Macroeconomic effects of precautionary demand for oil

by Alessio Anzuini, Patrizio Pagano and Massimiliano Pisani
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MACROECONOMIC EFFECTS OF PRECAUTIONARY DEMAND FOR OIL

by Alessio Anzuini*, Patrizio Pagano* and Massimiliano Pisani*

Abstract

We evaluate the macroeconomic effects of shocks specific to the oil market, which mainly reflect fluctuations in precautionary demand for oil driven by uncertainty about future supplies. A two-stage identification procedure is used. First, daily changes in the futures-spot spread proxy for precautionary demand shocks and the path of oil prices is estimated. This information is then exploited to restrict the oil price response in a VAR. Impulse responses suggest that such shocks reduce output and raise prices. Historical decomposition shows that they contributed significantly to the U.S. recessions in the 1990s and in the early 2000s, but not to the most recent slump.

JEL Classification: C2, E3, O41.
Keywords: vector autoregression, oil shock, futures, news.

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Introduction\textsuperscript{1}

The study of the effects of oil price changes on macroeconomic variables using Vector Autoregressive systems (VAR) has a solid tradition in the economic literature, dating back at least to Hamilton (1983). Yet Kilian (2009) shows that the proper identification of the type of shock is crucial, insofar as oil price changes are endogenous, the responses of macroeconomic variables may differ significantly depending on the underlying oil demand and supply shocks. For instance, an increase in the price of oil driven by a shock to aggregate world demand may not induce negative comovements of consumer prices and output, whereas price increases driven by demand for precautionary purposes — say, for fear of future supply disruptions — may spur inflation and curb output.

We focus on oil price changes induced by shocks referred to — following Kilian (2009) — as “oil market-specific” shocks, studying their effects on the main U.S. macroeconomic variables. We interpret these shocks as reflecting fluctuations in precautionary demand for oil driven by fears of future shortages.

To identify precautionary demand shocks and estimate their macroeconomic effects, we combine the methodologies of Faust, Swanson and Wright (2004) and Alquist and Kilian (2010). Following the latter, we infer shocks to precautionary demand for oil from changes in the futures-spot spread, while using the former’s two-stage strategy exploiting high-frequency financial market data.\textsuperscript{2} In particular, we first regress futures changes at various horizons on the change in the negative of the 12-month futures-spot spread to obtain the dynamic path of the oil price in response to shocks to precautionary demand. Second, we estimate a structural VAR to gauge the effects on output and prices in the United States, imposing that the response of the oil price to its own shock match the response estimated using futures data. We estimate the VAR on U.S. monthly data from January 1986 to December 2008. The variables are: oil spot prices (WTI grade), the Consumer Price Index (CPI) and the Chicago Fed National Activity Index (CFNAI).

The main results are the following. First, after an oil price shock driven by increased precautionary demand, the CPI rises significantly and remains above the baseline for an extended period. Economic activity declines, but the decrease becomes significant only after six months,

\textsuperscript{1}We thank Gianni Amisano, Marianna Riggi and seminar participants at the Bank of Italy for comments and suggestions. We are indebted to Michele Cavallo for sharing his data on the chronology of oil market events. Massimiliano Luppino and Giovanna Poggi provided valuable research assistance. Of course, we are solely responsible for any error. The opinions expressed in this paper do not necessarily reflect those of the Bank of Italy. Address: via Nazionale 91, 00184 Rome - Italy. E-mail: alessio.anzuini@bancaditalia.it; patrizio.pagano@bancaditalia.it; massimiliano.pisani@bancaditalia.it

\textsuperscript{2}Faust, Swanson and Wright (2004) used high-frequency financial market data to identify monetary policy shocks in a VAR. A similar approach is pursued by Bagliano and Favero (1999) and Cochrane and Piazzesi (2002).
with the trough 18-24 months after the shock. Second, shocks to precautionary oil demand almost completely explain the U.S. recession of the early 1990s and contributed significantly to that in the early 2000s. In the most recent slump, instead, their contribution was more muted. Furthermore, the precautionary demand shocks explain most of the deviation of inflation from the baseline in the early 2000s and about half of the deviations in the early 1990s and in 2007-08.

As a robustness check we estimate the response of futures prices to oil price changes (the first stage of our strategy) using only the daily event-dates classified by Cavallo and Wu (2012) as those on which oil prices move exclusively because of precautionary demand.3 We then impose this response in the VAR and find that impulse responses are not significantly different.

Our contribution relates to the debate on the macroeconomic effects of oil shocks. We proxy shocks to precautionary oil demand with the change in the oil futures-spot spread, like Alquist and Kilian (2010). These two authors work out sufficient conditions under which a mean-preserving shock to the uncertainty of oil supply (i.e. an increase in uncertainty that leaves the expected level of supply unchanged) lowers the spread. The channel through which this shock affects current spot and expected spot prices is inventory accumulation. In fact, recalling that the current spot price can be written as the sum of expected spot price and a convenience yield, since an increase in the uncertainty about future supply increases the convenience yield (that is the marginal willingness to pay for inventories rises), then in order to re-establish intertemporal marginal efficiency inventory holdings must be expanded.4

Our identification approach based on high-frequency data allows direct investigation of shocks to uncertainty about future net oil supply. Shifts in precautionary demand are ultimately driven by expectations about future availability of oil, which can change almost instantaneously in response to exogenous events, causing price to jump. This is why daily observations may help to single out movements in oil prices that should be attributed to a reassessment of future market tightness. More importantly, our strategy brings additional evidence that enhances the credibility of conclusions obtained under other identifying restrictions. In fact, our results on the macroeconomic effects of precautionary demand for oil are similar to those of Kilian (2009), where precautionary demand shock is defined as any real oil price movement that cannot be explained by changes in real economic activity worldwide or oil production.

3 Other contributions use the same strategy, but only in order to single out shocks to the actual supply of oil. For instance, Hamilton (2003) uses oil supply disruptions to detect oil price shocks. Hamilton (1985) singles out exogenous oil supply shocks by using dummy variables associated with certain events — presumably exogenous to developments in the U.S. economy — characterized by sharp rises in the nominal price of oil. Kilian (2008) derives a measure of oil supply shortfall for several oil-producing economies by comparing actual oil output with the counterfactual level extrapolated by the supply of similar countries not affected by the exogenous event.

4 However, it is not possible to rule out that the spread moves because of other factors, such as speculation on future levels of supply and demand. Speculative purchases of oil usually occur because buyer anticipates rising oil prices either due to changes in fundamentals or in anticipation of other agents’ actions. Speculative purchases may also be precautionary insofar as they reflect increased uncertainty about future demand or supply conditions (see Kilian and Murphy, forthcoming).
Finally, the system we estimate is similar to that used by Blanchard and Galí (2010), who estimate a six-variable VAR with nominal oil prices, three price indices (CPI, GDP deflator and wage index) and two activity variables (GDP and employment). One may criticize the absence of the federal funds rate from our VAR, since Bernanke, Gertler and Watson (1997), for instance, suggest that positive shocks to the price of oil induce a monetary policy response that can amplify the contractionary effects of the shock. However, Kilian and Lewis (2011) find no evidence of systematic Fed reaction to oil shocks after 1987, i.e. in the period covered in our analysis. Herrera and Pesavento (2009) show that since 1984 systematic monetary policy has been a negligible factor in the response of output growth and prices to oil price shocks. Blanchard and Galí (2010) suggest that the U.S. economy has become much more flexible since the 1980s, so greatly reducing the incentive to respond strongly to oil price shocks in order to avoid wage-price spirals as in the 1970s and so enabling the Federal Reserve to remain passive.\(^5\)

The rest of the paper is organized as follows. The next section illustrates how financial market information is used to estimate the dynamic path of oil prices following a shock to precautionary demand for oil. Section 2 shows the impulse responses and Section 3 provides some robustness checks. Section 4 calculates forecast-error variance decomposition and elaborates on the contribution of oil shocks to the historical path of output and consumer price inflation. The final section states forth some concluding remarks.

1 Price response to concerns over future tightness in the oil market

Our identification strategy is drawn from Faust, Swanson and Wright (2004); for details see Appendix A. We estimate the following equation at various horizons:

\[
\Delta_d f^h = \beta_h \Delta_d s_d
\]

where \(\Delta_d f^h \equiv f^h_d - f^h_{d-1}\) is the percentage daily change in the logarithm of oil futures prices with maturity \(h = 1, 2, 3\) months between day \(d\) and \(d-1\). The right-hand variable \(\Delta_d s_d\) measures the corresponding percentage change in the negative of the spread \(s_d \equiv -\frac{F^{12}_d}{P_d}\) between the 12-month oil futures \((F^{12}_d)\) and the oil spot price \((P_d)\). The estimated coefficients are imposed on the oil price response in the first three periods.\(^6\) The choice of the spread as an indicator of the change in precautionary demand follows from recent results by Alquist and Kilian (2010), for a two-country model in which increased uncertainty about future shortfalls in the oil-producing country causes the negative of the futures-spot spread to widen if the sensitivity of the marginal

\(^5\) Anzuini, Lombardi and Pagano (forthcoming) find that expansionary US monetary policy shocks drive up commodity prices, but the effects appear to be relatively limited.

\(^6\) Appendix B shows formally that these three restrictions are sufficient to identify the shock, as we have a three-variable VAR.
value of inventories is large enough, i.e. if the change in the marginal convenience yield in response to an increase in uncertainty is sufficiently large. Thus, since precautionary demand increases when uncertainty is higher, the negative of the futures-spot spread may be taken as an indicator of oil price fluctuations driven by precautionary demand. Alquist and Kilian (2010) also show that the spread is quite well correlated with an alternative measure of the precautionary demand component of the spot price proposed by Kilian (2009) and based on a structural VAR decomposition of the real price of crude oil. For the period 1989–2006, the correlation ranges from 39% at the 3-month horizon to 62% at the 12-month horizon. Given this result, we take the 12-month futures-spot spread as our indicator of the precautionary demand for oil, but — as we show below — our results are robust to different futures maturities.

We use daily data on the closing prices of spot and futures contracts on NYMEX. For the last week of a month, when 1-month-ahead futures are no longer quoted, we use 2 to 4-month-ahead contracts. We focus on the 12-month spread, for which we have a complete daily time series starting 13 January 1989. Our sample ends 31 December 2008.

Equation (1) indicates that each day the futures prices at different horizons change proportionally to the negative of the futures-spot spread $s_d$. The estimates are reported in Table 1.

Table 1: Responses of oil futures to oil price shock due to changes in precautionary demand

<table>
<thead>
<tr>
<th>$h$</th>
<th>benchmark</th>
<th>sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12-month</td>
<td>9-month</td>
</tr>
<tr>
<td>1</td>
<td>0.65 (0.02)</td>
<td>0.60 (0.02)</td>
</tr>
<tr>
<td>2</td>
<td>0.49 (0.01)</td>
<td>0.43 (0.02)</td>
</tr>
<tr>
<td>3</td>
<td>0.42 (0.01)</td>
<td>0.35 (0.01)</td>
</tr>
</tbody>
</table>

Note: for each horizon $h = 1, 2, 3$ the table reports the results of a regression of the percentage change in the futures prices at date $d$ on the change in the futures-spot spread with no intercept (equation 1). Standard errors in parentheses.

The first column gives our benchmark estimates. In the first month, the effect of the shock diminishes to almost two thirds of the original impact. It then falls to half the initial value over the next month. The standard errors suggest that all the effects are strongly significant.

To assess the sensitivity of our results we estimate the regressions using different calculations of the spread and sample sizes. First, we take the 9-month spread, for which we have a complete daily time series starting 1 January 1986. The results (column 2) do not change significantly.

7 The spread moves in the expected direction at times of major recent unforeseen events that should have been associated with shifts in the market’s uncertainty about future oil supply shortfalls such as the Persian Gulf War and the 2003 Iraq War (which should have caused the spread to narrow) and the Asian financial crisis in the late 1990s (which should have caused the spread to widen as world demand for crude oil fell, making a shortfall less likely).
Second, to assess the sample stability we limit the estimation to the last six years of the sample (2003-2008). Again the results are broadly unchanged (column 3). Finally, to assess whether the response is asymmetric, we limit the estimation to the days when the negative of the spread widens (and therefore precautionary demand for oil increases). Again, the results do not change significantly (last column).  

The final step in our identification procedure requires testing the forecasting efficiency of oil futures. We use average monthly data to test the assumption that futures provide efficient forecasts of oil prices. Specifically, we regress the percentage change in the spot price \( (p_t) \) between \( (t-h) \) and \( t \) on the basis, defined as the difference between the log of oil futures at date \( (t-h) \) with maturity \( t \) and the log spot price at \( (t-h) \):

\[
p_t - p_{t-h} = \gamma_1 + \gamma_2 (f_{t-h} - p_{t-h}) \tag{2}
\]

We use futures contracts with maturity from 2 to 4 months. We exclude the 1-month maturity, which as noted is not traded every day. The results are given in Table 2. The assumption that the slope coefficient \( (\gamma_2) \) is equal to one is strongly supported in all cases. The evidence in favor of the joint hypothesis of intercept of zero and slope of one is also clear. However, a non-zero intercept would not be a problem for the identification procedure since it can be traced to a constant risk premium, and we can think of the term premia in oil futures over such horizon as being time-invariant.

<table>
<thead>
<tr>
<th>( h )</th>
<th>intercept</th>
<th>slope</th>
<th>p-value</th>
<th>p-value</th>
<th>obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \gamma_1 )</td>
<td>( \gamma_2 )</td>
<td>( \gamma_2 = 1 )</td>
<td>( \gamma_1 = 0; \gamma_2 = 1 )</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.011 (0.011)</td>
<td>0.956 (0.585)</td>
<td>0.94</td>
<td>0.55</td>
<td>274</td>
</tr>
<tr>
<td>3</td>
<td>0.021 (0.018)</td>
<td>0.864 (0.488)</td>
<td>0.78</td>
<td>0.30</td>
<td>273</td>
</tr>
<tr>
<td>4</td>
<td>0.032 (0.023)</td>
<td>0.815 (0.515)</td>
<td>0.72</td>
<td>0.16</td>
<td>272</td>
</tr>
</tbody>
</table>

Notes: HAC standard errors in parentheses.

\(^8\)For a different view on this see Serletis (2012).

\(^9\)Since the futures contract overlap induces autocorrelation, we compute standard errors using Newey-West autocorrelation- and heteroskedasticity-consistent (HAC) standard errors, with a lag truncation parameter equal to \( 2(h-1) \).

\(^10\)Chernenko, Schwarz, and Wright (2004) and Chinn, LeBlanc, and Coibon (2005) find evidence supporting the efficiency of futures prices in predicting spot price changes. Alquist and Killian (2010) document that the no-change forecast has lower mean-squared prediction error than the futures forecast at the 1-month but not at the 3-month horizon; in terms of mean absolute prediction error the random walk forecast proves more accurate at all horizons.

\(^11\)Pagano and Pisani (2009) show that risk premia on oil futures are correlated with business-cycle indicators, such as manufacturing capacity utilization, at horizons longer than four months. More importantly, they show that at short horizons (less than 6 months) the assumption of constant risk premia produces forecasts of oil prices statistically undistinguishable from those obtained under the hypothesis of time-varying risk premia.
2 Impulse response analysis

In this section we report the impulse responses of the structural VAR estimation. The data set consists of three monthly variables from January 1986 to December 2008, namely the spot price of oil (WTI grade), the consumer price index (CPI), and a measure of economic activity (the Chicago Fed National Activity Index, CFNAI). All the variables are in log-levels.\textsuperscript{12} The VAR includes a constant and seasonal dummies. We choose 13 lags, according to the Akaike information criterion.\textsuperscript{13}

The starting date is dictated by the availability of futures prices and considerations concerning possible shifts in the stability of the relationship between oil prices and macroeconomic variables. As to data availability, the trading of WTI futures on the New York Mercantile Exchange (NYMEX) began in 1983 with a delivery period of up to six months at first, which was gradually extended in line with the substantial increase in the volume of trading. Other recent work suggests a possible change in the relationship between oil and the main macroeconomic variables starting in the 1980s (e.g. Blanchard and Gali, 2010, Edelstein and Kilian, 2009, and Herrera and Pesavento, 2009). The decreasing reactivity of macroeconomic variables to oil price shocks has been attributed to the change in the Federal Reserve’s monetary policy under Paul Volcker’s chairmanship. Herrera and Pesavento (2009) and Kilian and Lewis (2011) find no evidence of a systematic reaction to oil shocks after 1987. Blanchard and Gali (2010) suggest that more flexible labor markets and the decreasing share of energy in expenditures also contributed. Kilian (2009, 2010) instead emphasizes the changing composition of oil shocks. Without adopting any thesis on the ultimate cause of the possible change in the relationship between oil prices and U.S. economic performance, we focus on the sample starting in the mid-1980s. This prevents us from investigating the effects of the price spikes of the 1970s but avoids problems related to structural stability.

Figure 1 reports the responses to a 1-percent oil price shock. The 68 percent confidence bands are computed by Montecarlo integration. The response of the oil price is rather persistent, remaining significantly above the baseline for several months.

On impact, the CFNAI starts falling, and the decrease becomes significant after six months (Figure 1). The level of activity reaches a minimum between one and a half and two years after the shock and remains significantly below baseline for three and a half years.\textsuperscript{14} This result is similar — albeit more front-loaded — to that of Kilian (2009), who reports that after an unanticipated oil market–specific demand increase, real GDP gradually declines to a minimum after three years.

\textsuperscript{12}The CFNAI has been cumulated.

\textsuperscript{13}In monthly data, 12 lags are usually enough to eliminate residuals autocorrelation. In our case the Akaike criterion suggests that the correct specification is between 12 and 14 lags, depending on which lags are included in the test. We use 13 lags but results are virtually unchanged using 12 or 14 lags.

\textsuperscript{14}The shape of this impulse response does not change greatly when economic activity is proxied either by the index of industrial production or by the monthly GDP elaborated by Stock and Watson (http://www.princeton.edu/~mwatson/mdgp_gdi.html). Nor does it change even if we include, as an exogenous variable, the measure of global real economic activity developed in Kilian (2009).
and that reduction is statistically significant in year 3.

After a shock to precautionary demand for oil, the CPI rises, although only to a limited extent (Figure 1). The price index peaks quickly, just one month after the shock, and holds significantly above the baseline for several months. In this case too, our result is in line with Kilian (2009), who finds a sustained increase in the U.S. price level, which remains statistically significant even after three years.

3 Robustness checks

To assess the robustness of our identification strategy, we also follow an alternative approach, based on the history of oil price changes. This would require estimating the response of futures to oil price changes only in the case of those events that can be safely classified as shocks to precautionary demand. The classification is from Cavallo and Wu (2012), who attribute oil price changes on each trading day from 1984 to 2007 to different types of event. We use the events that they classify as reflecting precautionary demand shocks or being specific to the oil market (event-type 15-17 in their terminology). The sample of these events is exploited to run the following regressions:

$$\Delta_d f^h = \beta_h \Delta_d p_d$$  (3)

where, as above, $\Delta_d f^h$ is the percentage daily change in oil futures prices with maturity $h = 1, 2, 3$ months between day $d$ and $(d-1)$, and $\Delta_d p_d$ measures the daily change in the spot price. With respect to the benchmark equation (1), here we use a different right-hand-side variable. The intuition is that under the historical narrative approach the price changes only due to shifts in expectations of future tightness in the oil market, so we do not need a proxy for such shocks. As before, the estimated coefficients are imposed on the first three periods of the oil price response in the VAR.

Using Cavallo and Wu’s sample, we get just over a thousand event-day observations. The results are presented in the second column of Table 3, alongside our baseline. The historical narrative approach yields a more persistent and slightly flatter response of futures to spot price changes, as the response remains above those estimated using the change in the spread.

Figure 2 shows median impulse responses (dashed red line) to a 1-percent oil price shock in the same VAR as Section 2, restricted by using the new coefficients obtained with the historical narrative approach. To gauge how different they are, we also draw the impulse responses and their relative standard error bands under the benchmark identification strategy (solid blue line). Overall the results do not change greatly, in that the new impulse responses lie within the benchmark confidence bands. The response of the oil price is more persistent, while the decline in economic activity is slightly more muted, especially at shorter horizons. The impact on the CPI is very similar.
Figure 1: Estimated impulse responses

Notes: percent, bands represent 68 percent confidence intervals.
Figure 2: Estimated impulse responses

Notes: percent, bands represent 68 percent confidence intervals.
Table 3: Responses of oil futures to oil price shock due to changes in precautionary demand (historical narrative approach)

<table>
<thead>
<tr>
<th>$h$</th>
<th>benchmark</th>
<th>narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.65 (0.02)</td>
<td>0.75 (0.02)</td>
</tr>
<tr>
<td>2</td>
<td>0.49 (0.01)</td>
<td>0.70 (0.01)</td>
</tr>
<tr>
<td>3</td>
<td>0.42 (0.01)</td>
<td>0.64 (0.01)</td>
</tr>
</tbody>
</table>

Notes: The table reports for each horizon $h = 1, 2, 3$ the results of a regression of the percentage change in futures prices at date $d$ on the percentage change in the oil price with no intercept (equation 3). Standard errors in parentheses.

4 The contribution of oil-market-specific shocks to fluctuations in activity and prices

To evaluate the importance of shocks to the precautionary demand for oil, we compute the forecast error variance decomposition. The horizons at which forecast errors are calculated are indicated in the first column of Table 4.\(^{15}\) With respect to economic activity, the median ranges from 24 percent at the 12-month horizon to about 30 percent at longer horizons. However, the difference between the 16\(^{th}\) and the 84\(^{th}\) percentiles is extremely large (5 and more than 70 percent at the 2-year horizon), indicating that the central tendency is surrounded by great uncertainty. The share of the variance of the consumer price index is large at the short horizon, and between 20 and 30 percent thereafter.

Table 4: Forecast error variance decomposition at selected horizons

<table>
<thead>
<tr>
<th>$h$</th>
<th>CFNAI</th>
<th>CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>0.24 (0.04-0.63)</td>
<td>0.49 (0.30-0.64)</td>
</tr>
<tr>
<td>24</td>
<td>0.31 (0.05-0.71)</td>
<td>0.31 (0.16-0.49)</td>
</tr>
<tr>
<td>36</td>
<td>0.32 (0.07-0.66)</td>
<td>0.24 (0.10-0.42)</td>
</tr>
<tr>
<td>48</td>
<td>0.28 (0.08-0.57)</td>
<td>0.21 (0.08-0.40)</td>
</tr>
</tbody>
</table>

Notes: 68 percent confidence intervals in parentheses.

We gauge the contribution of precautionary-demand-driven oil price movements to the historical path of the CFNAI and CPI inflation through the cumulative effects of the sequence of oil price disturbances. We compute the effects by subtracting from their actual values the fitted (baseline) values in the estimated VAR. Naturally, these estimates are subject to considerable sampling uncertainty, so they should be considered as only suggestive. We focus on the last three U.S.

\(^{15}\)The variance decomposition was recovered by means of the algorithm described in Appendix B.
recessions as dated by the NBER, including the one that was still in progress when our sample ends (December 2008).

Figure 3 displays results for the CFNAI. The black line represents the actual data, the histogram the cumulative effect of oil-specific price shocks, net of all other shocks. That is, the historical decomposition shows how economic activity would have evolved if there had been only shocks to precautionary demand for oil.

The figure shows that precautionary demand had a considerable importance in explaining the 1990-91 recession, in fact accounting for the entire decline in the CFNAI. Oil-specific price shocks also appear to have played an important role in the recession of the early 2000s, accounting for about half the decline in CFNAI. These results confirm the findings in Kilian (2009), who attributes both the sharp spikes in the real price of oil in 1990-91, after the invasion of Kuwait, and in 1999–2000 to the increase in precautionary demand. However, our estimates suggest that oil-specific shocks played only a limited role of in the last recession. If anything, they only began to contribute – modestly – to the downturn in mid-2008.

This evidence is consistent with the findings of Kilian (2009) and Kilian and Murphy (forthcoming) that the oil price surge in the mid-2000s was driven by repeated positive shocks to the demand for industrial commodities. It is also in line with Kilian and Hicks (forthcoming) who show that after 2003 oil prices were driven up by world aggregate demand associated with the buoyant growth of the emerging economies, and not by precautionary demand.

With respect to the evolution of the CPI (Figure 4), cumulative shocks to the precautionary demand for oil explain almost all of the increase in inflation in the early 2000s; the importance of this factor was only half as great in 1990-91 and in the last recession.

5 Concluding remarks

We have examined the effects of oil-market-specific shocks – which following Alquist and Kilian (2010) we interpret as shocks to the precautionary demand for oil – on U.S. output and inflation. To identify the shocks we use high-frequency data to impose identifying restrictions on a monthly VAR. We assume that the response of oil prices to changes in precautionary demand is gauged accurately by that estimated using oil futures. The advantage of this procedure is that it permits direct estimation of shocks to expectations of future oil market tightness, which affect oil prices and other macroeconomic variables by moving the precautionary demand for oil.

Our finding is show that unforeseen oil price increases caused by expectations are inflationary and contractionary. Our analysis suggests that oil-market-specific shocks increase the CPI immediately and reduce U.S. economic activity with a lag of six months. Historical decomposition shows that the oil shocks we have singled out explain a good part of the U.S. recession of the early 1990s
Figure 3: Historical decomposition of the Chicago Fed National Activity Index

Notes: Time intervals represent recession periods as defined by the NBER.
Figure 4: Historical decomposition of US CPI inflation

Notes: Time intervals represent recession periods as defined by the NBER.
and a significant if smaller part of the downturn of the early 2000s, but were only a modest factor in the latest slump.
Appendices

A Identifying oil-market-specific shocks using futures

This Appendix relies heavily on Faust, Swanson and Wright (2004). We identify oil-market-specific shocks from futures contracts. The initial step is standard. From the estimated reduced form VAR we derive the structural form by relating the reduced-form residuals to the structural disturbances.

Consider the reduced-form VAR:

\[ A(L)Y_t = u_t, \]  
\[ (A1) \]

where \( Y_t \) is \( G \times 1 \), \( A(L) = \sum_{j=0}^{\infty} A_j L^j \) and \( A_0 = I \). We assume that \( A(L) \), which is a \( G \times G \) matrix, is invertible. Hence, the system can be written as:

\[ Y_t = B(L) u_t, \]  
\[ (A2) \]

where \( B(L) = A(L)^{-1} \).

We assume that the \( G \) reduced-form errors \( u_t \) are related to structural disturbances \( \varepsilon_t \) as follows:

\[ u_t = S \varepsilon_t, \]  
\[ (A3) \]

where \( S \) is a \( G \times G \) full rank matrix. The VAR in equation (A1) can be made structural by writing it in terms of the structural shocks:

\[ Y_t = B(L)S \varepsilon_t. \]  
\[ (A4) \]

Suppose the first column of \( S \) corresponds to the oil shock and call it \( \alpha \). The impulse response of all variables in the VAR to the oil shock is:

\[ B(L) \alpha = \sum_{j=0}^{\infty} B_j \alpha L^j. \]  
\[ (A5) \]

The \( g \)th element of the \( G \times 1 \) vector of lag polynomials \( B(L) \alpha \) gives the response of the \( g \)th variable to the oil-market-specific shock. The \( Bs \) are known, because they are implied by the reduced-form estimates. Hence, identifying the impulse response requires picking the \( G \) elements of \( \alpha \).

To identify oil-market-specific shocks we use the information contained in the futures contracts following changes in the precautionary demand for oil, with a two-step procedure: (i) derive the response of the expected oil prices from the futures, (ii) impose the equality between the VAR impulse response of oil prices to the oil shock and the response as measured by the futures. Let us first briefly illustrate point (ii) and then point (i).
A.1 Matching responses of oil prices

Suppose that in the case of no uncertainty the response of the oil price at time $h > t$ to an oil price shock at time $t$ is $r_h$, $h = 0, 1, \ldots G - 1$. Hence:

$$B_{h,oil}\alpha = r_h,$$  \hspace{1cm} (A6)

where $B_{h,oil}$ is the row of $B_h$ corresponding to the oil price. We can stack these $G$ equations to form:

$$R\alpha = r,$$

where the rows of $R$ are the relevant row vectors $B_{h,oil}$ and the elements of $r$ are the corresponding elements $r_h$. We get $B_{h,oil}$ from the reduced-form VAR estimates. The response of oil prices to an oil price shock, $r_h$, can be obtained by using the information contained in the futures.

This system has $G$ equations in $G$ unknowns (the elements of $\alpha$). Its solution, under the condition that $R$ is of rank $G$, is:

$$\alpha = R^{-1}r.$$  \hspace{1cm} (A7)

We next show how the response $r_h$ of oil prices to oil market-specific shocks can be measured directly from oil price futures market and explain what further restrictions we impose on the system.

A.2 Measuring oil price shocks using futures

The oil price futures contract $F$ for date $h > t$ is a bet on the spot price $P$ at date $h$. Parties to the $h$-period contract agree at time $t$ on a price $F^h$ for oil to be delivered at $h$. Under risk neutrality

$$F^h = E_tP_h$$  \hspace{1cm} (A8)

i.e. the futures price is equal to the expected spot price at the relevant date. Note that even under risk neutrality uncertainty affects the expected spot price through the convenience yield, because firms face costs in adjusting inventories (Alquist and Kilian, 2010; Pindyck, 1994).

We consider the change in the logarithm of oil futures prices $\Delta_d f^h \ (\equiv f^h_d - f^h_{d-1})$ between day $d$ and day $d - 1$. Hence, we can write:

$$\Delta_d f^h = E_d p_h - E_{d-1} p_h$$  \hspace{1cm} (A9)

where the right-hand-side is the log change in expectations about the spot price at the date $h$ due to the unanticipated event that has perturbed the oil market at date $d$. We focus on change in expectations due to oil-market-specific shocks. Following Alquist and Kilian (2010) we proxy this with the percentage change in the (negative) of the 12-month futures-spot spread $s_d \left( = -\frac{F^d_{12} - P_d}{F^d_d} \right)$.

In the robustness analysis (Section 3), instead, since we concentrate only on the dates classified by
Cavallo and Wu (2012) as shocks to precautionary demand, we directly use the log changes in spot prices $\Delta dp_d$.

In the VAR, the expected oil price at $h > t$ conditional on information in the dataset at time $t$ is:

$$E_t p_h = \sum_{i=0}^{\infty} B_{h+i,oil} S\varepsilon_{t-i}$$  \hspace{1cm} (A10)

The change in the expectation $\Delta df^h$ from day $d - 1$ to $d$ is due to changes in the expectations of shocks $\varepsilon$s over this day, $\Delta_d^t \varepsilon_d$, given that all the past $\varepsilon$s $(\varepsilon_{d-1}, \varepsilon_{d-2}, \ldots)$ are known at the outset. In order to single out the changes in expectations due to oil-market-specific shock $\varepsilon_d^{oil \, specific}$, we can use equation (A9) and write:

$$\Delta_d^h f^h = B_{h,oil}^\alpha \Delta_d^e \varepsilon_d^{oil \, specific} + B_{h,oil}^S \Delta_d^e \varepsilon_d$$  \hspace{1cm} (A11)

where $\alpha$ is the first column of $S$ and the matrix $S^*$, is equal to $S$ with the first column replaced by zeros. Without loss of generality we can assume that the second term is equal to zero: news on precautionary demand for oil does not lead the market to reassess its view on other sources of shocks (such as actual oil demand and actual oil supply). We obtain:

$$\Delta_d^h f^h = B_{h,oil}^\alpha \Delta_d^e \varepsilon_d^{oil \, specific}$$  \hspace{1cm} (A12)

Combining equations (A12) and (A6) we get:

$$\Delta_d^h f^h = r_h \Delta_d^e \varepsilon_d^{oil \, specific}$$  \hspace{1cm} (A13)

where $r_h = B_{h,oil}^\alpha$ is the impulse response of the oil price to the oil price shock at horizon $h$ and $\varepsilon_d^{oil \, specific}$ is measured with the changes in the negative of the futures-spot spread. Since this equation holds for every $h$, we substitute out the unobserved quantity $\Delta_d^e \varepsilon_d^{oil \, specific}$ with $\Delta df_d / r_0$ ($= \Delta ds_d / r_0$) to get:

$$\Delta_d^h f^h = \frac{r_h}{r_0} \Delta_d s_d$$  \hspace{1cm} (A14)

Equation (A14) indicates that on the day an oil specific shock hits the market, futures prices at different horizons should change proportionally. The proportionality factor is the same for each shock, while the magnitude of the shock can obviously differ. We estimate the factor of proportionality from the data on futures contracts and use the normalization $[r_0 = 1\%]$ to obtain the estimated $\hat{r}_h$ in our identification strategy.

These steps allow to recover the point estimate of $\alpha$. Given that $\alpha$ depends non-linearly, through $R$, on the reduced-form parameters estimates, the uncertainty surrounding these estimates translates into substantial uncertainty about $\alpha$. 

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B Constructing the $S$ matrix for the historical and the variance decomposition

In Appendix A, equation A7 recovers $\alpha$ as the first column of $S$. How can we continue and obtain the remaining columns of $S$? These are needed to get an estimate of the in-sample structural shocks and so run counterfactuals or historical decomposition exercises.

We can write:

$$S = \begin{bmatrix} \alpha & \alpha \\ (n \times 1) & (n \times (n-1)) \end{bmatrix}$$

hence,

$$SS' = \alpha \alpha' + \alpha \alpha' = \Sigma$$

or

$$\alpha \alpha' = \Sigma$$

$$\Sigma = \Sigma - \alpha \alpha'.$$

We should remember that $\Sigma$ is a reduced-rank matrix. Therefore, we have $n \times (n + 1)/2$ pieces of info (equations) from the reworking of the reduced-form estimates (the distinct elements of $\Sigma$) and $n \times (n - 1)$ free elements (unknowns) in $\alpha$.

Just looking at the order conditions (necessary) for identification, then we have that: for $n > 3$, the system is underidentified; for $n < 3$, it is overidentified; and for $n = 3$, it is just identified. This last result can be easily derived by equating the number of equations and the number of unknowns. To recover the actual values of the elements of the $S$ matrix we can use the singular value decomposition (SVD), or the spectral decomposition since $\Sigma$ is a square matrix, in order to obtain (given the ordering) a unique decomposition of $\Sigma$ subject to rank reduction:

$$\Sigma = U \Lambda U' = \left( U_1 \Lambda_1^{1/2} \right) \left( U_1 \Lambda_1^{1/2} \right)'$$

$$\Rightarrow \alpha = \left( U_1 \Lambda_1^{1/2} \right)$$

where the rows of $U_1$ are the eigenvectors associated with $\lambda_1$, the vector of the $n - 1$ non-zero eigenvalues of $\Sigma$ in decreasing order subject to the $U_1'U_1 = I_n$ normalization and $\Lambda_1 = \text{diag}(\lambda_1)$.

Therefore, we implement the following algorithm:

- estimate the reduced-form parameters from the autoregressive representation $A(L)$ and get the sample counterparts of $\Sigma$ and $B(L)$;
- use futures-contract-based exogenous information (and $B(L)$) to tie down $\alpha$;
• compute $\Sigma$ and its spectral decomposition to obtain $\alpha$.

It is worth noticing that with three variables, after imposing $\alpha$ as a first column in $S$, the permutation (the ordering) of the remaining two variables in the VAR system has no effect on the historical (and the variance) decomposition.

C Data sources

The following are the variables used in the VAR, with Datastream codes in capitals:

- Crude Oil-WTI Spot Cushing U$/BBL: CRUDOIL.
- Crude Oil futures U$/BBL: NCL[expiration date].
- U.S. Consumer price index - all items (1967=100 ): USCP67..F

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