Bjørnland, H. C., F. M. Nordvik, and M. Rohrer (2017). Supply flexibility in the shale patch: Evidence from North Dakota. CAMP Working Paper No. 2/2017, BI Norwegian Business School, Centre for Applied Macro-and Petroleum Economics.

Bjørnland, H. C. and L. A. Thorsrud (2016). Boom or Gloom? Examining the Dutch Disease in Two-speed Economies. *Economic Journal 126*(598), 2219–2256.

Bjørnland, H. C., L. A. Thorsrud, and R. Torvik (2018). Dutch Disease Dynamics Reconsidered. CAMP Working Paper No. 4/2018, BI Norwegian Business School, Centre for Applied Macro-and Petroleum Economics.

Boivin, J. and M. P. Giannoni (2007). Global Forces and Monetary Policy Effectiveness. *International Dimensions of Monetary Policy*, 429–478.

Boivin, J. and S. Ng (2006). Are More Data Always Better for Factor Analysis? *Journal of Econometrics 132*(1), 169–194.

Bresnahan, T. F. and V. A. Ramey (1993). Segment Shifts and Capacity Utilization in the US Automobile Industry. *The American Economic Review 83*(2), 213–218.

Brown, S. P. and M. K. Yücel (2013). The Shale Gas and Tight Oil Boom: U.S. States' Economic Gains and Vulnerabilities. *New York: Council on Foreign Relations*.

Cashin, P., K. Mohaddes, M. Raissi, and M. Raissi (2014). The Differential Effects of Oil Demand and Supply Shocks on the Global Economy. *Energy Economics 44*, 113–134.

Chiaie, S. D., L. Ferrara, and D. Gionnone (2017). Common Factors of Commodity Prices. *ECB Working Paper No 2111*.

Clark, T. E. and S. J. Terry (2010). Time Variation in the Inflation Passthrough of Energy Prices. *Journal of Money, Credit and Banking 42*(7), 1419–1433.

Cogley, T. and T. J. Sargent (2001). Evolving Post-World War II U.S. Inflation Dynamics. *NBER Macroeconomics Annual 16*, 331–373.

Corden, W. M. (1984). Booming Sector and Dutch Disease Economics: Survey and Consolidation. *Oxford Economic Papers 36*(3), 359–380.

Corden, W. M. and J. P. Neary (1982). Booming sector and de-industrialisation in a small open economy. *The Economic Journal 92*(368), 825–848.

Davis, S. J. and J. Haltiwanger (2001). Sectoral Job Creation and Destruction Responses to Oil Price Changes. *Journal of Monetary Economics 48*(3), 465–512.

Edelstein, P. and L. Kilian (2009). How Sensitive are Consumer Expenditures to Retail Energy Prices? *Journal of Monetary Economics 56*(6), 766—-779.

Fetzer, T. R. (2014). Fracking Growth. *CEP Discussion Paper*.

Feyrer, J., E. T. Mansur, and B. Sacerdote (2017). Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution. *American Economic Review 107*(4), 1313–1334.

Fratzscher, M., D. Schneider, and I. Van Robays (2014). Oil Prices, Exchange Rates and Asset Prices. ECB Working Paper 1689, European Central Bank.

Geweke, J. (1992). Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments. *Bayesian Statistics 4*, 169–193.

Gilje, E., R. Ready, and N. Roussanov (2016). Fracking, Drilling, and Asset Pricing: Estimating the Economic Benefits of the Shale Revolution. NBER working paper no. 22914, National Bureau of Economic Research.

Gylfason, T., T. T. Herbertsson, and G. Zoega (1999). A Mixed Blessing. *Macroeconomic Dynamics 3*(2), 204–225.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy 91*(2), 228–248.

Hamilton, J. D. (2008). Oil and the Macroeconomy. *The New Palgrave Dictionary of Economics, Second Edition, 2008*.

Hamilton, J. D. (2009). Causes and Consequences of the Oil Shock of 2007-08. *Brookings Papers on Economic Activity 40*(1), 215–283.

Hamilton, J. D. (2018a). Measuring Global Economic Activity. Mimeo, University of California at San Diego.

Hamilton, J. D. (2018b). Why You Should Never Use the Hodrick-Prescott Filter. *Review of Economics and Statistics*. (forthcoming).

Hamilton, J. D. and A. M. Herrera (2004). Comment: Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy. *Journal of Money, Credit and Banking*, 265–286.

Herrera, A. M. (2018). Oil price shocks, inventories, and macroeconomic dynamics. *Macroeconomic Dynamics 22*(3), 620–639.

Herrera, A. M. and E. Pesavento (2009). Oil Price Shocks, Systematic Monetary Policy, and The “Great Moderation”. *Macroeconomic Dynamics 13*(1), 107–137.

Kilian, L. (2009). Not All Oil Price Shocks are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review 99*(3), 1053–1069.

Kilian, L. and C. Park (2000). The Impact of Oil Price Shocks on the U.S. Stock Market. *International Economic Review 50*(4), 1267–1287.

Kilian, L. and C. Vega (2011). Do energy prices respond to US macroeconomic news? a test of the hypothesis of predetermined energy prices. *Review of Economics and Statistics 93*(2), 660–671.

Koop, G. (2003). *Bayesian Econometrics*. Wiley, Chichester.

Korobilis, D. (2013). Assessing the Transmission of Monetary Policy Using Time-Varying Parameter Dynamic Factor Models. *Oxford Bulletin of Economics and Statistics 75*(2), 157–179.

Krugman, P. (1987). The Narrow Moving Band, the Dutch Disease, and the Competitive Consequences of Mrs. Thatcher: Notes on Trade in the Presence of Dynamic Scale Economies. *Journal of Development Economics 27*(1), 41–55.

Lee, K. and S. Ni (2002). On the dynamic effects of oil price shocks: a study using industry level data. *Journal of Monetary Economics 49*(4), 823–852.

Loria, F. (2017). The Effect of Oil Price Shocks on U.S. investment: Size Matters. Mimeo, European University Institute.

Maniloff, P. and R. Mastromonaco (2015). The Local Economic Impacts of Hydraulic Fracturing and Determinants of Dutch Disease. *Colorado School of Mines, Division of Economics and Business Working Paper 8*.

Mohaddes, K. and M. H. Pesaran (2017). Oil prices and the global economy: Is it different this time around? *Energy Economics 65*, 315–325.

NAM (2015). National Association of Manufacturers - State Manufacturing Data Reports. http://www.nam.org/Data-and-Reports/State-Manufacturing-Data/.

Peersman, G. and I. V. Robays (2012). Cross-Country Differences in the Effects of Oil Shocks. *Energy Economics 34*(5), 1532 –1547.

Primiceri, G. E. (2005). Time -Varying Structural Vector Autoregressions and Monetary Policy. *The Review of Economic Studies 72*(3), 821–852.

Sachs, J. D. and A. M. Warner (1995). Natural resource abundance and economic growth. Working papers 5398, National Bureau of Economic Research.

Stock, J. H. and M. W. Watson (1996). Evidence on Structural Instability in Macroeconomic Time Series Relations. *Journal of Business & Economic Statistics 14*(1), 11–30.

Stock, J. H. and M. W. Watson (2005). Implications of Dynamic Factor Models for VAR Analysis. *NBER Working Paper* (11467).

Torvik, R. (2001). Learning by doing and the Dutch disease. *European Economic Review 45*(2), 285–306.

van Wijnbergen, S. (1984). The "Dutch Disease": A Disease After All? *The Economic Journal 94*(373), 41–55.

Wang, Z. and A. Krupnick (2013). A Retrospective Review of Shale Gas Development in the United States: What Led to the Boom? *Resources for the Future Discussion Paper 13-12*.

Weber, J. G. (2012). The Effects of a Natural Gas Boom on Employment and Income in Colorado, Texas, and Wyoming. *Energy Economics 34*(5), 1580–1588.

Wu, J. C. and F. D. Xia (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit, and Banking 48*(2-3), 253–291.

Appendices

Appendix A Data Description

Global Variables

	fred	id	Description
1	*Source:* Chiaie et al. (2017)	Global Activity	The Global Factor
2	*Source: EIA*	Oil price	US Refineries Acquisition Cost of domestic and imported crude oil deflated by CPI

Macro aggregates

	fred	id	Description
3	E318RC1Q027SBEA+ *USIEOX..B (Datastream*	Oil Investment	Private fixed investment: Nonresidential: Mining exploration, shafts, and wells + Equipment, mining, and oilfield machinery
4	RPI	Personal Income	Real Personal Income
5	FEDFUNDS	Interest Rate	Effective Federal Funds Rate
6	INDPRO	IP Index	Industrial Production Index
7	PPIACO	PPI	Producer Price Index for All Commodities
8	CPIAUCSL	CPI	CPI : All Items
9	SP500	S&P500	S&Ps Common Stock Price Index: Composite
10	PRFI	Residential Investment	Private Residential Fixed Investment
11	PNFI	Nonresidential Investment:	**Private Nonresidential Fixed Investment:
12	PCEPI	Private Consumption	Real Private Consumption Expenditure (chain-type quantity index)
13	DTWEXM	Trade Weighted U.S. FX Rate	Trade Weighted U.S. Dollar Index: Major Currencies
14	*Source: EIA*	Net Petroleum Imports	U.S. Net Imports of Crude Oil and Petroleum Products (Thousand Barrels per Day)
15	*Source: Census*	Net Trade in Goods	Trade in goods: Net trade

Disaggregate Industrial Production

	fred	id	Description
16	IPMANSICS	Manufacturing	IP: Manufacturing (SIC)
17	IPMINE	Mining	IP: Mining
18	IPUTIL	Utilities	IP: Electric and Gas Utilities
19	IPCONGD	Consumer Goods	IP: Consumer Goods
20	IPBUSEQ	Business Equipment	IP: Business Equipment
21	IPB52300S	Defense and space equipment	IP: Defense and space equipment
22	IPB54100S	Construction supplies	IP: Construction supplies
23	IPB54200S	Business supplies	IP: Business supplies
24	IPZ53010S	Materials excluding energy materials	IP: Materials excluding energy materials
25	IPB53300S	Energy materials	IP: Energy materials
26	IPG321S	Wood product	IP: Durable manufacturing: Wood product

Continued on next page

27	IPG327S	Nonmetallic mineral product	IP: Durable manufacturing: Nonmetallic mineral product
28	IPG331S	Primary metal	IP: Durable manufacturing: Primary metal
29	IPG332S	Fabricated metal product	IP: Durable manufacturing: Fabricated metal product
30	IPG333S	Machinery	IP: Durable manufacturing: Machinery
31	IPG334S	Computer and electronic product	IP: Durable manufacturing: Computer and electronic product
32	IPG335S	Electrical equipment, appliance, and component	IP: Durable manufacturing: Electrical equipment, appliance, and component
33	IPG3361T3S	Motor vehicles and parts	IP: Durable manufacturing: Motor vehicles and parts
34	IPG3364T9S	Aerospace and miscellaneous transportation equipment	IP: Durable manufacturing: Aerospace and miscellaneous transportation equipment
35	IPG337S	Furniture and related product	IP: Durable manufacturing: Furniture and related product
36	IPG339S	Miscellaneous	IP: Durable manufacturing: Miscellaneous
37	IPG311A2S	Food, beverage, and tobacco	IP: Nondurable manufacturing: Food, beverage, and tobacco
38	IPG313A4S	Textiles and products	IP: Nondurable manufacturing: Textiles and products
39	IPG315A6S	Apparel and leather goods	IP: Nondurable manufacturing: Apparel and leather goods
40	IPG322S	Paper	IP: Nondurable manufacturing: Paper
41	IPG323S	Printing and related support activities	IP: Nondurable manufacturing: Printing and related support activities
42	IPG324S	Petroleum and coal products	IP: Nondurable manufacturing: Petroleum and coal products
43	IPG325S	Chemical	IP: Nondurable manufacturing: Chemical
44	IPG326S	Plastics and rubber products	IP: Nondurable manufacturing: Plastics and rubber products

		Nonfarm Employment - States	
	fred	**id**	**Description**
45	ALNA	Alabama	All Employees: Total Nonfarm in Alabama
46	AKNA	Alaska	*All Employees: Total Nonfarm in Alaska
47	AZNA	Arizona	All Employees: Total Nonfarm in Arizona
48	ARNA	Arkansas	All Employees: Total Nonfarm in Arkansas
49	CANA	California	*All Employees: Total Nonfarm in California
50	CONA	Colorado	*All Employees: Total Nonfarm in Colorado
51	CTNA	Connecticut	All Employees: Total Nonfarm in Connecticut
52	DENA	Delaware	All Employees: Total Nonfarm in Delaware
53	FLNA	Florida	All Employees: Total Nonfarm in Florida
54	GANA	Georgia	All Employees: Total Nonfarm in Georgia
55	HINA	Hawaii	All Employees: Total Nonfarm in Hawaii
56	IDNA	Idaho	All Employees: Total Nonfarm in Idaho
57	ILNA	Illinois	All Employees: Total Nonfarm in Illinois
58	INNA	Indiana	All Employees: Total Nonfarm in Indiana
59	IANA	Iowa	All Employees: Total Nonfarm in Iowa
60	KSNA	Kansas	*All Employees: Total Nonfarm in Kansas
61	KYNA	Kentucky	All Employees: Total Nonfarm in Kentucky
62	LANA	Louisiana	*All Employees: Total Nonfarm in Louisiana
63	MENA	Maine	All Employees: Total Nonfarm in Maine

Continued on next page

64	MDNA	Maryland	All Employees: Total Nonfarm in Maryland
65	MANA	Massachusetts	All Employees: Total Nonfarm in Massachusetts
66	MINA	Michigan	All Employees: Total Nonfarm in Michigan
67	MNNA	Minnesota	All Employees: Total Nonfarm in Minnesota
68	MSNA	Mississippi	All Employees: Total Nonfarm in Mississippi
69	MONA	Missouri	All Employees: Total Nonfarm in Missouri
70	MTNA	Montana	*All Employees: Total Nonfarm in Montana
71	NENA	Nebraska	All Employees: Total Nonfarm in Nebraska
72	NVNA	Nevada	All Employees: Total Nonfarm in Nevada
73	NHNA	New Hampshire	All Employees: Total Nonfarm in New Hampshire
74	NJNA	New Jersey	All Employees: Total Nonfarm in New Jersey
75	NMNA	New Mexico	*All Employees: Total Nonfarm in New Mexico
76	NYNA	New York	All Employees: Total Nonfarm in New York
77	NCNA	North Carolina	All Employees: Total Nonfarm in North Carolina
78	NDNA	North Dakota	*All Employees: Total Nonfarm in North Dakota
79	OHNA	Ohio	All Employees: Total Nonfarm in Ohio
80	OKNA	Oklahoma	*All Employees: Total Nonfarm in Oklahoma
81	ORNA	Oregon	All Employees: Total Nonfarm in Oregon
82	PANA	Pennsylvania	All Employees: Total Nonfarm in Pennsylvania
83	RINA	Rhode Island	All Employees: Total Nonfarm in Rhode Island
84	SCNA	South Carolina	All Employees: Total Nonfarm in South Carolina
85	SDNA	South Dakota	All Employees: Total Nonfarm in South Dakota
86	TNNA	Tennessee	All Employees: Total Nonfarm in Tennessee
87	TXNA	Texas	*All Employees: Total Nonfarm in Texas
88	DCNA	District of Columbia	All Employees: Total Nonfarm in the District of Columbia
89	UTNA	Utah	All Employees: Total Nonfarm in Utah
90	VTNA	Vermont	All Employees: Total Nonfarm in Vermont
91	VANA	Virginia	All Employees: Total Nonfarm in Virginia
92	WANA	Washington	All Employees: Total Nonfarm in Washington
93	WVNA	West Virginia	All Employees: Total Nonfarm in West Virginia
94	WINA	Wisconsin	All Employees: Total Nonfarm in Wisconsin
95	WYNA	Wyoming	*All Employees: Total Nonfarm in Wyoming

Mining Employment - Oil States

	fred	id	Description
96	CONRMN	Mining in Colorado	All Employees: Mining and Logging in Colorado
97	KSNRMN	Mining in Kansas	All Employees: Mining and Logging in Kansas
99	SMU22000001021100001SA + SMU22000001021300001SA	Mining in Louisiana	All Employees: Mining: Oil and Gas Extraction + Support Activities for Mining in Louisiana

Continued on next page

100	SMU30000001000000001A	Mining in Montana	All Employees: Mining and Logging in Montana
101	SMU35000001000000001A	Mining in New Mexico	All Employees: Mining and Logging in New Mexico
102	SMU38000001000000001A	Mining in North Dakota	All Employees: Mining and Logging in North Dakota
103	SMU40000001000000001A	Mining in Oklahoma	All Employees: Mining and Logging in Oklahoma
104	SMU02000001021001301	Mining in Alaska	All Employees: Mining: Oil and Gas Extraction, Well Drilling, and Support Activities in Alaska
105	SMU06000001021100001SA + SMU06000001021300001	Mining in California	All Employees: Mining: Oil and Gas Extraction + Support Activities for Mining in California
106	SMU48000001021100001SA + SMU48000001021300001	Mining in Texas	All Employees: Mining: Oil and Gas Extraction + Support Activities for Mining in Texas
107	SMU56000001021100001SA +SMU56000001021311201SA	Mining in Wyoming	All Employees: Mining: Oil and Gas Extraction + Support Activities for Oil and Gas Operations in Wyoming

Additional Variables

	fred	**id**	**Description**
108	*Sources: Board of Governors of the Federal Reserve System and Wu and Xia (2016)*	Shadow Rate	Wu-Xia Shadow Federal Funds Rate
109	MCOILWTICO	WTI	Crude Oil Prices: West Texas Intermediate - Cushing, Oklahoma
110	*Source: OECD.Stat*	OECD	Gross domestic product for OECD countries (expenditure approach)
111	*Baumeister and Hamilton (2018)*		World Industrial Production Index
112	CES1021000001		All Employees: Mining and Logging
113	USCONS		All Employees: Construction
114	MANEMP		All Employees: Manufacturing
115	DMANEMP		All Employees: Durable goods
116	NDMANEMP		All Employees: Nondurable goods
117	SRVPRD		All Employees: Service Industries
118	USTPU		All Employees: TT&U
119	USWTRADE		All Employees: Wholesale Trade
120	USTRADE		All Employees: Retail Trade
121	USFIRE		All Employees: Financial Activities
122	USGOVT		All Employees: Government

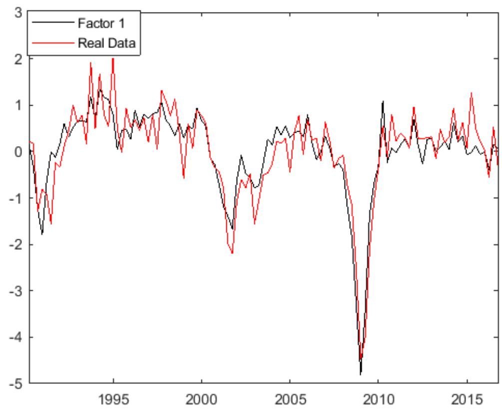
Table 2: Data description. ** Oil related employment is subtracted , ** Oil related investment is subtracted*

	Factor 1	Factor 2
Empl Tennessee	0.90	-0.15
Empl Illinois	0.89	0.05
Empl South Carolina	0.87	-0.08
Manufacturing	0.87	-0.06
Empl Pennsylvania	0.86	0.05
Empl Florida	0.85	-0.17
Business supplies	0.84	-0.11
Empl Texas	0.84	0.17
Empl Iowa	0.80	0.06
Nonresidential Investment	0.77	0.02
Empl California	0.77	-0.01
Machinery	0.72	0.31
Empl Oklahoma	0.71	0.23
Computer and electronic products	0.66	0.01
Real Private Consumption	0.61	-0.21
Interest Rate	0.54	-0.07
Real Personal Income	0.52	0.03

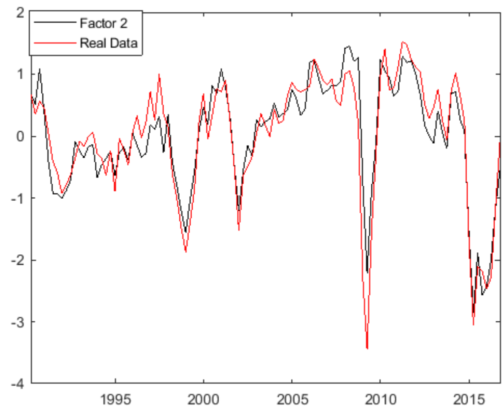
Table 3: Examples of data series with correlation above 0.5 with factor 1.

	Factor 1	Factor 2
Empl Texas: Oil	0.23	0.93
Empl Oklahoma: Oil	0.26	0.87
Empl New Mexico: Oil	0.36	0.82
Empl Colorado: Oil	0.29	0.82
Empl Wyoming: Oil	0.19	0.81
Empl North Dakota: Oil	0.06	0.81
Oil Investment	0.26	0.75
Empl Kansas: Oil	0.32	0.73
Empl California: Oil	0.13	0.70
Empl Louisiana: Oil	0.17	0.64
Mining	0.30	0.64
Empl Montana: Oil	0.29	0.60
Empl Alaska: Oil	0.03	0.56
Energy Materials	0.25	0.51

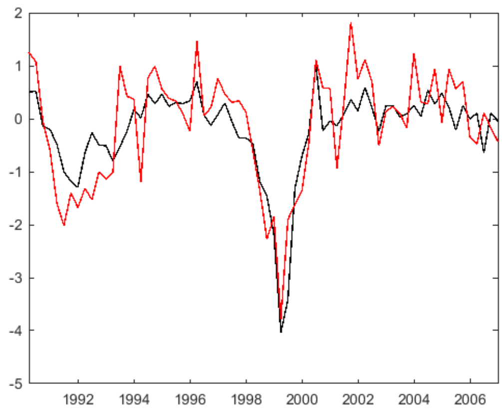
Table 4: Data series with correlation above 0.5 with factor 2.



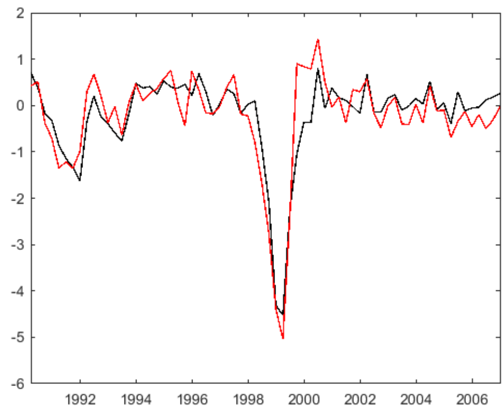
(a) Nonfarm in Illinois



(b) Mining in Texas



(c) Nonresidential Investment



(d) Manufacturing

Figure 10: Graphs of the estimated factors compared to data series. Frame (a) and (b) plots factor 1 and factor 2 respectively compared to real data; frame (c) and (d) plot the estimated values of macroeconomic series from Equation 1 compared to real data

Appendix B Estimation of a FAVAR model

B.1 Two Step Estimator Approach

In Section 3 of the main paper we described the benchmark model. Here we provide a more detailed overview of how the model is estimated. We start by repeating the main system equations.

The main two equations in our model are the factor equation (8) and the VAR equation (9):

$$X_t = \Lambda F_t + e_t, \tag{8}$$

$$F_t = b_{1t} F_{t-1} + ... + b_{pt} F_{t-p} + A_t^{-1} \Sigma_t \varepsilon_t. \tag{9}$$

where the common factors F_t contain both the unobservables latent factors,f_t and the observables factors y_t: $F_t = \begin{pmatrix} y_t \\ f_t \end{pmatrix}$

The time-varying parameters and covariances of the model follow random walk processes given by (10):

$$\begin{aligned} B_t &= B_{t-1} + \eta_t^B \\ \alpha_t &= \alpha_{t-1} + \eta_t^\alpha \\ log\sigma_t &= log\sigma_{t-1} + \eta_t^\sigma \end{aligned} \tag{10}$$

where B_t is the vector of all R.H.S. coefficients in (9), α_t is the vector of non-zero and no-none elements of the matrix A_t, and σ_t is the vector containing the diagonal elements of Σ_t .

The innovations in the model are assumed to be normally distributed with the following assumptions on the variance covariance matrix:

$$Var \left(\begin{bmatrix} e_t \\ \varepsilon_t \\ \eta_t^B \\ \eta_t^\alpha \\ \eta_t^\sigma \end{bmatrix} \right) = \begin{bmatrix} R & 0 & 0 & 0 & 0 \\ 0 & I_m & 0 & 0 & 0 \\ 0 & 0 & Q & 0 & 0 \\ 0 & 0 & 0 & S & 0 \\ 0 & 0 & 0 & 0 & W \end{bmatrix} \tag{11}$$

The system is then estimated in two steps. In the first step we estimate the unobservable factors f_t, while in the second step we estimate model parameters, conditional on the factors. Below we describe each step in greater detail.

B.1.1 Step1: Latent Factor Estimation

We start by extracting k principal components from X_t and obtain estimates of the latent factors, f_t. In doing so, we do not impose a constraint whereby the observable factors y_t are the common component. So if the variables in y_t are common components, they should be captured by the principal components. To remove y_t from the space covered by the principal components, we follow the approach advocated by Boivin and Giannoni (2007), and impose the constraint that observable variables are two of the factors in the first-step estimation. We denote the initial estimate of f_t by f_t^0, and iterate through the following steps:

1. RegressX_t on f_t^0 and the observed factors y_t and obtain $\hat{\lambda}_y^0$
2. Compute $\hat{X}_t^0 = X_t - \hat{\lambda}_y^0 y_t$
3. Estimate f_t^1 as the k principal components of $\hat{X}_t^0$
4. Repeat the procedure multiple times

This procedure guarantees that the estimated latent factors will recover dimensions of the common dynamics not already captured by the observable variables, y_t. Given the factors, F_t, we can estimate parameters in (8) and (9) independently of each other.

B.1.2 Step 2: The Gibbs Sampling Approach - Estimation of model parameters

Estimation of parameters in Factor Equation

Since the covariance matrix of the error terms in (8) is diagonal, we can estimate all the parameters equation-by-equation. The parameters are sampled using standard arguments for linear regression models (see Koop (2003)).

Block 1: $\Lambda^{post}, Var(\Lambda)^{post} | X, F, \Lambda^{prior}, Var(\Lambda)^{prior}, R$

Conditional on the priors specified in B.2, the posterior draws of factor loadings of equation i ,λ_i, and its variance $Var(\lambda_i)$ are:

$$\lambda_i^{post} = (Var(\lambda_i)^{post})^{-1}((Var(\lambda_i)^{prior})^{-1}\lambda_i^{prior} + R_{i,i}^{-1}F'X_i)$$
$$Var(\lambda_i)^{post} = \left((Var(\lambda_i)^{prior})^{-1} + R_{i,i}^{-1}X_i'X_i\right)^{-1}$$

for $i = 1, ..., N$.

Block 2: $R|X, F, \Lambda^{post}, \nu_0, \delta_0$

We draw the conditional posterior for R from inverse Gamma distribution:

$$R_{i,i}|... \sim IG(\frac{\nu_1}{2}, \frac{\delta_1^{(i)}}{2}) \tag{12}$$

$\nu_1 = \nu_0 + T$ and $\delta_1^{(i)} = \delta_0 + (X_i - \lambda_i^{post} F)^2$

Estimation of parameters in TVP VAR

The TVP VAR model in (9) is estimated by simulating the distribution of the parameters of interest, given the data and the priors specified in B.2. Following Primiceri (2005), Gibbs sampling is carried out in four steps, drawing in turn on time-varying coefficients (B_t), simultaneous relations (A_t), volatilities (Σ_t), and hyper parameters (Q, W, S), conditional on the observed data, estimated factors and the rest of the parameters. For further details we refer to Primiceri (2005).

B.2 Prior specification

We use an informative prior based on the training sample (from 1990:Q2 to 1999:Q4). Following Primiceri (2005) the mean and the variance of B_0 and α_o are chosen to be OLS point estimates and four times their variance of their estimates on initial subsample. For log σ_0, the mean of the distribution is chosen to be the logarithm of the OLS point estimates of the standard errors of the same time invariant VAR, while the variance covariance matrix is arbitrarily assumed to be identity matrix. Similarly, the mean and the variance of factor loadings from (8), Λ, are chosen to be OLS point estimates and four times their variance of their estimates from the training sample.

$$B_0 \sim \mathcal{N}(\hat{B}_{OLS}, 4Var(\hat{B}_{OLS}))$$

$$\alpha_0 \sim \mathcal{N}(\hat{\alpha}_{OLS}, 4Var(\hat{\alpha}_{OLS}))$$

$$log\sigma_0 \sim \mathcal{N}(log\hat{\sigma}_{OLS}, I_n)$$

$$\Lambda \sim \mathcal{N}(\hat{\Lambda}_{OLS}, 4Var(\hat{\Lambda}_{OLS}))$$

We use prior from Inverted Gamma distribution for variance-covariance matrix R .

$$R \sim IG(\frac{\nu_1}{2}, \frac{\delta_1}{2})$$

where $\nu_1 = \nu_0 + T$ and $\delta_1 = \delta_0 + (X - \hat{\Lambda}^{post} F)$. The priors for the remaining hyper-parameters are all from the Inverse-Wishart distribution:

$$Q \sim IW(k_Q^2(1 + dim_B)Var(\hat{B}_{OLS}), 1 + dim_B)$$

$$W \sim IW(k_W^2(1 + dim_W)I_p, 1 + dim_W)$$

$$S_i \sim IW(k_S^2(1 + dim_{S_i})Var(\hat{A}_{i,OLS}), 1 + dim_{S_i})$$

Following Korobilis (2013) the degrees of freedom are set to $dim_B = m \times m \times p$, $dim_W = m$ and $dim_{S_i} = 1, .., m-1$, and are larger than the dimension of the corresponding matrices, required to achieve a proper Inverse-Wishart distribution.

The benchmark results in this paper are obtained using the following values: $k_Q = 0.01$, $k_S = 0.1$, $k_W = 0.1$ and $\nu_0 = 10$, $\delta_0 = 10$. We refer to Appendix G for a discussion of this choice and of the robustness of the results to alternative prior specifications.

Appendix C Convergence of the Markov Chain Monte Carlo Algorithm

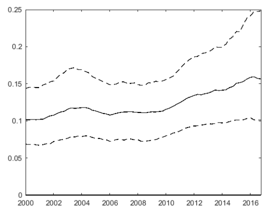
We perform 30,000 iterations of the Gibbs sampler. The first 15,000 draws are discarded and only every tenth of the remaining iterations is used for inference. The produced results are not sensitive to the number of discarded draws or the number of passes used for inferences. Following Primiceri (2005) and Baumeister and Peersman (2013b), we ascertain that our Markov chain has converged based on the inefficiency factors (IFs) for the posterior estimates of the parameters, that is the inverse of the relative numerical efficiency (RNE) measure proposed by Geweke (1992). Here the estimates are performed by employing a 4 percent tapered window used in computation of the RNE. As was noticed by Primiceri (2005), values of the IFs below or around 20 are regarded as satisfactory. As can be seen from the summary of the distribution of the inefficiency factors for different set of parameters, reported in Table 5, the sample seems to have converged. That is, all mean IF values are below 13 and 90 percent of the IFs are below 18., indicating modest autocorrelation for all elements.

	Median	Mean	Min	Max	10-th Percentile	90-th Percentile
B	6.26	5.54	0.96	21.04	3.02	10.45
Λ	0.96	0.94	0.40	1.80	0.70	1.27
Σ	3.94	3.44	0.78	9.85	1.59	6.70
A	4.00	3.32	1.65	11.47	2.12	7.10
V	13.47	13.32	3.77	25.08	8.91	18.24
R	0.97	0.96	0.56	1.68	0.73	1.27

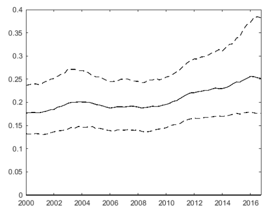
Table 5: Summery of the distribution of the IFs for different sets of parameters, where V is the set of hyperparameters $\{Q, S, W\}$

Appendix D Impulse Responses: Effect of oil price shocks on employment in the U.S. states

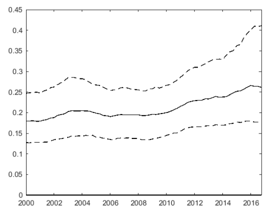
D.1 Oil Related Employment



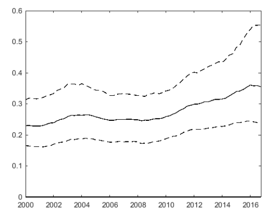
(1) Oil and Gas Extraction in Alaska



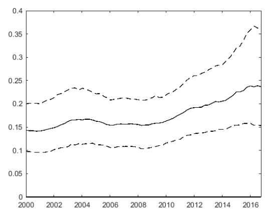
(2) Oil and Gas Extraction in California



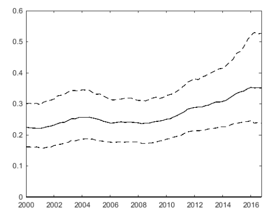
(3) Oil and Gas Extraction in Louisiana



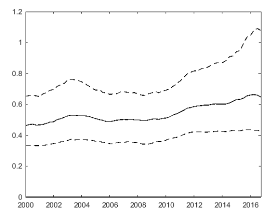
(4) Mining and Logging in Oklahoma



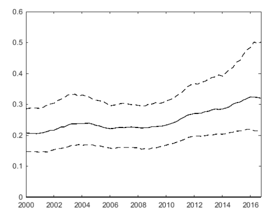
(5) Mining and Logging in Montana



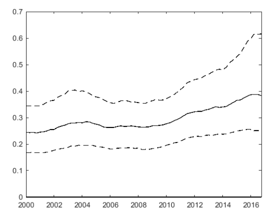
(6) Mining and Logging in New Mexico



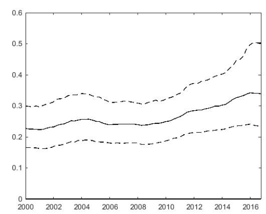
(7) Mining and Logging in North Dakota



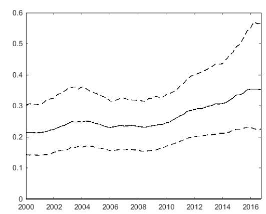
(8) Oil and Gas Extraction in Texas



(9) Oil and Gas Extraction in Wyoming



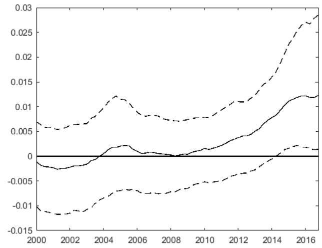
(10) Mining in Kansas



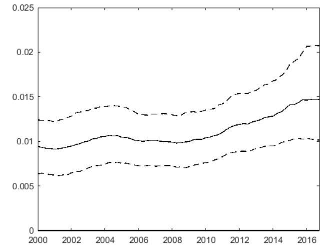
(11) Mining in Colorado

Figure 11: Impulse responses for Oil Related Employment after 4 quarters with 16-th and 84-th percentiles

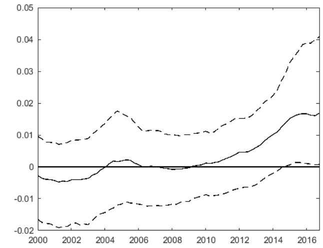
D.2 Nonfarm (non-oil) Employment



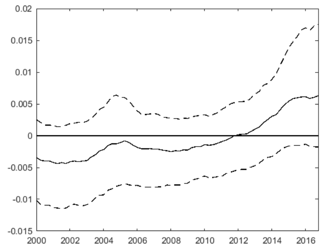
(1) Alabama



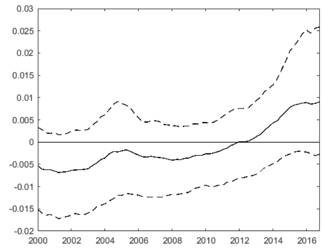
(2) Alaska



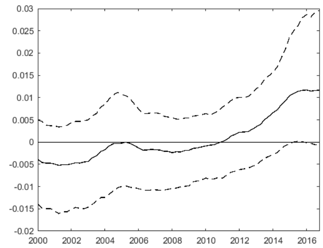
(3) Arizona



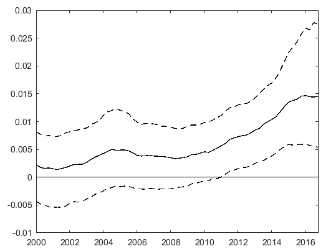
(4) Arkansas



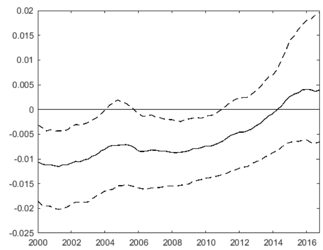
(5) California



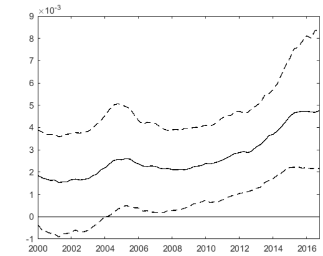
(6) Colorado



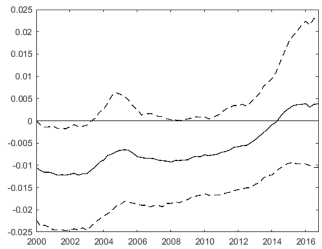
(7) Connecticut



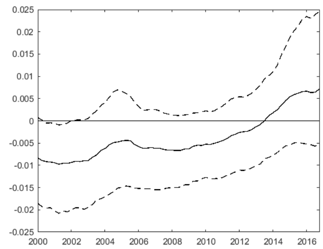
(8) Delaware



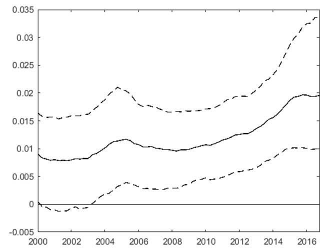
(9) District Columbia



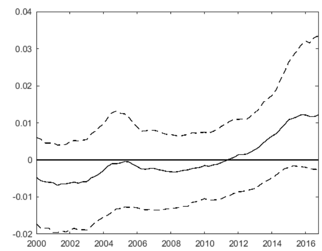
(10) Florida



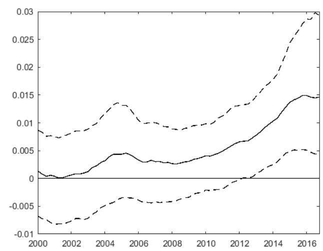
(11) Georgia



(12) Hawaii



(13) Idaho



(14) Illinois

(15) Indiana

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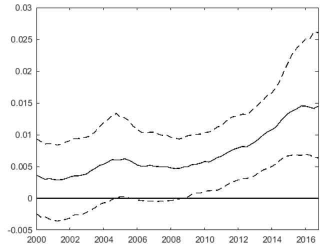
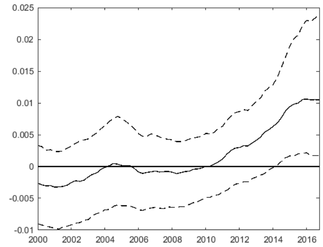
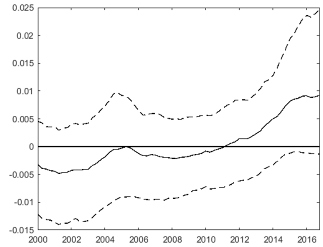


(16) Iowa



(17) Kansas



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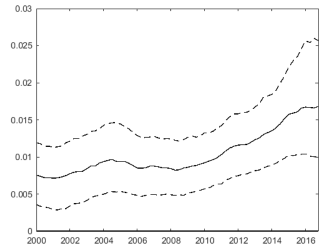
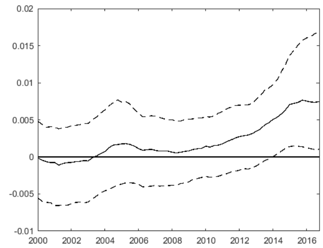
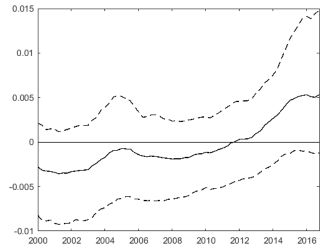


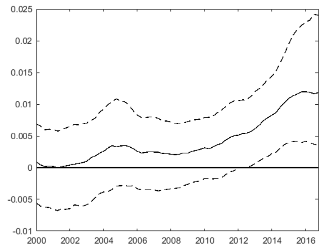
(19) Louisiana



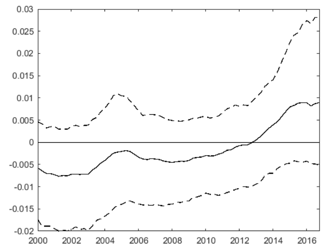
(20) Maine



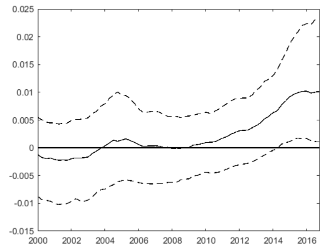
(21) Maryland



(22) Massachusetts



(23) Michigan



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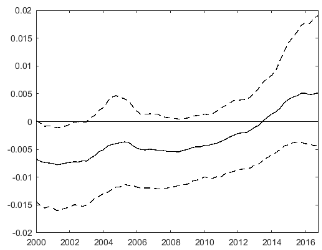
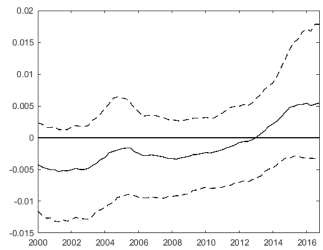
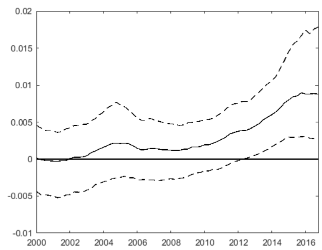


(25) Mississippi

(26) Missouri



(27) Montana



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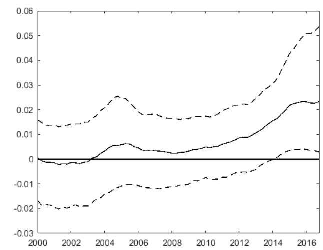

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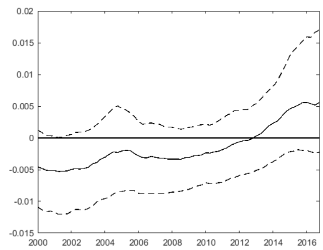

(30) New Hampshire

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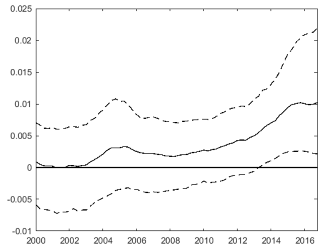
(31) New Jersey



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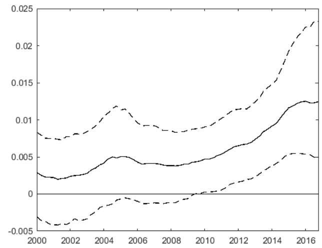
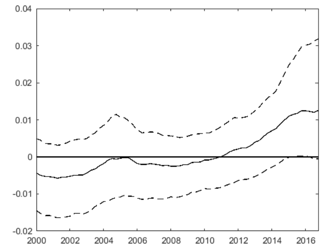
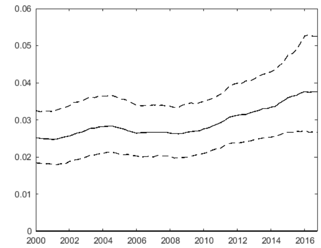


(33) New York



(34) North Carolina



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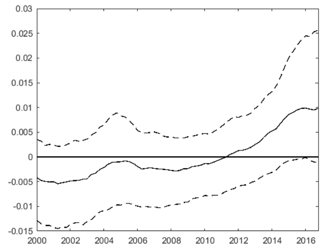

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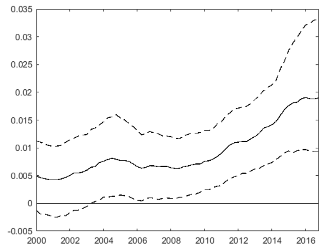

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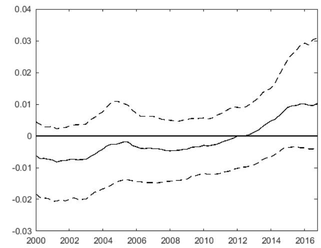

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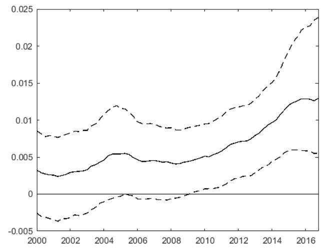
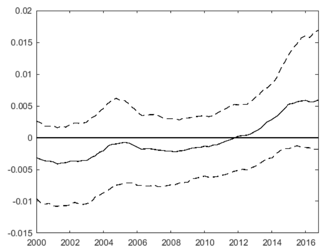
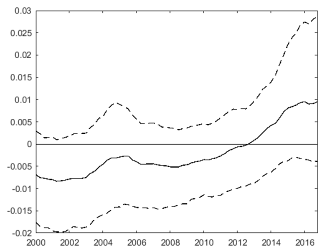


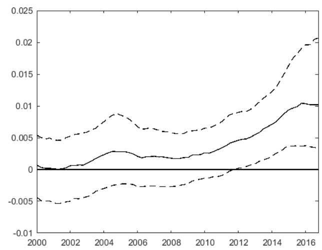
(39) Pennsylvania



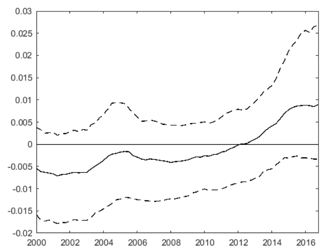
(40) Rhode Island



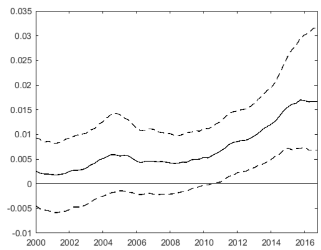
(41) South Carolina



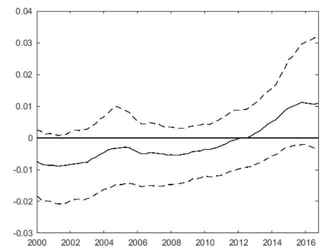
(42) South Dakota



(43) Tennessee



(44) Texas



(45) Utah

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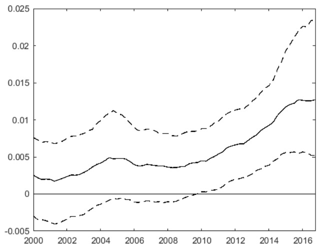
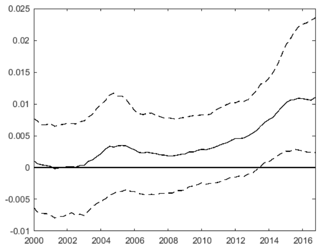
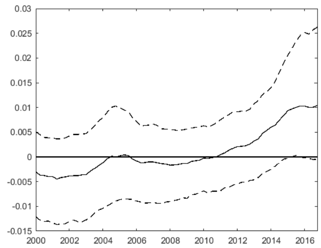


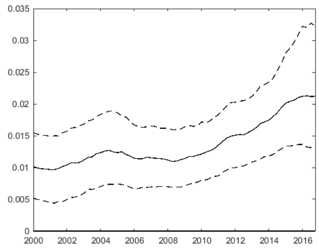
(46) Vermont



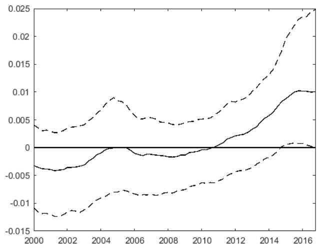
(47) Virginia



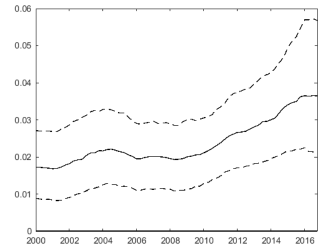
(48) Washington



(49) West Virginia



(50) Wisconsin



(51) Wyoming

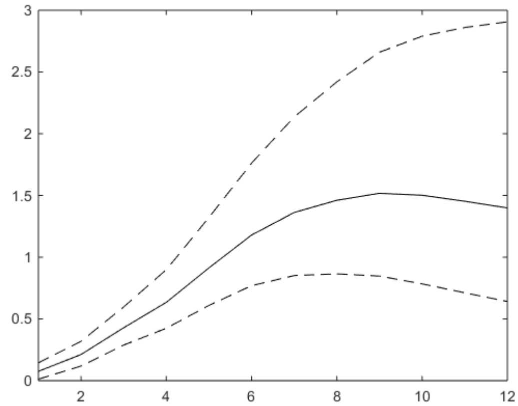
Figure 12: Impulse responses for Nonfarm Employment after 4 quarters with 16-th and 84-th percentiles

Appendix E Split Sample

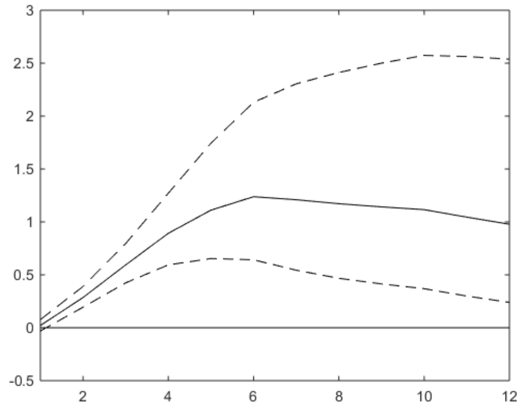
Below we present the impulse responses to an oil price shock for some key macroeconomic indicators. We obtain these results by estimating the model presented in Section 3.2 with constant coefficients and constant variance-covariance matrix: $B_t = B$ and $\Omega_t = \Omega$, for two subsamples: 1990:Q2-2006:Q4 and 2000:Q1-2016:Q4.

As Figures 13 and 14 illustrates, while oil-related investments increase in both sub-periods following an oil price shock, cf.cf. Figure 13 frame (a) and (b), non-residential investments, personal real income, and manufacturing show important differences in the two sub-samples. In the first period, they all contract as oil prices increase, cf.cf. Figure 13 frame (c) and Figure 14 frame (a) and (c) respectively. However, throughout the 2000s, the picture changes somewhat. Following a similar sized oil price shock, all three series increase temporally as oil prices increase, cf. Figure 13 frame (d) and Figure 14 frame (b) and (d) respectively.

Oil Investment

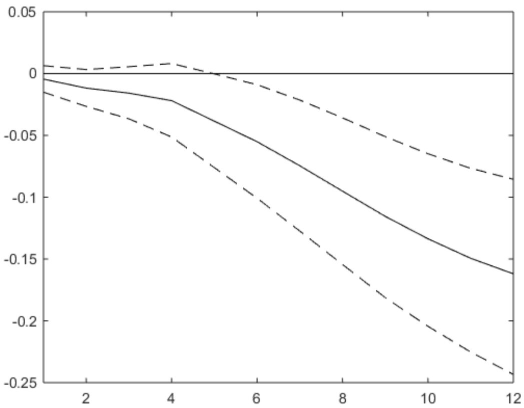


(a) 1990-2006

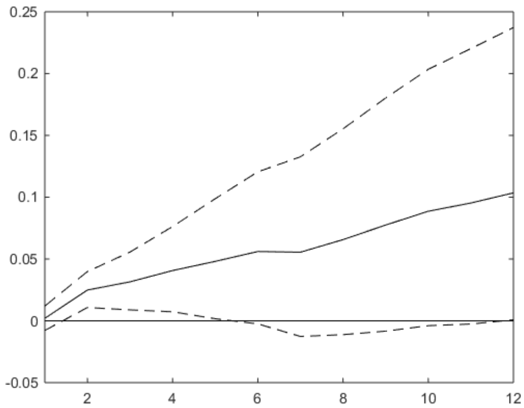


(b) 2000-2016

Nonresidential Investment



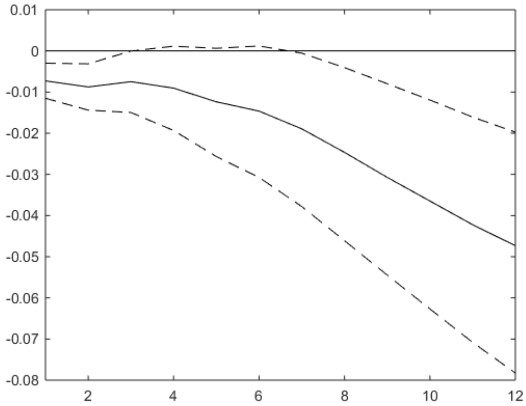
(c) 1990-2006



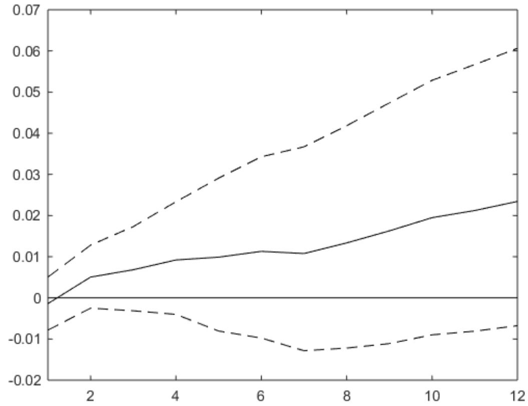
(d) 2000-2016

Figure 13: The effect of an oil price shock on Oil and Nonresidential (non-oil) Investment: Posterior median of impulse responses with 16-th and 84-th percentiles; Left column: estimated over subsample 1990:Q2-2006:Q4. Right column: estimated over subsample 2000:Q1-2016:Q4

Real Personal Income

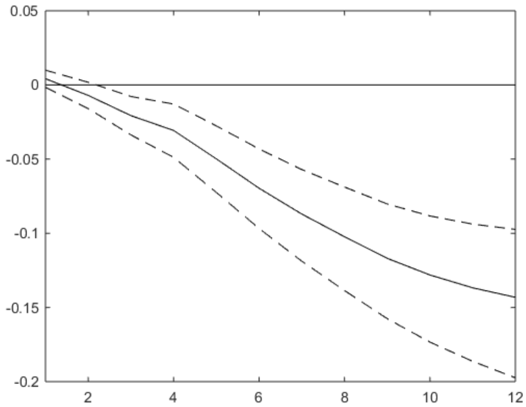


(a) 1990-2006

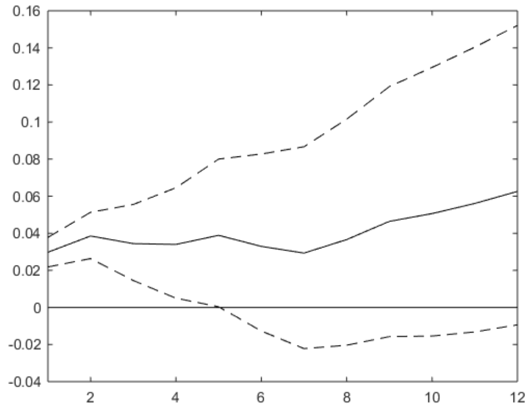


(b) 2000-2016

Manufacturing



(c) 1990-2006



(d) 2000-2016

Figure 14: The effect of an oil price shock on Real Personal Income and Manufacturing: Posterior median of impulse responses with 16-th and 84-th percentiles; Left column: estimated over subsample 1990:Q2-2006:Q4. Right column: estimated over subsample 2000:Q1-2016:Q4

Appendix F Where does the time variation come from?

Results presented in Section 4 and in Appendix E show a clear evidence of time-varying effects. However, this time variation in impulse responses could either be driven by heteroskedastic shocks [16] or the evolution of impulse responses over time due to drifting coefficients and other nonlinearities. Figure 15 presents plots of the posterior mean of the time-varying standard deviation of shocks in equation 5. From this figure we can see that the variance of oil price shocks increased substantially after the financial crisis of 2007/08 as well as after 2014. One concern is then whether the change in responses that we found is driven by high volatility shocks.

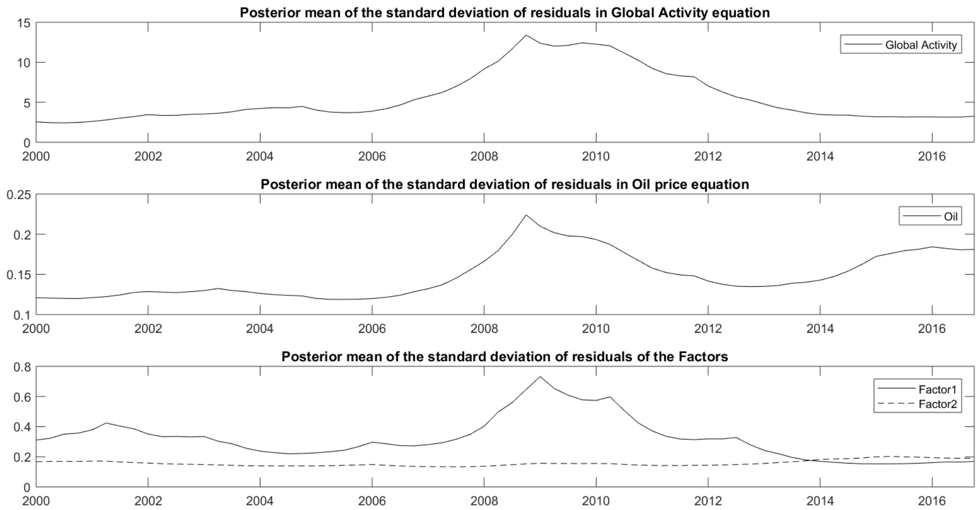
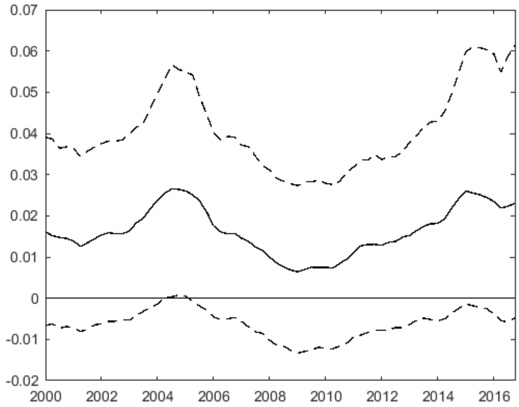


Figure 15: Posterior mean of standard deviation of residuals

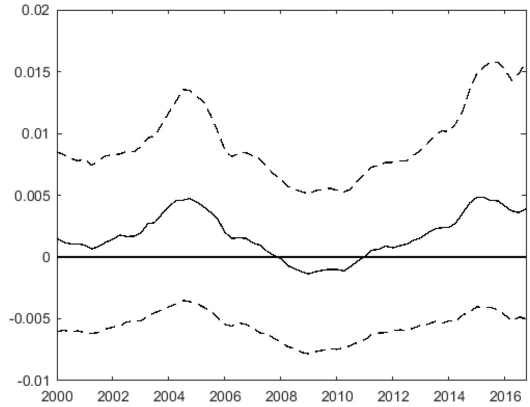
To address this issue, we estimate the model presented in Section 3.2 with constant coefficients, $B_t = B$, and drifting variance covariance matrix, $\Omega_t = A_t^{-1}\Sigma_t\Sigma_t'(A_t^{-1})$, which is the right model if we believe that time variation comes only from the size of the shocks. In doing so, we find that for those series for which in the benchmark model we found an upward shift in responses during the last part of the sample, we now obtain an upward shift in responses during the whole sample period, as coefficients are no longer allowed to vary over time (see Figure 16 that reports impulse responses for some of the main macroeconomic indicators to an oil price shock). Using a constant coefficient model we do not find that any changes in the way the U.S. economy has responded to an oil price shock during the last 16 years; in fact, the responses after 2014 seem to be at the same level as those of 2004/05. This confirms that it is the change in mechanisms that explains

[16] In a recent study by Loria (2017), the author shows that the responses in firms' investments depends on the size of oil price shock

why we obtain changes in the impulse responses.



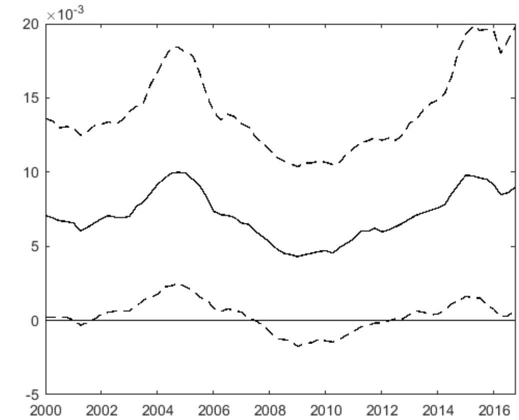
(a) Nonresidential Investment



(b) Real Personal Income

(c) Manufacturing

(d) Business supplies



(e) Illinois

(f) Texas

Figure 16: The effect of an oil price shock: Impulse responses from a constant coefficients model for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles

Appendix G Prior sensitivity

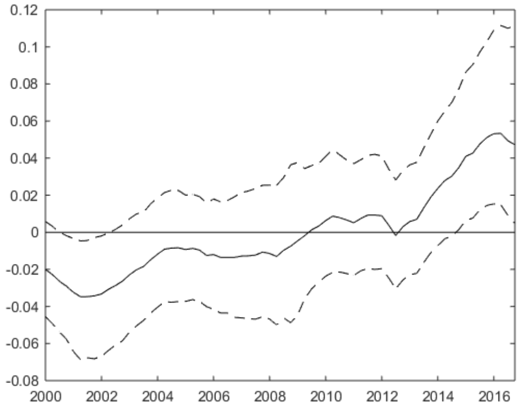
The results presented in this paper are based on particular prior specifications described in Appendix B. In the following we justify this choice and demonstrate the robustness of our conclusions to alternative prior specifications. We focus on alternative specifications of k_Q, k_S, and k_W, since the choice for other priors seems to be of minor importance (see e.g. Primiceri (2005)).

As it was noted by Primiceri (2005), the values for k_Q, k_S, and k_W, defined in Appendix B.2, do not parameterize time variation, but just define our prior beliefs about the amount of time variation in parameters. The setting of k_Q defines our beliefs about the amount of time variation in time-varying coefficients in Equation 5, while setting of k_W and k_S defines beliefs about the amount of time variation in stochastic volatility part of the same equation. It is worth noting that there is a trade-off between setting, for example, k_Q very high, but k_W and k_S very low: this will force most of the models fit to be picked up though time-varying coefficients, B_t. In the reverse case, setting k_S and k_W very high, but k_Q very low, the variation in B_t will almost be removed. Since we are interested in both allowing for variation due to changes in the responses of domestic factors to global shocks and due to changes in volatility of global variables, we will not consider any of the two extreme cases mentioned above. However, in Appendix F we consider a case with constant coefficients and stochastic volatility.

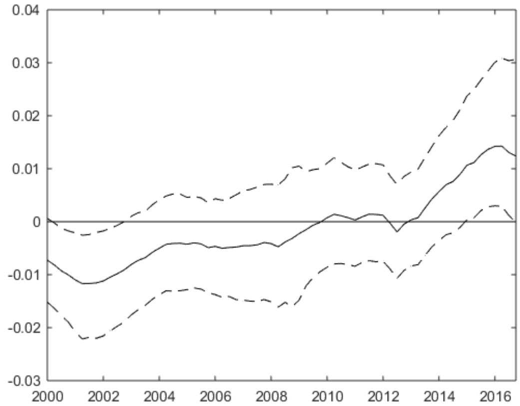
In order to be consistent with the literature [17] we set $k_Q = 0.01$. However, the results obtained with higher k_Q are very similar to the baseline model.

Similar to Primiceri (2005), we set $k_S = 0.1$. The motivation for setting $k_W = 0.1$ is the fact that the volatility of oil price and other international business cycle shocks has changed a great deal during last decade (see e.g. Baumeister and Peersman (2013a), Baumeister and Peersman (2013b)). Estimating the model with lower values of k_S and k_W we obtain a similar results to the benchmark case, however, if we set k_W to 0.01 and lower, we seem to miss high volatility of the oil price during the last downturn. Below we report impulse responses for macroeconomic aggregates for $k_Q = 0.1$, $k_W = 0.01$, and $k_S = 0.01$ changing each of these values one at a time.

[17] Korobilis (2013), Primiceri (2005), Cogley and Sargent (2001), and Stock and Watson (1996)



(a) Nonresidential Investment



(b) Real Personal Income

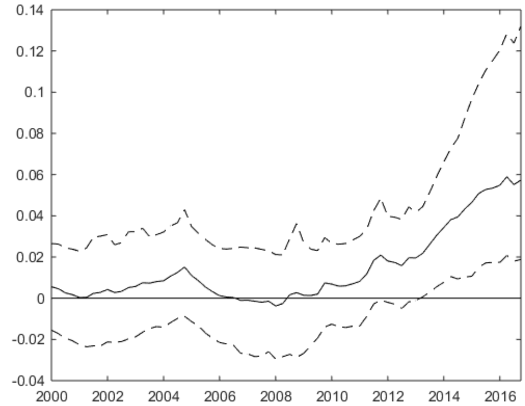
(c) Manufacturing

(d) Business supplies

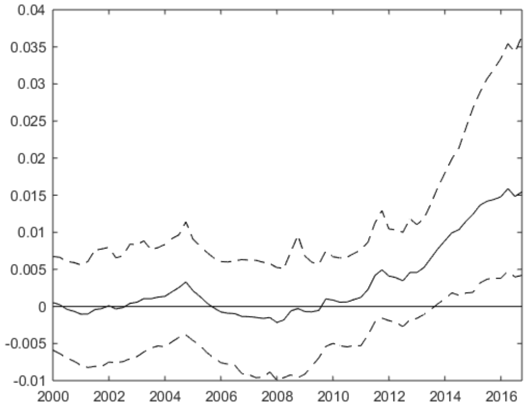
(e) Illinois

(f) Texas

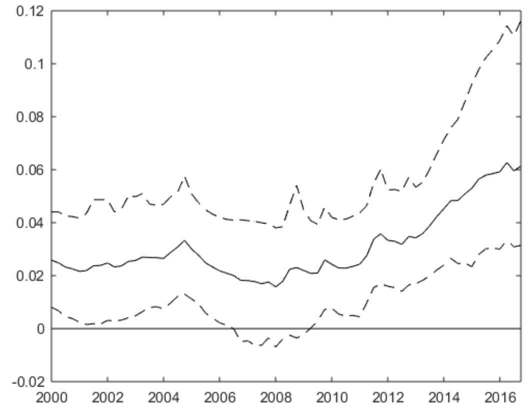
Figure 17: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles. Prior for $k_Q = 0.1$



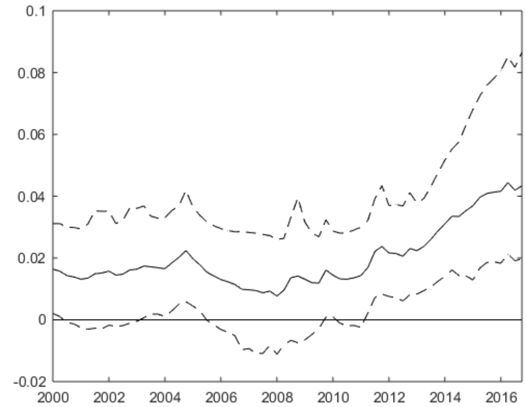
(a) Nonresidential Investment



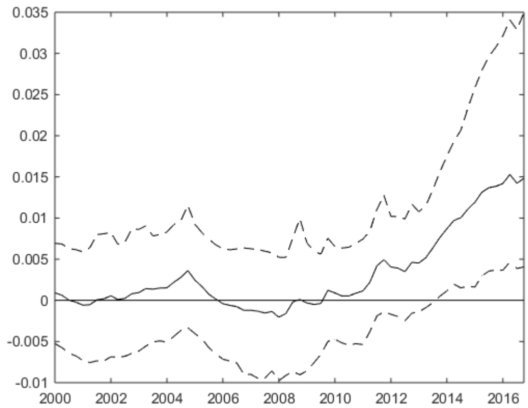
(b) Real Personal Income



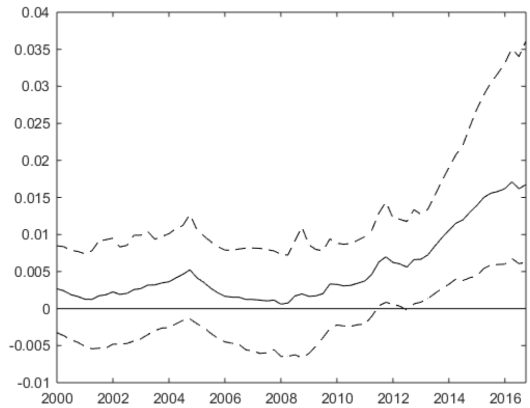
(c) Manufacturing



(d) Business supplies

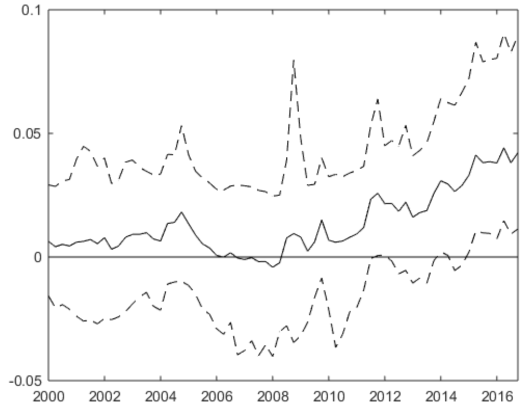


(e) Illinois

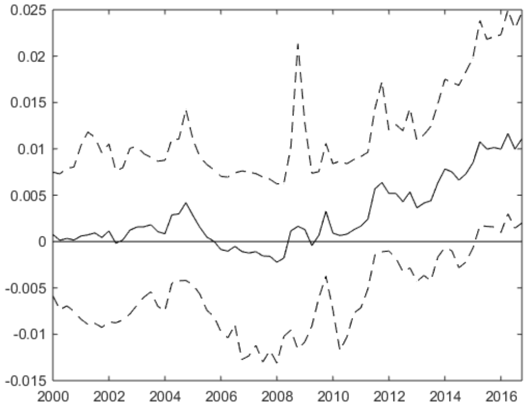


(f) Texas

Figure 18: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles. Prior for $k_S = 0.01$



(a) Nonresidential Investment



(b) Real Personal Income

(c) Manufacturing

(d) Business supplies

(e) Illinois

(f) Texas

Figure 19: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles. Prior for $k_W = 0.01$

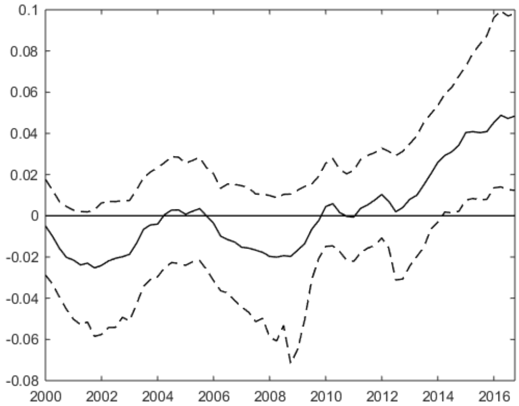
Appendix H Robustness to choice of variables

We estimate the model described in the main part of the paper using three different datasets. First, in Section H.1 we change the global activity measure to an estimate of industrial production for the OECD plus other major countries (Brazil, China, India, Indonesia, Russia, and South Africa) published by OECD Main Economic Indicators and extended from 2011:11 by Baumeister and Hamilton (2018).[18] In Section H.2 we use West Texas Intermediate (WTI) deflated by CPI as a measure of real oil prices. Section H.3 replaces both the observable factors in the VAR part with GDP for OECD countries as a measure of global economic activity and West Texas Intermediate (WTI) deflated by CPI as a measure of real oil prices. We also replace all employment series at state level with employment series divided by industries. In addition we remove all subcategories of durable and nondurable manufacturing, while we also add a shadow rate to our dataset.

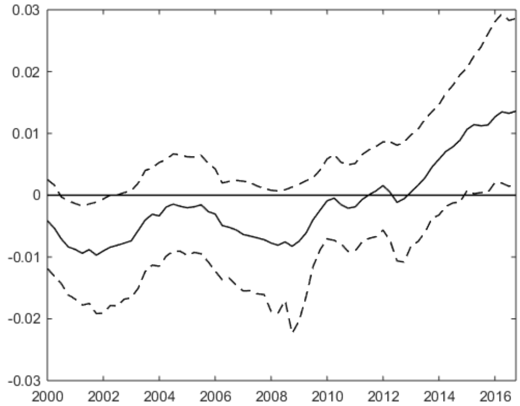
All new data series are described in Appendix A under subcategory "Additional Data." It turns out that our main results are robust to the implemented changes.

[18] Following suggestions by Hamilton (2018b) we isolate a cyclical component of this series by calculating the two-year change in the log.

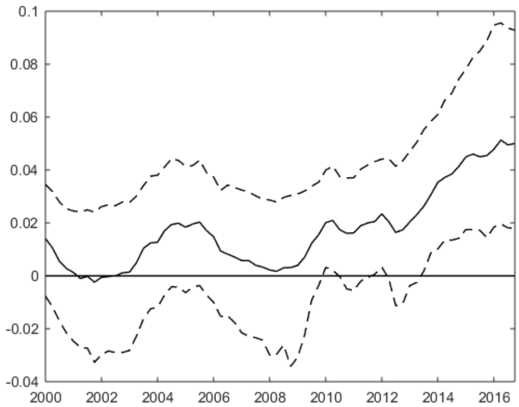
H.1 Robustness to the choice of global activity variable



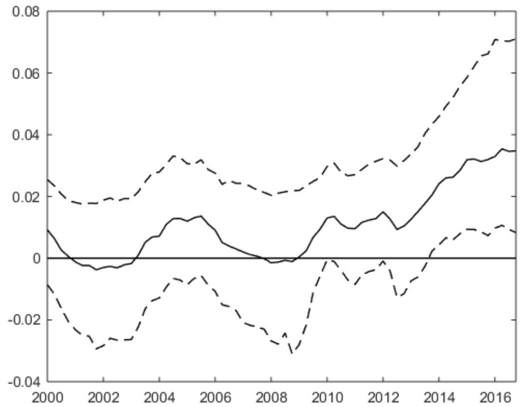
(a) Nonresidential Investment



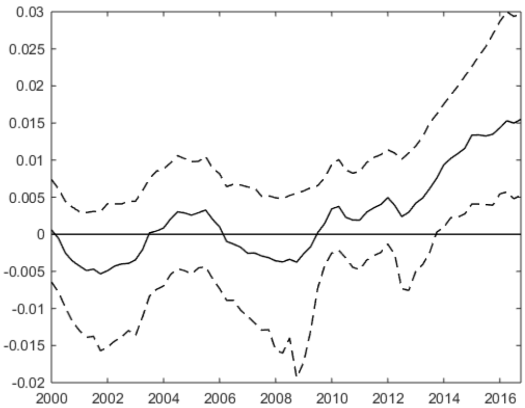
(b) Real Personal Income



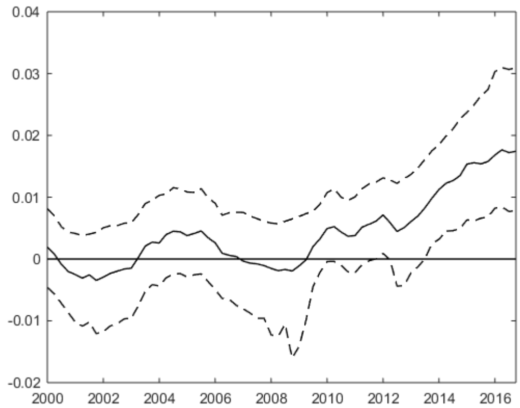
(c) Manufacturing



(d) Business supplies



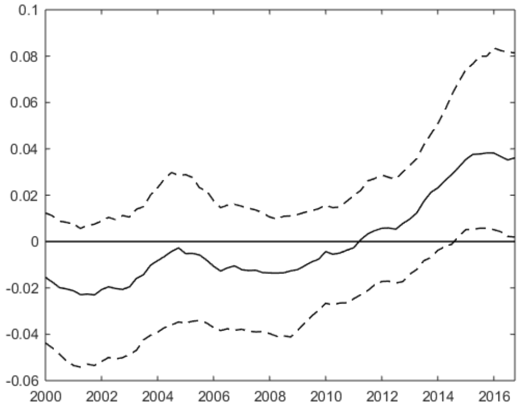
(e) Illinois



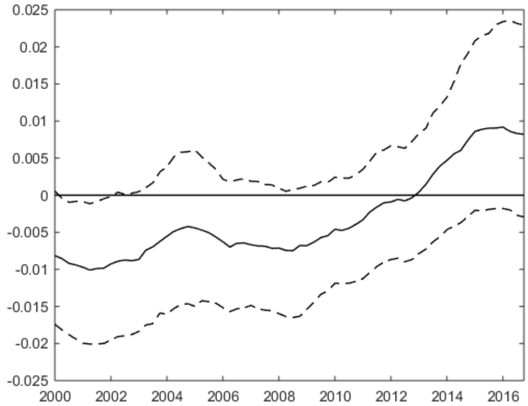
(f) Texas

Figure 20: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles from a model with alternative dataset, using a different global variable (see the main text for details).

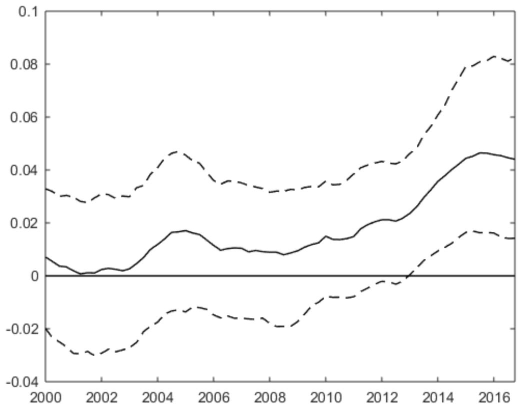
H.2 Robustness to the choice of oil price variable



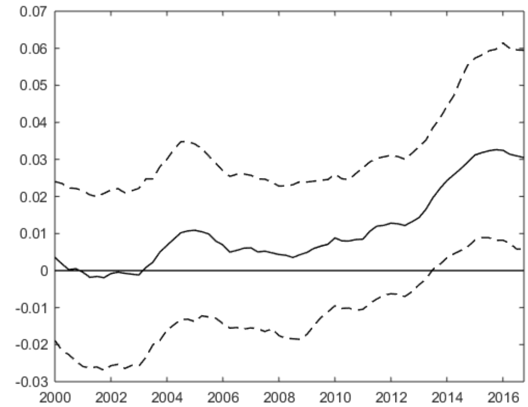
(a) Nonresidential Investment



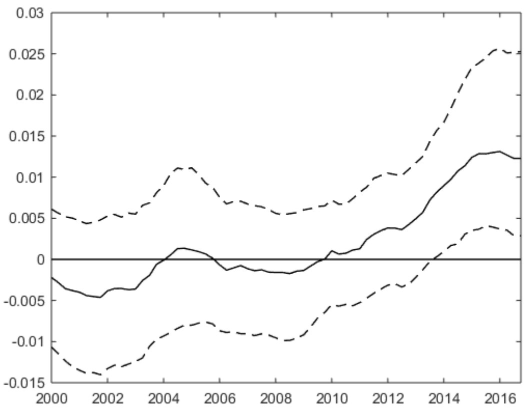
(b) Real Personal Income



(c) Manufacturing



(d) Business supplies

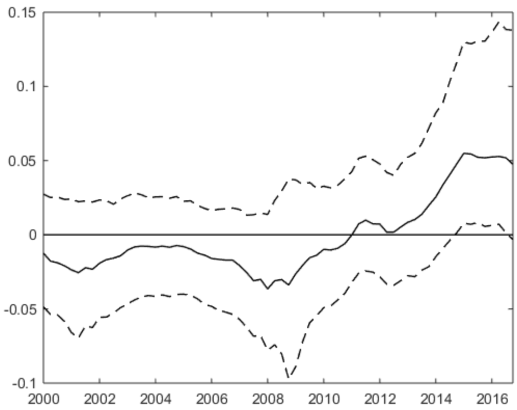


(e) Illinois

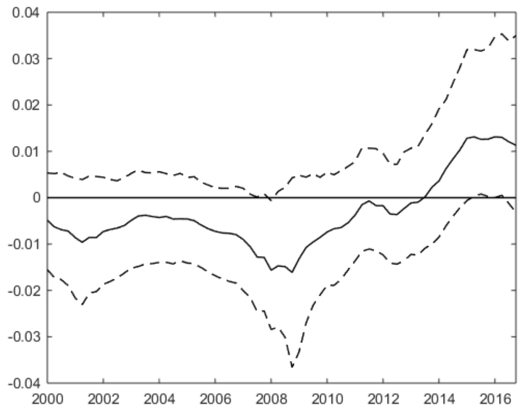
(f) Texas

Figure 21: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles from a model with an alternative dataset that uses a different oil price measure (see the main text for details).

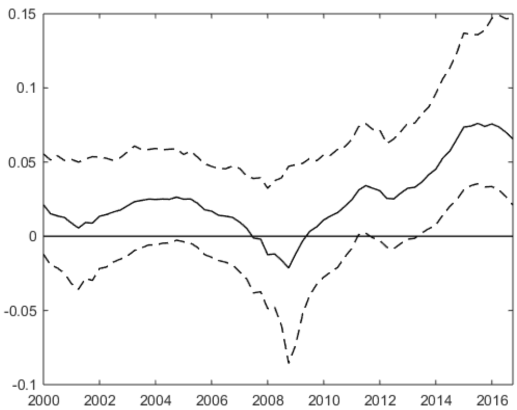
H.3 Robustness to the choice of various series



(a) Nonresidential Investment

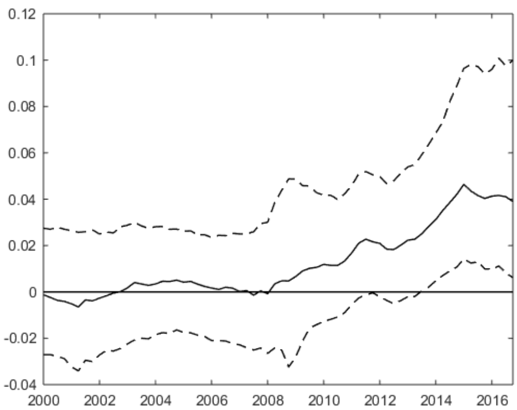


(b) Real Personal Income

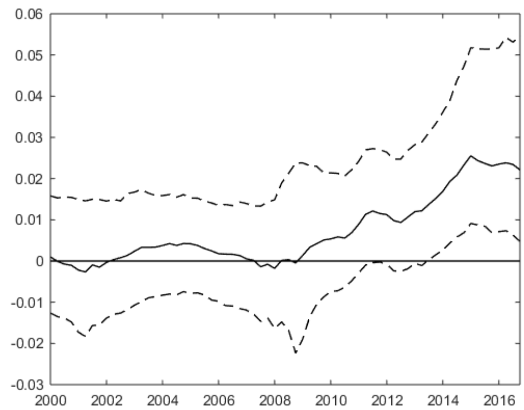


(c) Manufacturing

(d) Business supplies



(e) Employment Manufacturing



(f) Employment Wholesale Trade

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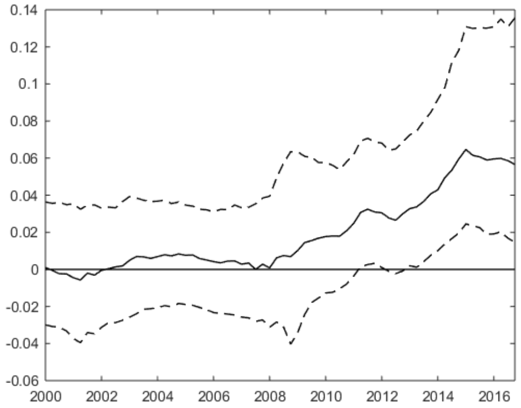
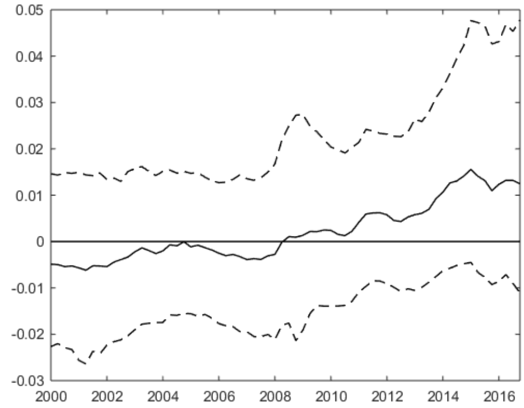
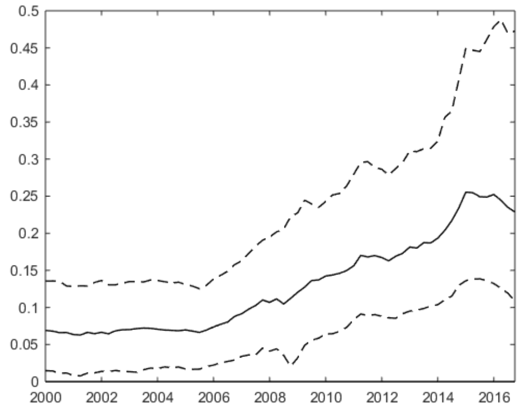


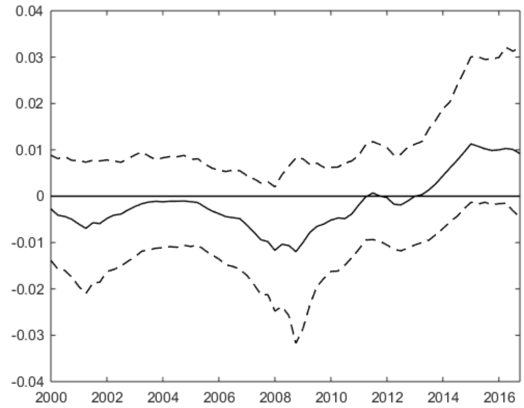
(g) Employment Durable goods



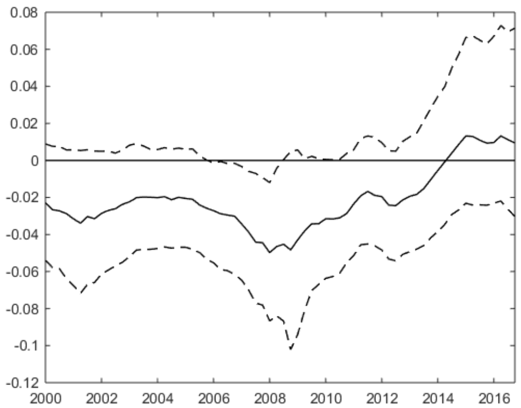
(h) Employment Nondurable goods



(i) Employment Mining and Logging



(j) Employment Retail Trade



(k) Employment Construction

(l) Employment Financial Activities

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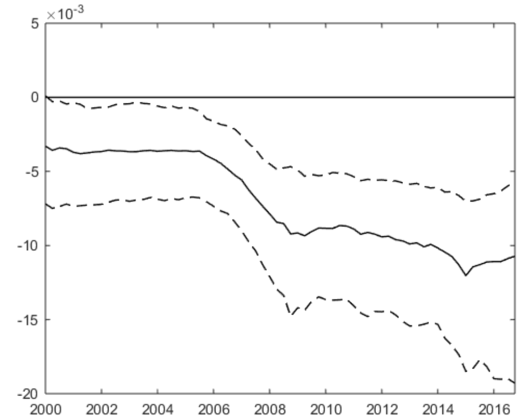
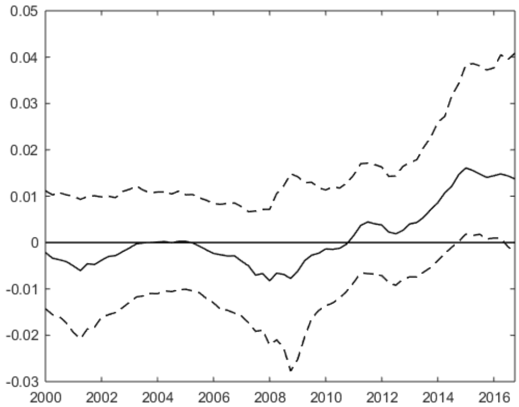


(m) Employment Government

(n) Employment Service Industries



(o) Employment Trade, Transportation and Utilities

Figure 22: The effect of an oil price shock: Impulse responses for selected indicators of the U.S. economy after 4 quarters with 16-th and 84-th percentiles from a model with an alternative dataset: we add new measures for both the observable factors, replace all employment series at the state level with employment series divided by industries. In addition we remove subcategories of durable and nondurable manufacturing. We also add a shadow rate to our dataset (see the main text for details).

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