Cracker Barrel: Disentangling Oil Price Shocks through the Crack Spread

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Abstract

This paper proposes a new methodology for differentiating oil demand and supply shocks using the information content of forward-looking asset prices for crude oil and refined products. Building upon the industry folk wisdom that demand and supply shocks have asymmetric passthrough dynamics through the product crack spread, the paper provides a new identification scheme without using quantity-based data. Our results suggest that the price rises of the late 1970s had a demand-driven component, the 1990-91 Gulf War shock reacted both to supply and precautionary demand shocks, the price spike in 2008 was driven more by expectations of future supply constraints than immediate demand pressures, and the recent collapse of prices in 2014 had both a demand and supply component. Oil demand and supply shocks, by our decomposition, are also shown to have different impacts on macroeconomic variables such as industrial production, unemployment, core inflation, and the Fed Funds rate, with implications for formulating an effective policy response to oil shocks.

Keywords: oil prices, oil shocks, sign restrictions, structural VAR.

JEL Classification Numbers: C32; E37; Q43; F4; G14.

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1 Introduction

Despite great strides in understanding oil prices shocks since the 1970s (recent surveys are provided by Barsky and Kilian (2004), Rogoff (2005), and Hamilton (2005)), economists are still debating the importance of oil in the macroeconomy and the formulation of appropriate policy responses. Recently, the literature has recognized a crucial distinction: oil shocks that originate from higher global demand have different macroeconomic impacts than those caused by disruptions in supply, with the important corollary that policymakers should also respond differently.

This paper presents a new methodology for distinguishing between oil demand and oil supply shocks using price instead of quantity-based signals, thus becoming an important complement to previous literature such as Kilian (2008a). In particular, our approach is motivated by the widely accepted folk wisdom in the practitioner community that oil demand and supply shocks have distinct impact on market prices of crude oil and the refined products due to the imperfect pass-through between the two sectors of the energy market.[1] Accordingly, we can empirically differentiate between the demand and supply shocks by studying the joint behavior of crude and product market prices. Using an intuitive application of sign restrictions as first introduced by Uhlig (2005), we generate a historical decomposition of oil price shocks. We also document how demand and supply have had starkly different impacts on macroeconomic variables such as output, unemployment, inflation, and the Federal Funds rate.

Our historical decomposition of oil prices debunks some common pieces of anecdotal wisdom while confirming others. Notably, we find that the price rises of the 1970s had an important demand-driven component, which is consistent with the findings in Kilian (2008a). This contrasts with the common belief that such price increases can be attributed exclusively to supply disruptions. Also, while the general rise in energy prices from 2002 to 2007 appears

[1] Examples of empirical studies of energy markets that document the imperfect pass-through between crude oil and refined product markets include, among others, Borenstein, Cameron, and Gilbert (1997), Borenstein and Shepard (2002), and Davis and Hamilton (2004).

to be demand-driven, the sharp spike in 2007-08 appear to be driven more by supply considerations with potential implications for both monetary policy and the subsequent economic recession. Lastly, the recent 2014 price collapse appears to be driven in almost equal measure by both demand and supply factors.

An important difference between our approach to identification and the alternatives proposed in previous literature is that we rely exclusively on asset price data, without using any information on physical quantities. Quantity-linked indicators of oil demand and supply, particularly world crude oil production, have difficulty explaining much of the history of oil price movements. This could be due both to the higher quality and the forward-looking nature of the financial price data. This suggests that forward-looking asset prices contain important additional information not fully captured by quantity-based indicators.

Our work builds on the insights of the work by Kilian (2008a), who first highlighted that the literature on the role of oil shocks in the macroeconomy has been relying on the objectionable assumption that all oil shocks are equal, while the economic mechanisms of demand shocks are distinct from those of supply shocks. Moreover, earlier literature has generally taken oil shocks as exogenous when studying the response of macroeconomic aggregates. This assumption overlooks the possible reverse causality from the global economy through oil demand to prices. These observations have important ramifications for policymakers. For instance, a central bank may raise interest rates in response to an endogenous demand-driven increase in the price of oil, while the optimal response to an exogenous cost-push oil supply shock is much less obvious, and depends on the trade-off between the direct inflationary effect of higher oil prices and their indirect counter-inflationary effect derived from their negative impact on aggregate output. Our work thus directly addresses the ongoing debate over whether US economic weaknesses in the late 1970s and 1980s were caused by oil supply shocks or by the contractionary monetary policy(e.g. Bernanke, Gertler, and Watson (1997), Barsky and Kilian (2002), and Hamilton and Herrera (2004)).

Our paper relates to a rich line of research using the information content of asset prices as macroeconomic signals. Recent applications in the oil and macroeconomics literature include Anzuini, Pagano, and Pisani (2007), Kilian and Vega (2008), and Alquist and Kilian (2009). The notion that prices of financial assets aggregate various sources of information has been the corner stone of the theory of efficient markets, e.g., Fama (1970, 1991). Financial prices are forward-looking and respond both to news about today and about the future. Thus, exploring the information content of financial prices offers a potentially fruitful approach to identification of oil demand and supply shocks. This approach complements the previous literature (e.g. Kilian (2008a), and Lippi and Nobili (2008)), which has based identification on the dynamics of both prices and quantities. By relying solely on financial asset prices, we circumvent the need for strong assumptions on the causal ordering between specific physical indicators of current supply and demand, such as shipping rates and world oil production, as well as the well-known measurement issues.

The remainder of the paper is organized as follows: Section 2 describes the model's framework and assumptions. Section 3 presents the empirical identification results. Section 4 studies how the identified supply and demand shocks relate with macroeconomic aggregates such as industrial production, unemployment, core inflation, and the Federal Funds rate. Section 5 concludes.

2 The Model

2.1 An Agnostic Model of the Energy Complex

Our model considers two types of shocks to oil prices: demand shocks and supply shocks.[2] Figure 1 shows the two types of shocks and their impact on the various sectors of the energy complex chain.

A (positive) supply shock, such as a Middle East military conflict, directly impacts crude oil markets (often called the "upstream" market), thus causing a primary increase in crude oil prices. This primary price jump imperfectly passes through into product markets and drives a secondary increase in product prices (the "downstream" market), thus resulting in a narrowing of the spread between the two prices (often referred to among industry practitioners as the "crack"). The imperfect pass-through can result from many sources of stickiness, such as a draw-down in an inventory cushion, menu costs, incomplete information, or seller market power.[3] Similarly, a positive demand shock, such as faster-than-expected growth of Chinese demand for gasoline, we argue, only imperfectly passes through from the gasoline market to the crude oil market.[4] Gasoline and other product providers may draw upon available inventories rather than increasing refinery demand for crude, and consumers may respond to higher product prices by switching to close substitutes, such as from gasoline to diesel. But regardless, as long as markets for crude and products are not instantaneously and perfectly competitive, the pass-through should be imperfect.[5]

[2]For expositional simplicity, we refer to a "positive" shock of any type as one which causes crude prices to rise.

[3]Borenstein, Cameron, and Gilbert (1997), Borenstein and Shepard (2004), and Davis and Hamilton (2004) provide empirical evidence of inventory adjustment costs at the level of product spot markets and some short-run market power at the wholesale and retail levels. Borenstein and Shepard (2004) suggests that the passthrough is largely complete by six weeks after the initial shock.

[4]Kilian (2008b) makes a similar assumption of the world crude oil market only responding to shocks in product markets with a lag.

[5]There is a potential third shock, namely refinery shocks that neither impact the crude nor the product market directly but rather the refineries that sit in between. However, shocks to the refinery complex seem to be insignificant relative to traditional demand and supply shocks. The construction or decommissioning of a refinery is a slow and involved engineering endeavor that requires multi-year lead times. Furthermore, planned maintenance and capacity upgrades are timed to occur after the end of the summer driving season and before the winter heating season, when demand for refined products are low, spare capacity is available,

Table 1: The asymmetric price responses to demand and supply shocks.

	Market Price Reaction		
Structural Shocks	crude oil prices	product prices	crack spreads
demand shock	$\uparrow$	$\uparrow\uparrow$	$\uparrow$
supply shock	$\uparrow\uparrow$	$\uparrow$	$\downarrow$

Our identification strategy is based on the insight that any imperfection in the pass-through allows us to distinguish oil demand and oil supply shocks purely through the joint behavior of asset prices for crude oil and refined products, or crude prices and crack spreads, allowing us to remain agnostic about the particular source of stickiness and independent of any interpretation over quantities, such as the amount of OPEC output cuts, which are nigh impossible to verify. Figure 2 shows the history of real log crude oil prices, seasonally adjusted, from 1971.01 to the present. Figure 3 shows the history of real log price spreads between crude oil and a blend of gasoline and heating oil, again seasonally adjusted, from 1971.01 to the present.[6]

In Table 1, we summarize the theoretical price impact of demand and supply shocks on prices of crude oil and refined products, and the resulting impact on the crack spread. A double-arrow represents a "first-order" high-magnitude impact while a single arrow represents a "second-order" pass-through impact. Upward and downward pointing directions represent positive/negative signs.

We see how a supply shock, ceteris paribus, causes the crack spread to widen, while a demand shock causes the crack spread to shrink. Other than this very simple yet natural

and the resultant market disruption would be minimal.

Hence, it is reasonable to assume the only refinery shocks that can potentially impact short-term price innovations are unexpected systematic outages in refinery capacity driven by natural events such as Katrina-Rita hurricane cycle of 2005 or the Gustav-Ike cycle of 2008. These unplanned outages are, by their nature, fundamentally exogenous. Using a measure of US refining capacity, we find refining shocks do not have any statistical power in explaining crude or product prices at the monthly frequency. This corroborates previous findings such as a study by the US Department of Energy, "Refinery Outages: Description and Potential Impact on Petroleum Product Prices," from March 2007, which finds refining shocks disappate within one month. Hence, in the interest of brevity, we ignore refining shocks in our main discussion.

[6] The ratio of the blend is set at two parts gasoline and one part heating oil over three parts crude oil. This blend, referred to as the 3-2-1 crack spread in the industry, is a widely used ratio to capture market movements across the entire heavy and light product spectrum.

model, we impose no additional structure. With this intuitive and agnostic framework in place, we turn to in a structural vector-autoregression in the next subsection.

2.2 Structural Identification using Sign Restrictions

Let p_t^{crd} be the log real price of crude oil and p_t^{pdt} the log real price of the refined product.[7] Consider a structural VAR model of the two price series

$$\mathbf{A}_0 \left(Z_t - \mathbf{A}(L)Z_{t-1}\right) = \varepsilon_t, \tag{1}$$

where Z_t is a vector of log prices,

$$Z_t = \begin{bmatrix} p_t^{crd} \\ p_t^{pdt} \end{bmatrix},$$

ε_t is a vector of mutually uncorrelated structural innovations, with the first element of ε_t being the demand shock, and the second being the supply shock,

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^{dmd} \\ \varepsilon_t^{sply} \end{bmatrix}. \tag{2}$$

We explicitly define the elements of the matrix A_0 as

$$\mathbf{A}_0 = \begin{bmatrix} a & B \\ A & b \end{bmatrix}^{-1}. \tag{3}$$

Next, let v_t denote the vector of reduced-form shocks, defined as

$$v_t = \mathbf{A}_0^{-1}\varepsilon_t = \begin{bmatrix} a & B \\ A & b \end{bmatrix} \begin{bmatrix} \varepsilon_t^{dmd} \\ \varepsilon_t^{sply} \end{bmatrix}. \tag{4}$$

[7] We focus attention on the product blend of gasoline and heating oil because those two products have the longest price history and are widely accepted as representing a fuller picture of the product spectrum than either of them does in isolation. Appendix A contains documentation of the sources of the data.

v_t is the residual vector in the reduced-form structural VAR model

$$Z_t - \mathbf{B}(L)Z_{t-1} = v_t.$$

We can equivalently express the above reduced-form model in terms of the crude oil price and the crack spread. Specifically, let p_t^{crk} denote the log "crack" spread, equal to the difference between the log product price p_t^{pdt} and the log crude price p_t^{crd}:

$$p_t^{crk} = p_t^{pdt} - p_t^{crd}.$$

Let u_t denote the vector of reduced-form shocks in the VAR system for the vector $(p_t^{crd}, p_t^{crk})'$. Then, reduced-form shocks u_t and the structural shocks ε_t are related by

$$u_t = \mathbf{B}\varepsilon_t, \quad \mathbf{B} = \begin{bmatrix} a & B \\ A - a & -(B-b) \end{bmatrix}. \tag{5}$$

Our agnostic model of the energy complex suggests that demand shocks and supply shocks have distinguishable impact on the crude oil price and the crack spread. As expressed in Table 1, a positive demand shock causes and increase in both the crude oil price and the crack spread, a contraction in supply causes an increase in the crude oil price and a reduction in the crack spread. To operationalize these sign restrictions, we must decide at what horizons to impose them: a structural shock affects the vector of prices observed on subsequent dates. We summarize the sign of the above restrictions in Table 2.

The above sign restrictions are convenient to express in the context of our structural VAR framework when the restriction horizon is limited to a single period, k=1. In that case, the sign restrictions are equivalent to two conditions, both stated in terms of the coefficients of the matrix $\mathbf{A}_0$ in (1).

Condition 1 ***(Demand Shock Impact)*** *A demand shock causes an increase in both the*

Table 2: Sign Conditions applied to Crude Oil prices and Blended Crack Spreads

	Structural Shocks	
Variables	oil demand[a]	oil supply[b]
crude oil price	+	++
crack spread	+	-

[a] A "+" (or a "-") sign means the impulse response of the variable is restricted to be positive (negative) to the structural shock.
[b] Here, the double "++" for the response of crude oil prices to oil supply shocks means the magnitude of the (positive) crude response must be greater than the magnitude of the "negative" blended crack spread response, i.e. $\left\|\phi^{sply}_{crd,k}\right\| > \left\|\phi^{sply}_{crk,k}\right\|$ where $\phi^{j}_{i,k}$ is the impulse response of variable j to a structural shock of type i for k periods.

product price and the crude oil price, with the larger increase in the product price, i.e. $0 < a < A$ *in (4).*

Condition 2 ***(Supply Shock Impact)*** *A supply shock causes an increase in the crude oil price and the product price, with the larger increase in the crude oil price, i.e.* $0 < b < B$ *in (4).*

We are facing a standard identification problem, which results in a single degree of freedom among the structural parameters being unidentified from the reduced-form estimates without additional restrictions on the model. Specifically, we normalize the unconditional covariance matrix of the structural shocks by setting the diagonal elements of the matrix $\mathbf{B}$ in (5) to unity:

$$\mathbf{B} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & -1 \end{bmatrix}$$

Let Σ denote the unconditional covariance matrix of the structural shocks ε_t, and Ω denote the unconditional covariance matrix of the reduced-form shocks μ_t,

$$\Sigma = E[\varepsilon_t \varepsilon_t'], \quad \Omega = E[\mu_t \mu_t'] \tag{6}$$

By assumption, the matrix Σ is diagonal. It's two diagonal elements Σ_{11}, and Σ_{22} are not directly observed. Instead, we can obtain a consistent estimate of the unconditional covariance matrix of the reduced-form shocks Ω, which is related to Σ by

$$\Omega = \mathbf{B}\Sigma\mathbf{B}' \tag{7}$$

Thus, we must base inference about four structural parameters, b_{12}, b_{21}, Σ_{11}, and Σ_{22}, on three identifiable reduced-form parameters, Ω_{11}, Ω_{12}, and Ω_{22}, which leaves the structural parameters unidentified.

As there is only a single degree of freedom, if we could fix a single parameter, b_{12}, all remaining parameters would be identified from the reduced-form estimates. We therefore express all unknown structural parameters, in particular b_{21}, as functions of b_{12}.

Starting from equation (7),

$$\Sigma = \mathbf{B}^{-1}\Omega(\mathbf{B}^{-1})' = \det(\mathbf{B})^2 \begin{bmatrix} -1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{12} & \Omega_{22} \end{bmatrix} \begin{bmatrix} -1 & -b_{21} \\ -b_{12} & 1 \end{bmatrix} \tag{8}$$

The assumption that the covariance matrix of structural shocks is diagonal implies that $\Sigma_{21} = 0$, and thus

$$(\Omega_{11} + b_{12}\Omega_{12})\, b_{21} - (\Omega_{12} + b_{12}\Omega_{22}) = 0.$$

and therefore,

$$b_{21} = \frac{\Omega_{12} + b_{12}\Omega_{22}}{\Omega_{11} + b_{12}\Omega_{12}} \tag{9}$$

Thus, we have expressed b_{21} as an explicit function of b_{12}. This is enough for our purposes: inequality constraints are based on restrictions on the impulse responses. But the impulse response constraints do not depend on the diagonal elements of Σ, they depend only on the elements of $\mathbf{A}(L)$ and $\mathbf{B}$. So, for example, if $\widehat{\phi}_k$ is the matrix of k-period impulse responses to reduced-form shocks, impulse responses to the single standard-deviation structural shocks are $\phi_k = \widehat{\phi}_k\mathbf{B}$, and the constraints on the impulse responses translate easily into constraints on the structural parameters.

If we further impose the sign restrictions over a single period, then the restrictions on the impulse responses implied by imperfect path-through of shocks from the crude-oil market to the refined-products markets limit the range of admissible values of the the single structural parameter b_{12}. Namely, imposing the sign restrictions over a single period leads to the following two conditions, which are equivalent to the conditions 1 and 2 above respectively:

Condition 3 ***(Restriction on*** $\boldsymbol{b}_{12}$***)*** *The estimated coefficient* b_{12} *must be positive and greater than 1.*

Condition 4 *(**Restriction on** $\boldsymbol{b}_{21}$) The estimated coefficient* b_{21} *must be positive.*

Thus, the above inequality constraints result from minimal theoretical assumptions and accordingly provide relatively weak restrictions on a single parameter. The sign restriction approach then identifies a subset of structural models such that the impulse responses are consistent with the sign restrictions derived from the theory. The approach exploits the fact that for any arbitrary identifcation matrix $\mathbf{B}$ satisfying $\mathbf{BB}' = \Sigma$, any other identification matrix $\widehat{\mathbf{B}}$ can be expressed as a product of $\mathbf{B}$ and an orthonormal matrix $\mathbf{H}$. The set of models satisfying the sign restrictions can be characerized as follows: For a given estimated of the reduced form vector auto-regression, take an arbitrary identification matrix $\mathbf{B}$ and compute the set of candidate structural models $\{\widehat{\mathbf{B}}\} = \{\mathbf{B}H \mid HH = I\}$. The subset of satisfying identifications is obtained by removing from the set those models that fail to satisfy the desired conditions. This leaves us with a set of satisfying b_{12}'s.

While it is possible to refine the identification further, doing so requires additional assumptions on the prior likelihood of various admissible values of the structural parameters. Moreover, studying parameters across a range of possible models has important conceptual limitations. For instance, the median and percentiles of the distribution of impulse responses across all admissible models, as is typically reported by the literature on sign restrictions, may not correspond to an impulse response of any particular admissible model (see Fry and Pagan (2007) and Kilian (2009) for a discussion of related issues).

A related paper Ahn and Kogan (2014) applies a different heteroskedasticity-based identification approach developed in Rigobon (2003). This approach exploits structural breaks in the conditional variance of demand and supply shocks. Assuming that nevertheless the structural parameters of the pass-through remain constant, full identification can be achieved and a single self-consistent value for b_{12} derived. This approach produces similar estimates for b_{12} and similar decompositions of oil price innovations into supply and demand component as the ones presented in this paper, adding confidence to our findings. However, it has the disadvantage of making other assumptions about the conditional volatility of shocks and does not take advantage of the intuitive and practioner folk wisdom inspired restrictions on the signs of the impulse responses. Hence, for the sake of brevity, we preserve these results for a different paper.

Another approach is to take advantage of the parsimony afforded by the two-dimensional structure of our VAR system and quantify the key properties of interest for all admissible models. As we discuss below, the inequality constraints in our model restrict parameter b_{12} to an interval. A natural approach is then to study the properties of the models corresponding to a sufficiently dense grid of points covering the feasible interval of values for b_{12} This approach is pursued, for instance, in Blanchard and Diamond (1989, 1990) and Davis and Haltiwanger (1999). As we demonstrate in the robustness section, the shape of the variance of crude oil prices explainable by demand and supply shocks remain consistent across a wide range of admissable b_{12}'s.

3 Empirical Results

Based on the Schwartz Information Criterion, we specify the VAR model for crude oil and refine product prices with lags up to two months, though we consider other lag lengths as a robustness check. While some of the properties of our model may be robust with respect to the precise value of b_{12}, it is generally popular to present a summarized view of the impulse responses and the historical decomposition by either showing the median and percentiles of the impulse responses (as in Uhlig (2005)) or show those corrresponding to a single point estimate of b_{12}. As suggested by Fry and Pagan (2007), we pursue this second approach and derive a single point-estimate of b_{12} which minimizes a loss function to ensure as close a match to the median impulse response as possible. We create a set of 2000 draws.

3.1 Impulse response of crude oil prices and crack spreads to demand and supply shocks

Figure 4 to 7 show the estimated impact of identified oil demand and supply shocks on crude oil prices and gasoline crack spreads. The central line corresponds to the impulse response derived from the loss-function minimizing paramter b_{12}, which is estimated to be b_{12}=1.784, which is not only positive but also greater than 1, thus consistent with the positive sign restrictions and satisfying condition 3 resulting from our intuitive framework. Also, the corresponding b_{21} derived from Equation 9, becomes b_{21}=0.717, thus satisfying condition 4 as well.[8] We construct confidence intervals for the impulse responses based on bootstrapping the reduced-form residual shocks. By construction, we see positive and significant impact of both demand shocks and supply shocks on crude oil prices. Demand shocks seem to have a longer-term impact than supply shocks on crude oil prices, as we shall confirm in the variance decomposition below. Regarding the crack spreads, Figure 4 shows -as expected- that supply shocks have initially a negative and statistically significant impact and then, this

[8]Incidentally, the exactly estimated parameter for b_{12} in Ahn and Kogan (2014) is 1.871, which results in nigh indistinguishable impulse responses and historical decompositions to those derived in this paper, lending confidence in our results.

effect is reversed (consistent with the imperfect passtrhough). While demand shocks report the opposite effect on crack spreads.

3.2 Oil price variation explainable by demand vs. supply shocks

Table 3 presents the fraction of variation in crude oil price and blended crack spreads explained by demand and supply shocks. Intuitively, we should expect oil demand shocks to capture an increasing share of variation in crude oil prices as the time horizon increases, since demand, driven by fundamentals such as economic growth and investments in efficiency, moves with more persistence than the highly volatile oil supply. And indeed, we find that most of the variation in oil prices is attributed to supply shocks rather than demand shocks at shorter horizons. However, the reverse is true at longer horizons.

Table 3: Variation in crude oil price and crack spreads explained by demand and supply shocks

	Oil Demand	**Oil Supply**
horizon	**crude oil prices**	
1	22.89	77.11
6	36.26	63.74
12	50.52	49.48
24	59.47	40.53
60	64.57	35.43
horizon	**crack spreads**	
1	33.50	66.50
6	21.91	78.09
12	21.39	78.61
24	21.88	78.12
60	22.62	77.38

Interestingly, we also find that supply shocks remain the dominant source of variation for crack spreads at all horizons, reporting a slight decrease after 12 months.

3.3 Historical impact of demand and supply shocks on crude oil prices

The decomposition of oil price dynamics from our sign-restriction -based identification is presented in Figures 8 and 9. For ease of visual comparison, we present the decomposition by showing the "historical cumulation" of demand and supply shocks separately as identified by our methodologies. In Figure 8 the shaded region shows the counterfactual price of crude oil if *only* the demand shocks identified occurred; a rise (fall) in the dotted line should be interpreted as a positive (negative) demand shock. Similarly, Figure 9 shows the cumulation of supply shocks. By definition, the demand and supply cumulations add up to the actual historical series of crude oil prices.

It is insightful to associate the decomposed history with anecdotes of major events in the global oil market.[9] Interestingly, we find that while demand was driving prices higher into 1973, the actual 1973:10 price jump was unsurprisingly attributed to a supply shock coinciding with the Yom Kippur War and the OPEC embargo. Then, after a slightly weakening from 1976 to 1978, there was another demand-attributed rise in crude prices through 1979 and 1980. This is partially consistent Kilian (2008a)'s own analysis of the price rise of 1979, which featured a powerful surge in its real global economic activity indicator. However, as with the 1973 episode, we also find a strong supply component to the 1979 price rise, more in line with popular wisdom associating the price spike with the Iranian Revolution of 1979 and disruptions from the Iran-Iraq War of 1980.

After peaking at around 1982, the demand-driven component of oil prices began a long and steady decline, which we believe is the result of a restructuring of the investments by the US, Japan, Europe, and other major economies into energy efficiency savings and diversification of energy sources away from hydrocarbons. However, there is a oil price spike in 1990, simultaneous with Saddam Hussein's invasion of Kuwait and the subsequent 1991 Gulf War, where Iraqi soldiers destroyed millions of Kuwati barrels.

[9] Yergin (1992) provides an excellent survey of the history of oil markets.

This episode is particularly instructive. Kilian (2008a) identifies the spike in 1990 purely as a precautionary demand shock, defined as an increase in oil prices by precautionary consumers in response to expectations of higher future supply and therefore price volatility.

However, there is a subtle but potentially important distinction between expected future supply shocks and precautionary demand shocks. Indeed, both are driven by concerns over future supply. But as markets respond to new expectations about future production, two possibilities emerge: product crack spreads may narrow as crude oil prices rise in anticipation of a future supply shortfall and a draw-down in inventories, or crack spreads may widen as precautionary consumers stockpile usable products.

By our methodology, the 1990 Gulf War price spike was largely a supply shock, though there was also an important demand-driven component. Despite operating at the monthly frequency, our methodology is powerful enough to identify both supply shocks and precautionary demand shocks has having occurred during the 1990 Gulf War episode.

In the 1990s, demand continued to regress downward until it reached a trough in 1997-1998, consistent with a sharp global economic contraction due to the Asian financial crisis of 1997 and the Russian debt default of 1998. Interestingly, supply shocks also hit a local trough that, we argue, was likely driven by concerns of excess supply, a ”negative” future supply shock. Indeed, popular periodicals of the time were prognosticating an eternity of cheap oil.[10]

But starting in around 2000, demand began a steady march upward again, with a dip in 2002 related to a mild recession in the US and other economies. Demand continued to surge into 2007, while supply shocks remained relatively stable, as China and other emerging economies enjoyed strong economic growth and high demand for commodities. However, we ascribe the price spike in 2007-08 as being as much driven by supply as demand shocks.

Again, we argue this is capturing expectations of future supply shortfalls, as the widely publicized “peak oil” hypothesis (where the world exhausts its finite supplies of conventional oil) gained widespread currency. The growth of emerging economies drove global demand

[10]The Economist magazine featured a cover story with the title “Drowning in Oil” in March 1999.

for oil steadily higher, but importantly triggered concerns over the ability of supply sources, which saw the rapid exhaustion of existing fields and scarce discoveries of new basins, to meet extrapolated needs. Pundits called for a “supercycle” with oil prices forecasted to reach and remain permanently higher than $150 or even $200 per barrel. Driven by such concerns, market participants and speculators caused crude oil prices to rise faster than demand prices, reaching a peak in the summer of 2008.

Following the crude oil price peak in the summer of 2008, the world economy sharply contracted due to the bursting of the US housing bubble and the credit market fallout from the bankruptcy of Lehman Brothers. Demand for oil fell, but the anticipated future supply fears fell even faster, together driving a rapid fall in real crude oil prices. The post-crisis decomposition of the behavior of oil prices also differs in surprising ways from established belief. We see the demand component of oil prices begin a strong recovery as the world economy recovered from recession, but most of the rapid rise since the trough in 2009 was due again to supply.

The results also intriguingly suggest that, given the largely supply-driven and contractionary nature of the oil price increases in 2007-08, the Federal Reserve was justified to resist pressure to increase rates to cool the economy and counteract potential inflationary spillovers.

Lastly, the rapid fall in oil prices starting in the summer of 2014 and which accelerated after the OPEC meeting in November of that year seems to be driven by a combination of supply factors, likely due to the surprising productivity of the U.S. unconventional shale oil and gas boom, and weaker demand from tepid global economic activity.

3.4 Robustness

3.4.1 Robustness over Identification

We have already mentioned how an alternative identification scheme based on heteroskedasticity presented in Ahn and Kogan (2014) delivers estimates for the VAR structural parameters which are consistent with our identification scheme based on sign restrictions, and for the sake of brevity, we omit showing the same results. However, the general consistency of the findings of both sign restriction approaches and the heteroskedasticity-based identification lends us confidence in the robustness of the methodology.

But we can go even further by testing the limits of our results to extreme estimates of the parameters. The simplicity of our two-variable framework allowed us to narrow the degree of freedom to a single variable b_{12}, with the other key variable b_{21} derivable from b_{12}. We demonstrate how our empirical results remain consistent throughout the range of feasible b_{12} that still satisfy conditions 3 and 4, which ranges from 1 to about 4. Figure 10 demonstrates, even including a value of b_{12} at 0, salient features of our results still hold. Namely, the variation in crude oil prices explainable by demand shocks rises as the horizon length increases, as expected according to our discussion earlier. The level of variation explained by demand is generally less of the variation of crude oil prices than supply shocks, except when b_{12} is pushed below 1 and approaches 0.

3.4.2 Robustness over Lag and Seasonality Adjustment

We chose to specify our VAR model with lags for four months based on the Schwartz Information Criterion. The Akaike Information Criterion suggests a lag of 9 months but this noticeably distorts the simulated impulse responses into non-smooth shapes, likely due to spurious correlation from overfitting the model.

We also used various different crude oil price benchmarks and different methods of adjusting for seasonality, and found no substantial differences to our results.

4 Relationship to Other Economic Indicators

In this section, we study the relationship between our decomposition of demand and supply shocks in the oil market to various macroeconomic indicators such as output, unemployment, and core inflation, motivated by our earlier discussion on the contrasting economic mechanisms driving global demand vs. supply shocks in the oil market.

4.1 Relationship to US macroeconomic indicators and monetary policy

We test whether our decomposed demand and supply shocks stimulate different responses on various macroeconomic indicators, such as industrial production, unemployment, inflation, and the Federal Reserve's interest rate targets 60 months ahead. To do this, we compute two unrestricted VARs. The first has the following endogenous variables: our decomposition of oil supply shocks, our decomposition of oil demand shocks, US industrial production, core CPI inflation, and the Fed Funds target rate, in that Cholesky causal ordering. The second VAR replaces US industrial production with the unemployment rate.

Figures 11 and 12 show the accumulated IRFs of these two unrestricted VARs. IND stands for industrial production, UNEMP for the unemployment rate, CPI CORE for core inflation, and FEDFUNDS for the Federal Funds target rate. We find the responses of industrial production, unemployment, core inflation, and the Fed Funds rate depends critically upon whether the oil shock was a demand shock or a supply shock, with both VARs providing fairly consistent results.

We first note that we found most of the IRFs between industrial production, unemployment, core inflation, and the Fed Funds rate, are in the expected sign. Industrial production (unemployment) responds negatively (positively) to increases in core inflation and the Fed Funds rate. Core inflation responds positively (negatively) to industrial production (unemployment). The only puzzle lies in the finding that core inflation seems to respond positively to increases in the Fed Funds rate.

4.1.1 Relationship to industrial production and unemployment

In Figure 11 we see that industrial production responds initially positively then negatively to demand shocks for oil but the effect is insignificant. However, the response to supply shocks is much more unambiguously negative and statistically, suggesting important differences in the economic transmission channel from oil prices to output identified by our decomposition.

Similarly, from Figure 12 we see that unemployment responds first negatively and then positively to demand shocks for oil but again the effect is insignificant. Meanwhile, the response of unemployment to supply shocks is consistenly positive if still insignificant. We did not include them in the figures, but we confirm that, as expected, demand for oil responds positively and significantly to increases in industrial production and negatively to increases in unemployment. However, supply shocks respond much more ambiguously to innovations in industrial production and unemployment.

4.1.2 Relationship to core inflation

Also, as one might expected, in both figures, we see core inflation responding positively to oil demand shocks and negatively to oil supply shocks both with high significance. This is much as textbook theory would suggest: an endogenous demand shock for oil from greater economic activity should push core inflation higher, while an exogenous supply shock exerts countervailing forces with inflationary spillover from higher oil prices but simultaneously weakening output. We also found that innovations to core inflation has no statistically significant impact on oil prices.

4.1.3 Monetary policy responses

Interestingly, we find that the Fed Funds rate also responds differently to different types of oil shocks. We expect that, a positive oil demand shock, being both inflationary and driven by aggregate demand, would elicit a statistically significant increase in the Federal Funds rate. However, the Federal Reserve faces a difficult trade-off between higher inflation and lower output when confronted with a cost-push shock such as an oil supply shock and their response should be moderated.

According to both Figures 11 and 12, the Fed Funds rate immediately increases in response to a demand-driven oil price shock and is statistically significant. Furthermore, the Fed Funds responds negatively to supply-driven oil shocks but significance is achieved only after about 6 months.

This suggests the Federal Reserve has been fairly successful in identifying the contrasting demand vs. supply drivers of oil price movements and responding accordingly. This disentanglement may thus help provide insight into the ongoing debate over whether oil supply shocks or contractionary monetary policy drove US economic weaknesses in the late 1970s and 1980s (e.g. Bernanke, Gertler, and Watson (1997), Barsky and Kilian (2002), and Hamilton and Herrera (2004)), but a fuller analysis is a topic for further research beyond the scope of this paper.

5 Conclusion

Recently, economists have recognized that not all oil price shocks are alike, but have demand and supply components with contrasting relationships with the broader macroeconomy. Previous attempts in the literature to disentangle these two shocks were only as good as the demand or supply indicators they chose, with strong assumptions made about causal ordering. This paper presents an alternate and more powerful decomposition approach, expressing intuitive theoretical insights into the pass-through structure of oil markets. The refined decomposition achieved is testament to the information content inherent in forward-looking market prices even when analyzed with fairly simple econometric identification schemes.

The resulting decomposition debunks some popular conceptions of the history of energy markets and corroborates others. Notably, part of the 1970s price rally was demand driven, the 1990-01 Gulf War price spike had both a supply shock component as well as a weak precautionary demand component, and the 2007-08 price rise and 2014-15 price fall were driven by supply as well as demand.

We also document how the decomposed oil demand and supply shocks have sharply different impacts on key macroeconomic variables such as output, unemployment, and core inflation. Thus, this paper is not only of interest to economists interested in drivers of oil prices but also should be useful for policymakers. Robust identification of the origins of a specific oil price shock is invaluable in judging an appropriate fiscal and monetary response. Further exploration and calibration of the proper policy responses to oil demand vs. supply shocks will require a more elaborate macroeconomic structure, and is an interesting topic for further research. However, the simplicity and intuitiveness of our methodology will likely make our decomposition results robust.

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Appendix

A Data Sources

For our crude price data, we use the benchmark West Texas Intermediate crude prices deliverable in Cushing, OK traded on the New York Mercantile Exchange (NYMEX). The market opened in April 1983, so from 1974.01 to 1983.03, we use the refiner composite crude acquisition cost tracked by the U.S. Department of Energy. From 1971:01 to 1973:12, we use construct prices using the U.S. Bureau of Labor Statistics Crude Petroleum Index.

For product prices, both gasoline and heating oil price data is available, but the history of gasoline prices is more extensive. From 2005.12 to present, we use the NYMEX RBOB gasoline futures price. From 1985.01 to 2005.11, we use the New York Harbor gasoline futures prices. Prior to January 1985, no futures markets were available so, from 1971.01 to 1984.12, we proxy for them using the U.S. Bureau of Labor Statistics Wholesale Gasoline price index. Similarly, for heating oil, we use the prompt NYMEX heating oil futures price deliverable to New York Harbor and extended backwards by the US Bureau of Labor Statistics Heating Oil Wholesale Price Index. All price data are adjusted for seasonality using the Census Bureau's X-12 ARIMA adjustment method.

Data on US refinery capacity is available from the US Department of Energy starting from 1984.12. We use the monthly measure of "operating capacity ," in contrast to "operable capacity," which is defined below. Operable capacity is defined as the "amount of capacity that, at the beginning of the period, is in operation, not in operation and not under active repair, but capable of being placed in operation within 30 days; or not in operation but under active repair that can be completed within 90 days." Of this, idle capacity is defined as the "component of operable capacity that is not in operation and not under active repair, but capable of being placed in operation within 30 days; or not in operation but under active repair that can be completed within 90 days." Hence, operating capacity, "the component of operable capacity that is in operation at the beginning of the period," can be also defined as operable capacity minus idle capacity.

We push backwards the operating capacity series by one period, e.g. reinterpreting the entry for the "beginning of 1985.01" to be the entry for the "end of 1984.12." We do this because a refinery outage that hits in the month of January and thus affects January crack spreads will only appear in the refinery operating capacity data starting in the month of February. We remove a smooth underlying trend via a Hodrick-Prescott filter to detrend lower-frequency planned fluctuations in national refinery capacity and isolate short-term unplanned shocks. The majority of unplanned refinery shocks are negative, in the sense that they reduce refinery capacity and demand for crude oil. This is unsurprising given the slow process to construct or upgrade a refinery but the relatively ease one can disrupt the fragile facilities. However, one can imagine a positive exogenous refinery shock, for instance an unexpectedly rapid construction or repair of a refinery. The US refinery data is broadly consistent with partial data on global unplanned refinery outages, available starting in 2003.

Data on world crude oil production is drawn from the Monthly Energy Review published monthly by the Energy Information Administration of the US Department of Energy. Data on shipping rates is taken from Lutz Kilian's website and extended using Baltic Dry shipping rate indices. For our measure of core inflation, we use the Consumer Price Index for all Urban Consumers less food and energy from the US Bureau of Labor Statistics. Federal Fund Target rates and US industrial production was taken from the FRED database of the Federal Reserve Bank of St. Louis.

B Figures

Figure 1: The two types of modeled shocks and their impact on the petroleum processing chain.

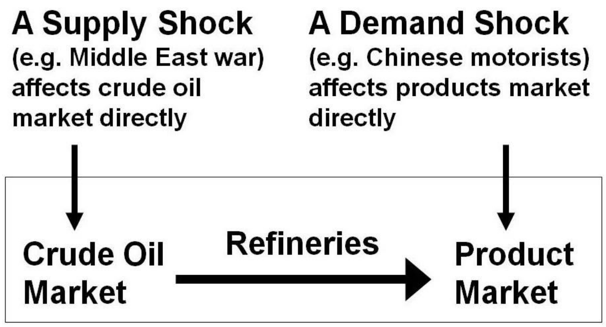

Figure 2: The history of real log crude oil prices over the 1971-2015 period. Data sources are described in Section A.

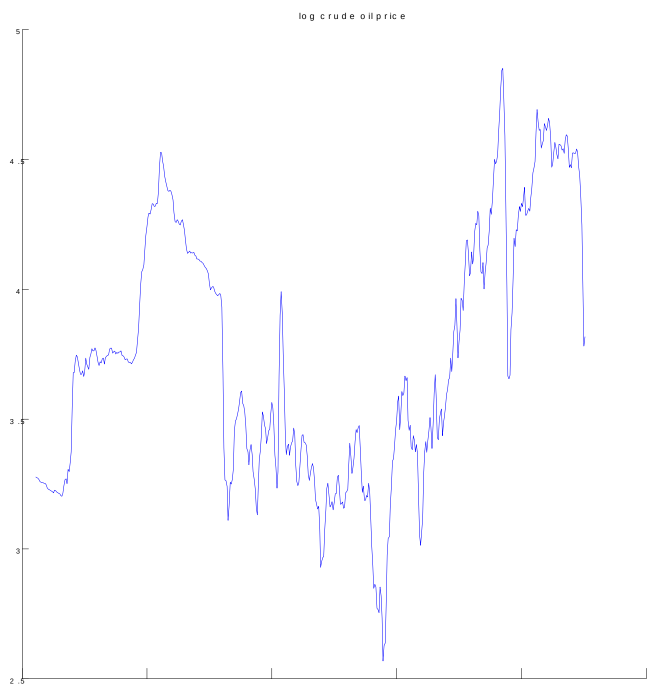

Figure 3: The history of blended 3-2-1 gasoline and heating oil crack spreads over the 1971-2015 period. Data sources are described in Section A.

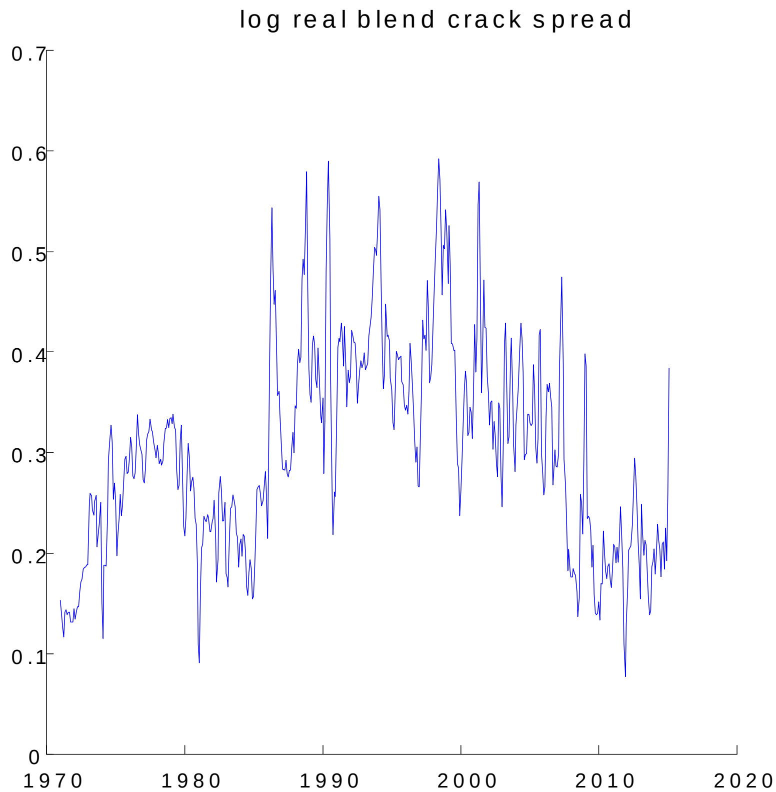

Figure 4: The impulse response of demand shocks on real prices of crude oil. The panel shows an impulse response of the log crude oil price to a one-standard deviation demand. Estimation is based on the 1971-2015 period. Data sources are described in Section A.

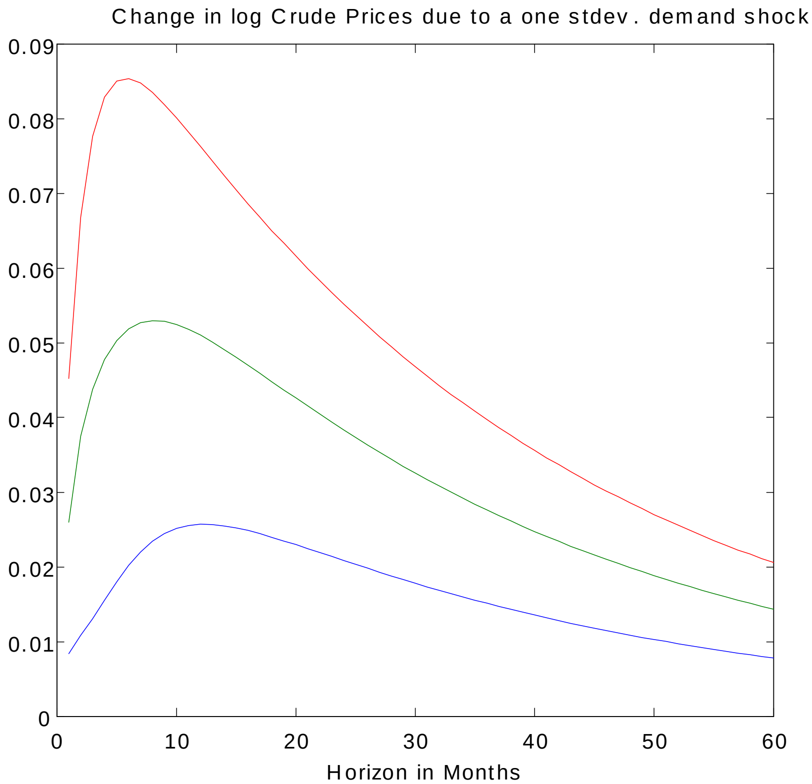

Figure 5: The impulse response of demand shocks on real blended crack spreads. The panel shows an impulse response of the log crack spread to a one-standard deviation demand. Estimation is based on the 1971-2015 period. Data sources are described in Section A.

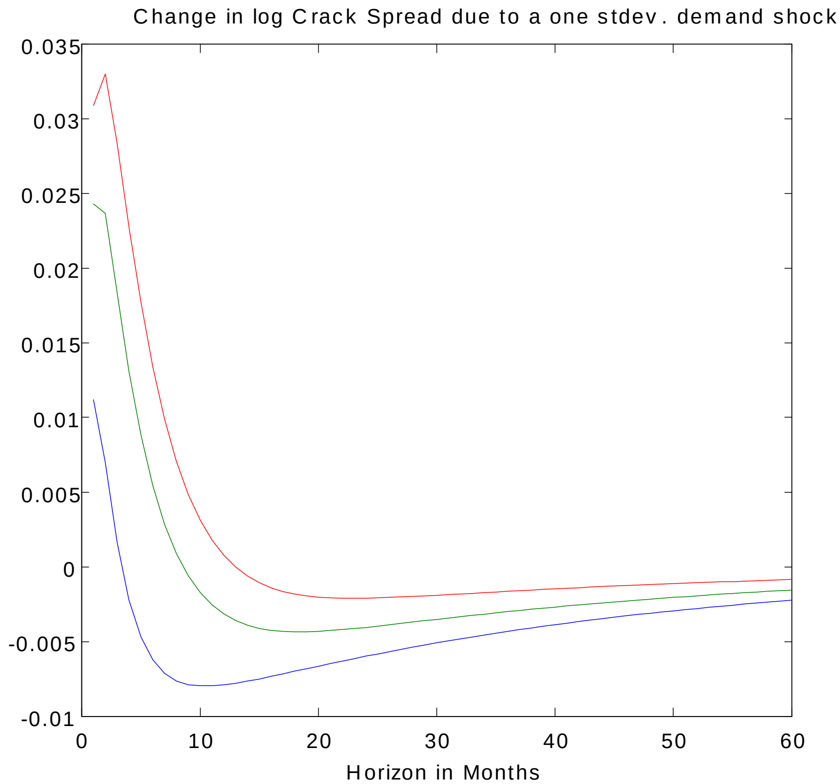

Figure 6: The impulse response of supply shocks on real prices of crude oil. The panel shows an impulse response of the log crude oil price to a one-standard deviation supply shock. Estimation is based on the 1971-2015 period. Data sources are described in Section A.

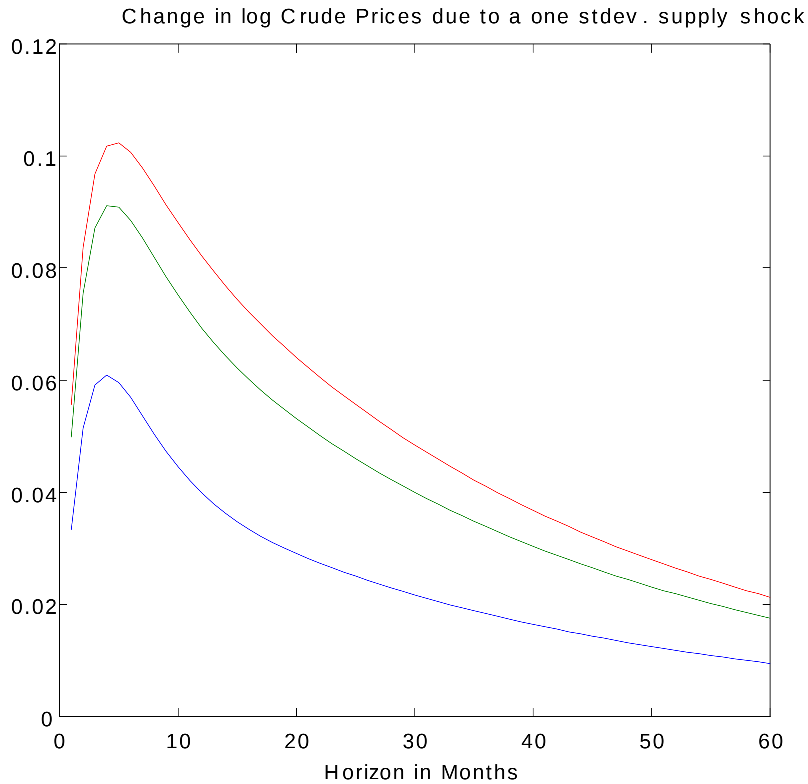

Figure 7: The impulse response of supply shocks on blended crack spreads. The panel shows an impulse response of the log crack spread to a one-standard deviation supply shock. Estimation is based on the 1971-2015 period. Data sources are described in Section A

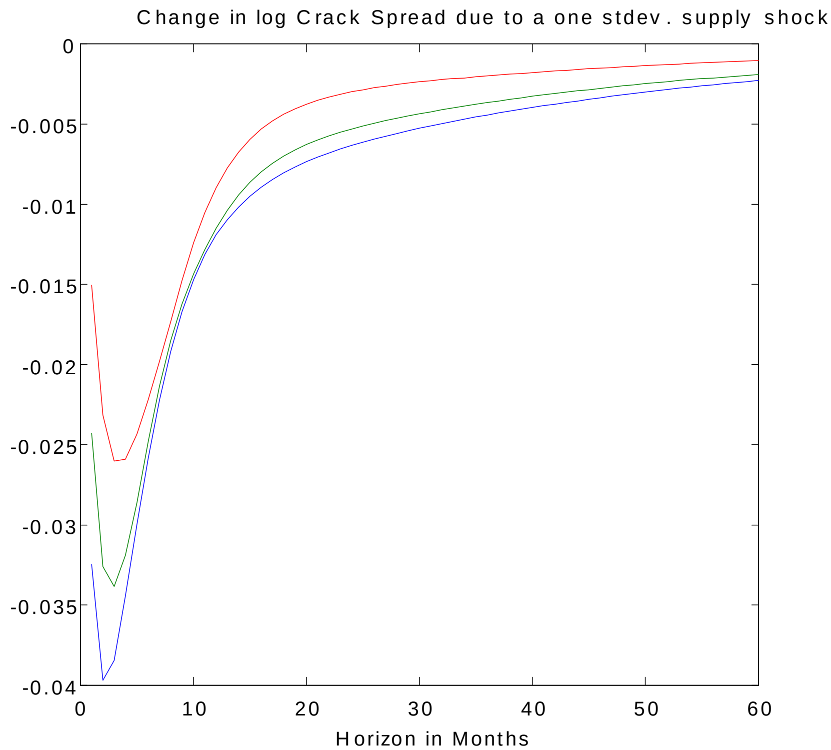

Figure 8: The historical accumulation of oil demand shocks on the real price of crude oil. The dotted line shows the cumulated history of supply shocks, while the blue line shows the original history of oil prices. A rise (fall) in the dotted line should be interpreted as a positive (negative) demand shock. Estimation is based on the 1971-2015 period. Data sources are described in Section A.

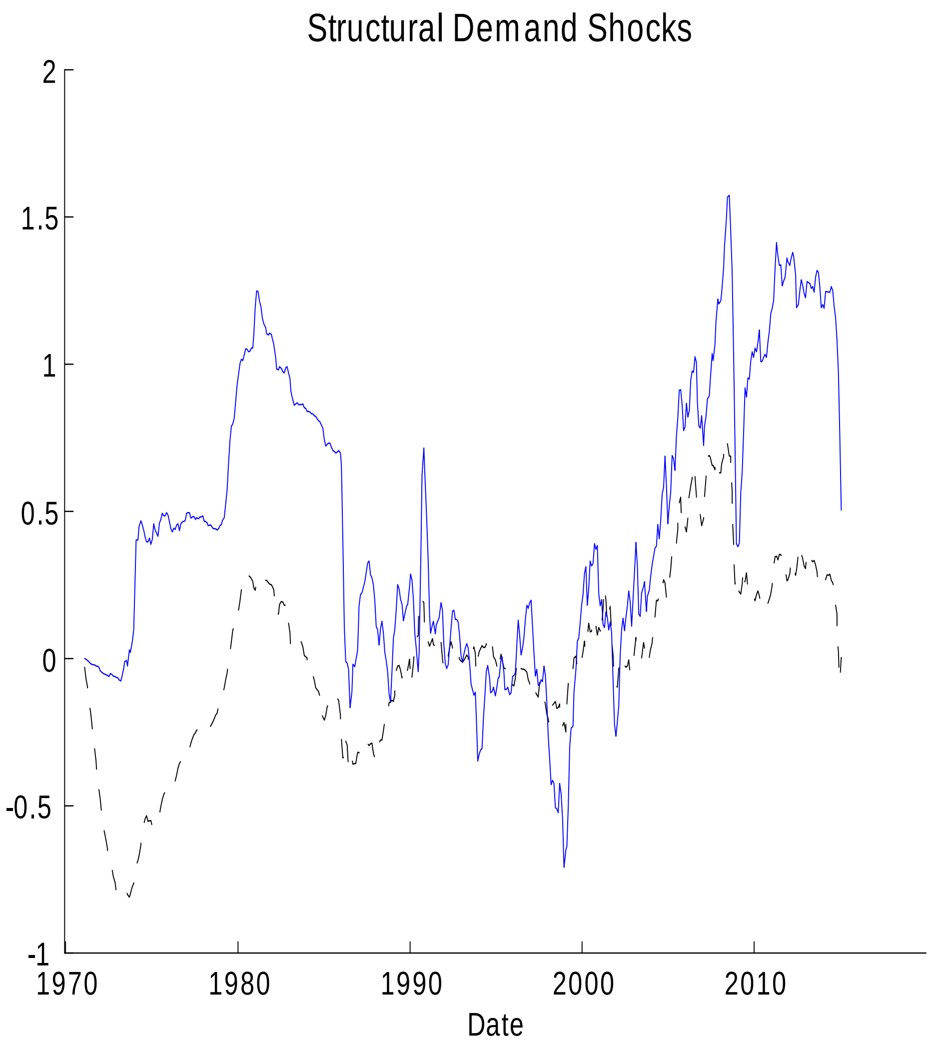

Figure 9: The historical accumulation of oil supply shocks on the real price of crude oil. The dotted line shows the cumulated history of supply shocks, while the blue line shows the original history of oil prices. A rise (fall) in the dotted line should be interpreted as a positive (negative) supply shock. Estimation is based on the 1971-2015 period. Data sources are described in Section A.

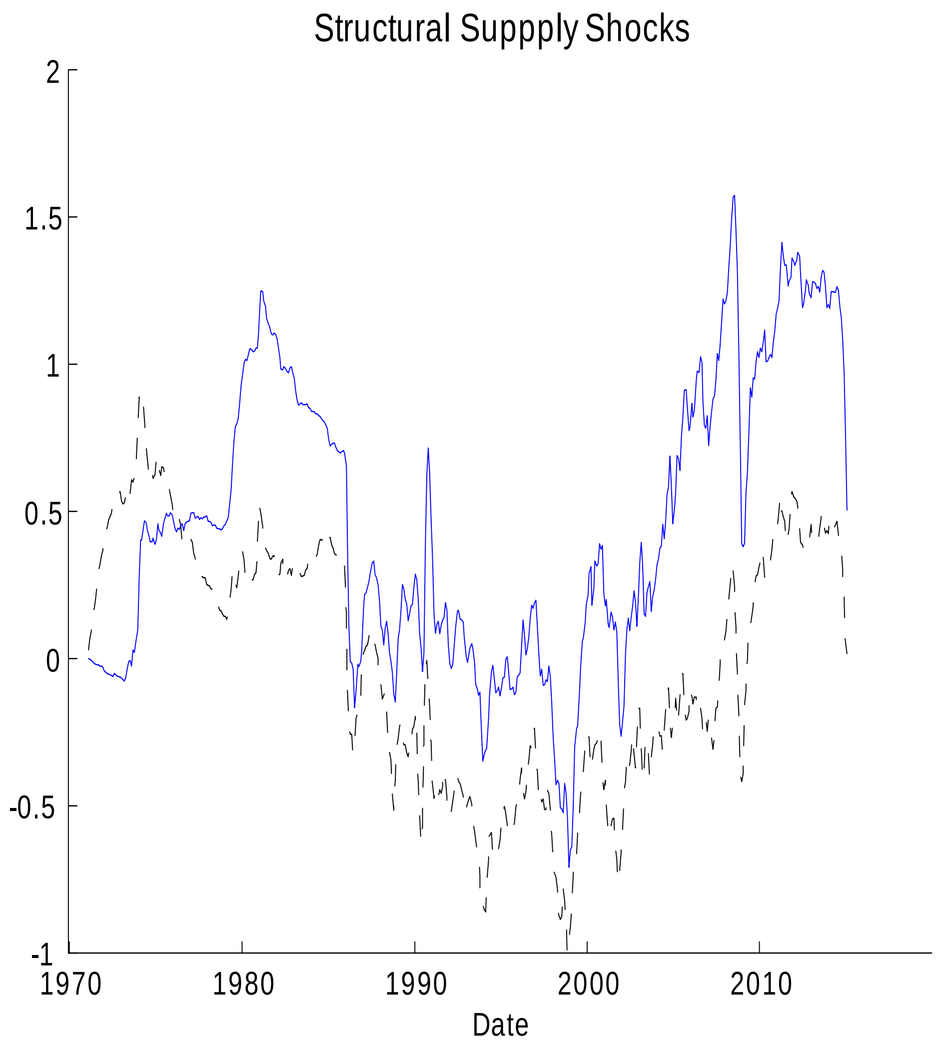

Figure 10: The robustness of the variance explainable by demand shocks to different estimates of $b_{12} \in \{0, 0.4, 0.8, ..., 4.0\}$.Estimation is based on the 1971-2011 period. Data sources are described in Section A.

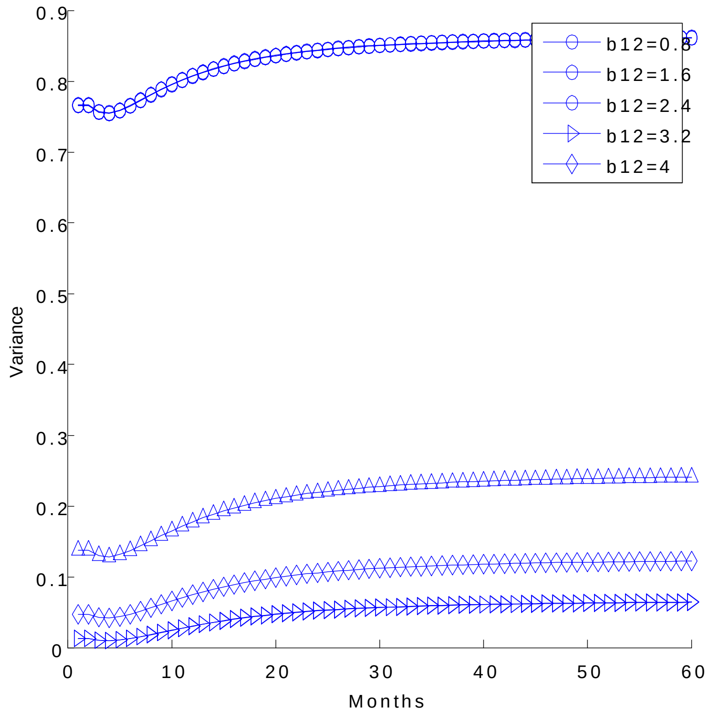

Figure 11: Accumulated IRFs of macroeconomic indicators to decomposed oil demand and supply shocks using industrial production. Data sources are described in Section A

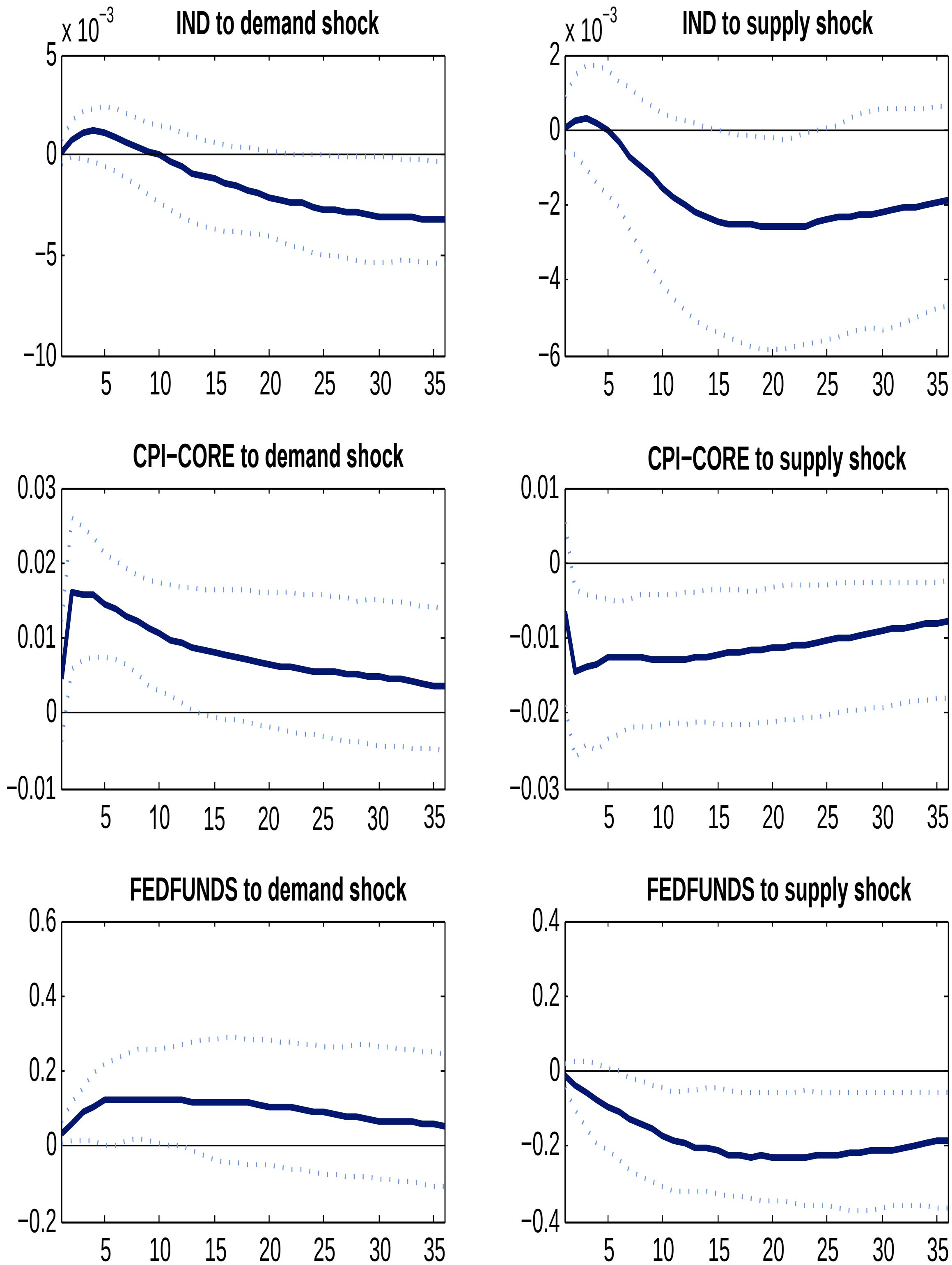

Figure 12: Accumulated IRFs of macroeconomic indicators to decomposed demand and supply shocks using the unemployment rate. Data sources are described in Section A