The Shale Revolution and Shifting Crude Dynamics

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Summary

Oil price fluctuates in response to both demand and supply shocks. This paper proposes a new methodology that allows for timely identification of the shifting contribution from the two types of shock through a joint analysis of crude futures options and stock index options. Historical analysis shows that crude oil price movements are dominated by supply shocks from 2004 to 2008, but demand shocks have become much more dominant since then. The large demand shock following the 2008 financial crisis contributes to the start of this dynamics shift, whereas the subsequent shale revolution has fundamentally altered the crude supply behavior.

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Crude oil continues to be a major energy source, playing a vital role in the proper functioning of the modern economy, despite growing international interest in renewables and the shale revolution in the US. Crude oil price fluctuates in response to both demand and supply shocks. Major events and structural changes can induce large variations in the expected magnitudes of the shocks, as well as their relative contribution to oil price movements. Seemingly identical oil price movements with different underlying driving forces can have vastly different implications for the aggregate economy, and for risk management practices across different industries.

Historically, research on oil centers around the impact of oil price fluctuations on the aggregate economy. More recent literature, e.g., Kilian (2009), recognizes the endogenous nature of oil price fluctuations and proposes to use structural VAR models to decompose the sources of exogenous shocks. Given certain identification assumptions, and assuming that the VAR structure is stable over a long enough time period, one can estimate the VAR structure with time-series data and analyze how different shocks interact with one another to impact oil price movement.

In reality, the VAR structure can vary over time, and timely identification of its variation is particularly important for risk management purposes. As a concrete example, oil price hikes induced by supply shocks are commonly regarded as negative shocks to the aggregate economy and bad news for the financial market. Supply shocks can also be a major threat to the bottom line of heavy energy users such as the airline industry, which often finds it beneficial to proactively hedge its exposures for fuel cost fluctuations. However, when oil price increases are induced by

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1See recent surveys of this literature by Brown and Yücel (2002), Jones, Leiby, and Paik (2004), and Huntington (2005).
2Several studies examine the reasonability and implications of the identification assumptions for such structural VAR models, e.g., Kilian and Murphy (2012), Baumeister and Hamilton (2018), and Caldara, Cavallo, and Iacoviello (2018).
demand shocks, they become the precursors of a strong economy and good news for the financial market. The negative impacts of demand shocks on the airline industry fuel costs can also be partially offset by a strong economy’s increased demand for air travel and hence airline revenue growth. The offsetting effect can partially negate the need for fuel cost hedging. The example of the airline industry illustrates how important timely and accurate prediction of the time variation in the relative contribution of the different types of shocks is not only for understanding crude price behavior, but also for predicting the impacts of oil shocks on different segments of the economy, and for managing the risk of oil price exposures across different industries.

This paper proposes an option-analytic methodology that allows real-time identification of the time-varying contributions from demand and supply shocks. The methodology uses variations of the S&P 500 Index (SPX) as a proxy for demand shocks, and projects crude oil futures price variation onto the SPX variation. The real-time identification relies on a joint analysis of crude futures options and stock index options, while allowing both stochastic volatility on the index return and stochastic loading of the crude futures on the stock index.

The stock index proxy highlights aggregate market demand, as reflected by the performance of the financial market of a dominant economy, rather than a narrowly-defined specific demand for oil. More importantly, by choosing a financial security index with actively traded options rather than an aggregate macroeconomic indicator (such as the gross domestic output), our approach can achieve sharper and real-time identification of the demand contribution variation through the options observations.

Each day, option prices across different strikes on a financial security present a complete picture of the market’s perception of the security’s risk level and its conditional return distribution over the horizon of the option’s expiry (Breeden and Litzenberger (1978)). In particular, the implied variance of an at-the-money option well approximates the market expectation of the future realized variance of the underlying security return over the span of the option maturity.\(^5\) The im-

\(^5\)See Carr and Wu (2016) for a formal proof of the approximate equality, as well as empirical evidence that option-implied information dominates GARCH-volatility estimators in predicting future realized volatility.
plied variance of an option is the variance rate input to the Black and Scholes (1973) and Merton (1973) (BMS) model such that the model value matches the observed option price. Under the BMS model environment, the implied variance is identical to the constant variance rate of the underlying security return. Under more general market conditions when the variance rate is allowed to be stochastic, the BMS implied variance represents the risk-neutral expected value of the future weighted average of the variance rates over the span of the option maturity, with the weight proportional to the BMS gamma of the option at that time (Carr and Madan (2002)). Given its intuitive economic meaning and its unique, monotone mapping with the option price, the BMS implied variance has been widely adopted both in the finance industry and in academia as a convenient transformation of the option price to provide a more stable and more intuitive quotation that better reflects the option’s information content. This paper proposes to take full advantage of the actively traded options on both the crude oil futures and the stock index, and extract real-time variance forecasts on the two series from the options observations.

In addition to the implied variance level, another piece of useful information comes from the slope of the option implied variance plot against the log strike-forward ratio, commonly referred to as the implied variance skew. The implied variance skew reflects the asymmetry (skewness) of the underlying return’s risk-neutral distribution. For the stock index, the risk-neutral return distribution is almost always negatively skewed due to investor fear of market crashes (Foresi and Wu (2005), and Wu (2006)). Another major driver of the negative return distribution is the well-documented negative correlation between the index return and its volatility (Carr and Wu (2017)), a result of the volatility feedback effect: Increasing systematic market volatility raises the discount rate and depresses the index valuation, thus generating a negative correlation between volatility shocks and index return.

When we project the crude futures return onto the stock index return, we follow classic asset pricing theory by assuming that only systematic risk is priced. Accordingly, both the fear of market crashes and the volatility feedback effect carry over to the market demand-driven component of the crude futures return, but neither effect applies to the projection residual. Thus, the negative skew
in the option-implied crude futures return distribution comes purely from the demand shock.

With the source of negative skew in the crude futures options pinned down, we can determine the loading of the demand shock on the crude futures at any point in time, as well as the relative variance contribution of demand shocks at that time, via the joint analysis of the implied volatility levels and skews from the crude futures options and the stock index options at that time. The identified demand shock variance magnitude and its crude oil loading are all in real time, depending only on the observed cross section of option implied volatilities from the two options markets on the same date, but with no dependence on any time series estimation over any sample period.

The options implied variance levels and skews from both markets vary strongly over time, as do our extracted market demand loadings on the crude oil. Historical analysis of crude futures options and stock index options data from 2004 to 2016 shows large short-term variations in the variance contribution of demand shocks. The analysis also identifies a broad shift in the underlying dynamics. The relative variance contribution estimates from demand shocks remained low between 2004 and 2008, fluctuating between 0 and 30%. Since then from 2009 to 2016, the estimates have become much higher, reaching as high as 80%.

We explore ex post explanations for the broad shift in the dynamics during our sample period, and identify several driving factors. First, the large negative demand shock from the Great Recession — triggered by the 2008 financial crisis — contributes to the sharp rise in the demand shock contribution around 2008.

Second, the large negative demand shock also induced drastic monetary policy actions, pushing the short-term interest rates around the world close to the zero lower bound. Datta, Johannsen, Kwon, and Vigfusson (2018) show that such a macroeconomic environment can drastically reduce the impact of supply shocks, or even reverse the direction of the impact. This muted, or even reversed, response to supply shocks allowed the impact of demand shocks to dominate over a sustained period of time long after the Great Recession.

Third, we find that the shale revolution has also fundamentally altered oil supply behavior.
The shale revolution refers to the recent surge in US tight oil production from shales, following technological advances in horizontal drilling and hydraulic fracturing that have drastically reduced the cost of enhanced oil recovery. According to production data from the Energy Information Administration (EIA), the US tight oil production was just over one million barrels per day in 2007. Production picked up pace in 2011 and had reached 5.5 million barrels a day in 2015, accounting for about 17% of the supply from the OPEC (the Organization of the Petroleum Exporting Countries).

The significant increase in tight oil production, both in absolute quantity and in market share, has had profound impacts on the OPEC behavior and crude price dynamics. We can see that before the shale revolution there were strong dynamic interactions between OPEC supply and crude prices, with changes in crude prices positively predicting future variations in OPEC crude supply. These dynamic interactions are consistent with what one would expect from a cartel that actively alters production to influence market prices and maximize profits. However, since 2011, such dynamic interactions have virtually disappeared. We conjecture that this muted response from OPEC countries reflects an acknowledgement of their diminished price-setting power and consequently lower incentive to attempt to use production cuts to raise crude oil prices.

When supply shocks dominate the crude oil price variation, the crude price increase mainly represents an increase in energy costs for production, and thus becomes a negative influence on the world economy. Regardless of whether it is because of the diminishing role of the OPEC cartel or because of the muted market response under the new monetary policy conditions, as the impact of supply shocks becomes muted, the impact of demand shocks starts to dominate. A decline in crude oil price signifies weakening demand, and hence is a bad signal for the economy. Reflecting this dynamics shift, low strike options on crude futures become more expensive relative to high strike options, and the option implied volatility slope against the strike price becomes more negative.

6To avoid confusion from oil shale, which is shale rich in kerogen, or oil produced from oil shales, the International Energy Agency recommends using the term “light tight oil” or “tight oil” for oil produced from shales or other very low permeability formations. The term “shale revolution” thus refers to the sharp increase in US oil production from shales or other very low permeability formations.
when investors start to worry that crude oil price drops indicate a weakening of demand, rather than worrying about crude price hikes as a gauge of production cost. These sentiment shifts allow us to identify the dynamics variation through the joint analysis of the stock index options and crude futures options.

Our identification approach both exhibits strong flexibilities and makes strong assumptions. One strong assumption is the use of a major financial index as the proxy for aggregate market demand. This assumption prevents us from talking about the specifics of explicit oil demand, but allows us to build a direct link between the financial market index and the crude oil price, thus enabling us to predict the variation of the time-varying contribution of demand shocks based on the forward-looking information in the two options markets. One key flexibility of our approach is its lack of dependence on the full specification of the supply and demand dynamics. As such, the approach allows us to identify the demand contribution at each date without specifying how and whether the dynamics are experiencing structural shifts. Estimating dynamics and identifying structural shifts are challenging econometric tasks. Our approach allows us to make the identification of the demand contribution variation without making judgements on its underlying dynamics.

Throughout history, oil prices have gone through many ups and downs. Prices go up when major oil fields are exhausted and productivity declines, when production is disrupted by war or other political crises, when producers reduce production deliberately (either through government regulation or via a cartel organization such as OPEC), and when a new demand (such as the start of the automobile era) or a new market (such as an emerging economy) cannot be met by supply fast enough. Prices go down when new technological advances reduce production costs and increase production capacity, when new, inexpensive energy sources (such as new oil fields or alternative energy sources) are found, and when recessions reduce demand for consumption. This paper focuses on the most recent decade, when technological advances in horizontal drilling and hydraulic fracturing have made enhanced oil recovery feasible at a competitive cost, and have significantly

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7See Hamilton (2013) for a historical overview, and Baumeister and Kilian (2016) for an analysis of the major events during the past 40 years.
expanded tight oil supply from the US.

More important, the recent decade has seen an explosion of options trading across many financial markets, and accordingly a valuable new information source for understanding the underlying dynamics variations. While the theoretical underpinning on the information content of options was established some forty years ago (Breeden and Litzenberger (1978)), academics, practitioners, and policy makers alike have only recently come to realize the growing importance of leveraging this information source for monitoring and managing market risks and sentiments (e.g., Birru and Figlewski (2012), Breeden and Litzenberger (2013), Kocherlakota (2013), and Datta, Londono, and Ross (2017)). Our paper can be regarded as part of this trend. By linking options on the stock index to options on crude oil futures, our approach allows real-time identification and monitoring of the variation of the relative demand contribution to crude oil price movements.

In linking the option implied variance level and slope to the underlying security return variance and the return covariance with the variance rate, we rely on the theoretical work of Carr and Wu (2016), who first proposed the idea of characterizing the option implied volatility surface of an underlying security based on its own near-term behavior without specifying the full long-run dynamics. The short maturity expansions of Medvedev and Scaillet (2007) can lead to similar linkages. Ait-Sahalia, Li, and Li (2019) also obtain similar linkages via functional expansions of stochastic volatility models.

In linking the implied variance skew of the crude futures options to that of the stock index, we rely on the classic asset pricing theory that only systematic risk is priced, and accordingly the volatility feedback effect only applies to the demand component of the crude futures movement. The literature, e.g., Chang, Christoffersen, Jacobs, and Vainberg (2012) and Carr and Madan (2012), has attempted to make similar identifications with the more direct assumption that the implied volatility skew is purely caused by the market risk component of the security return, without specifying the underlying mechanism. The volatility feedback effect that we propose is one mechanism that supports this assumption.
The rest of the paper is organized as follows. Section 2 decomposes the crude price shocks into demand and supply shocks with time-varying volatilities and loading, and builds the theoretical framework for identifying the time-varying contribution through the joint analysis of stock index and crude futures options. Section 3 extracts the time-varying demand contribution to crude price fluctuation from options on the S&P 500 Index and WTI crude futures. Section 4 examines the underlying drivers of the observed dynamics shift. Section 5 provides concluding remarks.

2 | TIME-VARYING SUPPLY AND DEMAND SHOCKS IN OIL DYNAMICS

Similar to common practice, we decompose the crude oil futures dynamics into demand and supply shocks. However, deviating from earlier literature, we do not focus on the average expected interactions between the two types of shocks, but rather highlight the time variation in the magnitudes of the two types of shocks and their impacts on the crude futures price.

To incorporate options data into our analysis, we comply with the option pricing literature and adopt the continuous time notation. We use $dW^s_t$ and $dW^d_t$ to denote supply and demand Brownian shocks, respectively, and model their time-varying impacts on the crude futures price dynamics $O_t$ via the following stochastic differential equation,

$$dO_t/O_t = \mu_t dt + \eta^d_t \sqrt{\nu^d_t} dW^d_t - \eta^s_t \sqrt{\nu^s_t} dW^s_t, \quad \eta^d_t, \nu^d_t, \eta^s_t, \nu^s_t \geq 0,$$

(1)

where we posit that positive demand shocks lead to oil price increase and positive supply shocks lead to oil price decline. We capture the time-varying expected magnitudes of the two types of shocks via the two instantaneous variance rates $\nu^d_t$ and $\nu^s_t$, and capture their time-varying impacts on the crude futures price using the two positive loading coefficients $\eta^d_t$ and $\eta^s_t$.

To enhance the separation of demand and supply shocks on crude futures, we use the variation of the US stock market, and specifically the S&P 500 Index (SPX), to proxy demand variation. SPX options are actively traded both on exchanges and over the counter. The literature often chooses
to proxy demand shocks with either some specific measure of oil demand, or some aggregate real economic strength measure. By using the S&P 500 Index as the proxy, we highlight the systematic financial market risk and how it interacts with oil price movements. More importantly, the choice of a financial security index with actively traded options, together with options on crude futures, allows us to better identify the time variation in the intensities of demand shocks and its contribution to crude futures movements.

With the SPX as a proxy for the demand shock \( (D_t) \), we model its dynamics as

\[
\frac{d D_t}{D_t} = \mu_d^d dt + \sqrt{v_t^d} dW_t^d.
\]

(2)

We can think of the specification in equation (1) as a projection of the crude futures movement onto the SPX movement \( dW_t^d \), and treat the projection residual \( dW_t^s \) as the orthogonalized, idiosyncratic supply shock. By nature of the projection, the two types of shocks are orthogonalized:

\[
\mathbb{E}[dW_t^d dW_t^s] = 0.
\]

(3)

The variance rate \( v_t^d \) on the stock index return varies strongly over time, and its variation shows highly negative correlation with the index return. We represent the variance rate dynamics as,

\[
dv_t^d = v_t^d dt + \sqrt{\omega_t^d} dZ_t^d, \quad \rho_t^d = \frac{1}{dt} \mathbb{E}[dW_t^d dZ_t^d] < 0.
\]

(4)

A major driver of the negative return-variance correlation is the well-known volatility feedback effect: Increasing systematic market volatility raises the discount rate and depresses the index valuation, thus generating a negative correlation between volatility shocks and index return.

Based on classic asset pricing theory, only the market risk is priced. Accordingly, the volatility feedback effect only applies to the market risk, and does not apply to the idiosyncratic supply shock. Therefore, we assume zero correlation between the idiosyncratic shock and its variance.
rate,

\[ \mathbb{E}[dW_t^s d\nu_t^s] = 0. \]  

(5)

Equations (1)-(5) only partially specify the crude futures dynamics because we leave the details of the dynamics for many stochastic processes unspecified, including the dynamics for \( \mu_t^o, \eta_t^d, \eta_t^s, v_t^s, \mu_t^d, \nu_t^d, \omega_t^d, \) and \( \rho_t^d. \) Our identification methodology allows us to identify the quantities of interest \( (v_t^d, \eta_t^d, \sqrt{v_t^d}) \) at each date without specifying or estimating the full dynamics. The three identified quantities allow us to track the variation, in real time, of the magnitude of the demand shock, the demand loading on the crude futures, and the percentage variance contribution from demand shocks.

In related literature, Kilian and Park (2009) strive to identify the impact of oil price shocks on US stock returns. Their analysis is in line with the traditional focus of estimating the average impact of oil shocks on the aggregate stock market via a VAR structure. Such VAR structures focus on the average expected response of a unit shock from a certain source. By contrast, our specification leaves the details of the expectation component, e.g., \( (\mu_t^o, \mu_t^d, \mu_t^s) \), unspecified. Instead, we lever the information content of the options market and focus on the identification of the time variation of the variance and covariance of the shocks. Whereas the structural VAR literature treats the expectation component of the VAR structure and the covariance matrix of the shocks as constants during the estimation period, our identification focuses on the time variation. The two approaches complement each other in analyzing different aspects of the crude oil price dynamics. While understanding the average VAR structure is important for academic insights, especially when the VAR structure is well-specified and stable over a long period of time, identifying the timely variation of variance contribution from different types of shocks is equally important, if not more so, for many practical applications.
2.1 | Identifying time-varying demand without specifying its full dynamics

Researchers have developed econometric methodologies to infer the price dynamics of a financial security based on its historical time series behaviors. These methodologies often rely on the assumption that some specified dynamics are a reasonable approximation of true behavior and the specification is stable for long enough of a sample period for it to be well identified from the time series during that sample period. However, when the financial security is equipped with an actively traded options market, the information available to researchers becomes much richer. In particular, from the observed option prices across different strikes at any given date, one can construct the full conditional risk-neutral return distribution over the horizon of the option expiry, with the help of some interpolation and smoothing across the discrete number of observed strikes, but without any assumptions on the underlying price dynamics.\(^8\) Our identification of the time-varying dynamics for the demand shocks relies on the rich information embedded in the observed option prices on the S&P 500 Index.

Instead of constructing the whole return distribution from the observed option prices across all strikes, we distill two important quantities from the distribution that are relevant for our dynamics setting. Specifically, it is well-known in the option pricing literature that the at-the-money option implied variance reflects market expectation of future realized variance and the slope of the implied variance plot against the log strike-forward ratio reflects the risk-neutral skewness of the underlying return distribution. Under our dynamics specifications for the market demand shocks in equations (2) and (4), the variance of the return distribution over a short horizon is captured by the instantaneous variance rate \(\nu^d_t\), and the skewness of the return distribution is generated by the covariance between the index return and proportional changes in its variance rate, \(\zeta^d_t = \sqrt{\nu^d_t} \omega_t^d \rho^d_t\).

We can therefore extract the variance rate and the covariance rate at each date from the at-the-

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\(^8\)The theoretical linkage between the conditional risk-neutral return distribution and the second derivatives of the option prices against the strike price has been established some forty years ago by Breeden and Litzenberger (1978). More recent efforts consider various interpolation and smoothing techniques to construct stable second derivatives from the observed option prices at a discrete number of strikes. Examples include Aït-Sahalia and Lo (1998), Figlewski (2009), Breeden and Litzenberger (2013), and Malz (2014).
money implied variance and its slope against the log strike-forward ratio.

We use $A^d_t$ to denote the at-the-money option implied variance for the stock index at some short option maturity and use $S^d_t$ to denote the slope of the option implied variance plot against the log strike-forward ratio $k = \ln K/D_t$ estimated around $k = 0$. The following proposition establishes a formal linkage between the at-the-money implied variance level $A^d_t$ and its slope $S^d_t$ on the one hand, and the variance rate $\nu^d_t$ and its covariance rate $\zeta^d_t$ on the other.

**Proposition 1** Under dynamics assumptions for the stock index in (2) and its variance rate in (4), the instantaneous variance rate of the index return ($\nu^d_t$) can be approximated by the short-term at-the-money option implied variance ($A^d_t$),

$$\nu^d_t = A^d_t. \quad (6)$$

The covariance rate ($\zeta^d_t$) between the index return and proportional changes in the variance rate can be approximated by the at-the-money option implied variance slope ($S^d_t$) against the log strike-forward ratio,

$$\zeta^d_t = 2S^d_t. \quad (7)$$

The online appendix provides a formal proof for the linkage. This proof builds on the Carr and Wu (2016) theoretical framework which allows timely identification of the levels of the variance rate and the covariance rate without fully specifying the underlying dynamics. Similar linkages can also be obtained via the short-maturity expansion of Medvedev and Scaillet (2007) or the functional expansion of Ait-Sahalia, Li, and Li (2019).

### 2.2 Identifying time-varying demand contribution to oil price movements

Proposition 1 establishes a formal linkage between the at-the-money option implied variance level and its slope on the one hand, and the variance rate and the return-variance covariance rate on
the other. This linkage can be used for both the stock index and the oil futures based on their corresponding options.

For the stock index, the return-variance covariance rate is always negative because of the volatility feedback effect: Increasing market risk reduces the stock market valuation. For crude oil, how negative the return-variance covariance rate is depends on how much of its return variation is driven by the demand shock as proxied by the stock index. The larger the demand shock contribution, the stronger the contribution of the volatility feedback effect, and accordingly the more negative the covariance rate will be. In the limiting case when the demand shock contribution is zero and the oil price movement is purely driven by the idiosyncratic supply shock, there will be no volatility feedback effect as it is a distinct feature of the market risk. In this limiting case, under our dynamics specification, the return-variance covariance rate will be zero, the oil return distribution will be symmetric, and the implied variance plot against the log strike-forward ratio will have a zero slope. Thus, the time variation in the slope of the implied variance skew plot for the oil futures options reflects the time variation in the demand shock contribution to the oil price movement.

The following proposition establishes the formal linkage between the implied variance level and skew for the index options and crude futures options on the one hand, and the demand shock contribution to oil price movement on the other.

**Proposition 2** Under dynamics assumptions for the crude futures and the stock index in (1)–(5), the demand shock’s loading on the crude futures \((\eta^d_t)\) can be directly computed from the implied variance level and implied variance skew differences between the crude oil futures and the stock index,

\[
\eta^d_t = \left( \frac{A^o_t S^o_t}{A^d_t S^d_t} \right)^{1/3}.
\]

**Proof.** Starting with the oil price dynamics decomposition in (1), since the two types of shocks are orthogonal as specified in (3) by virtue of projection, we can decompose the crude futures return
variance as,

\[ \nu_t^\sigma = (\eta_t^d)^2 \nu_t^d + (\eta_t^s)^2 \nu_t^s. \] (9)

By classic asset pricing theory, the idiosyncratic risk \((dW_t^s)\) shows no feedback effect and hence zero correlation with its variance rate \((\nu_t^s)\), \(\mathbb{E}_t[dW_t^s d\nu_t^s] = 0\) as stated in (5). We can attribute the return-variance covariance rate for the crude oil futures \(\zeta_t^o\) to its loading on the demand shock,

\[ \zeta_t^o = \frac{1}{dt} \left[ \eta_t^d \sqrt{\nu_t^d} dW_t^d + \eta_t^s \sqrt{\nu_t^s} dW_t^s \right] = \frac{(\eta_t^d)^2 \nu_t^d}{\nu_t^o} \zeta_t^d. \] (10)

Combining (9) with (10), we can represent the demand shock loading \(\eta_t^d\) as a function of the variance and covariance rates of the two financial security returns,

\[ \eta_t^d = \left( \frac{\nu_t^o \zeta_t^o}{\nu_t^d \zeta_t^d} \right)^{1/3}. \] (11)

Furthermore, from Proposition 1, we can represent the variance and covariance rates with the at-the-money option implied variance level and slope of the corresponding security,

\[ A_t^d = \nu_t^d, \quad S_t^d = \frac{1}{2} \zeta_t^d; \quad A_t^o = \nu_t^o, \quad S_t^o = \frac{1}{2} \zeta_t^o. \] (12)

Plugging (12) into (11), we can represent the demand shock loading purely as a function of the implied variance levels and slopes of the two options markets,

\[ \eta_t^d = \left( \frac{A_t^o S_t^o}{A_t^d S_t^d} \right)^{1/3}. \] (13)

Our identification relies on two mechanisms: First, the negative implied variance skew is generated by the negative return-variance covariance. Second, the degree of the negative return-variance
covariance for each security depends on the security’s loading on the market risk. The literature, e.g., Chang, Christoffersen, Jacobs, and Vainberg (2012), makes similar identifications with the more direct assumption that the implied variance skew is purely caused by the market risk component of the security return, without specifying the underlying mechanism. The volatility feedback effect that we propose is one mechanism that supports this assumption.

In addition to the volatility feedback effect, the price dynamics can also experience large random jumps. The jumps generate fat tails on the short-term return distribution. Market pricing of the jump risk distorts the return distribution and makes its risk-neutral counterpart more negatively skewed. This negative skew distortion partially reflects investors’ extreme aversion to market crash risk (Wu (2006)). By contrast, if the jumps come from firm-specific shocks, the absence of market pricing on the firm-specific risk will leave the firm-specific component intact and the risk-neutral return distribution will look more symmetric.

When both effects are present, the option implied variance skew on the stock index is not only driven by the volatility feedback effect, but is also driven by investor aversion to market crash risk. When we use the option implied variance skew of a financial security to identify its market risk component, we would expect its option skew to be more negative if its price crash contributes positively to the stock market crash. The effect is similar to that of the feedback effect. In our application to crude oil futures, when crude oil price movement is driven by demand shocks, a crude price crash indeed becomes a market concern as it is a reflection of demand crash. Thus, if the crude futures options show a negative implied variance skew due to concern about a crude price crash, the negative skew reflects the contribution from demand shock. By contrast, the traditional market concern for crude supply shocks is to the opposite direction. The market tends to worry about spikes in crude oil price and its negative impacts to the real economy. If such concerns dominate, the crude options implied variance skew are positive, a sign that the concern is more driven by supply than by demand. Our identification strategy remains robust whether the negative skew of the index options is driven by feedback effect or concern for market crash.
Another way of measuring the significance of the demand shock is through its relative variance contribution, which can also be represented in terms of the at-the-money option implied variance levels and skews of the two options markets,

\[
V C^d_t = \frac{(\eta^d_t)^2 \nu^d_t}{\nu^o_t} = \left( \eta^d_t \right)^2 \frac{A^d_t}{A^o_t}.
\]  

(14)

While the demand loading coefficient \( \eta^d_t \) captures the direction and magnitude of the oil price response to each unit of demand shocks, the variance contribution \( V C^d_t \) is analogous to an R-squared estimate, measuring the proportion of return variance in crude oil price movements that can be attributed to demand shocks.

One caveat for this alternative representation is that the variance contribution is always a positive number, no matter whether the demand loading is positive or negative. In general, we expect the demand loading to be positive because increased market demand tends to raise crude oil prices. Nevertheless, the estimate can indeed become negative when supply shocks dominate the oil price movements and the supply-driven oil price hikes induce a negative impact on the aggregate economy and the financial market. In this case, the negative loading estimate captures the inverse relation between the movements in the oil price and the stock market. In cases where the demand loading is negative, we propose to either truncate the variance contribution to zero or to add a negative sign to the variance contribution estimate to highlight the fact that these are periods where supply shocks dominate. Although demand shocks contribute positively to the oil return variance when the demand loading is negative, their contribution is the other way around and is induced by the negative impact of supply shocks on the market demand.

In reality, the skewness of the option-implied return distribution on crude oil futures can also vary for reasons not directly related to market demand. For example, when geopolitical risks are high, market can become concerned about oil supply and oil price hikes, the option implied variance skew can become positive. On the other hand, when OPEC members are at high risk of reneging on quotas and sharply increasing supply, market concerns about oil price drops can
drive the option implied variance skew to be negative. To the extent that these supply shocks have an impact on the aggregate economy and the financial market, they can be classified as demand shocks induced by supply shocks, and will be captured by our projection of the crude oil futures return onto the stock index return. Still, the remaining idiosyncratic supply-driven variations in the implied variance skew can add noise to our estimates of the demand shock loading. Since such idiosyncratic skew variations tend to happen more at short option maturities, we can mitigate their influence on our demand loading estimates by choosing options at intermediate maturities.

3 | Identifying Time-Varying Demand From Options

We estimate the relative contribution of demand shocks using options on NYMEX Light Sweet Crude Oil (WTI) futures and the S&P 500 Index (SPX). WTI crude futures and futures options are actively traded on the Chicago Mercantile Exchange (CME). We obtain daily futures and futures options data from the CME going back to the 1990s, but the options data quality is poor in the earlier part of the sample. We perform our analysis using data from January 2004 to April 2016. The options on WTI futures are American style. We use the Barone-Adesi and Whaley (1987) quadratic approximation to value the American options and transform the option prices into BMS implied volatilities. The SPX options are actively traded on the Chicago Board of Options Exchange (CBOE). The contracts are European style. We obtain historical daily closing prices and BMS implied volatilities on the SPX options from OptionMetrics over the same sample period.

3.1 | Constructing floating implied variance and skew series

We identify the demand contribution to crude oil price movements through the option implied variance levels and implied variance skews against the log strike-forward ratio on WTI futures options and SPX options. The exchange-listed option contracts have fixed strike prices and expiration dates. To construct floating implied variance time series at fixed log strike-forward ratios \(k\)
and time to maturities ($\tau$), at each date we perform local quadratic regression of implied variance against the log strike-forward ratio at each observed maturity to obtain implied variance estimates at fixed grids of log strike-forward ratios. The local quadratic smoothing uses a Gaussian kernel. The bandwidth is set to be proportional to $|k|$ (but with a minimum of 5%) so that the regression uses a larger bandwidth to smooth more for noisier, deeper-out-of-the-money options, but uses a smaller bandwidth to allow more variation and better fitting of the strong curvature around $k = 0$. When both a call option and a put option are available at a strike, we choose the option that is out of the money: call options for strikes greater than the futures price and put options for lower strikes. We filter the data to exclude options with settlement prices at one cent or lower, and data with extreme implied volatility estimates. After the data filtering, we perform the local quadratic smoothing in two passes. The first pass is with equal weighting. The second pass applies a weighting that discounts data points that deviate far from the first-pass smoothing. This two-pass approach adds robustness to the smoothed function as it is less affected by outlier observations.

Next, we perform linear interpolation on total variance against time to maturity at each moneyness level to obtain implied variance series at fixed time to maturities. Linear interpolation on total variance amounts to assuming a stable piece-wise constant forward variance term structure. The at-the-money forward implied variance represents a better approximation of the instantaneous variance rate at shorter option maturities. The term structure effect can become more significant at longer maturities, due to expected future variance movements, variance risk premium, and skew and convexity adjustments. Options trading activities on both the crude futures and the SPX are also concentrated at short maturities. Nevertheless, when the time to maturities become too short, the option values become small, and the effects of bid-ask spreads, data noises, and short-term idiosyncratic variations become more pronounced in the implied variance level and skew estimates. We extract the implied variance level and skew at three-month maturity to balance out the different considerations. While the qualitative conclusions remain the same, choosing a shorter maturity tends to generate noisier time series, whereas data at longer maturities become sparse.

With the three-month implied variance estimates at different log strike-forward ratios, we com-
pute the implied variance skew around $k = 0$ by taking the implied variance differences at $k = \pm 3\%$,

$$
S_t = \frac{I_t^2(k = 3\%) - I_t^2(k = -3\%)}{0.06}.
$$

(15)

To generate robust skew estimates, we require a minimum of 10 valid implied volatility quotes at each maturity to perform local quadratic smoothing and require a minimum of three valid maturities to perform total variance interpolation along the maturity dimension.

### 3.2 | Time-varying implied volatility level and skew

Figure 1 compares in Panel A the time series of the three-month at-the-money implied volatility on the crude futures options and the SPX options. The implied volatility levels for the crude futures options (solid line) stay above the implied volatility levels for the stock index (dashed line), suggesting that crude futures movements are more volatile than the stock index. During the sample period, the implied volatility for the crude futures averages at 32.72%, and varies over a wide range from as low as 13.23% to as high as 83.73%. The implied volatility for the stock index also varies significantly, from as low as 9.81% to as high as 63.86%, with an average of 18.66% over the same sample period.

The two series show more independent variations during the first half of the sample period, but more co-movements during the second half. If we divide the sample by half using December 2010 as the cutoff point, the cross-correlation between daily log percentage changes of the two series is estimated at 26% for the first half, and 41% since then. The financial crises in 2008-2009 induced large implied volatility spikes for both the crude futures and the stock index. The two series also experienced common upward moves during the European debt crisis in 2010-2011 and the China demand shock in 2015. On the other hand, between 2004 and 2007, the crude futures options implied volatility went up on several occasions while the SPX option implied volatility stayed low.

Panel B of Figure 1 compares the implied variance skew on crude futures options and the SPX
FIGURE 1 Time-varying implied volatility levels and skews for crude futures and stock index options. Lines plot the time-series of the three-month at-the-money implied volatility level in Panel A and the three-month implied variance skew in Panel B for options on the WTI crude futures (solid lines) and the SPX stock index (dashed lines).

options. The stock index implied variance skew has been well-known to be persistently negative across time periods and maturities. The magnitude of the negative skew varies strongly over time, being less negative during the calm period of 2004-2006, more negative during the 2008-2009 financial crises, the subsequent European debt crises in 2010-2011, and the China market crash in 2015.

In contrast to the persistently negative implied variance skew on the stock index options, the crude futures options show little skew in either direction during the first five years of the sample (from 2004 to 2008). The crude futures implied variance skew turned negative by the beginning of 2009, and has stayed mostly negative since then. The implied variance skew on the crude futures has also become increasingly co-moving with the implied variance skew on the stock index. If we again use the end of 2010 as the cutoff point, the cross-correlation estimate between daily changes of the two implied variance skew series is negative at −6% for the first half of the sample period, but becomes strongly positive at 21% since then. The increased co-movements between the crude futures and the stock index in both their implied variance levels and their implied variance
skews suggest that demand shocks, or market risk, played a more important role in crude futures movements in the second half of the sample.

### 3.3 Time-varying demand shock contribution to crude futures movements

The time variation of the implied variance levels and skews on the stock index options serves to highlight the time variation in the magnitudes of demand shocks and the volatility feedback effects on systematic market risk. By comparison, the time variation of the implied variance level on the crude futures options reflects the time variation in the contribution of both demand and supply shocks, while the time variation of the implied variance skew on the crude futures options mainly reflects the contribution variation of demand shock. Combining the implied variance levels and skews information from the two options markets, we can extract the relative contribution of demand shocks to the crude futures variation.

Specifically, from the interpolated at-the-money implied variance levels \((A_{\text{t}}^o, A_{\text{t}}^d)\) and implied variance skews \((S_{\text{t}}^o, S_{\text{t}}^d)\) from the two options markets, we can compute the oil loading coefficient on demand shocks \((\eta_{\text{t}}^d)\) as,

\[
\eta_{\text{t}}^d = \left( \frac{A_{\text{t}}^o S_{\text{t}}^o}{A_{\text{t}}^d S_{\text{t}}^o} \right)^{1/3}.
\]

Panel A of Figure 2 plots the time series of the estimated loading coefficients on demand shocks. The solid line represents monthly moving averages of the daily estimates to smooth over the short-term data noise. Before 2009, the demand loading coefficients showed large sample variations and went below zero for several extended sample periods. Because the stock index options skew \(S_{\text{t}}^d\) is persistently negative, the demand loading estimates can become negative if the crude futures options skew \(S_{\text{t}}^o\) becomes positive, which happened frequently before 2009. Since 2009, the demand loading coefficient estimates have become more consistently positive as the crude futures options skew has become more persistently negative.

Another way of looking at the demand shock contribution is through its relative variance con-
FIGURE 2 Time-varying demand shock contribution to crude futures movements. The solid line plots the loading coefficient on demand shocks ($\eta^d_t$) in Panel A and the percentage variance contribution from demand shocks to crude futures movements ($RC^d_t$) in Panel B. The lines are smoothed via monthly moving averages of daily estimates.

A. Demand-shock loading $\eta^d_t$

B. Variance contribution $VC^d_t$

Panel B of Figure 2 plots the monthly moving average of the relative variance contribution from demand shocks. When supply shocks dominate and the crude futures options market becomes concerned with oil price hikes, the options can show a positive implied variance skew and the demand loading becomes negative. While a negative demand loading also induces a positive variance contribution, we truncate the variance contribution to zero in the plot in such cases to emphasize the dominant role of supply shocks.

The variance contribution variation shows both large temporal variations and a broad structural shift around 2009. Before that, the demand shock contribution estimates are low and hover around zero. Since 2009, the demand shock contribution has become higher, and stayed high, for much of the remaining sample. During various periods from 2011 to 2015, the estimates reach over 80%.
4 | **Examining the Underlying Drivers of the Shifting Dynamics**

Our analysis of the two options markets shows that both the magnitudes of demand shocks and their relative contribution to crude futures movement vary strongly over time. Among large temporal movements, we also identify a broad dynamics shift during our sample period. The demand shock contribution to the crude futures movements stayed low during the first half of our sample period (from 2004 to 2008), but became much higher in the later period. This section examines the underlying drivers of this broad dynamics shift.

### 4.1 | Unusually large negative demand shocks

The start of the second half of our sample coincides with the Great Recession induced by the 2008-2009 financial crises. In US history the magnitude of this recession is second only to the 1930s Great Depression. Globally, the financial crises had negative impacts on world demand, and induced protracted debt crises in the Euro zone. In 2015, just as the US and Europe were getting back on an even financial keel, China, the world’s largest emerging market, experienced severe negative demand shocks that reverberated through both the US and the world’s financial markets. Therefore, compared to 2004-2007, a relatively quiet period, the second half of the sample period is unusual in both the magnitude and the frequency of large negative demand shocks.

These large negative demand shocks put downward pressure on the oil price, to the point that investors shifted from worrying about the negative economic impact of oil price hikes to worrying about persistently low aggregate demand. In this environment, low oil price is no longer perceived as the result of a beneficial supply shock, but rather an omen of weak aggregate demand.

When the magnitudes of demand shocks are expected to rise, the stock index options implied variance rises along with this expectation. Indeed, by combining options across different strikes around one-month maturity, the Chicago Board of Options Exchange (CBOE) has created a volatility index (the VIX) to track the time variation in market sentiment. The VIX has been dubbed as
the market’s “fear gauge.” Our interpolated three-month at-the-money implied variance level and skew represent similar gauges of market sentiment on financial market risk. When this risk is high, the sentiment can spread to the crude market. We use the implied variance skew of the crude futures options, relative to the implied variance skew of the stock index options, to quantify how much the demand risk has spread to the crude market.

4.2 | Changing responses to supply and demand shocks

In face of the financial crises and consequent recessions, central banks across the world hastened to cut short-term interest rates to stabilize financial markets and to stimulate economies. When the short-term rates were pushed to near the zero lower bound, central banks continued to push the longer-term interest rates lower through quantitative easing programs. The low interest rate environment lasted long after the financial crisis periods.

Under general market conditions, supply-driven oil price hikes have a negative impact on the aggregate economy. Many mechanisms have been proposed to account for the negative relation between supply-driven oil price increases and the aggregate economy. Among them, the classic supply side effect provides the most basic and direct explanation, in which rising oil prices are indicative of the reduced availability of a basic input to production. This effect can also explain the positive relation between oil price hikes and increases in inflation.

However, Datta, Johannsen, Kwon, and Vigfusson (2018) show that supply-driven oil price hikes do not always have a negative impact on the aggregate economy. Using a New Keynesian model, with an oil shock component, they establish that when the nominal interest rate is at the zero lower bound, rising oil prices and rising inflation may not increase the real rate, nor will they have a negative impact on the stock market. Thus, under the low interest rate environment since the financial crises, the aggregate economy and the stock market no longer respond to oil supply shocks the way they used to do. This more muted response makes an oil price hike less of a concern, even if it is driven by supply shocks and it becomes a positive signal if it is driven by
demand shocks. The net effect is a more positive co-movement between crude oil prices and the stock market, and a higher observed contribution from demand shocks.

4.3 | Shifting supply behavior since the shale revolution

Since the 1970s, the crude oil market has been dominated by OPEC, an intergovernmental organization of 13 crude-producing nations. Economists often cite OPEC as a textbook example of a cartel that coordinates members to reduce market competition. Still, the influence of OPEC has been periodically challenged by the recurring temptation for individual members to exceed production ceilings and pursue self-interest. More recently, the influence of OPEC has diminished by the development and expansion of other energy sources outside of its control.

The recent shale revolution represents one such challenge to the cartel’s price-setting power. The term “shale revolution” refers to the recent surge in US tight oil production from shales. To understand the behavior change of crude supplies and their impacts on crude price dynamics, we collect data on crude production from both OPEC countries and the US. While monthly production data are available from the Energy Information Administration (EIA) since 2004, US tight oil production is a recent endeavor, and its data start in 2007.

Over the decade 2006-2016, OPEC production was quite stable because of the cartel’s control, and hovered at around 30 million barrels per day, within a narrow range from 26 to 33 million barrels per day. The average annual growth rate was less than 1%. By contrast, in 2007, the US tight oil production started at just over one million barrels a day, picking up pace since 2011, with a sharp increase to its peak in 2015. At its peak in 2015, the US tight oil production reached 5.46 million barrels a day, about 17% of the total OPEC production. Over the whole sample period (2004-2016), the annual compounding growth rate for US tight oil production averages 13% per year.

As part of a cartel, OPEC member countries negotiate the quota for each participating country
and adjust the quota in response to demand and price variations. As part of profit maximization, any production increase is deliberately controlled to maintain an artificially high crude oil price. Oil rich, the OPEC countries can produce oil at a lower cost than other places. Historically, production by non-OPEC countries, including the US, was not significant enough to impact the OPEC’s price-setting power.

This situation started to change with the shale revolution. With advances in production technology, US companies have access to a much higher reserve via enhanced oil recovery, and can now produce large amounts of tight oil at a competitive cost. The sharp increase in US tight oil production, combined with softened demand since the Great Recession, has driven the crude oil price significantly below historical levels. When the OPEC-controlled price of crude oil falls, some US companies start to shut down operations and reduce tight oil production. Nevertheless, with new technological innovations driving the cost increasingly lower, tight-oil production is bound to develop when the crude price rises above a certain level. Such innovations in tight-oil production include, for example, multi-pad drilling, where the drilling rig only has to be moved as little as 20 feet before the next well can be drilled, drastically saving both time and cost. Another innovation is refracking of older wells, which can cost 75% less than drilling and fracking a new well. A recent report from energy consultancy Wood Mackenzie (2016) finds that US shale producers have become more adept at staying profitable, even with the low crude prices. The cost of production for US tight-oil operators has fallen by up to 40% over the past two years from 2014 to 2016.

We conjecture that the increasing significance of competitive US tight oil production reduces OPEC’s pricing-setting power. Tight oil production will pick up whenever the crude oil market price rises above a certain level, reducing the impact of the OPEC strategy and its incentives to manipulate price by reducing crude production.

To examine whether the shale revolution has actually affected the price-setting power and supply behavior of the OPEC cartel, we divide our sample into two broad periods, pre-shale revolution (from 2004 to 2010), and post shale revolution (from 2011 to 2016). We estimate the dynamic...
correlation between crude price and OPEC supply before and after shale revolution. Panel A plots the cross-correlogram between monthly log returns on WTI front-month futures prices and monthly log change in OPEC crude supply from 2004 to 2010. Panel B plots the cross-correlogram from 2011 to 2016. The bars represent the cross-correlation estimates at different leads or lags (in months). The dashed lines define the confidence bands at one standard deviation.

Interactions between crude price and crude production during these two time periods. Figure 3 plots the cross-correlation estimates between monthly log changes in OPEC crude production and monthly log changes in WTI front-month crude futures prices at different leads and lags. In each plot, the bars measure the correlation estimates. The two-dashed lines represent confidence bands at one standard deviation. The two panels (A and B) represent the two sub-sample periods.

Before 2010, crude price changes show strongly positive correlations with future OPEC production changes, suggesting that OPEC countries actively adjust their production in response to crude price changes, increasing production when the crude price rises and reducing production when the crude price falls. However, during the more recent sub-sample period since the shale revolution, the strong responses have all but disappeared. There is virtually no production response to the crude price movement during this later sub-sample period.

To examine the interactions in more detail, we focus on a one-quarter horizon and perform local linear lead-lag regressions. Panel A of Figure 4 estimates the one-quarter-ahead crude price
FIGURE 4 OPEC pricing-setting power and production behavior before and after shale revolution. Panel A plots the crude oil price response function to OPEC production changes. Panel B plots the OPEC production response function to crude price change. The functions are estimated using a local linear regression of one-quarter ahead responses to past one quarter changes. The solid lines are estimated using data from 2004 to 2010. The dashed lines are estimated using data from 2011 to 2016. The dash-dotted lines define the 10-90% confidence bands.

response function to OPEC production changes by performing a local linear regression of one-quarter-ahead WTI futures log returns against the past one quarter’s log change in OPEC crude supply. The solid line plots the estimated response function for the sample period from 2004 to 2010 and the dashed line plots the estimated response function for the period from 2011 to 2016. The dash-dotted lines define the 10-90% confidence band, obtained from bootstrapping.

First, the solid line stays above the dashed line across all production variations, capturing the historical observation that crude oil prices from 2004 to 2010 have gone up more than from 2011 to 2016. Second, the solid line is largely flat, suggesting that crude oil prices are not sensitive to OPEC production variations. Such a response function is very beneficial to OPEC producers as they can raise production without much of a price decline.

The behavior represented by the dashed line estimated for the period from 2011 to 2016 is very different. The slope of the dashed line is much more negative, and more so for production increases than for production cuts. Thus, it appears that since the shale revolution, while cutting
OPEC production is ineffective in raising the crude oil price, increasing OPEC production can significantly lower the crude price. The price-setting power of OPEC becomes weaker in this later sample period.

The change to the price-setting power of OPEC has fundamentally influenced the incentive for OPEC countries to control their production. Panel B of Figure 4 estimates the one-quarter-ahead OPEC production response function to crude price changes via a local linear regression of one-quarter-ahead log change in OPEC production against the past one-quarter’s WTI futures log return. The solid line captures the OPEC response to crude price variations before the shale revolution. The line is strongly positively sloped, suggesting that in controlling supply OPEC actively responds to crude price movement: Increasing supply when the price is high and cutting supply when the price is low. It appears that since 2011 such an active response has all but disappeared, as the dash line in Panel B becomes virtually flat.

The historical events during this period support our analysis. Crude prices dropped sharply from June 2014. One would expect the OPEC countries to reduce production in order to prevent such a price collapse. This time, however, Saudi Arabia, a key member of OPEC, signaled its reluctance to sacrifice market share to defend oil prices. A few months later, at the 166th OPEC meeting, on November 27, 2014, members as a whole decided to maintain the quotas because of the adamant position of Saudi Arabia. Apparently, Saudi Arabia was trying to avoid a repetition of the 1980s scenario when it systematically lost output share in order to defend prices amid a general increase in oil production by non-OPEC countries.

Due to the endogenous nature of oil prices and quantities, it is difficult to separately identify the demand and supply curve. Even in the structural VAR setting, one needs to make assumptions on the price elasticity of one to identify the price elasticity of the other. Baumeister and Hamilton (2018) show that seemingly plausible restrictions on oil supply elasticity maps into implausible values of oil demand elasticity, and vice versa. Caldara, Cavallo, and Iacoviello (2018) propose to set both elasticities with information outside the VAR setting. The same endogeneity issue can
bias our lead-lag correlation and regression estimates. Nevertheless, our analysis relies less on the absolute quantities of the potentially biased sensitivity estimates, and more on their relative variation through the two sub-sample periods. The behavioral changes we have identified in relation to OPEC production since the shale revolution at least partially explain the reduced magnitude of supply shocks. This, combined with muted demand responses to supply shocks in a low interest rate environment and the occurrence of several large negative demand shocks, makes the contribution from demand shocks much more prominent during the second half of the sample.

5 | CONCLUDING REMARKS

The 2008-2009 financial crises have triggered a chain reaction from financial markets to real economies. The ripple effect has also extended to the oil market, leading to changing behaviors in oil producers, shifting dynamics in oil prices, and different market reactions to oil price movements.

The spreading crises and subsequent recessions have suppressed market demand for oil much more than the oil cartel OPEC can salvage. The ensuing low interest rate environment dampens the potential supply-side effect of oil shocks on the aggregate economy, long after the crises are over. The shale oil revolution provides an additional buffer to crude supply shocks. The net result is that both crude supply shocks and their impacts have become muted, and demand shocks are becoming a more important source of the crude oil price variation. Investor concern has shifted from worrying about crude price hikes as a production cost gauge to worrying about crude price drops as an indication of weakening aggregate demand.

This paper shows that one can make effective and timely inferences, about structural shifts in crude oil price dynamics and market concerns, from the joint behavior of crude future options and stock index options, without pre-specifying how and when the dynamics are about to shift.

Accurate and timely identification of these shifts has fundamental implications for economic
Historically, economists strive to quantify the negative impact of oil price increase on the aggregate economy. Such estimation implicitly assumes that the oil price increases are due to supply shocks. The estimates are no longer applicable when oil price fluctuation is mainly driven by demand shocks. Similarly, oil supply shocks represent harmful shocks to heavy oil users, such as the airline industry, but when crude price movements are dominated by demand shocks, their negative impact on fuel expenditure can be partially compensated by the simultaneous increase in revenue due to higher demand. Shifting dynamics therefore calls for time-varying fuel cost hedging strategies, an important topic for future research.

Large negative demand shocks may not recur in the near future, or at least so we hope. Quantitative easing programs have gradually been unwound, and the short-term interest rates around the world may not stay near the zero lower bound forever. And while it is facing change, OPEC continues to play an important role in the oil market and the world economy. Thus, the broad dynamics shift we have observed during our sample period of 2004 to 2016 may just be a small and temporal variation in the longer picture of human history. Looking ahead, the only constant we foresee is the constant change in the relative composition of shocks and responses in the oil market. It remains crucially important to closely monitor these variations. The option-analytic framework that we propose in this paper provides a simple and robust approach for this important task of real time risk monitoring. In the future, by pooling information from other options markets, researchers can potentially follow similar approaches in obtaining timely variance decompositions along more interesting dimensions.
REFERENCES


