4-2016

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Oil Shock Effects and the Business Cycle

A thesis submitted in partial fulfillment of the requirement for the degree of Bachelor of Arts in Economics from The College of William and Mary

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April 16th, 2016
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Abstract

This paper uses a linear projection method proposed by Jorda (2005) to model how the United States business cycle affects the response of output to positive oil price shocks. I use a nonlinear specification for oil price increases, introduced by Lee, Ni, and Ratti (1995), which internalizes a number of popular theories in the macroeconomic literature for the determinants of the magnitude of the oil-output response. I first confirm the results of Lee, Ni, and Ratti (1995), that conditional expected volatility of oil price predictions at the time are important for the output response, with more recent data and an alternate estimation framework. Using a model that allows for coefficient state-switching between periods of low and high output growth, I show that output may be more vulnerable to unexpected oil price increases in the quarters immediately preceding NBER recession periods, although output still does not appear more vulnerable in the recession itself. I lastly discuss what these results indicate regarding possible interpretations of several popular theories of the oil-output response mechanism.
1 Introduction

The macroeconomic literature of the past thirty years has seen a wealth of studies that try to show whether oil price changes affect real output growth. Following the landmark study Hamilton (1983), which found strong evidence of oil price changes affecting and even Granger causing growth, numerous studies have attempted to show whether similar results can be found empirically using more modern data. The general approach of most of these modern studies has been to find situations in recent sample periods where the basic oil-output relationship found in Hamilton (1983) still holds. Empirical methods for those studies typically involve modeling techniques that acknowledge potential asymmetries or nonlinearities in the oil-output response, including those that censor data to examine only oil price increases, consider demand and supply shocks as distinctly separate, or other studies that use recent oil prices to determine how an oil price increase should affect economic actors’ expectations about the future.

Few studies, however, have asked whether the macroeconomic state of the United States economy at the time of an oil shock matters for the magnitude of the output response. This study, in the same spirit as past papers exploring possible response asymmetries in the literature, will ask whether the the response of output to a positive, unexpected oil price shock is at all determined by the US business cycle at the time of the shock.

I will also discuss my findings in the context of several popular theories regarding the mechanisms by which oil prices affect output. Those will include the theory of costly reallocation theory, investment postponement due to uncertainty, and asymmetric responses of monetary policy. My results will better inform which interpretations of these theories’ implications over the business cycle are consistent or inconsistent with my empirical observations. Following the lead of previous studies, I will discuss how the ability of these theories to explain my findings reflects upon the importance of their respective mechanisms in the oil-output relationship.
This paper will begin with a first section summarizing the existing literature on oil shocks, with a particular focus on popular theories for the mechanisms by which oil prices affect output. In section 3 I then review a number of commonly-used modeling techniques for nonlinear oil price specifications, tying the rationales for those models back to their theoretical justifications. In section 4, I summarize recent results in Kilian and Vigfusson (2014), which used different modeling techniques than my own (including a different construction of an oil shock variable) to provide an alternate story for my same research question. Section 5 will lay out my initial hypotheses for what the prominent theories of oil-output effects reasonably prescribe for the nature of any cyclical asymmetry. Section 6 describes my own empirical method, with a particular emphasis on how my method differs from those of prior studies and how it may offer a new interpretation of the relationship between the business cycle and the magnitude of an oil shock’s output response. Finally, I then offer my own empirical results in section 7 and discuss their potential implications before briefly summarizing my conclusions in section 8.

2 Literature Review

2.1 Introductory Studies

The seminal paper Hamilton (1983) used twenty-eight years of oil prices and US macroeconomic data to conclude that oil price fluctuations have a large and statistically-significant impact on US output growth. Considering that nearly all US recessions in the Hamilton (1983) sample period were preceded by large oil price increases, that paper went a step further in concluding that oil price increases were a major factor in “timing, magnitude, and/or duration of at least some of the recessions prior to 1973.” But even that early paper found that the size and statistical significance of the output response was much smaller in the (then small sample) of periods after 1973.

This issue of statistical significance in more recent data continued as more modern data
became available. Hooker (1996), in an effort to conclude whether oil prices were a suitable instrument for output, concluded that oil prices post-1973 no longer Granger caused output. Potential explanations of this phenomena are numerous, including fundamental structural differences in the economy post-1973, differences in whether oil price fluctuations in the two periods reflect primarily supply or demand shocks (As Kilian(2008) and Kilian and Vigfusson (2014) claim), or differences in the typical sign of price changes between the two periods (as Mork(1989) claims and Hamilton (2003) supports).

Since Hooker (1996), much of the economic literature on oil shocks has focused on determining the circumstances under which the oil-output relationship of Hamilton (1983) may still hold. The chief method of answering that question has been to acknowledge the presence of asymmetries in the magnitude of output’s response to oil shocks that depend on one of several factors. These include the nature of the oil shock’s source, oil price dynamics in the periods leading up to the shock, and the sign of the shock. My models in this paper will account for a number of these commonly-discussed asymmetries in my effort to determine whether the business cycle is a major determinant in output’s response to these shocks.

2.2 Theories of the Oil-Output Response Mechanism

There is no universally-accepted economic theory for how oil price changes affect output. The most accepted method, and also most intuitive, are what Kilian and Vigfusson (2011) call “direct” effects. Simply, an unexpected increase in oil prices for an oil importing economy will result in a net transfer of wealth abroad, with the magnitude of the transfer dictated by households’ and firms’ price elasticity of oil demand and expenditure shares for energy. On the supply side, this could result in less output produced by the firm and higher prices for consumers. For households, this will cause a decrease in purchasing power. Interestingly, however, theoretical models that account for these direct mechanisms alone do not ascribe a significant output re-
response to oil price changes. Kim and Loungani (1992) included energy price changes in a real business cycle framework through a direct, supply-side effect alone and found its inclusions did not substantially increase the predictive value of their model. The authors did acknowledge that this supply side direct effect was likely not capturing the entirety of the output response mechanism.

Importantly, both the demand and supply-side “direct” effects imply symmetry between positive and negative oil price changes. That is, if these mechanisms are the only significant factor tying output to oil prices, then an oil price decrease should stimulate production and increase household purchasing power (thus increasing output) by the same amount that an oil price increase diminishes them.

The empirical results of Mork (1989, 1994) necessitated increased focus on alternative mechanisms for output’s response to oil shocks. Mork (1989) found that the results of Hamilton (1983), that oil price changes are significant factors in determining output growth, did not retain their statistical significance when extended to a more recent data set, but that oil price increases, when considered alone, retained a negative and statistically significant effect on output growth. The effects of oil price decreases were not statistically significant, and at some lag lengths had potentially counterintuitive coefficient signs. Similar asymmetric effects of output to positive and negative shocks were found by Hamilton (1996 and 2003), Lee Ni and Ratti (1995), Balk Brumen and Yucel (2002), and Elder and Serletis (2010) among others. Herrera, Lagao, and Wada (2002) found a similar sign-based asymmetry in the response of industrial production to oil prices. Davis and Haltiwanger (2001) used plant-specific data on US manufacturing to find that oil price increases stimulate US manufacturing job destruction, while price decreases do little for job creation.
2.2.1 Reallocaton Theory

To explain this observation, subsequent theoretical literature has proposed alternate stories of more indirect channels for oil price’s output effects that can better explain this asymmetry. One popular theory, reflected in theoretical models by Davis (1987) and Hamilton (1988), involves costs associated with reallocation of specialized labor and capital between sectors. In an economy where labor and capital can instantly and frictionlessly transition between economic sectors to accommodate changes in demand, an oil price change shifting demand between sectors may have little aggregate effect on economic output. However, if there are costs to reallocating labor or capital between sectors (for instance, between an energy-efficient product and its energy-inefficient substitute) or if this reallocation takes time, then a shift in demand associated with a relative oil price change will decrease aggregate output in the short run, until markets can adjust. Importantly, this costly reallocation will be triggered regardless of the sign of an oil shock. ¹ For example, a large oil price increase may cause a costly demand shift from gas-guzzling SUVs to electric cars, but an oil price decrease could also necessitate allocation by decreasing the opportunity cost of purchasing an energy-inefficient (but perhaps otherwise cheaper) vehicle. The reallocation effect could either reinforce the output dampening effects of oil price increases, while dampening (or reversing altogether) any stimulative effects of an oil price decreases. ²

¹ Hamilton (1988) also adds that this unemployment attributable to sectoral frictions may be voluntary or involuntary. That is, an individual put out of work due to changing energy prices could remain out of work either because they cannot find a job in another sector (specifically, the sectoring that would theoretically pick up the “slack” in demand from their past sector) or because they are waiting until conditions improve in the sector where they specialized.

² Recent evidence by Ramey and Vine (2010) also suggests that this allocation effect may be important for intra-sectoral allocations as well. Their study found a substantial amount of capacity underutilization in the American automobile industry attributable to shifts in demand within that same industry - specifically between cars of different size and capacity.
2.2.2 Uncertainty Theory

The second major theory for indirect oil-output effects regards oil price uncertainty. It predicts that an oil price change, regardless of sign, can increase consumers’ and investors’ uncertainty about future oil price predictions. Bernanke (1983) and Pindyck (1991) use intuitive principles from real option theory to show that in the face of increased uncertainty, investors are more likely to postpone irreversible investment decisions and await new information. Pindyck (1991) likens an irreversible investment decision to a call option, in that the ability to still make some irreversible decision holds some value and is “killed”, like a call option, when the investor makes their decision. Thus an increase in uncertainty over future oil prices, coming from either an oil price increase or decrease, could cause investors to postpone decisions on investments whose future value depends on energy prices. The same thinking can be identically applied to consumers deciding whether to purchase a durable good. When choosing between a fuel-efficient or cheaper fuel inefficient car, for instance, consumers may prefer to postpone their purchase if high uncertainty regarding future oil prices makes them uncertain about the value of gasoline purchases they will need to incur over the life of the vehicle. By this channel the uncertainty effect, like the reallocation effect, would amplify the negative output response to an oil price increase and potentially offset any positive output response from an oil price decrease.

Several prominent studies have tried to quantify the magnitude of this uncertainty effect. Ferderer (1996) found that a variable tracking monthly standard deviations of oil prices had a negative and statistically significant effect on industrial production. Elder and Serletis (2010) used Generalized Autoregressive Conditional Heteroskedasticity In-Mean methods to estimate one-period ahead standard deviations of oil price forecast errors as a proxy for uncertainty at each point in their sample period. They included this volatility variable alongside variables for positive and negative oil price changes in a structural VAR to measure effects on output. Their study found expected oil price forecast error volatility to have a negative and statistically
significant effect on output. The inclusion of the volatility variable in their VAR system also exacerbated the asymmetry between positive and negative shocks, which is consistent with the above theory of investment postponement, to the extent that forecast error volatilities are a useful proxy for uncertainty. This effect was even substantial enough to assign negative estimates for the response of output growth to negative price shocks, indicating that an oil price decrease would actually stifle output instead of stimulating it (although the sign of that response was not statistically significant).

Kellogg (2010) found sector-specific, micro-empirical evidence for this uncertainty theory, albeit in an industry closely tied to oil prices. Specifically, their study found that on-shore oil drilling companies in Texas do, on average, reduce their drilling activities in the face of higher uncertainty in oil prices, as measured by implied volatility in oil price futures on the New York Mercantile Exchange. Furthermore, the magnitude of this response was similar to that predicted by theoretical models.

2.2.3 Monetary Policy

A third proposed mechanism for indirect oil effects is monetary policy. Bohi (1989) first suggested that some of the output response to oil price changes may not be attributable to the price changes themselves, but rather to a possible tendency of the Federal Reserve to respond to an oil price increase with tighter monetary policy, restraining any inflationary pressures. Bernanke, Gertler, and Watson (1997) provided empirical support for this proposal, concluding that a major factor in the output effect of net oil price increases (an oil shock metric explained in the 'Common Asymmetric Models’ section below) was the subsequent response of monetary policy. This theory has been presented as both a general hypothesis on the oil-output relationship as well as an explanation of the positive and negative oil shock asymmetry phenomenon. Its ability to explain this asymmetry hinges on a secondary hypothesis that the Federal Reserve is
more likely to tighten monetary policy in response to a possibly inflationary oil price hike than it is to loosen policy in the face of an oil price decrease.

Apart from Bernanke, Gertler, and Watson (1997), evidence for monetary policy effect has been mixed. Balke, Brown, and Yucel (2002) used a similar approach as Bernanke, Gertler, and Watson (1997) to ask whether the monetary policy effect could fully explain the asymmetric output response found in previous oil shock research. Balke, Brown, and Yucel (2002) did find evidence of monetary policy responding to oil prices asymmetrically (tightening after price increases but loosening less, or not at all, after a decrease). They also conducted a counterfactual experiment, modeling the response of output to oil shocks if the federal funds rate were held constant. The output response in this counterfactual still showed an asymmetric response of output to price increases or decreases, even without any Federal Reserve response, suggesting this mechanism cannot explain the entirety of the oil-output asymmetry puzzle.3

It is worth noting that not all researchers in the field agree that there is an asymmetric output response to positive and negative oil shocks at all. Kilian and Vigfusson (2009, 2011) in particular have argued that previous researchers’ reliance on asymmetry in slope coefficients for positive or negative oil shocks could lead to invalid results by not directly showing asymmetry in impulse responses, which is the asymmetry that economists should be primarily concerned with. As such, Kilian and Vigfusson (2009) advocates the use of impulse responses themselves to demonstrate asymmetry, and holds that many previous studies’ findings lose much of their strength under this new framework. Hamilton (2010) responds to these concerns by recalling the full weight of economic literature cataloguing this asymmetry, and questioning some of the model selection decisions made by Kilian and Vigfusson (2009). Hamilton (2010) also notes

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3Hamilton and Herrera (2004) also raised additional concerns regarding the method used in Bernanke, Gertler, and Watson (1997), specifically regarding the number of lagged variables included in their model (which, while motivated by the Akaike Information Criteria, was less than typically used in the literature) and the feasibility of the monetary policy moves that Bernanke, Gertler, and Watson (1997) prescribed to eliminate a downturn following a positive oil shock. For their part, the authors responded with Bernanke Gertler and Watson (2004), saying that incorporating the suggestions of Hamilton and Herrera (2004) did not qualitatively alter their results.
that nonlinear oil effect models perform significantly better in out-of-sample forecasts than either linear models or models which include both linear and nonlinear terms for oil shocks.⁴

3 Common Nonlinear Oil Price Specification

With these three common theories in mind, macroeconomic literature has yielded several different ways to nonlinearly represent oil price changes for use in empirical models. This short summary will address three relevant and often-cited examples.

3.1 Simple Censoring Method

The method introduced in Mork (1989), the first paper to take empirical note of this asymmetry, is undoubtedly the simplest. It defines two separate variables for measuring the magnitudes of oil price changes, being

\[ \sigma_t^+ = \max(0, \sigma_t - \sigma_{t-1}) \]
\[ \sigma_t^- = \min(0, \sigma_t - \sigma_{t-1}) \]

where \( \sigma_t \) is defined as the log of a nominal price for oil (in the case of Mork (1989), it was a combination of the producer’s price index for crude oil and the refiner’s acquisition cost). With this nonlinear specification, Mork (1989) found his negative and statistically significant output response to a positive shock, and a statistically insignificant (and sometimes negative) response of output to a price decrease. But as Hooker (1996) notes, while Mork (1989) used some modern data in his model, his sample still extended back to 1949, when the oil-output relationship has been demonstrated to be much stronger. Excluding data before the 1970s greatly weakened his results.

⁴For some of the concerns of Kilian and Vigfusson (2009) pertaining to constructing impulse responses, Hamilton (2010) also suggests using a linear projection method as introduced by Jorda (2005). A similar method is utilized in this paper to construct impulse responses.
The explanation given by Hamilton (2003) is that the simple censoring specification, while allowing positive and negative shocks to affect growth asymmetrically, still does not do enough to capture the nonlinearities in this system. In particular, as Hamilton (2003) notes, nonlinear representations of oil price changes should involve both the change from the current period’s price of oil and some element incorporating that change’s effect on future expectations of oil prices. For instance, in the reallocation story, what may be important is economic actors’ expectations of the persistence of an oil price change. That is, consumers are more likely to alter their demand for goods (and trigger costly reallocation) if they have reason to believe that prices will stay high (or low). In the alternative, the uncertainty story suggests that an oil price change’s output effects may be dictated by how the price change affects individuals’ uncertainty moving forward. If the change adds uncertainty in their future oil price expectations, then that mechanism will either dampen or stimulate investment.

3.2 Net Oil Price Increase

Hamilton (1996) introduced another way to specify oil price changes. As Figure 1 shows, a number of changes in oil prices have come either just after oil price decreases, or amidst an otherwise downward trend in prices. For Hamilton (1996, 2003, 2010), an oil price increase that is insufficient to offset recent price decreases cannot be expected to change the behavior of consumers. Consequently, Hamilton (1996, 2003) constructed a new method of specifying oil price changes, termed the net oil price increase. It constructs

\[ \sigma_{t}^{+\text{net}} = \max(0, \sigma_{t} - \sigma^{*}_{t}) \]

where \( \sigma^{*}_{t} = \max(\sigma_{t-1}, \sigma_{t-2}, \cdots, \sigma_{t-12}) \)

with \( \sigma_{t} \) in most studies defined as the log of a quarterly nominal price of oil.
Figure 1: Quarterly Percent Change of Real Oil Price, 1973:Q1 - 2014:Q4. Calculated as 100 times the producer’s price index for crude oil, deflated by the GNP deflator.

That is, the net oil price increase variable assumes a positive value when current oil prices are higher than the maximum in the past 3-years, and zero otherwise. \(^5\) It is my belief that this measure most directly accounts for economic actors’ expectations about the persistence of an oil price increase. To see this, consider three scenarios - (1) An oil price comes amidst a steady upward trend; (2) Prices increase in a period of general price declines but the increase is insufficient to offset recent downward movements; and (3) The increase comes amidst steady price decreases, but is large enough to offset recent price declines.

In (1), the net oil price increase will be assigned a nonzero, positive value. When oil prices are trending upward, consumers and investors are convinced, after another oil price increase, 

\(^5\)Hamilton (1996) originally specified \(\sigma_t^*\) as the maximum in the past 1-year period, but Hamilton (2003) found that the 3-year measure likely better captures the nonlinearity in oil price responses.
that they will stay high for some time. In (2), $\sigma_{t, net}^+$ assumes a value of zero. Prices may have recently increased but the increase is insufficient, in light of prices’ general downward trend, to convince consumers and investors that they will stay high. Finally, in (3), prices have been trending downward, but the recent oil price increase is so high that it offsets those decreases. This relatively large increase is likely enough to convince economic actors that prices will not return to normal quickly, as prices would need a sizable decrease to return to their pre-change level (or successive smaller oil price decreases - in which case the shock will still be persistent).

This net oil price increase variable, and its inherent emphasis on persistence, models some of the aforementioned oil-output theories more directly than others. Consistent with the reallocation theory, economic actors’ expectations of shock persistence would certainly be important in their decisions to shift their demand to different industries. Persistence is also likely important in the monetary policy theory, when the Federal Reserve’s is deciding whether to raise rates in the face of an oil price increase. But persistence is not a driving factor in the uncertainty theory. In fact, perceived persistence of a shock could decrease uncertainty about future prices, leading to increased investment (by which logic persistent positive shocks should have smaller values, not larger ones).

### 3.3 GARCH Standardization

A nonlinear representation of oil prices that should more closely embody the uncertainty story of shock propagation was introduced by Lee, Ni, and Ratti (1995) - henceforth LNR. Their method standardizes forecast errors in oil price movements, from a model based on lagged price changes, by the conditional expected volatility of those forecast errors. Specifically, they estimate conditional expected volatility with a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, with one autoregressive component and one moving average component. That is,
\[
\Delta r_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \Delta r_{t-i} + e_t
\]

where \(e_t \sim N(0, h_t)\), and

\[
h_t = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 h_{t-1}
\]

The oil price change variable used in modes then becomes

\[
e^{\pm, x}_t = \max \left( \frac{e_t}{\sqrt{h_t}}, 0 \right)
\]

In LNR, as well as each subsequent study that has implemented this method, \(r_t\) is the real price of oil (LNR use a combination of the producer’s price index and the refiner’s acquisition cost, deflated by the GNP deflator).  

When we consider the expected volatility of future forecast errors as a proxy for uncertainty in the oil market (as Elder and Serletis (2010) did, using a similar construction), the logic behind this GARCH standardization is consistent with the uncertainty theory. Consider a price increase delivered in a period of high expected volatility of oil prices. If that increase is much less than actors’ expected volatility, then they may amend their volatility expectations downward. With volatility acting as a proxy for uncertainty, and per the theory of Bernanke (1983), this decrease in perceived volatility could actually stimulate investment, partially mitigating the price increase’s negative output effect. Conversely, a price increase much larger in magnitude compared to expected volatility would plausibly increase individuals’ subsequent uncertainty,

\(^{6}\)There is some debate in the literature on whether the real or nominal price of oil is generally most appropriate in these sorts of models. Specifically, Hamilton (2010) argues that households may make spending decisions according to the nominal price of oil, not the real price, because nominal oil prices are so visible to the average consumer. While argument makes some intuitive sense, I will follow all previous studies I have seen utilizing the LNR method by using a real price of oil.

\(^{7}\)While LNR do not explicitly reference the uncertainty theory in the study introducing this method, I believe that theory is the most justifiable explanation for using their method. LNR rationalize this method by saying that an oil price increase delivered in a high volatility period may be seen as “transitory” by economic actors.
compounding the price increase’s other recessionary effects. Thus, scaling an unexpected oil price change up or down based on expected volatility seems to be a reasonable way to represent nonlinearities in this system.

4 Summary of Past Results on Oil Output Response, Conditional on Macroeconomic States

With this background literature established, I now consider the study Kilian and Vigfusson (2014), which used different modeling techniques to address research questions similar to my own. That study used a net oil price increase framework to analyze how the impulse response of output to unexpected oil price increases depends on the state of the economy when that shock is delivered. The model of Kilian and Vigfusson (2014) is as follows,

\[ \Delta r_t = \alpha_1 + \sum_{i=1}^{4} \beta_{11,i} \Delta r_{t-i} + \sum_{i=1}^{4} \beta_{12,i} \Delta y_{t-i} + e_{1,t} \]

\[ \Delta y_t = \alpha_2 + \sum_{i=0}^{4} \beta_{21,i} \Delta r_{t-i} + \sum_{i=1}^{4} \beta_{22,i} \Delta y_{t-i} + \sum_{i=0}^{4} \gamma_i \Delta r_{t-1}^{net,+3yr} + e_{2,t} \]

\[ \Delta r_t^{net,+3yr} = \max(0, r_t - r_t^*) \]

In this model, \( \Delta y_t \) is defined as the first difference in logs of output, and \( \Delta r_t \) is the first difference in logs of the real price of crude oil, as measured by the refiner’s acquisition cost and deflated by the consumer price index. The net oil price increase variable \( \Delta r_t^{net,+3yr} \) is constructed per Hamilton (2003), so that \( r_t^* \) is the maximum oil price seen in the past three years.

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8An additional debate exists in the literature regarding which measure of oil prices to use in research. Hamilton (2010) recommends using the producer’s price index for crude oil, as it has been found to more closely follow the gasoline prices actually faced by average consumers. The refiner’s acquisition cost is an alternate measure, sometimes used because it is less affected by oil price controls in the 1970s.
Therefore, when $\Omega_{t-1}$ is defined as the lagged items in the model, the conditional impulse response function at horizon $h$ to an oil price shock of size $\delta$ (defined as the standard deviation of unexpected price movements $e_1$) at each point is calculated as

$$I_{\Delta y}(h, \delta, \Omega_{t-1}) = E(\Delta y_{t+h}|e_{1t} = \delta, \Omega_{t-1}) - E(\Delta y_{t+h}|\Omega_{t-1})$$

Kilian and Vigfusson (2014) - henceforth KV - estimated the model above and plotted how hypothetical oil shocks of given sizes ($\delta$ or $2\delta$) would affect output if delivered at different points in time. Their conclusions most relevant to my analysis are those that say the conditional response of output to an unexpected oil price change is not systematically linked to the state of the US business cycle at the time of the shock. They then made the conclusion that the US economy is not necessarily more vulnerable to an oil shock in a recession or in the periods immediately preceding one. The primary figure that KV used to draw this conclusion is shown in Figure 2. This figure uses the coefficients estimated from their model above to predict the impulse response of output growth after eight quarters to unexpected oil price change of fixed magnitude. The differences in responses over the sample come from the net oil price increase specification. If past oil prices do not allow a given $\delta$ magnitude price increase to yield a large, nonzero $\Delta r_t^{net,+3yr}$, then the response of output will be smaller.

From this figure, they saw no systematic relationship between the impulse response at 8 quarters and the business cycle state when the hypothetical shock was delivered. That is, they saw that while the impulse responses at 8 quarters in some recessionary periods are of above-average magnitude, there were also plenty of expansionary periods where the effect was of greater magnitude.
5 Prevailing Theories and Business Cycle Interpretations

Given that my research questions of oil shock effects conditioned on the business cycle has seldom been addressed in the literature (Kilian and Vigfusson (2014) is the only one that I am aware of which directly addresses it), there has been little theoretical discussion of how the magnitudes of the prevailing indirect oil-output effects should change based on the business cycle. In this section, I will attempt to extend the economic logic behind these theories to draw hypotheses for how their effects should change with the cycle. In my empirical results and subsequent discussion, I will address whether the data is consistent with these interpretations. In general, this paper will treat rejections of these hypotheses as evidence against the importance of a given mechanism or, at least, as evidence of a need to refocus interpretations for how these mechanisms affect output.

In the reallocation theory, aggregate output drops when specialized labor and capital makes
a costly transition between sectors following a demand shift. My interpretation of reallocation
theory through the business cycle hinges on whether a given oil price change is more or less
likely to necessitate this costly transition in a high or low output state. In my interpretation,
the reallocation theory should dictate larger output-diminishing effect in an expansion than in
a recession. To understand this interpretation, consider two examples. In the first, oil prices
increase sharply amidst a booming expansion. In the second, the same magnitude price increase
hits during a recession.

In an expansionary period, it can be assumed that most or all sectors in the economy are
working at or near their full capacity. That is, most of the specialized labor and capital (the im-
portant determinants in the reallocation theory) associated with a given sector is already being
employed or utilized. Now consider an oil price spike, which decreases demand for energy-
dependent goods, while simultaneously increasing demand for less energy-intensive alterna-
tives. With decreased demand, energy-inefficient sectors will be forced to lay off specialized
employees and sell specialized capital. The less energy-dependent sector, by contrast, has a
potential opportunity to capitalize on this demand shift, but they will only be able to do so if
they can increase production to meet it. This will require them to utilize more specialized labor
or capital. However, as the specialized labor and capital within their own sector is already being
used in this booming expansion, they must transition labor and capital that is not already spe-
cialized for their industry (in theory, the capital and labor released by the energy-inefficient in-
dustry), which costs time and resources. This will trigger the all-important transition necessary
for the reallocation theory, amplifying the output-dampening effects of the oil price increase.

In a recessionary period of low demand, this scenario will play out differently. The energy
inefficient sector will still be forced to under-utilize its specialized labor and capital, which
would decrease output ceteris paribus. But in a recession, the energy-efficient industry likely
has specialized labor and capital within the sector that is being unused or under-utilized. Con-
sequently, increasing production to meet rising demand (and offset the production decreases of the energy-inefficient industry) only requires the energy-efficient industry to re-employ capital and labor that is already specialized for the sector. This could lessen or avoid altogether the costly transition of labor and capital between sectors to which the reallocation theory attributes a large portion of the aggregate output response.

The monetary policy theory seems to suggest the same relationship - oil shocks should be connected with larger growth decreases in an expansion than in a recession. If the Federal Reserve is adhering to a Taylor principle or similar rule for policymaking, then it will focus on fulfilling its dual mandate of price stability and maximum employment. In the face of an oil price rise, the Federal Reserve should be more willing to increase interest rates to fight ensuing inflation when employment is already high - that is, in an expansion. In a recession, where inflation and employment are generally already low, the Federal Reserve would likely increase the federal funds rate less, or not at all, when faced with rising oil prices.

There is less evidence a priori that the uncertainty theory should dictate varying magnitude responses at different points in the business cycle. On one hand, it seems plausible (and this paper’s results will verify) that oil price uncertainty is generally lower in expansions - periods of relative stability - than in recessions. A plausible interpretation of the uncertainty theory is that a large, unexpected oil price increase in tranquil times will cause economic actors to increase their uncertainty by a larger margin, depressing investment potentially more than in turbulent times. That said, it also seems likely that the increased uncertainty associated with a price change could be more persistent in a period of already high general uncertainty. I will rely on my empirical results and further exploration to shed light on how this mechanism may change over the cycle.

With this paper I hope to answer the general empirical question of how the business cycle affects the magnitude of an oil-output and use my results to support or refute these plausible ex-
tensions of indirect output response mechanisms. I will answer these questions directly, with a model of oil shocks effects over the business cycle. Chiefly, I wish to allow for oil shocks in low and high output states to have different effects, by incorporating different coefficients for shocks delivered in low or high output periods. This approach will be very different from KV’s, which pooled those periods together to estimate coefficients. KV also entertained, at the conclusion of their study, the possibility that the net oil price increase that they used (per Hamilton (2003)) was not the closest representation of the actual nonlinearities in oil response mechanisms, acknowledging that a different oil shock mechanism could change their conclusions. By using the LNR price specification as an alternative to the net oil price increase, I will also explore this question with a specification accounting more directly for the uncertainty theory.

This paper is not intended as a critique of KV, nor will my results be directly comparable to KV’s, due to a number of different modeling choices. For one, I will not focus my discussion on any figures plotting the impact of hypothetical oil shocks, as in Figure 2 from KV. Rather, I will construct average impulse responses for output based on a different measure of oil price changes before asking whether the impulse response for an oil shock delivered in a high output state is statistically significantly different from one delivered in a low output period. By conducting this study, I hope to bring together the basic empirical questions suggested by KV and the LNR method of modeling oil prices, along with theory in the literature justifying the uncertainty effect, to shed additional light on this research question.

6 Methodology

Throughout this paper, I will use a quarterly dataset ranging from Q1:1973 to Q4:2014. By avoiding pre-1973 data, I hope to bypass a number of data issues and potential structural breaks between pre and post-1973 data, as cautioned by KV (2011). All data was gathered from the Federal Reserve Bank of St Louis Economic Data research database. As stated in the introduc-
tion, I will use the real price of crude oil for my subsequent analysis, measured by the producer’s price index for crude oil and deflated by the GNP deflator.

This section will summarize my empirical approach, addressing differences between my models and those in the existing literature, as relevant. I will begin by showing and justifying my implementation of LNR’s GARCH standardization method. Next I will explain the linear projection method that I implement to estimate impulse response functions, used by Jorda (2005) and extended to recent fiscal policy research by Auerbach and Gorodnichenko (2013). This section will conclude by showing how I will incorporate state-switching coefficients into the linear projections to allow impulse responses to differ depending on the business cycle state at the time of an oil shock.

6.1 LNR’s GARCH Specification

Motivated by recent literature supporting the uncertainty theory of the oil-output response, this paper will use the LNR representation of oil price changes. That paper used past oil price changes to forecast current oil prices and extract unexpected price movements (represented by forecast errors), and modeled a GARCH(1, 1) process for expected forecast error volatility at each point in time. This imposed the following structure

$$
\begin{align*}
    r_t &= \alpha_0 + \sum_{i=1}^{4} \alpha_i r_{t-i} + e_t \\
    \text{where } e_t &\sim N(0, h_t), \text{ and} \\
    h_t &= \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 h_{t-1}
\end{align*}
$$

Finally, the oil price change variable used in my subsequent models becomes

$$
e_{t+1}^{+,*} = \max\left(\frac{e_t}{\sqrt{h_t}}, 0\right)
$$
There is literature directly supporting this specification. First, as mentioned in the introduction, the recent paper Elder and Serletis (2010) has shed new light on the importance of the uncertainty effect, so constructing an oil price variable that directly accounts for it seems worthwhile. That said, the Elder and Serletis (2010) method and the constructions of equations (1) and (2) have some important differences. First, Elder and Serletis use a structural VAR estimation method, whereas I implement a less restrictive linear projection approach (this decision is explained more fully in the following subsection). Second, Elder and Serletis model the importance of oil uncertainty by including a separate GARCH In-Mean estimated volatility variable in their VAR. While this can show how oil price volatility directly affects output, it does not allow for interactions between oil price changes and conditional volatilities. Insofar as the interaction between these two variables dictates output response, as LNR suggest, the variable \( e_t^{+,*} \) may be the more appropriate method to incorporate \( h_t \) into this sort of model.

There is also direct literature with evidence that this variable is a reasonable representation of nonlinearity in output responses. Hamilton (2003) developed a hypothesis test for whether a given nonlinear oil price specification sufficiently captures nonlinearities in the output response. Specifically, Hamilton (2003) considers the following,

\[
y_t = \mu(x_t) + \sigma' z_t + \epsilon_t
\]

Where \( z_t \) are variables assumed to have a linear effect on output growth \( y_t \) and \( x_t \) are variables whose effect on output growth is potentially nonlinear. By modeling \( \mu \) as the outcome of a random field, Hamilton (2003) represents \( \mu(\tau) \) for an arbitrary non-random \( \tau \) as a random variable with variance \( \lambda \) and mean \( \alpha_0 + \alpha' \tau \). By constructing a test statistic for the null hypothesis of \( \lambda = 0 \), which assumes that the function \( \mu \) has the linear form \( \alpha_0 + \alpha' \tau \), Hamilton (2003) directly tests for linearity of the unobserved function of \( x_t \). Hamilton (2003) resoundingly rejects the null hypothesis of linearity when \( x_t \) includes lagged oil price changes and \( z_t \) includes
lagged growth rates of output. However, when $z_t$ was supplemented to include the LNR nonlinear specification for oil price changes (which can still be included in the $z_t$ vector as the effect of $\epsilon_t^{*,+}$ values themselves on output is still assumed to be linear), Hamilton (2003) could not reject the null hypothesis of $\mu$ being linear, with a p-value of .48. This indicates that the LNR oil price specification sufficiently captures any nonlinearities in the output response to oil price changes, and any other unobserved nonlinearities are less significant. Notably, the p-value of .48 for the LNR specification was much higher than that for the Mork (1989) simple censoring model (p = .08), or the net oil price increase model of Hamilton (2003) with a three-year maximum price window (p = .21). 9 Rodriguez (2009) reinforced this conclusion by showing that the the LNR specification is the only one of those three nonlinear representations whose failure to reject that null hypothesis of linearity (that is, a null hypothesis that the specification properly accounts for the system’s nonlinearities) is not sensitive to small changes in the sample period. That led to Rodriguez’s (2009) declaration that this specification is ”the most appropriate non-linear specification under study.”

I also limit my model to positive oil shocks for several reasons. First, the studies Hamilton (2003), Rodriguez (2009), and Mendoza and Vera (2010), which concluded that this method was a reasonable representation of oil nonlinearities, only included this censored measure in that certification. Also, inclusion of another impulse response variable ($\epsilon_t^{*,-}$) for negative price changes altered my results for positive price movements’ impulse responses only very slightly. Analyzing the impulse responses for price decreases also provided little additional economic insight into business cycle asymmetries or oil-output response mechanisms, only confirming prior results in the literature that price decreases have little interpretable effect on output.

---

9These same results were replicated by Mendoza and Vera (2010), which used the same hypothesis testing method to reach similar conclusions about the suitability of the LNR method over the net oil price increase.
6.2 Linear Projection Method

To calculate impulse responses of output to oil shocks, as represented by the LNR variable, I will implement a linear projection method recently introduced into fiscal policy literature. Proposed by Jorda (2005) and extended by Auerbach and Gorodnichenko (2013), the method is used to directly estimate impulse responses using OLS regressions. Auerbach and Gorodnichenko (2013) use this method to calculate how the output response to unexpected fiscal spending changes with the business cycle. The similarity of that research question to my own makes their method particularly attractive.

Before incorporating terms into the model to accommodate switches in the business cycle, I introduce the basic structure of the model below,

\[ Y_{t+s} = \alpha_s + \Psi_s X_{t-1} + \Phi_s \Delta r_{t-1} + \Pi_s e_t + \sigma_u u_{t+s} \tag{4} \]

where \( s \) is iterated from 0 to 10 to construct the impulse response over ten quarters and includes a contemporaneous response. \( Y_t \) in this model is one hundred times the first difference in logs of real gross national product. After estimation, the parameter estimates for \( \{\Pi_s\}_{s=1}^{10} \) serve as the direct impulse responses in output to a one-unit shock to the standardized unexpected oil shock variable \( e_t^{+,*} \) (that is, a shock to \( e_t \) of magnitude \( \sqrt{\Pi_t} \)). The variable \( \Delta r_t \) is defined as one hundred times the first difference in logs of the producer’s price index for crude oil, deflated by the GNP deflator. The vector \( X_{t-1} \) contains four lags of one hundred times the first difference in logs of real gross national product, the import price deflator, GNP deflator, and average hourly earnings of production and nonsupervisory employees in manufacturing. It also includes four

\[^{10}\text{Note that this structure, and that of the linear projections to follow, assume that } e_t^{+,*} \text{ has a contemporaneous effect on output, but } Y_t \text{ does not affect } e_t^{+,*} \text{ contemporaneously. In that respect, the assumptions in this setup are similar to a recursive structure in a VAR, where } e_t^{+,*} \text{ is placed first in the ordering. This assumption has been made in numerous VAR models of oil shock effects, including KV (2014).}\]
lags of the levels of the civilian unemployment rate and 3-month treasury bill rate. This composition of control variables mimics that of LNR (1995) and Mork (1989) and is similar to those used in Hamilton (1996). The selection of four quarterly lags is also common in the literature with LNR, Mork (1989), Rodriguez (2010), Hamilton (2003), and Hamilton (2010) electing for it, among others.\footnote{Kilian and Vigfusson (2009) is one example of a model using 6 lags. Per the recommendation of Hamilton (2010), I elect for parsimony and select 4 quarterly lags.}

### 6.3 Linear Projection Method with State-Switching Coefficients

To construct a model allowing for different impulse responses to an oil shock in separate macroeconomic states, I estimate a slight variation on the procedure in Auerbach and Gorodnichenko (2013).

\[
Y_{t+s} = \alpha_{s,E} + \alpha_{s,R}F(z_t) + F_v(z_{t-1}) \cdot \Psi_{R,s}X_{t-1} + (1 - F_v(z_{t-1})) \cdot \Psi_{E,s}X_{t-1} + \\
F_v(z_{t-1}) \cdot \Phi_{R,s}\Delta r_{t-1} + (1 - F_v(z_{t-1})) \cdot \Phi_{E,s}\Delta r_{t-1} + \\
F(z_t)\Pi_{R,s}e_t^{+,*} + (1 - F(z_t))\Pi_E,e_t^{+,*} + u_{t+s},
\]

(5)

where \( F(z_t) = \begin{cases} 0 & \text{if } z_t > \bar{z} \\ 1 & \text{if } z_t \leq \bar{z} \end{cases} \) \hspace{1cm} (6)

In model of equations (5) and (6), the switching variable \( z_t \), which governs the system’s positioning in a high or low output growth state, mimics Auerbach and Gorodnichenko’s switching variable of a seven quarter centered moving average of output (real gross national product). The symbol (\( \cdot \)) represents a vector dot product, and \( F_v(z_{t-1}) \) is a vector constructed so that each lagged value in \( X_{t-1} \) is scaled by the value of \( F \) in the period when that lagged value was realized. Note that, for ease of exposition, I will refer throughout this paper to the \( F(z_t) = 0 \) and \( F(z_t) = 1 \) states as expansion and recession, respectively. This does not refer to their NBER official status as an expansion or recession period, but merely whether the seven period average
of output growth in that period is above or below the sample period average. When I refer to NBER recessions specifically, I will explicitly indicate such.

6.4 Rationale and Roadmap for Results

I chose this method over a VAR for several reasons. First, this method imposes less restrictions on the progression of an output impulse response through different time horizons. This is because in a VAR, impulse responses are created by successively multiplying the relevant shock by the same autoregressive matrix. This assumes that the same slope coefficients govern the progression of a shock at all response horizons. This linear projection method has no such restriction, allowing fundamentally different responses at different horizons, should the data suggest them. Using a VAR approach with state-switching autoregressive matrices to construct impulse responses would also require me to impose strong assumptions about where the US economy is on the business cycle at different time horizons following an initial oil price shock. For example, Auerbach and Gorodnichenko (2012) had to assume that, when a fiscal spending shock was delivered in a recession, the US economy stayed in that strong recession for the entirety of their impulse response (otherwise one would have to begin applying a separate autoregressive matrix to build the impulse response at the moment the economy tends to switch states). By shedding the structural VAR framework, I allow the projections of each time horizon over time to automatically incorporate averages of the economy’s actual transitions between expansion and recession. Finally, Hamilton (2010) suggest utilizing a similar method from Jorda (2005) to allay concerns from Killian and Vigfusson (2009) about constructing impulse response functions for unexpected oil shocks.

12Auerbach and Gorodnichenko (2012, 2013) also utilize a novel smooth transition, whereby $F(z_t)$ can hold values between 0 and 1. I opted to exclude that element of their method, so that $F(z_t)$ becomes an indicator function for whether $z_t$ is above or below the sample average. My first reason for this was that it makes interpretation of impulse responses more straightforward. Secondly, to me this stark division between categorizing different periods seems to provide more convincing conclusions.
The model of equations (5) and (6) will allow me to plot the impulse responses of output to an oil shock, as specified by LNR. This is estimated directly, with \( \{\Pi_{s,E}\}_{s=0}^{10} \) and \( \{\Pi_{s,R}\}_{s=0}^{10} \) as the impulse response to a shock delivered in an expansion and recession, respectively. I will then use a simulation method to determine whether any differences between the two impulse responses are statistically significant. In tying the results of this analysis back to theory, I will offer evidence for or against certain plausible extensions and interpretations of the oil-output mechanism.

7 Empirical Results

7.1 Summary Statistics

Before presenting the empirical results of the models based on equations (5) and (6), I present several summary figures for variables relevant in constructing my oil shock measures.

First, the estimates for the GARCH model, represented in equations (1) and (2) and used to extract both the forecast errors for oil price changes \( e_t \) and the conditional expected variance at each quarter \( h_t \), are presented in Table 1. Recall that the \( \alpha \) parameters show how past oil price changes predict future movements, and \( \gamma \) terms tell how past volatility and squared errors affect current expectations of volatility. The slope parameter estimates in Table 1 match the sign, basic magnitude, and general statistical significance of those from LNR.\(^{13}\) The series of forecasts errors \( e_t \) (non-standarized) estimated from equation (1) are plotted in Figure 3. The expected oil price volatility \( \sqrt{h_t} \), at each quarter in the sample, estimated by equation (2), is shown in Figure 4. The standardized, positive forecast errors series \( e_t^{+,s} \) standardized by \( \sqrt{h_t} \) per equation (3) is plotted in Figure 5.

\(^{13}\)The estimate for \( \alpha_4 \), which shows how price movements four quarters prior affect current forecasts, does lose its statistical significance. The estimate is quite small in magnitude, however, so I chose to keep it in the estimation equations, to remain consistent with prior studies.
7.2 Baseline Results - Motivating the LNR Specification

Table 1: Parameter Estimates of Equations (1) and (2), Data from Q3:1950-Q3:2015

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>-0.3741479</td>
<td>0.1213819</td>
<td>0.002</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.2924525</td>
<td>0.0753401</td>
<td>0</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>-0.4504266</td>
<td>0.0792682</td>
<td>0</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>0.1872282</td>
<td>0.060828</td>
<td>0.002</td>
</tr>
<tr>
<td>$\alpha_4$</td>
<td>-0.0423769</td>
<td>0.0636947</td>
<td>0.506</td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>0.3683564</td>
<td>0.0523252</td>
<td>0</td>
</tr>
<tr>
<td>$\gamma_1$</td>
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<td>0.1876395</td>
<td>0</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>0.4911652</td>
<td>0.0432837</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 3: Quarterly Forecast Errors for Real Oil Price Changes, $e_t$. Plotted Q1:1973-Q4:2015.

As a baseline for comparison, and to confirm the results of previous research, I first present results for a setup completely linear in unexpected oil price changes. That is, I estimate a linear projection model pursuant to equation (4), but with the positive standardized oil shock variable $e_t^{+\times}$ replaced by the forecast errors themselves, $e_t$. Figure 6 shows the impulse response of output to a one standard deviation shock in $e_t$ (defined as the sample mean of the conditional
volatility $\sqrt{h_t}$ and henceforth designated as magnitude $\delta$). Dotted lines in the impulse response figure, and in all subsequent figures, indicate eighty percent confidence intervals, as constructed by Newey-West standard errors with 4 autoregressive lags $^{14}$. This represents a one-tailed hypothesis test at the 10% significance level, with heteroskedasticity and serial correlation-robust standard errors. It is worth noting that these confidence intervals are actually broader than

---

$^{14}$This paper follows the same method as LNR (1995), as well as subsequent papers using the same nonlinear oil price specification, in treating the variables $e_t^{+,*}$ and $e_t^+$ as non-stochastic in the linear projection regressions. While this seems standard in the LNR specification in the literature, it is a well-founded concern that even Newey-West standard errors are perhaps not capturing the true standard errors in this setting, given that these variables were generated as residuals from a separate regression equation. In pursuing this subject in future research, I intend to circumvent this issue using block bootstrapping, or some other simulation-based method for computing standard errors and conducting hypothesis tests.
Figure 5: Quarterly Positive Standardized Forecast Errors for Real Oil Price Changes, $e_t^{+,\ast}$. Plotted Q1:1973-Q4:2015.

many used in oil shock literature. Elder and Serletis (201), for instance, report one standard error confidence bands for their impulse responses.

Figure 6 shows the issue encountered by researchers such as Mork (1989), Hooker (1996), Hamilton (1998, 2003), and many others, while confirming their general results in my framework. Particularly, the size of the output growth response to an oil shock, while the correct sign, is of surprisingly small magnitude and only slight statistical significance for quarters 3 and 7. As Mork (1989) first argued, this is likely because the measure $e_t$ is including negative oil price changes, which do not share the same basic relationship with output as their positive counterparts.

Figure 7 shows the impulse response of output growth rates to the same magnitude shock, but based on a variation on equation (4) that includes only positive forecast errors, $e_t^+$. As the figure shows, this increases both the magnitude and statistical significance of the output response.

15 The largest response at horizon 3 indicates only a .1 percent drop in output growth due to a $\delta$ magnitude oil price increase.
growth response. Specifically, at horizons three and four the impulse response rejects the null hypothesis of no output response, accepting the alternate hypothesis of a negative response in output growth at the 10\% significance level. In both of those quarter horizons, the response’s magnitude is over twice that of the linear model, around .39 and .29 percent output growth reductions, respectively.

As LNR argued and Hamilton (2010), Rodriguez (2010), and Mendoza and Vera (2009) confirm, this measure may not capture the nature of the nonlinearity in output growth’s response to oil prices. It particularly does not account for what a price movement at a given point in time will mean for people’s expectations for oil prices in the near future.

### 7.3 Modeling a Basic LNR Specification

I present in Figure 8 the impulse response of output growth in a linear projection model most closely resembling Lee, Ni and Ratti’s (1995) model. As a first contribution, this paper will attempt to replicate the results of LNR (1995) with a more recent data sample and the linear projection method of Jorda (2005). Specifically, I wish to show that the LNR nonlinearity specification yields more results of higher magnitude and statistical significance than the censored impulse response of Figure 7. This impulse response is obtained by estimating equation (4) as it appears above, and plotting values for $\{\Pi_s\}_{s=0}^{10}$. The figure shows the response to a one-unit magnitude shock in $c_t^+,^*$, meaning a positive unexpected price movement whose size is exactly equal to the conditional expected volatility of oil (i.e. $\sqrt{h_t}$) in the quarter when the shock is delivered.

Figure 7 does display more statistically significant output responses to an oil shock. The eighty percent confidence bands displayed show no overlap with zero at the 3, 4, or 5 quarter response horizons. Additionally, all three of these quarters are significant at the .05 significance level. This is in contrast to Figure 6, which only shows one statistically significant result at
the .05 level, at quarter 3. The magnitude of these response has also increased from Figure 6, with the largest responses at horizons of 3 and 4 quarters both around a .40 percent decrease in quarterly output growth.  

Figure 6: Impulse Response of Output to $\delta$ magnitude shock in $e_t$. Linear setup.

The fact that this yields meaningful results is itself a victory for the uncertainty theory. If the conditional volatility of unexpected oil prices has no bearing on the associated output response, then we would expect the interaction of $e_t$ and $h_t$ to muddle the impulse response results from Figure 7. From Figure 8, its inclusion seems to have sharpened the results and their statistical significance. With $h_t$ acting as my proxy for oil price uncertainty, Figure 8 is evidence for the importance of considering it in our investigation of oil’s output effects.

Note that this first construction of coefficients $\{\Pi_s\}_{s=0}^{10}$ pools low output and high output growth periods together to show average expected responses over the whole sample, as specified

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16The magnitude of these responses is lower than those report in LNR (1995). This is most likely due to my choice of a later sample period of 1973-2015, compared to theirs of 1950-1986. It is well documented by Mork(1989) and Hooker (1996) among others that output response to oil shocks were significantly larger in magnitude in the mid 20th century
7.4 Modeling Impulse Responses with State-Switching Coefficients

This next model yields two separate impulse responses for a one-unit unexpected standardized oil price increase in $e_t^\pm$ - one for a shock delivered in a low output growth period and second for high output growth periods. In the terms of equation (5), these two impulse responses are estimated directly as $\{\Pi_{R,s}\}_{s=0}^{10}$ and $\{\Pi_{E,s}\}_{s=0}^{10}$, where $R$ and $E$ refer to “recession” or “expansion”, respectively.

Figure 9 shows these two impulse response of output growth. Several features stand out. First, the output response to an oil shock delivered in a low output growth period (“recession”) becomes statistically significant after 3 quarters and remains statistically significantly negative until 6 quarters after the initial shock. The magnitude of the output growth drop is also substan-
Figure 8: Impulse Response of Output to One Unit Magnitude Shock in $e_t^{+,*}$. Positive standardized unexpected price movement.

tially higher in the recessionary regime than was report in the pooled regime of Figure 8, with quarterly output growth drops around .60 percent reported in the periods 3, 4, and 5 quarters after a shock. The high output growth period response, by contrast, behaves somewhat erratically for the first two quarters after a shock, only becoming marginally statistically significantly negative at the 3 and 5 quarter horizons. These two negative responses are less statistically significant than their low output period counterparts, and less in magnitude (both around an expected .30 percent output growth drop, roughly half the magnitude of the peak response in the recession periods).

Recall from the Methodology portion of this paper that the linear projection method used in

\[ \Pi_{E,s} \]}

\[ \text{is estimated in a separate regression, the probability of at least one of the impulse responses suffering from a Type I error is higher than in a VAR framework. I interpret a string of significant results, as in the recession impulse response, as much stronger evidence against Type I errors.} \]
Auerbach and Gorodnichenko (2013), which this model roughly utilizes, already incorporates the average transitions of the economy from low to high output state periods. That is, if the economy on average tends to switch output growth states following an oil shock, then this impulse response will already incorporate that transition (so there is no need to “switch” to another set of coefficients at such a juncture). It therefore may be useful to consider the typical length of these two output growth periods, so we know whether the duration of these impulse responses are typically spent in the same business cycle state. Figure 10 shows what portion of points in the sample in a given business cycle state are still in that business cycle state \( x \) periods later. As Figure 10 shows, for both the recession and expansion periods, the economy is typically still in the same state for up to seven periods.\(^{18}\) Given that any interesting asymmetries in the output impulse responses disappear after about six or seven periods, this indicates that the economy is generally still in the same business cycle state for the horizons of interest in the output response.

The critical question remains of whether the visual differences between the two regimes in Figure 9 represent a statistically significant asymmetry. To determine whether these differences are statistically significant, I construct confidence intervals around the difference between the two. This difference is defined as \( \{ \Pi_{R,h} - \Pi_{E,h} \} \), and eighty percent confidence intervals for this statistic at each response horizon were computed via simulation. Ten thousand random draws were taken from two normal distributions with a mean for each horizon given by \( \Pi_{R,h} \) or \( \Pi_{E,h} \) and variance given by the square of the Newey-West standard error for each estimate. The two series were differenced and confidence intervals were defined by the 10th and 90th percentiles of the resulting difference series. Given that asymmetries are defined directly from the impulse responses, I hope to avoid many of the issues raised by Kilian and Vigfusson (2009) regarding assessing asymmetries using slope coefficients alone.

\(^{18}\)The recession portion reaches and remains at a point below \(.5\) because there are slightly fewer low output states in the data.
Figure 9: Impulse Response for Output Growth to One-Unit Shock to $F(z_t)e_t^{+,*}$ or $(1 - F(z_t))e_t^{+,*}$.

The result of these calculations is shown in Figure 11, where the solid line indicates the mean difference between the two output responses at each horizon, and the dotted lines indicate confidence intervals. The asymmetries between the high and low output states are statistically significant at the .10 significance level at the 2, 4, and 6 quarter horizons. Additionally, the 3 and 5 quarter response horizon’s confidence bands only slightly straddle zero. When using error bands of one standard deviation, which are not atypical in past oil shock literature, both of these differences are significant as well.

8 Discussion and Implications

The sign of the difference between these two states has significance regarding the importance of the prevailing indirect theories of the oil-output response mechanism.
8.1 Inconsistencies with Theory

As I argue in this paper’s introduction, a plausible extension of the reallocation theory suggests that the output-dampening response of an oil shock attributable to the allocation effect should be larger in an expansion than in a recession. This is because sectors with under-utilized specialized labor and capital, which will describe most sectors in a recession, can quickly and easily take advantage of increased demand for their sector by hiring or using labor or capital already specialized for the sector. In an expansion, when each sector is close to full factor utilization, increasing production to offset demand shifts requires a costly transition of specialized labor or capital from an energy-inefficient sector to an energy-efficient one.

The data do not seem to support this extension of the allocation theory. By contrast, the impulse responses in Figure 9 show oil shocks in a low output period having a larger magnitude effect on output than in a high output period. With a similar logic as Balke, Brown, and Yucel (2002) used for the monetary policy effect, the inability of the allocation theory to explain this empirical observation casts some doubt as to the importance of this reallocation theory. If this
mechanism were a chief driver for the magnitude of any output effect, one would expect the sign of this empirical asymmetry to follow that implied by theory.

Similarly, the direction of this asymmetry conflicts with the theory that monetary policy drives the majority of output’s oil response. One would expect the Federal Reserve to be more willing to increase interest rates after an oil price increase if the economy is in an expansionary period - prompting a larger negative output response. Given the larger response in the recession periods, this too casts doubt on the importance of the monetary policy theory - at least in its ability to explain this apparent asymmetry.

8.2 Other Potential Interpretations of Theory

As the theoretical question of allocation theory’s varying effects based on the business cycle has not been extensively explored in the current literature, it is worthwhile to entertain some alternate interpretations that may be consistent with my empirical results, and assess their plausibility in the light of each theory’s intuitive justifications.
For the reallocation theory to be consistent with my empirical results necessitates an economically plausible story by which the frictions preventing sectors from reallocating labor and capital are exacerbated when there is excess slack in the economy. One potential explanation would be if a particular oil price shock were to depress demand for one sector without increasing demand for another. In that scenario, when specialized labor and capital are released from one sector due to decreased demand, they could be expected to remain unemployed or un-utilized for a longer period, given the slack already present in most sectors. This could potentially exacerbate the decrease in output growth, consistent with the results above. However, this is predicated on the absence of a sectoral demand increase associated with the oil shock. If there was such a demand increase, then that sector could increase production to have a smaller net decrease in output. As I explain above, the ease by which that sector can increase production would be helped by a recession, not harmed by it.

I find it implausible that an oil shock could decrease demand in one sector without increasing it in another. In the end, the sorts of high value durable goods whose consumption has a real impact on output, and whose value is dependent upon the price of energy (such as motor vehicles), have a substitute with some differing level of energy efficiency. For instance, expensive, fuel efficient hybrids or electric cars have an obvious substitute of a less energy efficient, but likely less-expensive, conventional vehicle. Any decrease in demand for a gas-guzzling SUV could reasonably be expected to be accompanied by increased demand for its energy efficient alternatives. Simply, a relative price change between two substitutes should increase quantity demanded for one and decrease it for another. The quality of consumers responding to an oil price change by delaying spending decisions altogether is, for this reason, a characteristic of the uncertainty theory - not the reallocation theory.

Another possible interpretation of the cyclicality of the reallocation theory may center around the Hamilton (1988) observation that some of the unemployment associated with sec-
toral reallocation may be voluntary. That is, specialized employees laid off from their preferred, higher productivity sector may voluntarily refuse to transition to another sector under the hope that conditions will improve in the sector of their past employment. If this sort of voluntary employment were more likely in a recessionary period, then that could explain the empirical observation above with existing reallocation theory components.

But this interpretation also fails to stand up to scrutiny. In a general expansionary period where an employee loses their job due solely to an energy price increase, that employee may have reason to believe that prices will drop again, allowing an employer in that same sector to rehire him or her to increase production to meet now-normalized demand. In a recessionary period, however, that employee has less reason to believe he would be rehired expeditiously. This is because, with increase slack in his sector generally, his probability of being rehired - even if oil prices change favorably soon - is less, simply because the industry has more unemployed specialized labor to choose from. Unemployed labor in an industry whose demand is depressed by an oil price change would thus be more likely to search for a job in another sector in a recession - theoretically lessening the negative effects of reallocation.

A third interpretation seems more economically plausible. To the extent that allocative disturbances require some upfront costs for a firm looking to increase production to capitalize on them, the ability of a firm to buoy aggregate demand may be dependent on its ability to obtain easy credit to pay those costs. In a recessionary period of low growth and higher financial uncertainty, a firm would almost certainly have more difficulty obtaining the credit necessary to hire more workers and employ more capital, which is a necessary step in picking up the demand “slack” of other sectors whose demand shrunk after an oil price change.

This financial conditions-based approach to interpreting the magnitude of this allocation effect is somewhat different from past literature’s. In discussions in Kilian and Vigfusson (2009), and Hamilton (1988), among others, the focus for discussions of the allocation theory has been
on the likelihood of oil price changes to trigger the need for allocation. But extensions of that logic, as outlined above, should suggest less output responses in a recession, not more. My empirical results above seem to call for a shift in focus regarding this effect, to one acknowledging how financial conditions may deepen the severity of reallocation costs. Interestingly, KV (2014), using their net oil price increase model above, did show a statistically significant correlation between the magnitude of their hypothetical output responses and the Chicago National Financial Conditions Index (a commonly-used indicator of financial stress), but no correlation between output response and the business cycle. Perhaps their net oil price model, which I argue most directly accounts for mechanisms similar to the allocation effect, was detecting an importance in credit conditions tied to this potential source of asymmetry.

8.2.1 The Applicability of the Uncertainty Theory

Given these inconsistencies between my empirical results and the plausible implications of these theories, a natural remaining candidate to explain the business cycle asymmetry is the remaining uncertainty theory. First, the mere fact that the above extensions of the two other major theories for indirect oil-output effects have difficulty directly explaining my results adds some credence to uncertainty theory which, by not strongly indicating a direction for the business cycle asymmetry a priori, does not directly conflict with the results above.

The uncertainty theory could go further and help actively explain these results if one of two connections exist. First, it may be that increased uncertainty - which will reasonably come from any oil price change that is large compared to economic actors’ expectations - has a larger impact in a recessionary period than in an expansion. This hypothesis has a certain plausibility. Perhaps investors and consumers have a threshold level of uncertainty that they are able to tolerate in making a decision, and any excess uncertainty beyond that threshold will cause them to postpone irreversible investment or consumption to await new information - per real option
theory. In this case, in a recessionary period with already-heightened financial uncertainty, the added uncertainty from relatively large oil price fluctuations could be enough to pass a threshold level and postpone decisions, leading to an output drop. Under this interpretation, a price change could reasonable cause a more severe output growth drop in an already low output period.

A much simpler, and perhaps less ad-hoc uncertainty story for the results above would follow if oil price changes simply cause more uncertainty in a recession than in an expansion. This would not necessitate any difference in how investors or consumers internalize a given amount of perceived uncertainty, if it can be shown that their bands for oil price uncertainty react more severely or persistently to unexpected shocks in a recession.

I can use the behavior of my oil price uncertainty proxy, $\sqrt{h_t}$, to shed some additional light on what may be driving this difference. Recall first tha Elder and Serletis (2010) showed a similarly-constructed conditional volatility measure had a negative and statistically significant effect on output growth. Therefore, if perceived oil price volatility increases more in a low output period, or stays high for longer, then that could help explain the regime differences in Figure 10.

Granted, the validity of this argument is dependent upon the ability of my GARCH estimate for expected volatilities to closely resemble market participant’s actual expectations. Admittedly, $h_t$ is likely an imperfect representation of expected volatilities, as it assumes that actors in the economy have no more information than is embodied in the GARCH model itself. However, there is evidence to suggest that this approximation is reasonable. Kellog (2010) used implied volatilities from futures contracts to compute expected volatility, which almost certainly represents a closer approximation of the actual information set available to investors and consumers in the real world. His study found that a GARCH representation of volatility matched implied future volatilities relatively closely - and much more closely than models depending on lagged volatilities alone to compute expectations. I leave the exercise of testing my results above with
implied volatilities from futures contracts to later research.

To help address this issue, I calculate an additional linear projection, very similar in form to the model implied by equations (5) and (6). The difference will be in the dependent variable, which is changed to \( h_t \), to see how a shock to \( e_{t+*}^- \) tends to affect \( h_t \) dependent upon the output state at the time. The impulse response implied by those estimations is shown in Figure 12. An additional figure tracking the difference of the two impulse responses, with 80% confidence bands, is shown in Figure 13.

Figure 12: Impulse Response of \( h_t \) to one-unit shock in \( e_{t+*}^- \), dependent on business cycle state.

As these figures show, at the early impulse response horizons there are no statistical difference in the expected increase of conditional volatility \( h_t \) to a shock in \( e_{t+*}^- \). However, beginning at the quarter three horizon and continuing several more quarters, the low output regime has a much higher volatility response to oil shocks than the high output regime. Figure 13 confirms the statistical significance of this positive difference.

Recall that \( h_t \) is constructed using an equation of the following form,
Figure 13: Differences between output states’ impulse responses of \( h_t \) to a shock in \( \varepsilon_t^{+,*} \)

\[
h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1}
\]

It follows that the differences above must be driven either by a difference in average volatilities between the two states through the \( h_{t-1} \) term, or the typical path of unexpected oil prices in low output periods, through \( \varepsilon_{t-1}^2 \). To understand the first, consider that the impulse response in Figure 12 delivers a shock to \( \varepsilon_t \) of magnitude \( \sqrt{h_t} \). In this case, the estimated terms of my GARCH process dictate that \( h_{t+1} \approx 1.7h_t \) (because \( \varepsilon_{t-1} \) in equation (2) equals \( \sqrt{h_t} \)). That is, the increase in the level of \( h \) from the period before to the period after the shock is a product of the initial size of \( h \). Consequently, it could be that the impulse response in Figure 12 shows a larger increase of \( h \) to an oil shock in a recession simply because \( h_t \) tends to be higher in low output periods (which the averages of \( h \) between the two states does suggest), and thus \( h_{t+1} \) increases by a larger factor. This source of different \( h_t \) responses would not shed much light on any meaningful economic process, as it is simply a mechanical artifact of levying a \( h_t \)-sized
shock on both periods.

Figure 12 allays most concerns regarding the importance of this mechanism. If larger average volatilities in recessions were driving a majority of the variation above, then I would expect to see a large difference between the two responses at earlier horizons that gradually decays over time, with a particularly large response in the one quarter response. Tellingly, Figure 12 shows the opposite. Responses at quarter 1 and 2 are almost identical for the two states, and only later does the recessionary state response substantially diverge from the expansionary one.

In my opinion, this tells a more meaningful economic story about the average dynamics of unexpected price movements $e_t$ in the two regimes. That is, Figure 12 indicates that a large, unexpected oil price movement in a recession (increasing conditional volatility) portends more surprise price movements in the near future, while a price change in an expansion is more likely to be an isolated event. To the extent that economic actors are rational and realize that an oil price movement in a low output state is more likely to come before further unexpected price movements, it is seem reasonable that their uncertainty resulting from a price increase will be larger in a recessionary period. Per uncertainty theory, this should result in more delayed investment and consumption - consistent with the larger output growth response in those periods, shown above.

9 Conclusions

In all, my findings in this paper offer strong support for the uncertainty theory of the oil-output relationship. First, my paper was able to replicate the general results of LNR (1995) using more recent data and a linear projection method proposed by Jorda (2005) to directly estimate

\footnote{Low output periods do have a higher average conditional volatility than high output periods. However, this difference does not seem substantial enough to drive asymmetries above, as the above explains.}
impulse responses. Given that the logic behind the LNR specification is most consistent with the uncertainty theory of oil-output effects, statistical significance when accounting for it shows that volatility plays an important role in output responses to oil shocks.

My results for impulse responses in different business cycle states also provides meaningful insight into the potential workings behind several prevailing theories of the oil-output response mechanism. My empirical results show a statistically significantly greater negative response of output to unexpected oil price increases in a low output growth period than in a high growth one. These results are arguably inconsistent with the monetary policy-focused perspective of Bernanke, Gertler, and Watson (1997).

These results are also inconsistent with what I believe to be the most natural extension of the Hamilton (1988) reallocation theory to the business cycle. Namely, capital and labor slack in the economy should make it easier for firms to take advantage of demand changes without triggering costly sectoral reallocation. An interpretation of reallocation effects that is generally consistent with my empirical results centers around the possible importance of credit conditions in capitalizing on these same demand shifts. A correlation suggestively similar to this effect was also reported in KV(2014). This paper’s results advocate for greater analysis of the importance of financial conditions in determining the role of allocative demand disturbances.

Uncertainty theory can help to explain the asymmetries I detect empirically. Specifically, impulse response analysis shows that unexpected oil price movements in a low output period portend unexpected movements in the near future more often than price movements in an expansion. To the extent that economic actors internalize this probability in determining their level of uncertainty, this effect could delay more investment and consumption in a recessionary period than in an expansion, consistent with my results above. This paper joins the likes of Ferderer (1997) and Elder and Serletis (2010), showing that the uncertainty theory likely does have a meaningful impact on the output response to an oil shock.
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