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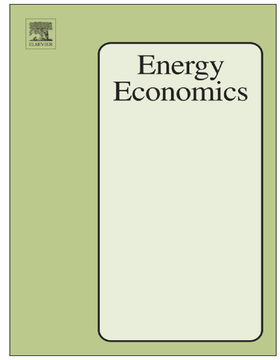

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Which oil shocks really matter in equity markets?

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Abstract

This paper examines the relationship between structural oil shocks and US equity markets. The recent oil shock decomposition of Ready (2018) is reconsidered and refined, providing a clearer delineation between shocks to equity market discount rates and aggregate demand, leading to an oil shock specification which attributes substantially more explanatory power to the latter in explaining equity market variation. Providing links with the literature dating back to Kilian and Park (2009), an explicit role is given to precautionary demand shocks using an independent measure constructed from oil futures data, reducing the role of the supply shocks obtained as the final residual in the recursive identification scheme. In an extended sample that allows an analysis of the oil/equity market relationship since the global financial crisis, the modified aggregate demand shocks have approximately twice as much explanatory power for stock return variation than the demand shocks of Ready (2018). The importance of these shocks in driving oil price changes and equity market volatility has only increased since the financial crisis, with the role of supply shocks diminishing. Once these demand effects are accounted for, there is little relationship between precautionary demand shocks and equity returns, in contrast to the existing literature.

Keywords
Supply and demand shocks, stock markets, precautionary demand, volatility.

JEL Classification Numbers
G10, G15, Q41, Q43

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1 Introduction

Despite the important role played by crude oil in the world economy, the links between oil price changes, the broader economy and financial asset prices is not clearly understood. It is often argued that this is due to the complexity of the multiple mechanisms which drive crude oil markets. Research has shown oil prices may be influenced by a range of unobserved supply and demand style shocks. Thus, it is plausible that the effect of these shocks on both the economy and equities may be dependent on the nature of the shock, obscuring the relationship when simply looking at raw oil price changes. This contention has prompted the development of various methods for identifying oil price shocks, often producing conflicting results.

This paper revisits the recently developed SVAR decomposition of oil price shocks proposed by Ready (2018), and refines the identification scheme in several ways. It is shown that the original definition of risk shocks based on the VIX index leads to significant underestimation of the impact on US equity markets of aggregate demand based oil shocks, due to the conflation of information relating to aggregate demand present in volatility. It is shown that using an estimate of the variance risk premium (VRP) to identify risk shocks alleviates this issue. Providing a link to previous literature, it is also shown that the identified supply shocks of Ready (2018) are related to an exogenous measure of precautionary demand, reflecting future oil supply uncertainty rather than contemporaneous supply changes. Finally, the time-varying role of oil shocks is considered in an extended sample, with a clear shift in the mechanism driving oil price changes from supply to demand identified around the global financial crisis (GFC). To assess the economic importance of the identified shocks, the link between oil shocks and equity returns and realised volatility is examined. An important result is that aggregate demand shocks constructed here explain close to 25% of the monthly variation in S&P500 returns, around twice that explained by the shocks constructed under the Ready (2018) decomposition. The demand shocks constructed here are also significantly related to S&P volatility, and while the explanatory power is relatively low, demand shocks constructed under the Ready (2018) approach are not significantly related to volatility and offer no explanatory power. Finally it is shown that once these demand effects are accounted for, there is little relationship between precautionary demand shocks and equity returns, in contrast to results in Kilian and Park (2009) which emphasised their role. Overall, the results presented here offer more detailed insights into the supply and demand shocks underpinning oil price changes.

The seminal work to consider the importance of deconstructing oil price shocks was Hamilton (1983), who first suggested the link between oil prices and real output is explained only by considering by both supply and demand side shocks separately. Hamilton (2003) extends Hamilton (1983) characterising the relationship as nonlinear. Hamilton (2003) finds that only oil price increases have an effect on the economy, and that this impact is stronger following a period of stability in prices. They suggest that the relationship is due to oil supply shocks disrupting consumption and investment. To determine whether there is a causal interpretation, exogenous oil price movements are isolated using disruptions to global petroleum supplies as a measure of the shocks magnitude. These disruptions are then used as instruments for oil price shocks to explain the nonlinear relationship. Hamilton (2003) concludes by noting that it may not necessarily be the disruption-induced price changes driving the relationship between oil and the macroeconomy. Rather, it may be the psychological impact of exogenous supply disruptions on policy and consumption that are of greater importance than actual oil price movements. This point becomes the focus in later research through a new oil shock labelled precautionary demand. Barsky and Kilian (2004) suggests these exogenous disturbances to the oil market do not necessarily cause price increases, they may be caused by shifts in the precautionary demand for the commodity in response to the threat of political events. This form of demand is distinct from that associated with improving global macroeconomic conditions. In this sense, innovations to the price of oil may depend on supply, aggregate demand and precautionary demand shocks, and it is through these shocks that oil price changes may impact the macroeconomy.

Much of the more recent research has followed Kilian (2009), who decomposes oil price changes into supply, demand and precautionary demand shocks. It was found that supply and demand shocks only accounted for 4% of the variation monthly oil price. Precautionary demand shocks, on the other hand, which are unclassified by the identification scheme and therefore represent unexplained variation, captured 77% of the variation. Kilian and Park (2009) found that these shocks explained very little of the contemporaneous variation in monthly US stock returns with aggregate demand shocks in fact contributing the least to oil price variation, a somewhat perplexing result as the information in demand shocks would be expected to be important in relation to equity movements. Kim and Vera (2018) find that the results of Kilian (2009) still apply to more recent sample periods. Kolodzeji and Kaufmann (2014) reconsider the analysis of Kilian (2009), by separating oil production used into OPEC and non-OPEC production showing that shocks from OPEC production have a significant impact on prices. In contrast to the approach of Kilian (2009), who explicitly define supply shocks, Ready (2018) employs a decomposition that only defines oil demand and risk shocks, with supply shocks representing elements which are unclassified by the decomposition. As a result, Ready (2018) finds that the vast majority of variation in oil prices is attributable to supply with demand playing a much less important role. Overall, it appears as though the precautionary demand shocks defined in Kilian (2009), or the supply shocks of Ready (2018) both act as a catch-all for unexplained variation in the monthly oil price.

The rest of the paper is organised as follows. Section 2 outlines the identification strategy of Ready (2018) and presents two new refinements. Section 3 shows the empirical oil shock decompositions and presents some further empirical validation of the underlying identifying assumptions. Sections 4 and 5 present the results on the relationship between the identified oil shocks and US equity market returns and volatility, respectively. Section 6 offers some concluding remarks.

2 Oil Shock Construction

Three variants of the recursive identification scheme proposed by Ready (2018) are considered, all of which rely on the use of returns on a portfolio of listed oil producing firms to identify demand and supply shocks to oil prices. The key insight is that such firms will be affected by demand shocks, but have a natural hedge against supply shocks. Ready (2018) provides a stylised model to justify this assumption, the intuition of which can be summarised as follows. A rise in oil price due to increased demand should enable producers to sell at least as much oil at a higher price, leading to increased profits. However, in a world where oil resources are depletable and new reserves are difficult/timely to develop, an increase in price due to difficulties in production will lead to a lower quantity sold, leaving profits (and therefore equity returns) for these firms largely unaffected. Furthermore, the forward-looking nature of these equity returns should ensure that this logic applies to not only contemporaneous supply and demand shocks, but also anticipated supply and demand shocks. As noted by Ready (2018), how stringently this exclusion restriction can be applied is dependent on the parameters of the theoretical model, meaning that the scheme must be validated empirically. Ready (2018) provides some compelling anecdotal evidence that the supply and demand shocks have the correct signs in regressions with economic growth/activity and behave in justifiable ways around prominent historical events such as the Gulf War. A more direct validation is given in Section 3.1 where it is shown that supply shocks derived from alternative identification schemes fail to contradict this exclusion restriction.

The *baseline* specification follows Ready (2018), using essentially the same three variables to provide a decomposition of monthly oil price movements into supply and demand shocks using the above intuition. For the spot oil price returns Δp_t, the closest expiry (contract 1) NYMEX WTI crude oil futures contract at month end is used and is obtained from the U.S. Energy Information Administration (EIA). As in Ready (2018), short dated futures contracts are favoured so as to focus on unexpected changes in oil prices. Monthly returns on the World Integrated Oil and Gas Producers Index, used as the main identifying variable R_t^{Prod}, was sourced from Datastream. Finally, the monthly VIX S&P 500 implied volatility index, denoted v_t, was sourced from the CBOE to function as a proxy for discount factor shocks in the equity market. Defining $X_t = [v_t \; R_t^{Prod} \; \Delta p_t]'$, a recursive scheme is used to identify the shocks in a structural VAR methodology with

$$X_t = C + \sum_{i=1}^{P} \Phi_i X_{t-i} + AZ_t \tag{1}$$

where the structural shocks are given by

$$Z_t = \begin{bmatrix} m_t \\ d_t \\ s_t \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{12} & a_{22} & 0 \\ 1 & 1 & 1 \end{bmatrix}, \quad Var(Z_t) = \begin{bmatrix} \sigma_m^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{bmatrix} \tag{2}$$

The lag length $P = 1$ was chosen by BIC. The matrix A is restricted such that the innovations to the VIX are treated as observable equity market discount rate shocks m_t, and the returns on the oil producing firms are not subject to supply shocks s_t, as per the discussion above. The shocks are normalised to sum up to the total change in oil prices. This scheme directly identifies the demand shock d_t, while the supply shock is assumed to be the final residual in the model.

Two variations of this identification scheme are also considered. Firstly, it is argued that only the variance risk premium (VRP) component of the VIX is desirable to use as an observable series of discount rate shocks. The remaining volatility component adds noise that is potentially correlated to the business cycle, clouding identification and potentially subsuming part of the demand shocks. Furthermore, demand and supply shocks are effectively orthogonalised to the sum of the components of the VIX, precluding analysis of the oil shocks impact on equity market volatility. Therefore a *modified* identification scheme is proposed which utilises an estimate of the VRP. The method detailed by Bekaert and Hoerova (2014) is applied to construct the VRP, defined as

$$VRP_t = VIX_t^2 - E_t[RV_{t+1}] \tag{3}$$

where VIX_t^2 is the current squared one-month S&P500 implied volatility and $E_t[RV_{t+1}]$ is a one-month forecast of S&P500 realised volatility. Realised volatility for each month (RV_t) is calculated by taking a monthly sum of daily squared returns. Higher frequency intraday returns are not available back to the start of the sample period considered. The forecasting model used here is

$$RV_t = \alpha + \beta RV_{t-1} + \varepsilon_t. \tag{4}$$

Based on this AR model, forecasts of the the one-month realised volatility are obtained which is then used in equation 3 to provide the VRP.

Finally, the interpretation of the final residual in the recursive scheme as a supply shock is refined by also considering precautionary demand shocks as potentially contributing to these residuals. We consider shocks similar to those developed by Alquist and Kilian (2010), who define precautionary demand shocks as oil market specific demand shocks driven by uncertainty over future supplies of oil. Such shocks were shown to be potentially important by Kilian (2009), who apply this label to the residual from their own recursive SVAR scheme. To identify the precautionary demand shock, an estimate of the convenience yield is constructed from a simple no-arbitrage condition on the log of the n month futures price ($f_t^{(n)}$) as suggested in Alquist, Bauer, and Diez de los Rios (2014). They present a model such that

$$f_t^{(n)} = y_t + ni_t^{(n)} - n\delta_t^{(n)} \tag{5}$$

where y_t is the log spot price, $i_t^{(n)}$ is the nominal interest rate that investors can borrow at between times t and $t+n$, and $\delta_t^{(n)}$ is the n month raw convenience yield. To form this estimate of $\delta_t^{(n)}$, the 3 month expiry contract (contract 4) was obtained from the EIA, as well as the 3 month LIBOR sourced from the St Louis Federal Reserve FRED database[1]. The use of such a proxy for precautionary demand was explored by Alquist and Kilian (2010), who showed a striking similarity between such a measure and the residual estimate from Kilian (2009) over a sample from 1989 to 2006. However, concern was raised in that work about an apparent structural change in the spread during 2003 due to increased speculation in the oil futures market. Figure 1 plots our estimate of the $\delta_t^{(3)}$ from July 1986 to December 2016, together with the projection onto Working's T-index which estimates speculation using data on open interest in oil futures [2]. Over this longer sample, the shift down in the convenience yield appears to be longer lasting than the three years at the end of the sample discussed in Alquist and Kilian (2010). It also appears to be well captured by the trend present in the T-index. Therefore the projection onto the space orthogonal to this measure of speculation is taken as the final proxy for the convenience yield (CY).

Innovations to this CY variable, denoted c_t, are obtained as the residuals from the VAR model in (1) with CY included in levels. The precautionary demand shocks are then defined as the projection of the *modified* supply shocks onto the space of c_t that is orthogonal to the *modified* risk and demand shocks. As with the previous specifications, the final residual in this model is tentatively labelled an oil supply shock, though it must be acknowledged that it will also reflect any shocks not identified in the scheme. It's interpretation as a supply shock would suggest that it would be negatively related to equity returns, a prediction that is empirically examined in Section 4. This approach utilizing both the VRP and CY is labelled the *full* identification scheme below.

[1]This estimate is somewhat agnostic about the dynamics of the underlying series. An alternative would be the Kalman filtering approach of Schwartz (1997) which decomposes the spot price into non-stationary (fundamental) and stationary (convenience yield) components whose random shocks are correlated. The correlation of the components has potential implications for demand and supply shocks, suggesting that use of that framework would require structural identification within the unobserved component model.

[2]The measure was calculated in accordance with the methodology described in Buyuksahin and Robe (2014).

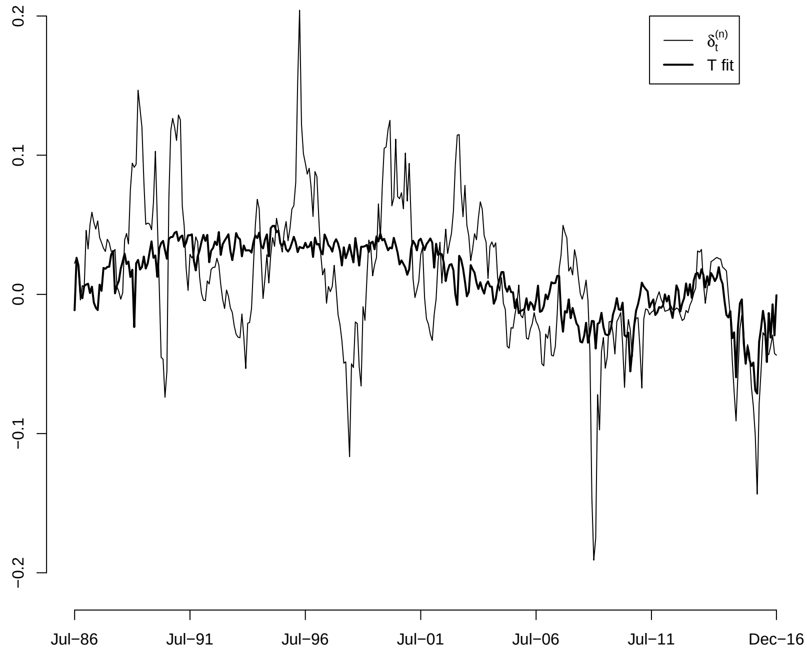

Figure 1: Financialization of Oil Price Futures. The lighter line is the raw convenience yield, $\delta_t^{(3)}$. The heavy line is the projection of the futures spread on the T-index.

Figure 2 plots the monthly series central to the subsequent empirical analysis over the sample period July 1986 to December 2016. The top panel shows the evolution of the spot oil price. The series is dominated by effects of the Gulf war starting in 1990, falls in prices to recent lows during the Asian crisis and large price rises and subsequent collapse triggered by the global financial crisis (GFC). The next panel shows the month end levels of the VIX. The VIX exhibits long term cycles in the level of volatility dominated by peaks around the 1987 stock market crash, the Asian financial crisis, the dot-com collapse 2000-2001 and the GFC period. While the VRP in the next panel follows a broadly similar pattern, it differs from the VIX in that the long-term slow moving component in volatility is not evident, though the risk premium clearly rises during times of market turmoil when the VIX reaches its peaks. Finally CY in the lower panel rises during the Gulf war reflecting precautionary demand during this uncertain time. Apart from a very brief peak in 1996, CY rises again in the lead up to the invasion of Afghanistan and the Iraq war, again seemingly reflecting higher levels of precautionary demand for oil.

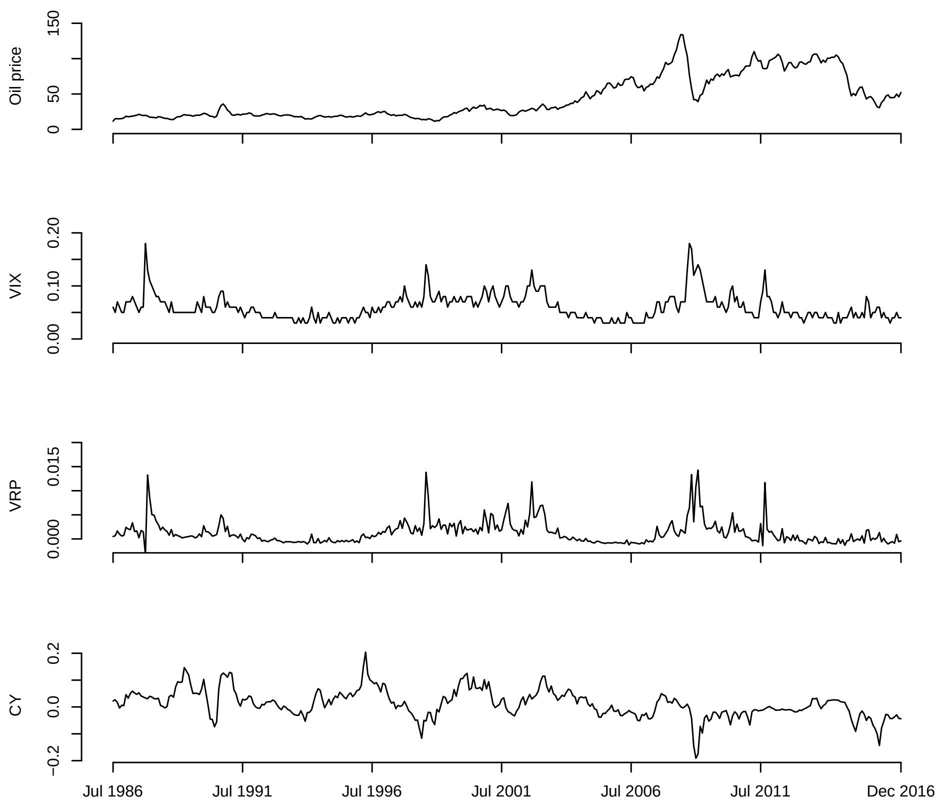

Figure 2: Top panel: Spot oil prices. Second panel: Month end levels of the VIX index. Third panel: Volatility risk premium estimates from 3. Bottom panel: estimate of the convenience yield.

3 Empirical Oil Shock Decomposition

The subsequent empirical results are based on three specifications. *Baseline* uses the identification scheme of Ready (2018). *Modified* is based on the identification scheme of Ready (2018) but replaces the VIX with the VRP in an effort to identify the aggregate demand and risk shocks more cleanly. Finally, *Full* is the full identification scheme, using the VRP and the CY to help identify precautionary demand shocks separate from supply shocks. While Ready (2018) used data up to 2011, the extended sample range in this study enables a first look at the stability of the oil/equity market relationship after the onset of the GFC. Therefore, all results are reported over two subperiods, July 1986 - Dec 2007 and Jan 2008 - Dec 2016.

Table 1 reports the variance decomposition of oil price changes, given the three identification schemes and across the two sub-periods. Starting with the *Baseline* scheme in the first sub-sample, it is clear that supply shocks are the dominant source of variation accounting for 90% of the variation in oil prices with aggregate demand shocks accounting for about 10%. This finding is qualitatively consistent with Ready (2018), though the exact proportions differ due to variation in the data and samples periods used. The *Modified* scheme leads to a very similar decomposition in the same sub-sample, with supply shocks still accounting for 91% of the variation. However moving to the *Full* identification scheme offers an interesting insight. When the precautionary demand shock is included it accounts for 30% of the variation, with around 61% still attributable to supply. This role of precautionary demand is substantial, though not of the same magnitude as found in Kilian (2009), resulting from the attempt to directly identify these shocks here.

Moving to the results for the second period from Jan 2008 - Dec 2016 (lower panel), the *Baseline* approach now shows that the impact of aggregate demand shocks becomes more important relative to the earlier sub-period (10.4% to 19.2%) and supply shock become somewhat less important (89.2% to 76.4%). Risk shocks also begin to play a small role in this period. Under the *Modified* identification scheme, aggregate demand plays even more of an important role, accounting for 24% of the variation. Interestingly, under this identification scheme the risk shocks play no role with all of the variation attributable to the demand shocks. This is consistent with the argument in Section 2 that the using the VIX conflates information relating to aggregate demand present in volatility, and using the VRP to identify the risk shocks strips out this misclassification. This change leads to a more important role for aggregate demand than previously identified. Moving to results for the *Full* identification scheme, it is clear that precautionary demand remains an important component, accounting for 19% of the variation in oil prices. However, it explains less of the supply shock identified under the preceding schemes than in the first sub-sample which contained important geopolitical events such as the Gulf war and the invasions of Afghanistan and Iraq.

Overall, the results of the variance decomposition indicate that aggregate demand shocks may be more important than previously thought, supply shocks have become less important and a significant portion of previously measured supply shocks are not contemporaneous supply shocks but reflect precautionary demand reflecting uncertainty about future supply.

Table 1: **Oil Shock Variance Decomposition**

Panel A: July 1986 - Dec 2007	*Baseline*		*Modified*		*Full*	
Shock	Stdev	% of Var.	Stdev	% of Var.	Stdev	% of Var.
Risk (V_t)	0.017	0.0%	0.017	0.0%	0.017	0.0%
Demand (D_t)	0.084	10.4%	0.075	8.3%	0.076	8.5%
Supply (S_t)	0.246	89.2%	0.249	91.3%	0.203	61.1%
Precautionary (P_t)					0.142	30.0%
Panel B: Jan 2008 - Dec 2016	*Baseline*		*Modified*		*Full*	
Shock	Stdev	% of Var.	Stdev	% of Var.	Stdev	% of Var.
Risk (V_t)	0.059	4.4%	0.017	0.0%	0.030	1.2%
Demand (D_t)	0.122	19.2%	0.135	23.8%	0.128	22.7%
Supply (S_t)	0.243	76.4%	0.240	75.8%	0.204	57.1%
Precautionary (P_t)					0.117	18.9%

Note: The table presents the annualised standard deviations for each oil shock component together with the percentage of variance explained by each (orthogonal) shock. *Baseline* is the identification scheme of Ready (2018). *Modified* uses the VRP to identify risk and aggregate demand shocks. *Full* uses the VRP as well as the CY to identify precautionary demand shocks.

3.1 Validation of Shock Decomposition

The validity of the shocks identified in this paper hinges on the assumption that returns on the oil producers stock index are unaffected by the true supply and precautionary demand shocks driving oil prices. This exclusion restriction holds with the resulting shocks produced with the approach above by construction. However, finding that supply and precautionary demand shocks identified by alternative schemes are correlated with oil producers stock returns would present a significant challenge to the fundamental idea underlying the above decomposition. Hence, the exclusion restriction used here and in Ready (2018) can then be tested using the regression

$$R_t^{Prod} = \alpha + \beta_1 s_t^* + \beta_2 p_t^* + \varepsilon_t \tag{6}$$

where s_t^* and p_t^* are alternative supply and precautionary demand shocks respectively, as developed under alterative identification schemes.

First considered are the supply shocks of Kilian (2009), which are derived from direct observation of changes in production of crude oil globally. While this definition of supply shocks has been criticized by Kolodzeji and Kaufmann (2014) as being too restrictive, it provides a test of the exclusion restriction in the sense that dependence between these shocks and the oil producer returns would constitute strong evidence against the identifying assumption relied upon in this paper. More problematic is the testing of precautionary demand shocks from that scheme, which are defined as the residual of the recursive scheme after accounting for supply and demand shocks. Kolodzeji and Kaufmann (2014) argue that the index of worldwide real economic activity in Kilian (2009) reflects little more than transportation costs, rendering the identified demand shocks inadequate. Ready (2018) points out that the measure will not capture anticipated variation in aggregate demand, leaving these to the precautionary demand. These arguments imply that p_t^* will likely be contaminated by aggregate demand shocks, providing a poor test of the exclusion restriction. Therefore, the shocks derived from a SVAR identified via sign restrictions by Kilian and Murphy (2014) are also considered. That paper provides supply and speculative demand[3] shocks derived under much weaker assumptions based on sign restrictions, providing potential evidence against the exclusion restriction. Finally, the direct measure/proxy for precautionary demand used in this paper, innovations to the convenience yield c_t, can be used in a final test of the exclusion restriction. Table 2 presents the results from these regressions over the first sub-sample July 1986 - Dec 2007[4].

Table 2: **Indirect Testing of Supply Exclusion Restriction**

	Shock	β	S.E.	P-value
Kilian (2009)	Supply	0.0017	0.0048	0.720
	Prec. D.	0.0094	0.0033	0.005
Kilian and Murphy (2014)	Supply	-0.0011	0.0038	0.766
	Spec Dem.	0.0055	0.0036	0.123
Current Paper	CY	-0.0244	0.1245	0.845

Note: The table presents regression results testing the exclusion restrictions on supply and precautionary demand shocks using equation 6. The heteroscedasticity and autocorrelation robust standard errors of Newey and West (1987) are presented. P-value is for a t-test of $\beta_i = 0$.

The t-tests for the null of $\beta_1 = 0$ using either set of supply shocks fail to produce evidence against the identifying assumption at standard significance levels. Likewise, the speculative demand shock of Kilian and Murphy (2014), which should encompass precautionary demand, is found to be an insignificant regressor. However, the precautionary demand shock of Kilian (2009) is a significant regressor with a positive coefficient. This could be taken as evidence against the exclusion restriction, although the sign of the coefficient is consistent with the argument

[3] The definition of speculative demand is broader than just the precautionary demand examined here. Again, the test is looking for anecdotal evidence against the exclusion restriction.

[4] We thank the authors of Kilian (2009) and Kilian and Murphy (2014) for making their data and code available. These datasets do not encompass the second post-GFC sub-sample.

that these shocks are instead contaminated by aggregate demand. This is further supported by the regression with the direct measure of precautionary demand based on the convenience yield, which is insignificant at conventional levels. Hence, the results fail to produce compelling evidence against the identifying assumption that returns on the oil producers stock index are unaffected by supply and precautionary demand shocks.

4 Oil Shocks and US Equity Market Returns

To assess the economic meaning of the identified shocks, a similar regression framework to Ready (2018) is used where the impact of shocks on both equity returns and volatility is examined. This section presents regression results analysing the dependence between the aforementioned oil shocks identified under each of the schemes and US equity market returns. Such relationships are not causal, but instead provide clarity over the interconnection between these markets, the heterogeneous relationship between equities and different types of oil shock and how such exposures might need to be hedged. The regressions under both the *Baseline* and *Modified* schemes is given by[5]:

$$r_t = \beta_0 + \beta_1 m_t + \beta_2 d_t + \beta_3 s_t + \varepsilon_t, \tag{7}$$

whereas the regression based on shocks from the *Full* scheme is:

$$r_t = \beta_0 + \beta_1 m_t + \beta_2 d_t + \beta_3 s_t + \beta_4 p_t + \varepsilon_t. \tag{8}$$

Table 3 presents the estimation results for equations 7 and 8 for both subperiods. Coefficient estimates and standard errors are reported along with the univariate R^2. Starting with the regression using the shocks from the *Baseline* scheme, risk and supply shocks have a negative effect on returns whereas demand shocks have a positive impact. In this case, proportionally speaking, risk shocks are the most important in terms of equity market variation. In contrast, the demand shocks identified under the *Modified* scheme have approximately twice the explanatory power as the *Baseline* shocks, and are now far more important than risk shocks. This shift in importance from risk to demand shocks again emphasizes the importance of using a direct measure of risk premium which excludes the potentially confounding effect of demand in identifying risk shocks. These results also suggests a strong downward bias in what Ready (2018) terms 'oil beta' related to demand shocks (β_2). While Ready (2018) shows that such a relationship does exist when demand shocks to oil prices are considered, the relationship is found to be much stronger under the *Modified* scheme as the demand component has largely been re-

[5]The extant literature has often looked for asymmetry in the effect of positive/negative oil shocks on the economy and financial markets. Results not reported here found no evidence of this asymmetry, with the exception of the precautionary demand shocks in the second sub-sample. The resulting asymmetric estimates had no explanatory power so are excluded to save space.

moved from the risk shock. Contrasting the two subperiods shows a decline in the β_2 coefficient on aggregate demand shocks for both the *Modified* and *Full* schemes. However, the increased volatility of these shocks (see Table 1) is enough to drive a substantial increase in the overall correlation between oil price changes and equity market returns in this subperiod (up from -0.14 to 0.39). This increase in interconnectedness coincides with a time when conventional monetary policy had little scope to alleviate steep declines in economic activity, consistent with the results of Serletis and Xu (2018). Though still significantly negatively related to equity returns, supply shocks continue to exhibit relatively low explanatory power. Though precautionary demand may play an important role in explaining movements in the oil market, estimation results here based on the *Full* scheme reveal that these shocks contain little economically meaningful information related to equity market returns. Results in the lower panel show that risk shocks play a more important role post GFC and there is still a redistribution of explanatory power from risk to demand shocks, though the difference is a little smaller than in the first sub-period. Unlike the results of Kilian and Park (2009) who find that the negative impact of oil on stock markets prior to the GFC is primarily driven by precautionary demand, these shocks had little impact on returns prior to the crisis under the *Full* identification scheme here. They are neither statistically significant, or economically so with an $R^2 = 0.005$. This is likely due to the use of precautionary demand as a catch-all final residual in under their identification scheme. It is worth noting that the supply shock here is now the catch-all but only has a modest role. As it has the correct sign in the first sub-period to be interpreted as a supply shock, this lends support to the claim that this can be interpreted as a supply shock. While this coefficient becomes positive in the second period, as does the precautionary demand shock coefficient, neither can be statistically distinguished from zero at any reasonable level of significance.

Table 3: **S&P 500 Returns and Structural Oil Shocks**

Panel A: July 1986 - Dec 2007	*Baseline*		*Modified*		*Full*	
Shock	β_i	R^2_{Univ}	β_i	R^2_{Univ}	β_i	R^2_{Univ}
Constant	0.007		0.007		0.007	
	(0.002)		(0.002)		(0.002)	
Risk (m_t)	-5.412	0.399	-3.276	0.152	-3.341	0.151
	(0.340)		(0.538)		(0.530)	
Demand (d_t)	0.592	0.117	0.980	0.254	0.967	0.253
	(0.101)		(0.185)		(0.179)	
Supply (s_t)	-0.113	0.036	-0.137	0.055	-0.167	0.054
	(0.029)		(0.037)		(0.055)	
Precautionary (p_t)					-0.075	0.005
					(0.053)	
Observations	258		258		258	
Adjusted R^2	0.547		0.454		0.455	
Panel B: Jan 2008 - Dec 2016	*Baseline*		*Modified*		*Full*	
Shock	β_i	R^2_{Univ}	β_i	R^2_{Univ}	β_i	R^2_{Univ}
Constant	0.004		0.004		0.004	
	(0.003)		(0.003)		(0.003)	
Risk (m_t)	-2.381	0.545	-7.148	0.417	-4.052	0.414
	(0.209)		(0.950)		(0.555)	
Demand (d_t)	0.618	0.159	0.704	0.251	0.735	0.249
	(0.121)		(0.096)		(0.098)	
Supply (s_t)	0.028	0.001	0.047	0.004	0.026	0.004
	(0.036)		(0.048)		(0.098)	
Precautionary (p_t)					0.057	0.000
					(0.051)	
Observations	108		108		108	
Adjusted R^2	0.696		0.661		0.653	

Note: The table presents the regression of S&P500 index returns on identified shocks from the three identification schemes, across two sub-samples. The heteroscedasticity and autocorrelation robust standard errors of Newey and West (1987) are in parentheses. *Baseline* is the identification scheme of Ready (2018). *Modified* uses the VRP to identify risk and aggregate demand shocks. *Full* uses the VRP as well as the CY to identify precautionary demand shocks.

5 Oil Shocks and US Equity Market Volatility

This section presents regressions analysing the relationship between the identified oil shocks and equity market variability, as captured by monthly realized volatility. The regressions based on shocks identified under both the *Baseline* and *Modified* schemes are given by:

$$\begin{aligned} ln(RV_t) &= \beta_0 + \beta_1 V_t \mathbb{I}_{V_t>0} + \beta_2 V_t \mathbb{I}_{V_t<0} + \beta_3 D_t \mathbb{I}_{D_t>0} + \beta_4 D_t \mathbb{I}_{D_t<0} \\ &+ \beta_5 S_t \mathbb{I}_{S_t>0} + \beta_6 S_t \mathbb{I}_{S_t<0} + \varepsilon_t, \end{aligned} \tag{9}$$

whereas the regression based on shocks from the *Full* scheme is:

$$\begin{aligned} ln(RV_t) &= \beta_0 + \beta_1 V_t \mathbb{I}_{V_t>0} + \beta_2 V_t \mathbb{I}_{V_t<0} + \beta_3 D_t \mathbb{I}_{D_t>0} + \beta_4 D_t \mathbb{I}_{D_t<0} \\ &+ \beta_5 S_t \mathbb{I}_{S_t>0} + \beta_6 S_t \mathbb{I}_{S_t<0} + \beta_7 P_t \mathbb{I}_{P_t>0} + \beta_8 P_t \mathbb{I}_{P_t<0} + \varepsilon_t \end{aligned} \tag{10}$$

These specifications are designed to highlight the asymmetry in the impact of the oil shocks on volatility. Table 4 reports the estimation results for both equations 9 and 10, again for both subperiods. Starting with the effect of positive and negative risk shocks in the first sub-sample, it again becomes clear that using the VIX directly in the *Baseline* scheme is undesirable. In this setting a positive risk shock coincides with an increase in volatility, while a negative risk shock carries a coefficient with a sign implying a reduction in volatility, but is statistically insignificant. Once again, it appears that some of the movement in this initial estimate of risk shocks is driven by movements in volatility itself. This situation is rectified under the *Modified* and *Full* schemes, which show that any shock to discount rates is associated with higher equity volatility, irrespective of sign. This refinement in the identification scheme again results in a greater role for demand shocks as measured by the bivariate R^2, largely driven by negative shocks. This pattern of increasing volatility with both positive and negative shocks is repeated for the demand, supply and precautionary demand, though the effect is often asymmetric. Negative demand shocks lead to a greater increase in volatility under the *Modified* and *Full* schemes. There is also a pronounced asymmetry in the effect of precautionary demand shocks, with an increase in precautionary demand caused by uncertainty over future supply having a significant effect on volatility, while a negative shock has little impact. Overall, precautionary demand shocks seem to be more important in explaining volatility relative to returns, perhaps due to the fact that these shocks reflect forward looking uncertainty by definition. This is especially prominent in the shorter second sub-sample which includes the Libyan revolution, the Arab Spring and the EU decision to impose an oil import embargo on Iran.

Table 4: **S&P 500 Volatility and Structural Oil Shocks**

Panel A: July 1986 - Dec 2007	*Baseline*		*Modified*		*Full*	
Shock	β_i	R^2_{Biv}	β_i	R^2_{Biv}	β_i	R^2_{Biv}
Constant	-6.878		-7.098		-7.154	
	(0.112)		(0.098)		(0.113)	
Pos. Risk ($m_t > 0$)	107.463	0.266	82.061	0.164	82.257	0.163
	(11.946)		(15.059)		(14.001)	
Neg. Risk ($m_t < 0$)	17.960		-61.680		-63.167	
	(32.206)		(28.353)		(29.112)	
Pos. Demand ($d_t > 0$)	7.617	0.016	8.150	0.105	8.603	0.108
	(3.000)		(3.468)		(3.463)	
Neg. Demand ($d_t < 0$)	-6.565		-18.619		-18.462	
	(3.875)		(4.032)		(4.133)	
Pos. Supply ($s_t > 0$)	1.891	0.025	3.570	0.055	3.109	0.047
	(1.022)		(0.979)		(1.429)	
Neg. Supply ($s_t < 0$)	-1.925		-2.201		-1.424	
	(1.343)		(1.327)		(1.496)	
Pos. Precautionary ($p_t > 0$)					4.551	0.032
					(1.598)	
Neg. Precautionary ($p_t < 0$)					-2.836	
					(2.171)	
Observations	258		258		258	
Adjusted R^2	0.278		0.258		0.259	

Panel B: Jan 2008 - Dec 2016	*Baseline*		*Modified*		*Full*	
Shock	Stdev	R^2_{Biv}	Stdev	R^2_{Biv}	Stdev	R^2_{Biv}
Constant	-7.037		-7.148		-7.247	
	(0.190)		(0.187)		(0.168)	
Pos. Risk ($m_t > 0$)	43.187	0.276	141.839	0.304	83.579	0.357
	(9.612)		(31.994)		(20.407)	
Neg. Risk ($m_t < 0$)	1.838		-111.394		-62.169	
	(13.106)		(30.016)		(14.730)	
Pos. Demand ($d_t > 0$)	9.466	0.060	4.832	0.154	2.148	0.143
	(6.055)		(5.713)		(4.120)	
Neg. Demand ($d_t < 0$)	-8.099		-14.930		-14.862	
	(4.713)		(4.349)		(4.076)	
Pos. Supply ($s_t > 0$)	3.506	0.047	2.226	0.044	-3.760	0.011
	(2.137)		(3.019)		(2.432)	
Neg. Supply ($s_t < 0$)	-6.504		-3.712		0.286	
	(2.383)		(1.839)		(2.215)	
Pos. Precautionary ($p_t > 0$)					19.763	0.183
					(3.431)	
Neg. Precautionary ($p_t < 0$)					-11.059	
					(2.604)	
Observations	108		108		108	
Adjusted R^2	0.321		0.392		0.534	

Note: The table presents the regression of S&P500 index log realized volatility on identified shocks from the three identification schemes, across two sub-samples. The heteroscedasticity and autocorrelation robust standard errors of Newey and West (1987) are in parentheses. R^2_{Biv} is from a regression with positive and negative shock variables for each class of shock alone. *Baseline* is the identification scheme of Ready (2018). *Modified* uses the VRP to identify risk and aggregate demand shocks. *Full* uses the VRP as well as the CY to identify precautionary demand shocks.

Moving to the results for the second subperiod Jan 2008 - Dec 2016, the patterns in the signs of asymmetries remains the same, though the effect of positive demand or supply shocks are no longer significant and negative supply shocks becoming significant. While the relative explanatory power of demand shocks increase again moving from the *Baseline* and *Modified* scheme, risk shocks continue to play an important role in the post GFC period, a result consistent with those reported in the return regressions above.

6 Conclusion

The paper has revisited the relationship between oil price changes and US equity markets through a modification of the SVAR identification scheme of Ready (2018). It is shown that simple modifications to the framework reveal much stronger links between aggregate demand shocks to oil prices and equity market variation than previously reported. The explanatory power for these shocks on equity returns is roughly twice that found with the original Ready (2018) shocks, both before and after the GFC. The effect on stock volatility is smaller, but still significant (only) under the new identification schemes. While supply shocks remain the largest component of oil price movements, they have only modest explanatory power for equity market returns prior to the start of the GFC, and no effect since. An explicit role is given to precautionary demand shocks, which are shown to play a sizable role in moving oil prices, particularly in the early sub-sample. In contrast to the previous literature, the link between these precautionary demand shocks and equity market returns is generally small. The role of precautionary demand in moving stock volatility is more noticeable, likely due to the fact that these shocks reflect forward looking uncertainty by definition.

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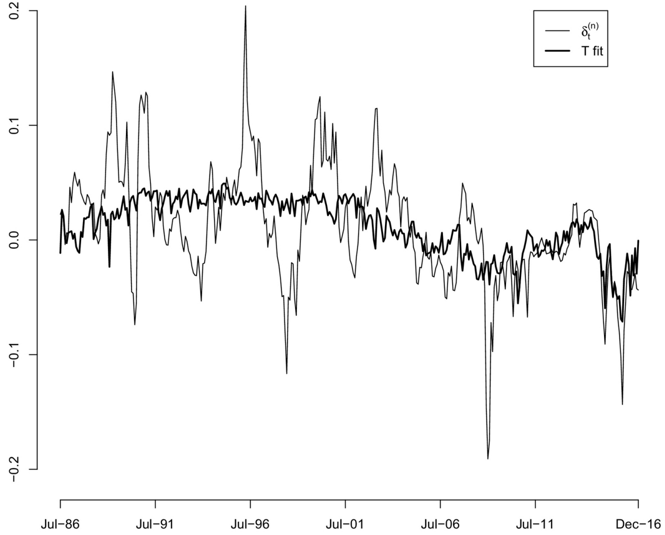
Highlights

- Presents a refined structural identification of oil price shocks.
- Aggregate demand shocks to oil prices have a larger role than previous estimates.
- Aggregate demand drives relationship between oil prices and stocks since the GFC.
- Precautionary demand shocks drive oil prices, but are unrelated to stock returns.
- Aggregate demand shocks and equity market volatility link is established.


0.2
0.1
0.0
-0.1
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$\delta_t^{(n)}$
T fit
Jul-86
Jul-91
Jul-96
Jul-01
Jul-06
Jul-11
Dec-16

Figure 1

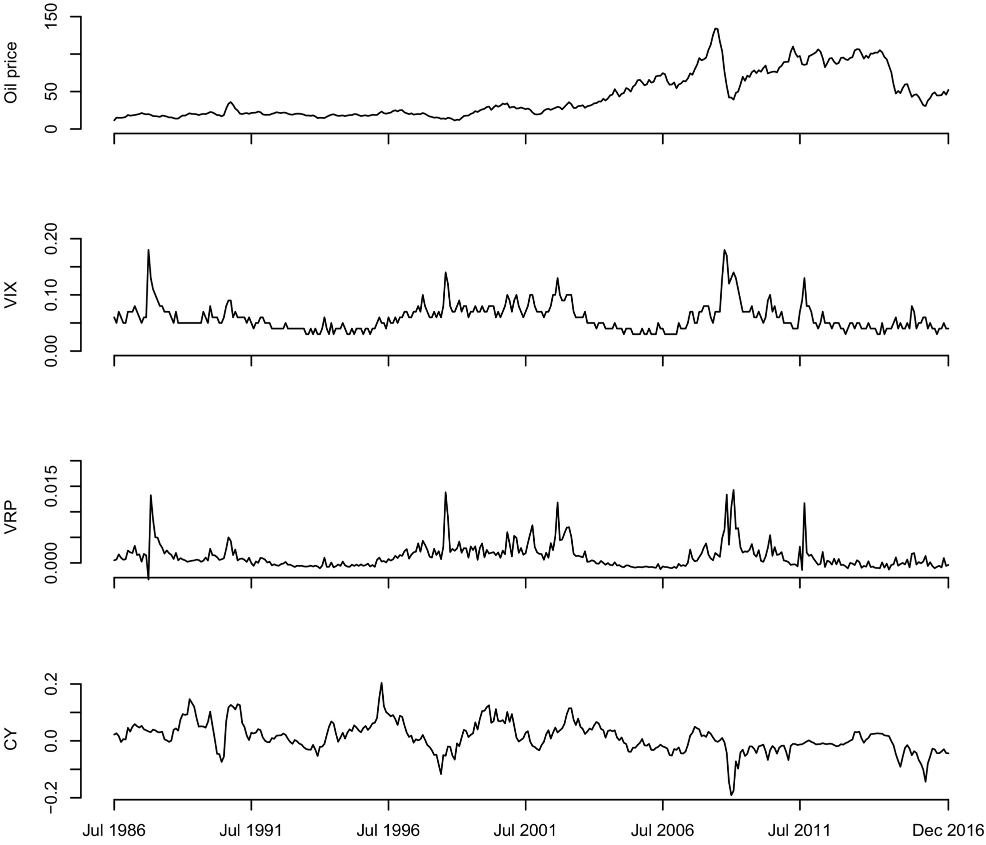
Oil price
150
50
0
VIX
0.20
0.10
0.00
VRP
0.015
0.000
CY
0.2
0.0
−0.2
Jul 1986
Jul 1991
Jul 1996
Jul 2001
Jul 2006
Jul 2011
Dec 2016

Figure 2