Shale Revolution and Shifting Crude Dynamics

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Abstract

Crude prices are subject to both demand and supply shocks. Major events and structural changes can induce large variations in intensities of the two types of shocks, as well as their magnitudes of impacts on crude price movements. This paper proposes a theoretical framework that allows us to extract the time variation in demand and supply shocks through a joint analysis of crude futures options and stock index options. Historical analysis shows that crude futures price movements are dominated by supply shocks in the earlier half of our sample from 2004 to 2008, but have become much more demand-driven since then. The large demand shock from the Great Recession, triggered by the 2008 financial crisis, contributes to the start of the dynamics shift. The shale revolution, on the other hand, has fundamentally altered the crude supply behavior. Since 2010, technology advances in horizontal drilling and hydraulic fracturing, together with other innovations, have enabled rapid increase of U.S. tight oil production from shale at increasingly competitive cost. The increasing tight oil production has undercut the price-setting power of the OPEC, and has lowered the OPEC's incentive to self-regulate its production. As a result of the dynamics shift, investors have also been shifting from worrying about crude price hikes as a production cost gauge to crude price drops as an indication of weakening demand. The shifting dynamics have fundamental implications for optimal fuel cost hedging by heavy crude users such as the airline industry.

JEL Classification: C13, G13, Q41, Q47

Keywords: crude futures; crude futures options; stock index options; supply shocks; demand shocks; crude production; shale revolution; optimal fuel cost hedging policy

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1. Introduction

As a major energy source, crude oil plays a vital role for the proper functioning of the modern economic society. Its price fluctuation often sends shocking waves to all segments of the economy. For heavy users such as the airline industry, unexpected price shocks to the jet fuel can be the main source of risk to the industry's operating cost and the bottom line. Understanding the crude price behavior is vitally important for such industries to manage their risk. In particular, crude prices are not only subject to different types of shocks either from demand or supply side, but their relative contributions can also vary strongly over time. Timely and accurately predicting the time variation in the relative contribution of different types of shocks is crucial for the optimal hedging decision.

In this paper, we use the US stock market performance to proxy the demand variation, and project crude oil futures price variation onto the S&P 500 index (SPX) variation, while allowing stochastic loading on the stock index and stochastic volatility on both the index return and the projection residual of the crude futures return. We propose a theoretical framework that allows us to extract the time variation in the relative contribution of demand shocks through a joint analysis of crude futures options and the stock index options.

We do not directly model the full dynamics of the stochastic volatilities, but model the near-term dynamics on the option implied volatility on the stock index and the crude futures. Under such a setting, we show that the at-the-money forward implied variance represents a short-maturity approximation of the conditional expectation of the underlying return variance, and the implied variance slope against log relative strike against forward approximates the covariance between the index return and return variance. For the stock index, it is well documented that both the return-variance covariance and the implied variance slope are mostly negative. We posit that a major underlying driver for the negative covariance between the index return and return variance is the volatility feedback effect: Increase in systematic market volatility raises the discount rate and depresses the index valuation. Furthermore, since the volatility feedback mechanism is through the market pricing of systematic return risk, it is applicable only to the systematic component of returns on other securities such as the crude futures. Accordingly, we assume that the projection residual return on the crude futures is orthogonal to the residual return variance, and that the implied variance slope against relative strike on the crude futures is mainly driven by the volatility feedback effect of its loading on the stock index. With these assumptions, we can extract the time-varying loading and the relative variance contribution of the demand shock from the option implied variance level and slope from the index options and the crude futures options, without fully specifying how the loadings and variance contributions should vary over time.

Options on the SPX index are actively traded on the Chicago Board of Options Exchange (CBOE) while options on the WTI crude futures are actively traded on the Chicago Mercentile Exchange. We obtain data on both, transform the option prices into option implied volatilities according to the Black and Scholes (1973) and Merton (1973) model, and perform smoothing and interpolation to generate floating implied variance level and slope time series at a fixed time to maturity. We then apply our theory and transform these estimates into a time series of relative variance contribution from systematic demand shocks to the crude price fluctuation. Between 2004 to 2008, the relative variance contribution estimates from demand shocks are, fluctuating between zero to 30%. Since then, the estimates have become much higher and have reached as high as 80%, highlighting a shift in the crude market dynamics.

The dynamics shift is a combined result of several developments. First, the large negative demand shock from the Great Recession, triggered by the 2008 financial crisis, contributes to the start of the dynamics shift. Second, the shale revolution has fundamentally altered the crude supply behavior. Since 2010, technology advances in horizontal drilling and hydraulic fracturing, together with other innovations, have enabled rapid increase of U.S. tight oil production from shale at increasingly competitive cost. The increasing tight oil production has undercut the price-setting power of the Organization of the Petroleum Exporting Countries (OPEC), and has lowered the OPEC's incentive to self-regulate its production.

Since the 1970s, the crude market has been dominated by the OPEC, which is an intergovernmental organization of 13 crude-producing nations. Economists often cite OPEC as a textbook example of a cartel that coordinates to reduce market competition. Since the 1980s, OPEC has started setting production targets for its member nations. Still, their influence has been periodically challenged by the recurring temptation for individual OPEC member countries to exceed production ceilings and pursue conflicting self-interests, and more recently by the development and expansion of other energy sources outside of OPEC control.

The recent shale revolution presents one such challenge to the cartel's price setting power. The revolution is the result of advances in oil and natural gas production technology, which have enabled increased production of oil and natural gas in the US at increasingly competitive production cost levels. Oil production can be classified into three phases: primary, secondary, and tertiary. Primary oil recovery is limited to hydrocarbons that naturally rise to the surface, or those that use artificial lift devices, such as pump jacks. Secondary recovery employs water and gas injection, displacing the oil and driving it to the surface. Utilizing these two methods of production can leave up to 75% of the oil in the well. The way to further increase oil production is through the tertiary recovery method, which is also known as Enhanced Oil Recovery (EOR). Although more expensive to employ on a field, EOR can increase production from a well to up to 75% recovery. OPEC productions are mainly from the first two phases with low production costs relative to the rest of the world. The low production cost and the abundant reserves are what give OPEC countries the market price-setting power. Nevertheless, recent technological advances in horizontal drilling and hydraulic fracturing in the US has drastically reduced the cost of EOR.[1] In the US, the tight oil production was merely over one million barrel per day in 2007, representing just 4% of OPEC supply. The production has picked up pace since 2011, reaching 5.5 million barrels a day during its peak in 2015, representing 17% of OPEC supply.

The drastic increase in tight oil production, in terms of both absolute quantity and market share, has generated profound impacts on OPEC behaviors and crude price dynamics. Before the shale revolution, we identify strong dynamic interactions between OPEC supply and crude prices: Changes in crude prices positively predict future variations in OPEC crude supply. These dynamic interactions are consistent with what one expects from a cartel who actively alters productions to produce price impacts to increase their profits. However, such dynamic interactions have virtually disappeared since 2011. By contrast, the US tight oil production reacts strongly and positively to the crude price shock, increasing its production when crude price increases while cutting production when price drops. The muted response from OPEC countries reflects their realization of their diminished price-setting power and accordingly their lowered incentive in attempting to use production cuts to raise crude prices.

The diminishing role of the cartel has profound impacts on the crude price behavior. When supply shocks dominate the crude price variation, crude price increase represents mainly an increase in energy cost for production and hence a negative force for the overall economy. On the other hand, as supply shocks have become more muted and demand shocks start to dominate, crude price decline represents mainly weakening demand and hence a bad signal for the economy. Reflecting this dynamics shift, low strike options on the crude futures become more expensive relative to high-strike options, and the option implied variance slope

[1] To avoid confusion from oil shale, which is shale rich in kerogen, or oil produced from oil shales, the International Energy Agency recommends to use the term “light tight oil” or “tight oil” for oil produced from shales or other very low permeability formations.

against relative strike becomes more negative as investors start to worry more about crude price drops as an indication of weakening demand, rather than worrying about crude price hikes as a production cost gauge.

This shifting dynamics has important implications on the overall economy, and particularly so on companies that depend heavily on oil as their source of cost such as the airline industry. In a supply-shock dominated era, oil price fluctuation represents production cost fluctuation for the economy, and it is often desirable for airline companies to fully hedge their energy exposure in order to reduce fluctuations in their bottom line. By contrast, in the new demand-shock dominated era, oil price starts to positively co-move with the business cycle, and thus simultaneously affects the demand-driven revenue and the fuel cost. The demand-induced revenue variation partially cancels out the fuel cost variation, thus reducing the need for fuel cost hedging. We derive optimal dynamic hedging strategies for an airline company based on its revenue exposure to demand shocks and cost exposure to crude price shocks, and show that the optimal strategy is to fully hedge the fuel cost when its variation is fully idiosyncratic, but only partially hedge the fuel cost when crude futures has a large demand shock component. The exact strategy for a company depends on the exposure of its revenue to the stock market performance and the exposure of its cost to the crude futures variation. Assuming a company with unit revenue exposure to the stock index and unit cost exposure to the crude futures, we compute the time series of the optimal hedging ratio for the company based on the estimated demand-shock contribution to the crude price fluctuation. The estimates for the optimal hedging ratio are close to 100% in the earlier part of our sample from 2004 to 2008, but have dropped sharply since then to only about 50%.

The rest of the paper is organized as follows. The next section reviews the literature that lays the background for the analysis. Section 3 decomposes the crude price shocks into demand and supply shocks with time-varying intensities, and proposes a theoretical framework to identify the time variations through options. Section 4 describes data sources and summary time-series behaviors for crude prices, crude production, and the stock market performance. Section 5 examines how the crude price interacts with crude production and the stock market performance and how the interaction change since the shale revolution. Section 6 extracts the time-varying demand contribution to crude price fluctuation from options on the S&P 500 index and WTI crude futures. Section 7 examines the implications of the time variation in the relative strength of the two sources of shocks on optimal fuel cost hedging for the airline industry. Section 8 concludes.

2. Background

Oil entered human history as an energy source in the mid 1800s.[2] The United States started and dominated the crude production and consumption until 1970s, when the center of the crude market started shifting to the Persian Gulf. Throughout history, oil prices have gone through many cycles of ups and downs. Prices tend to go up when major fields are exhausted and production decline, when production is disrupted by war or other political crisis, when producers reduce production deliberately, either through government regulation or via a cartel organization such as OPEC, to enhance profit, and when a new demand (such as the start of the automobile era) or a new market (such as the emerging market) arise that cannot be met by supply fast enough. Prices go down when new technological advances reduce production cost 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

[2]See Hamilton (2013) for a historical overview, and Baumeister and Kilian (2016) for an analysis of the major events during the past 40 years..

made enhanced oil recovery feasible at competitive cost, and have drastically expanded the tight oil supply from the US. This new advance, as is often termed the shale revolution, along with technology advances on other energy sources such as biofuel, wind, and solar energy, has the potential to shift the center of energy production from the Gulf region back to the US again.

Historically, economic research centers around the impact of oil price fluctuation on the aggregate economy. See recent surveys of this literature by Brown and Yücel (2002), Donald W. Jones and Paik (2004), and Huntington (2005). Empirically, the literature has identified a negative relation between oil price movements and the aggregate economy.[3] As a representative example, Donald W. Jones and Paik (2004) estimate an oil price elasticity of GDP between -0.05 and -0.06. Out of the many channels that have been proposed to account for the inverse relation, the classic supply-side effect provides the most basic and direction explanation, in which rising oil prices are indicative of the reduced availability of a basic input to production.

Such analyses often treat oil price fluctuations as exogenous shocks to the economy, but it is important to realize that oil price can also fluctuate as responses to aggregate economic shocks that influence the demand for energy consumption. To capture such interactions, Kilian (2009) proposes a structural VAR model that decompose the real price of crude oil into three sources of shocks: crude supply shocks, shocks to the global demand for all industrial commodities, and demand shocks specific to the global crude oil market. Such VAR-type models resolve the endogeneity issue of traditional one-directional causality analysis, and can capture the average interaction patterns among the different types of shocks during the estimation period.

The relative contribution of different types of shocks can vary strongly over time. Major events and structural changes can also induce large variations in the underlying dynamics. Traditional VAR-type econo-

[3]Empirical studies and surveys include, among many others, Rasche and Tatom (1977), Mork and Hall (1980), Darby (1982), Hamilton (1983), Gisser and Goodwin (1986), Jones and Leiby (1996), Segal (2011).

metric models are not fully equipped to capture such time variation. In this paper, we propose to use forward-looking options data, and lever the recent advances in option pricing theory to achieve the identification of the time-varying contributions without the need to fully specify the potentially shifting dynamics. Our model builds on the work by Carr and Wu (2016), who first propose the idea of characterizing the option implied volatility surface based on its own near-term behavior but without specifying its full long-run dynamics. Since their objective is to characterize the shape of the whole option implied volatility surface, they need to make structural assumptions on the near-term dynamics of all implied volatilities. By contrast, as our chief objective is to extract the underlying security return variance and return-variance covariation, we can make much more localized assumptions to obtain simpler linkages between the option implied variance level and slope against strike on the one hand, and the variance and covariance of the underlying security return.

Our methodology is somewhat related to Chang, Christoffersen, Jacobs, and Vainberg (2012), who propose to compute the beta of individual stocks based on the risk-neutral skewness constructed from the stock options relative to the risk-neutral skewness constructed from the stock index options by assuming that the idiosyncratic return component has zero skewness. While our construction is based on dynamics assumptions instead of distributional behaviors, the informational sources for the two approaches are similar.

In other related works, Christoffersen, Jacobs, and Li (2016) analyze the jump intensities and risk premiums embedded in crude futures and futures options. Chiang, Hughen, and Sagi (2015) propose to estimate latent oil risk factors using both derivative prices and oil-related equity returns. Trolle and Schwartz (2009) propose a stochastic volatility for pricing commodity derivatives and identify two unspanned volatility factors from NYMEX crude oil derivatives.

3. Time-Varying Supply and Demand Shocks in Crude Price Dynamics

Crude oil price movements can be driven by both supply shocks and demand shocks. Major events and structural economic changes can also induce large variations in the magnitudes of the two types of shocks, as well as their impacts on the crude price movements. This paper models the crude futures dynamics via these two types of shocks, and highlights the effects of time variation in both the magnitudes of the two types of shocks and their impacts on the crude futures price variation.

Crude oil traded at different regions can have different prices, and different futures contracts have been written on different types of crude products. While we do compare different oil price series and inspect their similarities and differences, our analysis has a U.S. focus. Thus, the main subject for analysis is futures and futures options on the NYMEX Light Sweet Crude Oil (WTI), traded at the Chicago Mercantile Exchange (CME).

Formally, let dW_t^s and dW_t^d denote supply and demand Brownian shocks, respectively. We model their time-varying impacts on the crude futures price dynamics O_t via the following stochastic differential equation,

$$dO_t/O_t = \mu_t^o dt + \eta_t^d \sqrt{v_t^d} dW_t^d - \eta_t^s \sqrt{v_t^s} dW_t^s, \quad \eta_t^d, v_t^d, \eta_t^s, v_t^s \geq 0, \tag{1}$$

where positive demand shocks lead to oil price increase while positive supply shocks lead to oil price decline. We capture the time-varying intensities of the two types of shocks via the two instantaneous variance rates v_t^d and v_t^s , and capture their time-varying impacts on the crude futures price using the two positive loading coefficients $\eta_t^d > 0$ and $\eta_t^s > 0$. Through separate modeling of supply and demand shocks and allowing time variation in both their intensities and their impacts, we strive to identify the time-varying contribution of the two types of shocks to the crude price fluctuation.

To enhance the separation of demand and supply shocks on crude futures, we use the variation of the U.S. stock market, and specifically the S&P 500 index (SPX), to proxy the demand variation. Options on the SPX index are actively traded on the Chicago Board of Options Exchange (CBOE). Historically, the literature often chooses to proxy demand shocks with some aggregate real economic strength measures, such as the global real economic activity measure used by Kilian (2009). Our choice of a financial security index with actively traded options, together with options on crude futures, allow us to better identify the time variation in the intensities of demand shocks and its contribution to crude futures movements.

It is important to note that by "demand shocks," some studies focus squarely on the specific demand for crude, rather than the overall economic strength. In this paper, by using the S&P 500 index as the proxy, we are highlighting the systematic market risk and how it interacts with crude oil price movements.

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

$$dD_t/D_t = \mu_t^d dt + \sqrt{v_t^d} dW_t^d. \tag{2}$$

We project the crude futures movement onto the SPX movement, and treat the projection residual as the orthogonalized, idiosyncratic supply shock dW_t^s, with $\mathbb{E}[dW_t^d dW_t^s] = 0$.

With the stock market index as the proxy for demand risk, we can think of the crude futures variation within the framework of the classic capital asset pricing model, with dW_t^d denoting the systematic market risk, and the projection residual dW_t^s denoting the idiosyncratic crude risk. The demand shock loading η_t^d can be interpreted as the crude beta on the stock market index.

It is difficult to predict the direction of financial security prices, but it is much easier to predict the financial security return variance. It is well documented that financial security return variance and covariance are strongly persistent and predictable. Many models have been proposed to predict the return variance and co-variance based on their autoregressive behaviors (Engle (2004)). A time-varying crude beta estimate would reflect the time-varying demand (market risk) contribution to the crude futures movements. In particular, when demand shocks dominate the crude futures variation, the beta estimates will be highly positive and the correlation between returns on the crude futures and the stock index will be high. By contrast, when crude movements are dominated by demand shocks, we expect a small beta estimate and a low correlation between the two return series.

Estimating the crude return beta and its correlation with the index return using historical returns is backward looking; by contrast, the options market is the natural forward-looking market for volatility and higher moments. In what follows, we propose a theoretical framework that allows us to extract the time-varying demand shock contribution to crude futures movements based on the crude futures options and the SPX index options.

3.1. Identify time-varying demand intensity without specifying its full dynamics

If we were to specify the fully dynamics for the instantaneous variance rate v_t^d, as in, for example, Heston (1993), we would be able to estimate the model parameters and extract the variance rate time series from observations on the SPX index option prices. This is the standard approach taken in the traditional option pricing literature. The drawback of this approach is that a pre-fixed specification may fail to capture potential shifts in the underlying dynamics. In this paper, we adopt a new framework developed by Carr and Wu (2016) and Carr and Wu (2017) that allows us to extract time-varying demand intensities without fully specifying the underlying dynamics.

Instead of specifying the full dynamics on the instantaneous variance rate v_t^d, the new framework specifies the partial, near-term behavior of the option implied volatilities across different strike prices K and expiries T, under the risk-neutral measure $\mathbb{Q}$,

$$dI_t^d(K,T)/I_t^d(K,T) = m_t dt + \sqrt{\omega_t^d} dZ_t^d, \tag{3}$$

where the Brownian shock dZ_t^d is assumed to be common across all option contracts, with $\rho_t^d = \mathbb{E}[dW_t^d dZ_t^d]/dt$ denoting the correlation between changes in implied volatilities and the index return. For the stock market index, the correlation is often observed to be negative, capturing the volatility feedback effect of the market risk: Positive shocks to the volatility of the market risk increase the discount rate and, holding everything else equal, lowers the valuation on the stock market.

We allow both the correlation ρ_t^d and the volatility of volatility coefficient ω_t^d to vary over time. They can follow some stochastic processes driven by multiple forces, and their dynamics can change over time. Our result does not depend on their exact specification.

For each option contract, the implied volatility is the volatility input to the Black and Scholes (1973) and Merton (1973) option pricing equation that leads to an option valuation matching the observed option price. Over the past decades, the Black-Merton-Scholes (BMS) model has evolved from an option pricing model to a commonly adopted option price transformation function. Transforming option prices into BMS implied volatilities help exclude arbitrage opportunities between the option and the underlying, and highlight the information content in the option prices.

Carr and Wu (2016) assume a similar proportional dynamics but further apply exponential dampening along the maturity dimension, which reduces the implied volatility variation at longer maturities. By performing our analysis at a fixed time to maturity (e.g., three month), we can ignore the term structure effect and adopt a simplier specification.

No dynamic arbitrage dictates that the risk-neutral expected return on an option contract is the riskfree rate. We assume zero interest rates and attribute the expected option return via an expansion around the BMS option pricing equation, $B(t, D_t, I_t; K, T)$,

$$0 = \mathbb{E}_t^{\mathbb{Q}}\left[\frac{dB}{dt}\right] = B_t + \frac{1}{2}B_{DD}D_t^2 v_t^d + \frac{1}{2}B_{II}\omega_t^d I_t^d + B_{DI}D_t I_t \gamma_t^d, \tag{4}$$

where $B_t, B_{DD}, B_{II}, B_{DI}$ denote the time derivative (theta), the second price derivative (gamma), the second volatility derivative (volga), and the cross derivative against price and volatility (vanna) of the BMS pricing equation. $\gamma_t^d = \sqrt{v_t^d \omega_t^d}\rho_t^d$ denotes the instantaneous covariance rate between the index return and percentage changes in the implied volatility.

Plug in the partial derivatives of the BMS pricing relation, divide both sides by dollar gamma (assuming it is strictly positive), and rearrange, we can arrive at a simple quadratic form on the implied variance smile at a fixed time to maturity τ,

$$I_t^2 = A_t^d + 2\gamma_t^d k + \omega_t^2 k^2, \tag{5}$$

where $k = \ln K/D_t$ is the log relative strike moneyness measure and A_t^d denotes the at-the-money forward implied variance at $k = 0$.

The at-the-money forward implied variance relates to the implied variance dynamics by

$$A_t^d = v_t^d + 2m_t A_t^d \tau + A_t^d \gamma_t^d \tau - \frac{1}{4}(A_t^d)^2 \omega_t^2 \tau^2, \tag{6}$$

which converges to the instantaneous variance as maturity approaches zero. We use the at-the-money forward implied variance on the SPX options at a short maturity as an approximate proxy for the demand intensity v_t^d: $A_t^d = v_t^d$ as $\tau \to 0$.

Furthermore, equation (5) shows that we can extract the covariance between return and volatility γ_t^d from the at-the-money implied variance skew against the log strike moneyness,

$$S_t^d \equiv \left.\frac{\partial I_t^2}{\partial k}\right|_{k=0} = 2\gamma_t^d. \tag{7}$$

Therefore, with the SPX index options, we can identify the demand shock intensity v_t^d from the at-the-money implied variance at a fixed time to maturity, and we can identify the covariance of the demand shock with the shock intensity γ_t^d from the implied variance skew against log strike moneyness, without ever specifying the full dynamics of the demand shock, and thus without the need to make stationarity assumptions on the dynamics.

Equation (3) specifies the near-term dynamics for implied volatilities at fixed strikes and expiries. We can derive the corresponding dynamics for the floating at-the-money forward implied variance at a fixed time to maturity τ by adjusting for the "sliding" along time and moneyness,

$$dA_t^d = dI_t^2(K,T) + \frac{\partial A_t^d}{\partial \tau}dt + \frac{\partial A_t^d}{k}\frac{dD_t}{D_t} = m_t^A A_t^d dt + 2A_t^d\sqrt{\omega_t^d}dZ_t^d + 2\gamma_t^d\sqrt{v_t^d}dW_t^d. \tag{8}$$

Given the short-maturity approximation $v_t^d = A_t^d$, equation (8) also approximates the corresponding dynamics for the instantaneous variance rate v_t^d. In particular, the covariance rate between the instantaneous percentage changes in the variance rate and the index is four times the covariance between the fixed-strike, fixed-expiry implied volatility series and the index return,

$$\zeta_t^d \equiv \mathbb{E}\left[\frac{dv_t^d}{v_t^d}, \frac{dD_t}{D_t}\right] = 4\gamma_t^d. \tag{9}$$

Therefore, the at-the-money implied variance skew against relative log strike reflects half the covariance between percentage changes in the instantaneous variance rate and the index,

$$S_t^d = \frac{1}{2}\zeta_t^d. \tag{10}$$

According to classic asset pricing theory, the volatility feedback effect is a distinct feature that can be used to distinguish between market risk and idiosyncratic risk. Since only market risk is priced, only market risk increases can induce an increase in discount rate and hence a reduction in valuation. Thus, we expect a stronger negative correlation ρ_t and accordingly a more negative implied variance skew S_t^d for the stock index than for other financial securities with a large proportion of idiosyncratic movements, and we expect the option implied variance skew to be steeper for financial securities with a larger proportion of the market risk. The next subsection formalizes this idea and identifies the demand shock (market risk) contribution to the crude futures movements based on the option implied variance skew difference between the SPX index options and crude futures options.

3.2. Identify time-varying demand shock contribution to crude futures movements

From crude futures options, we can analogously estimate the at-the-money implied variance level A_t^o and its skew against relative log strike S_t^o.

By way of projection, the demand shock dW_t^d and the projection residual dW_t^s are independent of each other. Thus, applying the short-term approximation of the instantaneous variance rate with the at-the-money implied variance, we can decompose the crude futures return variance as

$$A_t^o = (\eta_t^d)^2 v_t^d + (\eta_t^s)^2 v_t^s = (\eta_t^d)^2 A_t^d + (\eta_t^s)^2 v_t^s. \tag{11}$$

By classic asset pricing theory, the idiosyncratic risk is not priced and hence there is no feedback effect between the idiosyncratic risk dW_t^s and its variance (v_t^s), $\mathbb{E}_t[dW_t^s dv_t^s] = 0$. Then, we can attribute the crude option implied variance skew to the feedback effect of its market risk component, which is then linked to the SPX index option skew:

$$S_t^o = \frac{1}{2}\mathbb{E}\left[\frac{dv_t^o}{v_t^o}, \frac{dO_t}{O_t}\right] = \frac{(\eta_t^d)^3 v_t^d}{v_t^o}\frac{1}{2}\mathbb{E}\left[\frac{dv_t^d}{v_t^d}, \frac{dD_t}{D_t}\right] = \frac{(\eta_t^d)^3 A_t^d}{A_t^o} S_t^d. \tag{12}$$

Therefore, combining the at-the-money implied variance and the skew estimators from the index options and the crude futures options on a given date t, we can obtain a corresponding estimate on that day's demand shock loading on the crude futures (η_t^d) as well as the relative variance contribution of demand shocks to crude futures variation (RC_t^d),

$$\eta_t^d = \left(\frac{S_t^o A_t^o}{S_t^d A_t^d}\right)^{1/3}, \quad RC_t^d = \frac{(\eta_t^d)^2 A_t^d}{A_t^o}. \tag{13}$$

By assuming pure diffusive price dynamics for the stock index and the crude futures, and by imposing the implications from the classic asset pricing theory, we link the at-the-money option implied variance to the variance rate of the underlying return, and link the option implied variance skew against the relative strike to the contribution of the feedback effect of the market risk, and in our particular application, the demand shock contribution to the crude futures movement.

In practice, the price dynamics can deviate from our pure diffusive assumptions. For example, the stock index can jump randomly. In the presence of such random jumps, the short-term return distribution tend to have fatter tails. The market pricing of risk further distorts the return distribution and makes its risk-neutral counterpart more negatively skewed (Polimenis (2006)). This negative skew distortion partially reflects the market's extreme aversion to market crash risk (Wu (2006)). In this case, the option implied volatility skew on the stock index is not purely driven by the volatility feedback effect, but is also driven by investor aversion to market crash risk. When we use the option implied 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 stock market crash. The effect is thus similar to that of the feedback effect. Take our application to crude futures as an example, when crude price movement is driven by demand, crude price crash indeed becomes a concern as it is a reflection of demand crash. Thus, if the crude futures option implied variance shows a negative skew due to concern on crude price crash, one can interpret the negative skew as a contribution from the demand shock, the stronger the negative skew, the larger contribution from the demand shock. By contrast, the traditional market concern for crude is often to the opposite direction, because the market tends to worry about oil price hikes and its negative impacts to the real economy. If such concerns dominate, the crude options implied variance skew would be positive, showing that the concern is more driven by supply than demand.

In implementation, since our model assumptions do not allow positive implied variance skew, when we observe positive skews from crude futures options, we set the skew to zero and attribute all variations to supply shocks. The stock index options are always negatively skewed during our sample period.

4. Data Collection and Summary Behavior

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 refers to oil extracted from wells in the US and sent via pipeline to Cushing, Oklahoma. The product itself is very light and very sweet, making it ideal for gasoline refining. WTI is the main benchmark for oil consumed in the US, and is the main choice of reference for our analysis. 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 data quality is poor in the earlier part of the sample. We perform our analysis using data from January 2004 to April 2016.

In addition to using WTI futures as the main reference for crude price movements, we have also collected front-month futures price series on ICE Brent Crude Oil (Brent), as well as the Jet Kerosene FOB Singapore Cargo price (JET), all in US dollars per barrel. About two thirds of crude contracts around the world reference Brent Blend, making it the most widely used marker of all. Nowadays, "Brent" refers to oil from four different fields in the North Sea: Brent, Forties, Oseberg and Ekofisk. Crude from this region is light and sweet, making them ideal for refining diesel fuel, gasoline and other high-demand products. Furthermore, since the supply is water borne, it is easy to transport to distant locations. By contract, the WTI supplies are land-locked and it is relatively expensive to ship the WTI supplies to certain parts of the globe. Jet kerosene is a blend of hydrocarbons, a product of petroleum refining belonging to the middle distillate group. The product grade covered by ICIS pricing is A-1, which has a stricter specification compared to normal kerosene and normally used in commercial airliners. We use the JET price as a proxy for airline jet fuel cost, a major consideration for the airline industry.

NYMEX crude oil futures contracts expire on the third business day prior to the 25th calendar day of the month prior to the month on which the contract is written. The options on the crude 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 implied volatilities.

The SPX options are actively traded on the Chicago Board of Options Exchange (CBOE). We obtain daily closing prices and implied volatilities, among other information, on the SPX options from OptionMetrics over the same sample period. The SPX options are European style. The contracts expire on the third Friday of the expiration month.

To understand the behavior of crude supplies and their impacts on crude price dynamics, we collect data on crude production from OPEC countries over the same period. To highlight the contribution of the shale revolution, we also collect data on US tight oil production. All the production data are from the Energy Information Administration (EIA), available in monthly frequency since 2004. Since the US tight oil production is a recent endeavor, the data start in 2007.

Production is only one metric for the crude supply, which we use for illustrative purpose. Other metrics, such as crude inventories (or stocks) can be critical for the short-run crude price movements. Nevertheless, it is difficult to measure inventory with accuracy, as oil can be stored in tanks, boats, and pipes, or underground in strategic reserves. Rig count is another measure that can foretell the variation of production. However, not all rigs are created equal. Modern rigs, especially for tight oil production, are highly efficient and much cheaper per barrel of oil than older rigs.

4.1. Crude price movements over the past decade

Figure 1 plots the time series of the three crude price proxies from 2004 to 2016. The jet fuel price moves closely with the crude futures prices, but the jet fuel price tends to stay above the crude futures prices, mainly because jet fuel must comply with higher standards of usage, and as a result has higher production cost.

[Figure 1 about here.]

The two futures price series mostly lie on top of each other, only with occasional deviations. For example, between 2011 and 2015, the Brent futures prices became higher than the WTI futures prices. This difference is partly driven by a sharp increase in the US tight oil production as the result of the shale revolution. The price difference has since then become smaller.

4.2. Crude production fluctuation over the past decade

Figure 2 compares the time series of OPEC crude supply (solid line, scale on the left side) with the the US tight oil production (dashed line, with scale on the right side), all in units of million barrels per day (mbb/d). During the past decade, the OPEC production has been quite stable due to the cartel control, hovering around 30 million barrels per day within a narrow range from 28.8 million to 32.8 million barrels per day. By contrast, the US tight oil production started at just over one million barrels a day in 2007, but the production has picked up pace since 2011 and shows a sharp increase up to its peak in 2015. At the peak, the US tight oil production reaches 5.46 million barrels a day, about 17% of the OPEC production. Since reaching its peak in 2015, the US tight oil production has started to decline, in response to the sharp drop in oil prices.

[Figure 2 about here.]

Historically, crude productions are dominated by the OPEC countries. By forming a cartel, the OPEC countries have been able to control crude production quantity to rip the highest consumer surplus. The member countries negotiate quota for each participating country and adjust the quota in response to demand and price variations. The nature of maximizing consumer surplus is that the production increase is deliberately controlled to maintain an artificially high crude price. The OPEC countries are oil-rich countries, where oil can be produced at a lower cost than at other places. As a result, non-OPEC countries, including the US, had historically not been significant enough to impact OPEC's price-setting power.

This picture starts to change with the shale revolution. With advances in production technology, particularly in horizontal drilling and hydraulic fracturing, US companies can dip into a much higher reserve via enhanced oil recovery, and produce large amount of tight oil with competitive cost. The sharp increase in US production from 2011 to 2015 highlights the capacity increase as a result of new technology, which, combined with softened demand since the Great Recession, was ultimately able to drive the crude price significantly below historical levels. When the crude price falls close or below the tight oil production cost, some of the companies started to shut down operations and reduce production, leading to a reduction in US tight oil production. Nevertheless, with new technological innovations driving the cost increasingly lower and more competitive, the production is bound to come back as soon as the crude price rises above a certain level. Such innovations include, for example, multi-pad drilling, with which 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 (Mackenzie (2016)) finds that U.S. shale producers have become more adept at staying profitable, even with the current low crude prices. By cutting costs throughout development and improving production efficiency, the cost of production for U.S. operators fell by up to 40 percent over the past two years.

Table 2 lists the average production cost for the top crude producing economies as of 2016. Countries in the Middle East have the lowest production cost at just about 10 dollars per barrel. Russia, Indonesia, US, and Norway have production costs at about 20 dollars per barrel. The recent development in fracturing technology allows the US to produce tight oil at a reasonably low cost of $23.35 per barrel. Production cost in other countries become increasingly higher.

5. Shifting Dynamic Interactions Between Crude Price and Production

We conjecture that the increasing significance of the competitive US tight oil production is bound to cut into the price-setting power of the OPEC countries as they can no longer effectively raise crude prices by agreeing to cut their own production. When the market price rises above a threshold value, the US tight oil production will come in, reducing the impact of the production cut from OPEC countries. Furthermore, the weakened price-setting power also reduces the effectiveness and increases the cost of production cut, thus reducing the OPEC countries' incentives to do so. This will, ultimately, lead to the breakdown of the cartel.

5.1. Shifting OPEC behavior since the shale revolution

To examine whether the shale revolution has affected the price-setting power and the behavior of the OPEC cartel, we divide the sample into two broad periods, pre-shale revolution from 2004 to 2010, and post shale revolution from 2011 to 2016. We estimate the dynamic interactions between crude price and crude production during these two time periods.

Figure 3 plots the dynamic cross-correlation estimates between monthly log percentage changes in OPEC crude production and monthly log percentage changes in Brent crude futures prices at different leads and lags.[4] In each plot, the bars measure the correlation estimates. The two-dashed lines represent the confidence bands at one standard deviation. The two panels (A and B) represent the two sub-sample periods.

[Figure 3 about here.]

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

As expected, the future crude price response to past production changes is weak during both time periods. From both panels, we observe weak negative correlations between current production and future price changes over about a quarter.

Figure 4 estimates the one-quarter-ahead crude price response function to OPEC production changes by performing a local linear regression of one-quarter ahead Brent front-month futures price percentage changes against the past one quarter's OPEC crude supply change. 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. First, the solid line stays above the dashed line across all production variations, capturing the historical observation that the oil prices have gone up more from 2004 to 2010 than

[4]Given the strong co-movements, using WIT futures price or the jet fuel price to proxy the crude price generates similar interaction patterns. For the interaction analysis, we match the OPEC behavior with the more global Brent futures prices and the US tight oil production with the more local WTI futures price.

from 2011 to 2016. Second, although both lines are downward sloping at most regions, the slope variations differ. The solid line has a more negative slope when the production goes down, but the slope flattens and even becomes positive when the production goes up, suggesting that cutting OPEC production raises the crude price more than increasing OPEC production lowers the crude prices. Such a response function is very beneficial to the producers as they can either cut production to increase profit margin or raise production without suffering much of a price decline.

[Figure 4 about here.]

The opposite observations are true for the dashed line estimated for the period from 2011 to 2016. The slope is flatter for production cuts than for production increases. Thus, since the shale revolution, while increasing OPEC production can still impact the crude price negatively, cutting OPEC production becomes less effective in raising the crude prices.

The changing price-setting power of OPEC production has fundamental influences on the psychology and incentive for OPEC countries to control their productions. Figure 5 estimates the one-quarter-ahead OPEC production response function to crude price changes via a local linear regression of one-quarter ahead OPEC production changes against the past one quarter's Brent futures price change. The solid lines capture the OPEC response to crude price variations before the shale revolution, which are strongly positively sloped, suggesting that the OPEC responds actively to the crude price movement in controlling their supply: Increasing supply when price is high and cutting supply when price is low. Such active response has all but disappeared since 2011, as the dash line is virtually flat.

[Figure 5 about here.]

The historical events during this period tell a similar story. The crude prices dropped sharply starting in June 2014. Historically, one would expect the OPEC countries to reduce production in order to present the collapse of the crude prices. This time however, Saudi Arabia, a key member of the OPEC, signaled its reluctance to sacrifice market share to defend oil prices. At the 166th meeting on November 27, 2014, OPEC as a whole decided to maintain the quotas unchanged due to the adamant position of Saudi Arabia. Apparently, Saudi Arabia was trying to avoid repeating the events in the 1980s when it systematically lost output share in order to defend prices amid a general increase in oil production from non-OPEC countries. It could be the case that Saudi Arabia has decided that the current situation with tight oil is similar to the one in the 1980s, and our estimated weakened price response function justifies Saudi's reluctance to cut production. With a flat price response function, cutting OPEC production cannot raise the crude price much and is therefore no longer a profit maximizing strategy.

5.2. The increasingly prominent role of US tight oil production

US tight oil production was only a small component of the world crude supply before 2011. Since then, its rapid growth has taken the world by surprise and has had profound impacts on the crude market. Figure 6 plots the dynamic interaction between US tight oil production and WTI front-month futures price changes since 2011 under different leads and lags. The plots show that the crude price changes have strong positive predictions on future tight oil production. Furthermore, this prediction is at longer leads (as far as one year ahead) than for OPEC production before 2011. The strong reaction suggests that the high oil price is a strong motivation for the development and enhancement of shale oil extraction and production technologies. The longer leads may reflect the distinct life cycle of tight oil production. A traditional deep water well in the Gulf of Mexico (WTI) or in the North Sea (Brent) can produce oil for 20 years at a relative steady rate of flow. By contrast, the US shale oil wells typically have a production life of 18-24 months. Once the well has been drilled and is production, the peak oil flow occurs in three-four months, with a rapid trail off over the next 12-18 months. The relatively short and predictable flow for oil allows the oil companies more flexibility and efficiency in managing their drilling and production activities in response to market price fluctuations.

[Figure 6 about here.]

The tight oil production variation also shows weak negative impacts on crude prices at long lags, highlighting the profound change the shale revolution has brought to the crude market.

The increasing production capacity of the US tight oil production can serve as a breaking point for the OPEC cartel. The new competition is likely to drive the price closer to the marginal cost level, reducing the prospect of sustained oil price hikes in the near future, especially ones that are deliberately driven by OPEC manipulation. The shale revolution is enabled mainly through technological advances that make historically unattainable energy sources available at reasonable cost. It may represent a trend, as new technological innovations make more energy sources (including gas, oil, and other energy sources such as wind and solar) available at increasingly competitive prices.

5.3. Shifting relations between the crude and the stock market

Crude price varies with both demand shocks and supply shocks. The two sources of shocks generate different co-movements with the stock market. When supply shocks dominate crude price movements, the crude price should exhibit low or even negative co-movements with the stock market; but when demand shocks dominate, the crude price can have a positive beta loading on the stock index. Thus, through a rolling estimation of the crude beta on the stock market index, we can obtain an understanding on the time variation of the relative contribution of the two types of shocks to the crude price movement.

Figure 7 plots in Panel A the rolling beta estimates on the two crude futures returns with a one-year rolling window. Before 2009, the beta estimates on the two crude series hover around or below zero, suggesting that supply shocks dominate the crude price variation. After 2009, however, the beta estimates become highly positive as the relations are more dominated by demand shocks. Comparing the two beta series, the beta estimates on the WTI futures are slightly higher than the estimates on Brent futures, as the WTI is more representative of the US market.

[Figure 7 about here.]

Panel B of Figure 7 plots the rolling correlation estimates between the crude futures returns and the index return. While correlation estimates are close to zero or negative before 2009, it reaches as high as 50% around 2010-2011, highlighting a structural shift in the composition of the shocks in the crude futures movements.

6. Identify Time-Varying Demand Contribution from Options

In this section, we strive to identify the time-varying contribution of demand shocks to the WTI crude futures movements through a joint analysis of WTI crude futures options and the S&P 500 index options. Section 3 has laid out the theoretical framework that underlies the identification. This section first describes the empirical implementation and then discusses the empirical findings.

6.1. Construct floating implied variance and skew series from exchange-listed options

The theory identifies the demand contribution to crude price movements through the option implied variance levels and implied variance skews against log strike moneyness on crude futures options and SPX index options. The exchange-listed option contracts have fixed strikes and expiry dates. To obtain floating implied variance series at fixed log strike moneyness (k) and time to maturity (τ), we first perform local quadratic regression of implied variance against relative log strike price at each observed maturity to obtain implied variance estimates at fixed grids of log strike moneyness. Our theoretical derivation in (5) shows that under the proportional parallel shifting dynamics assumption in (3), the implied variance at each maturity can be represented as a quadratic function of the log relative strike k. Thus, a quadratic function of the implied variance in relative strike represents a natural functional form for smoothing and interpolation along the moneyness dimension. We perform local quadratic fitting to accommodate deviations from the parallel dynamics assumption.

The local quadratic smoothing uses a Gaussian kernel. We set the bandwidth to be proportional to $|k|$ (but with a minimum of 5%) so that we smooth more for noisier, deeper-out-of-the-money options, but uses a smaller bandwidth to obtain better fitting of the strong curvature and dense data 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 futures and put options for strikes lower than futures. We filter the data to exclude options with settlement prices at one cent or lower, and data with extreme implied volatility estimates (either smaller than 10% or greater than 150%). 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 discounting data points that deviate far from the first-pass smoothing.

In the next step, at each moneyness level, we perform linear interpolation on total variance against time to maturity to obtain implied variance series at fixed time to maturities. Equation (6) shows that the at-the-money forward implied variance represents a better approximation of the instantaneous variance rate at short option maturities. The term structure effect can become more significant at longer maturities, due to expected variance movements (drift), variance risk premiums, and skew and convexity adjustments. Options trading activities on both the crude futures and the SPX Index are also concentrated at short maturities. On the other hand, when the time to maturities are too short, the option values become small, and the effects of bid-ask spreads, data noises, and expected discontinuous movements become more pronounced in the implied volatilities level and skew estimates. For our analysis, we extract the implied variance and variance skews at three-month maturity to balance out the different considerations. While the qualitative conclusions remain the same, choosing a maturity shorter than three months tend to generate noisier time series, whereas data at longer maturities become more sparse.

With the three-month implied variance estimates at different moneyess, we compute the implied variance skew around $k = 0$ by taking the implied variance differences at $k = \pm 3\%$,

$$S_t = \frac{I_t^2(k = 3\%) - I_t^2(k = -3\%)}{0.06}. \tag{14}$$

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

6.2. Time-varying options implied volatility and skew on crude futures and the stock index

Figure 8 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 three-month at-the-money implied volatility for crude futures averages at 32.72%, and varies from 13.23% to 83.73%. The corresponding implied volatility for the stock index averages at 18.66%, and varies from 9.81% to 63.86%.

[Figure 8 about here.]

The two series show more independent variations during the first half of the sample, but more co-movements during the second half. If we as before use December 2010 as the cutting point, the cross-correlation between daily log percentage changes of the two series is estimated at 26% before the shale revolution, and 41% since the shale revolution. Thus, since the shale revolution, not only does the futures return show more positive correlation with the stock index return, but also the crude futures option implied volatility shows stronger co-movements with the stock index option implied volatility. The financial crises in 2008-2009 induced large implied volatility spikes for both the crude futures and the stock index. In addition, the two series have experienced common upward moves in 2010, 2011, and 2015. By contrast, between 2004 and 2007, the crude futures options implied volatility went up in several occasions while the SPX option implied volatility stayed at very low levels.

Panel B of Figure 8 compares the implied variance skew on crude futures options and the SPX options. The stock index implied variance skew has been well-known to be persistently negative across time periods and maturities, a feature that is shared by options across all major world stock market indexes and reflects investor concerns on stock market crashes (Foresi and Wu (2005)). The magnitude of the negative skew varies over time, less negative during the calm period in 2004-2006, more negative during the 2008-2009 financial crises and subsequent European debt crises in 2010, as well as during market corrections in 2011 and 2015.

In contrast to the persistently negative implied variance skew on the stock index, the crude futures options show little skew of 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 have stayed mostly negative since then and have become increasingly co-moving with the implied variance skew of the stock index. If we again use the end of 2010 as the cutting point, the cross-correlation estimate between daily changes of the two implied variance skew series is negative at -6% before the shale revolution, but becomes strongly positive at 21% since then. The increased co-movements between the crude futures and the stock index, in terms of returns, implied volatilities, and implied variance skews, suggest that demand shocks, or systematic market risk, are playing an increasingly important role in the crude futures movement since the shale revolution.

6.3. Time-varying demand shock contribution to crude futures movements

Options on the stock index reveal time-varying magnitudes of demand shocks and volatility feedback effects on systematic market risk. Combining this information with options on crude futures, we can extract the relative contribution of demand shocks to the crude futures variation. Specifically, from the interpolated at-the-money implied variance $((A_t^o, A_t^d))$ and implied variance skew (S_t^o, S_t^d), we can compute the relative variance contribution from the demand shocks to the crude futures variation (RC_t^d), as in (13)

$$RC_t^d = \frac{(\eta_t^d)^2 A_t^d}{A_t^o}. \tag{15}$$

Since our model assumes zero skew contribution from the orthogonalized supply shocks and negative skew contribution from demand shocks, in computing the demand shock contributions, we truncate the crude futures option implied variance skew to zero if the estimates become positive. Figure 9 plots the time series of the estimated percentage relative variance contribution from demand shocks. The dotted lines represent the daily estimates while the solid lines represent monthly moving averages.

[Figure 9 about here.]

The demand shock contribution stayed low and hovered around zero before 2009, but since then have become much stronger and contributes to more than half of the crude futures variation. The shifting patterns are similar to the rolling correlation estimates between returns on the crude futures and the stock index returns in Figure 7, even though the two graphs come from completely different information sources: The rolling-window correlation estimates in Figure 7 capture the price behaviors of the crude futures and the stock index, whereas the identification of the variance contribution in Figure 9 relies mostly on the option implied variance skew.

A couple factors have contributed to the shifting dynamics. The initial shift was induced by the large demand drop after the financial crises, which has made the demand shock more prominent, and less likely to be absorbed by supply variation. Afterwards, the rapid rise in the US tight oil production has reduced the price-setting power of the OPEC cartel and has muted the effect of supply variation on oil price fluctuation.

7. Optimal Fuel Cost Hedging for the Airline Industry

Heavy energy consumers such as the airline industry often confront the difficult but important question of whether it is appropriate (or how much) to hedge their energy consumption cost variation with crude futures. Intuitively, large oil price fluctuations can induce large and undesirable fluctuations to the bottom line of these companies, suggesting a need to hedge.[5] Nevertheless, through the decomposition of crude price movements into demand and supply shocks with time-varying intensities, we show in this section that the optimal hedging policy is not a static decision, but depends crucially on the relative strength of the two types of shocks in the crude price fluctuation. Time variation in the relative strength calls for variation in the optimal hedging decision.

To illustrate the idea, it is convenient to perform a stylized decomposition of the bottom line of a company with heavy energy consumption into two components: (1) revenue, which is mainly driven by market demand and which we assume positively co-move with business cycle and hence the stock index performance, and (2) fuel cost. If the company does not hedge its fuel cost variation, we can decompose the company's stock performance as following the bottom line and reflecting responses to both revenue (demand) shocks and fuel cost shocks,

$$d\frac{UA_t}{UA_t} = \beta_r \frac{dD_t}{D_t} - \beta_c \frac{dO_t}{O_t}, \quad \beta_r, \beta_c \geq 0, \tag{16}$$

where we assume that the revenue is positively exposed to the stock market ($\beta_r > 0$) and the cost of the

[5]See Morrell and Swan (2006) for a general discussion on the general practice of airline fuel cost hedging. Carter, Rogers, and Simkins (2006) analyze the performance of 28 airline companies and show that airlines that hedge their fuel costs have Tobin's Q ratios 5-10% higher than those that do not hedge. Rao (1999) estimates the benefit of hedging with futures and find a 23% decline in quarterly income volatility from his assumed hedging policy. Lim and Hong (2014) show evidence that hedging reduces airline operating cost. Rampini, Sufi, and Viswanathan (2014) show how collateral requirements can constraint the hedging practice of firms in financial distress.

company is positively exposed to the crude futures price ($\beta_c > 0$). Since the crude price movements are by itself driven by crude supply shocks and demand shocks, we can plug in the crude future dynamics in (1) to have

$$\frac{dUA_t}{UA_t} = \mu_t^a dt + (\beta_r - \beta_c \eta_t^d)\sqrt{v_t^d} dW_t^d + \beta_c \eta_t^s \sqrt{v_t^s} dW_t^s. \tag{17}$$

Fully hedging the fuel cost with crude futures would leave the company's performance purely exposed to demand shocks,

$$\frac{dHA_t}{HA_t} = \beta_r \sqrt{v_t^d} dW_t^d. \tag{18}$$

The two equations allow us to compare the relative benefits and costs of hedging fuel costs with crude futures. When oil price fluctuation is dominated by supply shocks, $\eta_s \gg \eta_d$, hedging can remove the second component of the variation term and reduces the variation of the company's bottom line. On the other hand, when the supply shocks are muted and the crude variation is dominated by demand shocks, hedging the fuel cost can actually increase the volatility of the bottom line, chiefly because the demand shock component of the crude movement can partially cancel out the revenue fluctuation for a pro-cyclical company.

In practice, the optimal hedging strategy depends on the relative composition of the crude futures variation, as well as the sensitivities of the company's revenue and cost to the stock market index and the crude futures movements, respectively. If we can estimate the revenue and cost sensitivities and can predict the time variation in the relative variance contribution of demand and supply shocks to crude futures, we can devise a dynamic hedging strategy that minimizes the conditional variation of the bottom line. Formally, let h_t denotes the optimal fraction of hedging against fuel cost. The partially hedged bottom line dynamics becomes

$$\frac{dPA_t}{PA_t} = (\beta_r - (1-h_t)\beta_c \eta_t^d)\sqrt{v_t^d}dW_t^d + (1-h_t)\beta_c \eta_t^s \sqrt{v_t^s}dW_t^s.$$

If we choose h_t to minimize the bottom line variation,

$$\min_{h_t} \quad \left(\beta_r - \beta_c(1-h_t)\eta_t^d\right)^2 v_t^d + \beta_c^2(1-h_t)^2(\eta_t^s)^2 v_t^s, \tag{19}$$

the first-order conditional leads to the following optimal hedging ratio,

$$h_t = 1 - \frac{\beta_r}{\beta_c}\frac{\eta_t^d v_t^d}{v_t^o}. \tag{20}$$

Timely identification of (v_t^o, v_t^d, η_t^d) from options allows one to devise a dynamic hedging strategy that minimizes the expected variation from the company's bottom line. In particular, if we plug in the estimates on the demand shock loading η_t^d and the at-the-money implied variances, we can represent the dynamic hedging ratio as

$$h_t = 1 - \frac{\beta_r}{\beta_c}\left(\frac{S_t^o}{S_t^d}\right)^{1/3}\left(\frac{A_t^d}{A_t^o}\right)^{2/3}. \tag{21}$$

The optimal hedging policy asks for a full fuel cost hedge when crude futures movements have zero loading on demand shocks ($\eta_t^d = 0$) but reduces the hedging ratio as the demand shock contribution to the crude futures movement increases.

The changing behaviors in crude futures and options have important implications for the fuel cost hedging practice in the airline industry. When supply shocks dominate crude price movements, the profitability of the airline industry can be severely harmed by fuel cost variations, in particular because supply-driven shocks are less related to the demand of the airline industry and represent a stand-alone risk factor that the airline industry must try to cope with. To avoid the undesirable situation of both declining demands for travel and increasing oil price, it is desirable for the airline industry to use crude futures to hedge its jet fuel cost variation.

Nevertheless, the rationale for fully hedging the fuel cost variation becomes questionable when the crude price movements become more dominated by demand shocks. When demand shock dominates crude price movement, the airline industry can expect lower jet fuel prices when demand is low and higher jet prices when demand is higher. The positive co-movement between demand for travel and the jet fuel price can partially cancel each other, ameliorating the impact on the bottom line. Thus, the shifting to demand-induced jet price movements reflects a reduced need for fuel cost hedging by the airline industry.

In Figure 8, we compute the optimal hedging ratio at each date based on implied variance and skew estimates and by assuming a unit exposure of revenue to the market demand and a unit exposure of the cost to crude futures variation ($\beta_r = \beta_c = 1$). The dotted line represents the daily estimates and the solid line denotes a monthly moving average.

[Figure 10 about here.]

The plot shows that full fuel cost hedging is often optimal in the early part of the sample, but the optimal hedge ratio has become much lower, hovering around 50%, since the shale revolution, due to the increasing contribution of demand shocks to the crude fluctuation.

The actual optimal hedge ratio for a particular airline company will depend on the revenue and cost sensitivity to the stock market and crude performance, respectively. Nevertheless, Figure 8 highlights the dynamic nature of the optimal fuel cost hedging for airline industries.

8. Concluding Remarks

With the shale oil revolution and new technological advances on alternative energy sources, the consensus appears to be that fuel prices will remain depressed. The empirical analysis provides evidence on how exactly shale oil production has impacts the oil industry. The evidence on the interactions between oil price and production show that since the shale revolution, the OPEC can no longer be the price setter for fuel and are accordingly losing incentives to regulate their own production to increase oil prices.

As a result of the shifting dynamics, crude price movements have been shifting from being dominated by supply shocks to being dominated by demand shocks. Investor concerns are accordingly shifting from worrying about crude price hikes as a production cost gauge to worrying about crude price drops as an indication of weakening aggregate demand. We show that one can effectively and timely infer the shifting crude dynamics and market concerns from the joint behavior of crude future options and stock index options.

These shifts have fundamental implications for economic analysis in general and for the fuel cost hedging practice in the airline industry in particular. Crude supply shocks represent unexpected and harmful shocks to the airline industry. When crude price movements are dominated by crude supply shocks, it is prudent to hedge the crude price variation via crude futures contracts to mitigate excess volatility in the bottom line of the industry. Nevertheless, when crude price movements are dominated by demand shocks instead, as it is happening now, fully hedging the fuel cost variation becomes less desirable, because demand-driven crude price movements tend to positively co-move with demand for the airline travel, and can therefore partially cancel out the volatility in demand. We decompose the crude futures movement into demand and supply shocks and derive the optimal fuel cost hedging policy for an airline company as a function of the company's revenue sensitivity to the demand shocks, the company's cost sensitivity to the crude futures movements, and the relative demand shock contribution to the crude futures movements. The timely identification of demand shock contribution from options allows a company to dynamically update its fuel cost hedging to minimize the volatility in its bottom line.

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Table 1
Return correlation at different frequencies
Entries report the cross-correlation estimates of returns on JET fuel price, Brent front month futures price, and WTI front month futures price at different frequencies.

Pair	(JET,Brent)	(JET,WTI)	(ICE, WTI)
Daily	0.588	0.506	0.793
Weekly	0.761	0.705	0.882
Monthly	0.890	0.859	0.968
Quarterly	0.913	0.876	0.975

Table 2
Cost of producing a barrel of oil
Entries report the average cash cost to produce a barrel of oil or gas equivalent in 2016, based on data from March 2016 from Rystad Energy Ucube.

Country	Gross Tax	Capital Spending	Production Costs	Admin/Trans. Costs	**Total**
Saudi Arabia	0.00	3.50	3.00	2.49	8.99
Iran	0.00	4.48	1.94	2.67	9.09
Iraq	0.91	5.03	2.16	2.47	10.57
Russia	8.44	5.10	2.98	2.69	19.21
Indonesia	1.55	7.65	6.87	3.63	19.70
US Non-Shale	5.03	7.70	5.15	3.11	20.99
Norway	0.19	13.76	4.24	3.12	21.31
US Shale	6.42	7.56	5.85	3.52	23.35
Canada	2.48	9.69	11.56	2.92	26.65
Venezuela	10.48	6.66	7.94	2.54	27.62
Nigeria	4.11	13.10	8.81	2.97	28.99
Brazil	6.66	16.09	9.45	2.80	35.00
UK	0.00	22.67	17.36	4.30	44.33

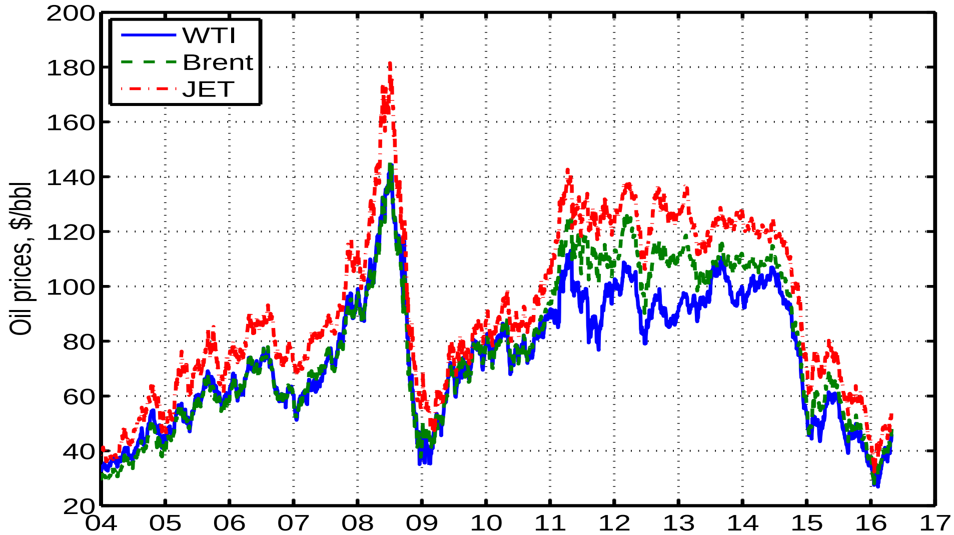

Figure 1
Time series of crude prices
The three lines represent the time series of WTI front-month futures prices (solid line), Brent front month futures price (dashed line), and the Jet Kerosene FOB Singapore Cargo price (dashed-dotted line).

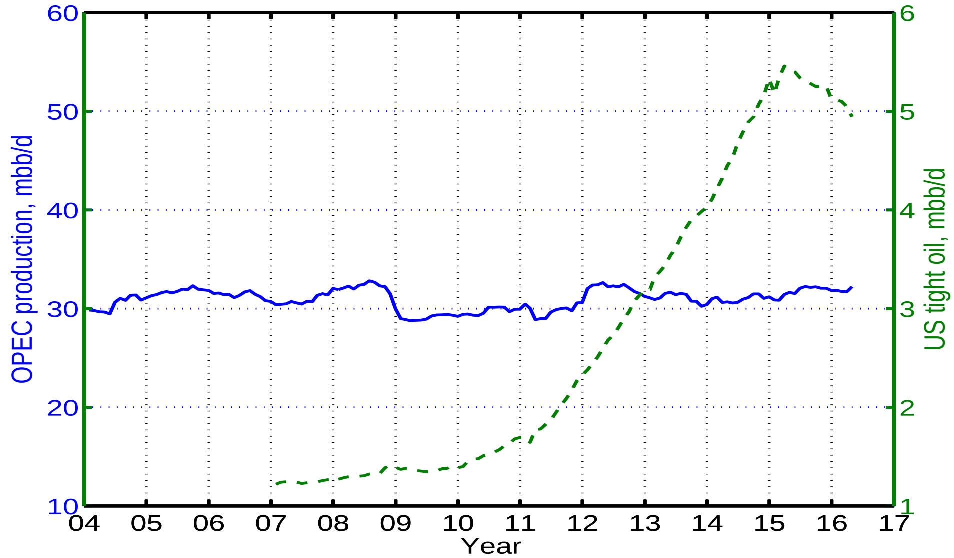

Figure 2
Time series of oil production from OPEC and the US
The solid line denotes the time series of the OPEC crude supply from 2004 to 2016, with units on left side. The dashed line shows the time series of the US tight oil production, with units on the right side.

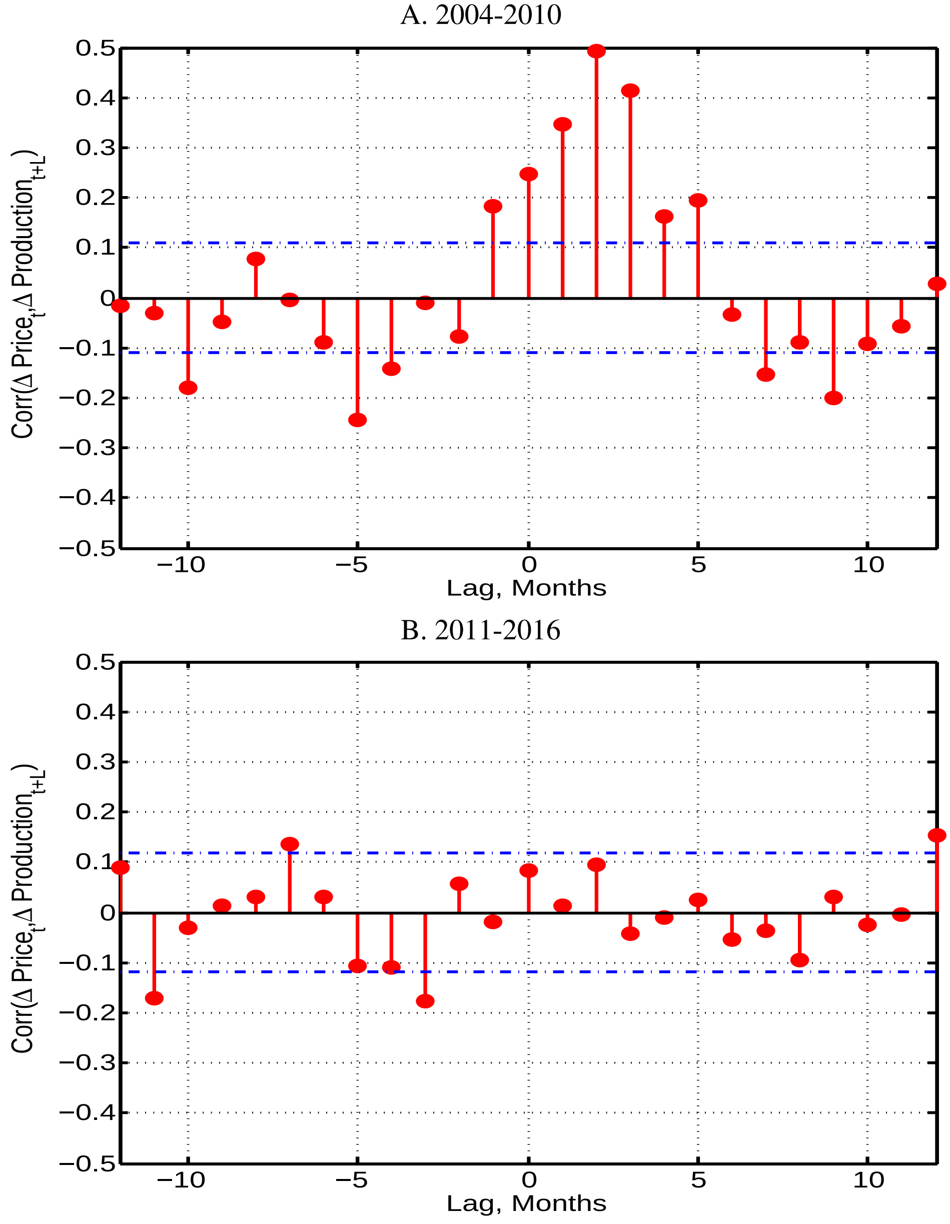

Figure 3

Interaction between crude price and OPEC supply before and after shale revolution

Panel A plots the cross-correlogram between monthly log returns on Brent front-month futures prices and monthly log change in OPEC crude supply estimated with data from 2004 to 2010. Panel B plots the cross-correlogram estimates using data from 2011 to 2016. The bars represent the cross-correlation estimates at different leads or lags (in months) and the two dashed lines in each panel represent the confidence bands at one standard deviation.

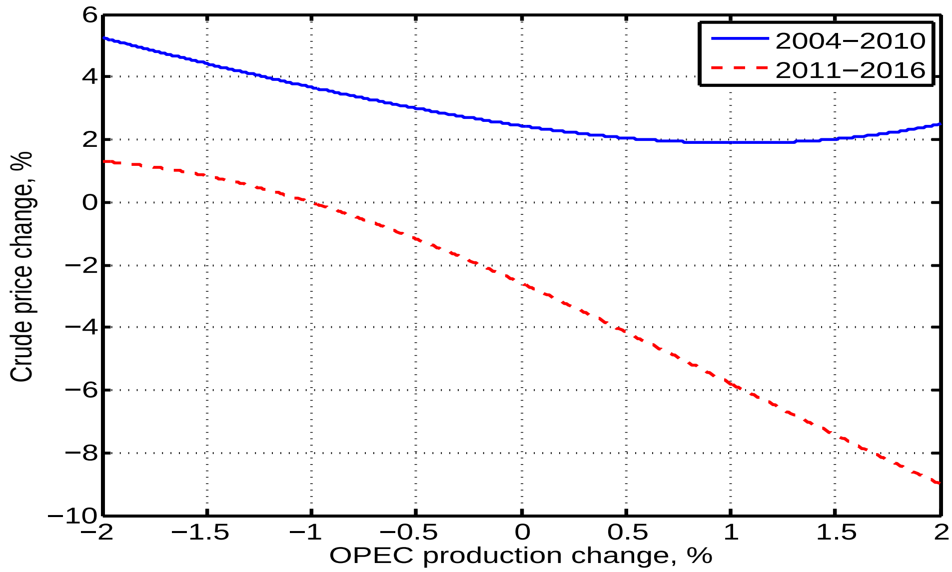

Figure 4
OPEC pricing-setting power before and after shale revolution
Lines plots the crude response function to OPEC production changes, estimated using a local linear regression of one-quarter ahead Brent front-month futures price percentage changes against the past one quarter's OPEC crude supply change. The solid line is estimated using data from 2004 to 2010 and the dashed line from 2011 to 2016.

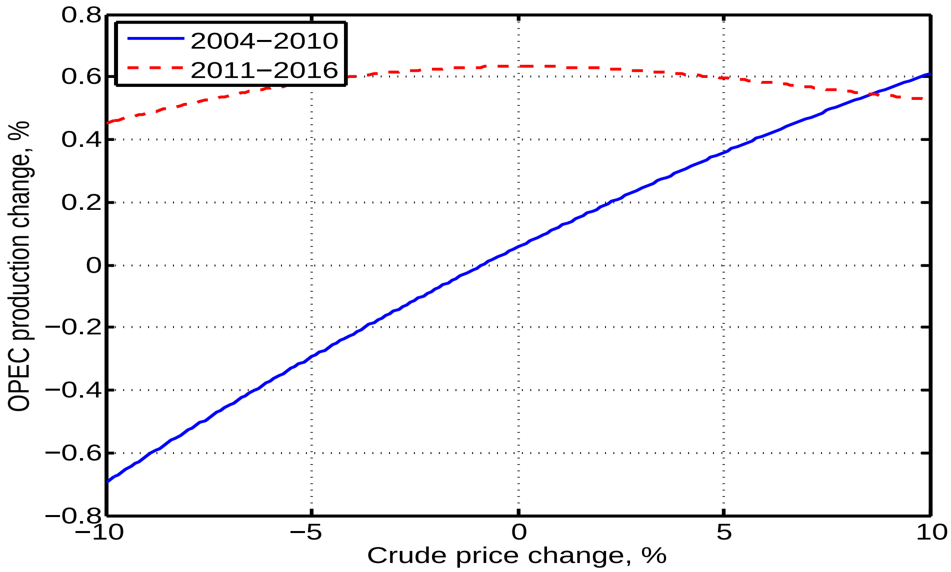

Figure 5
OPEC response to crude price movements before and after shale revolution
Lines plots the OPEC production response to crude price changes, estimated using a local linear regression of one-quarter ahead OPEC production changes against past one quarter's Brent front-month futures price percentage change. The solid line is estimated using data from 2004 to 2010 and the dashed line from 2011 to 2016.

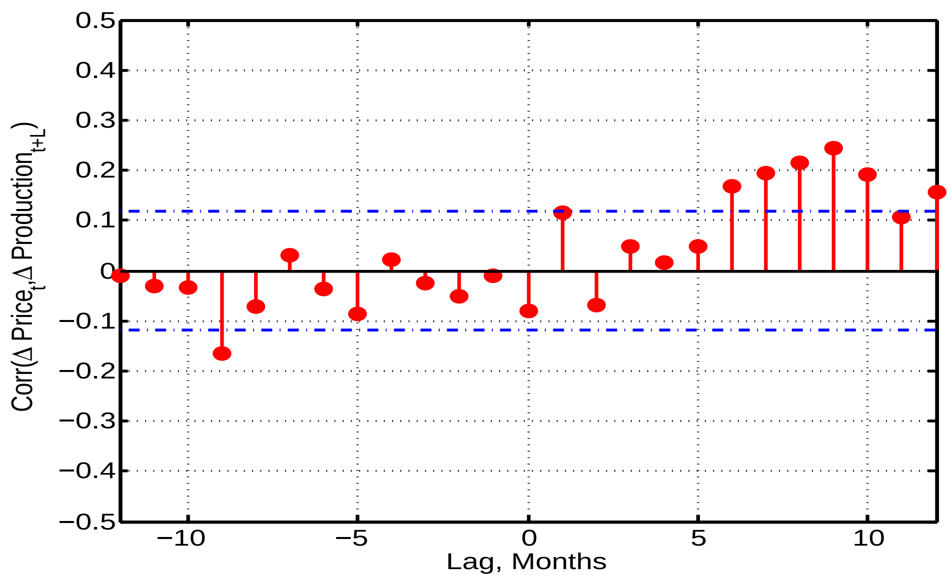

Figure 6

Interaction between crude price changes and US tight oil production

The bars show the cross-correlation estimates between monthly log returns on WTI front-month futures prices and monthly log change in US tight oil production at different leads and lags, estimated with data from 2011 to 2016. The two dashed lines represent the confidence bands at one standard deviation.

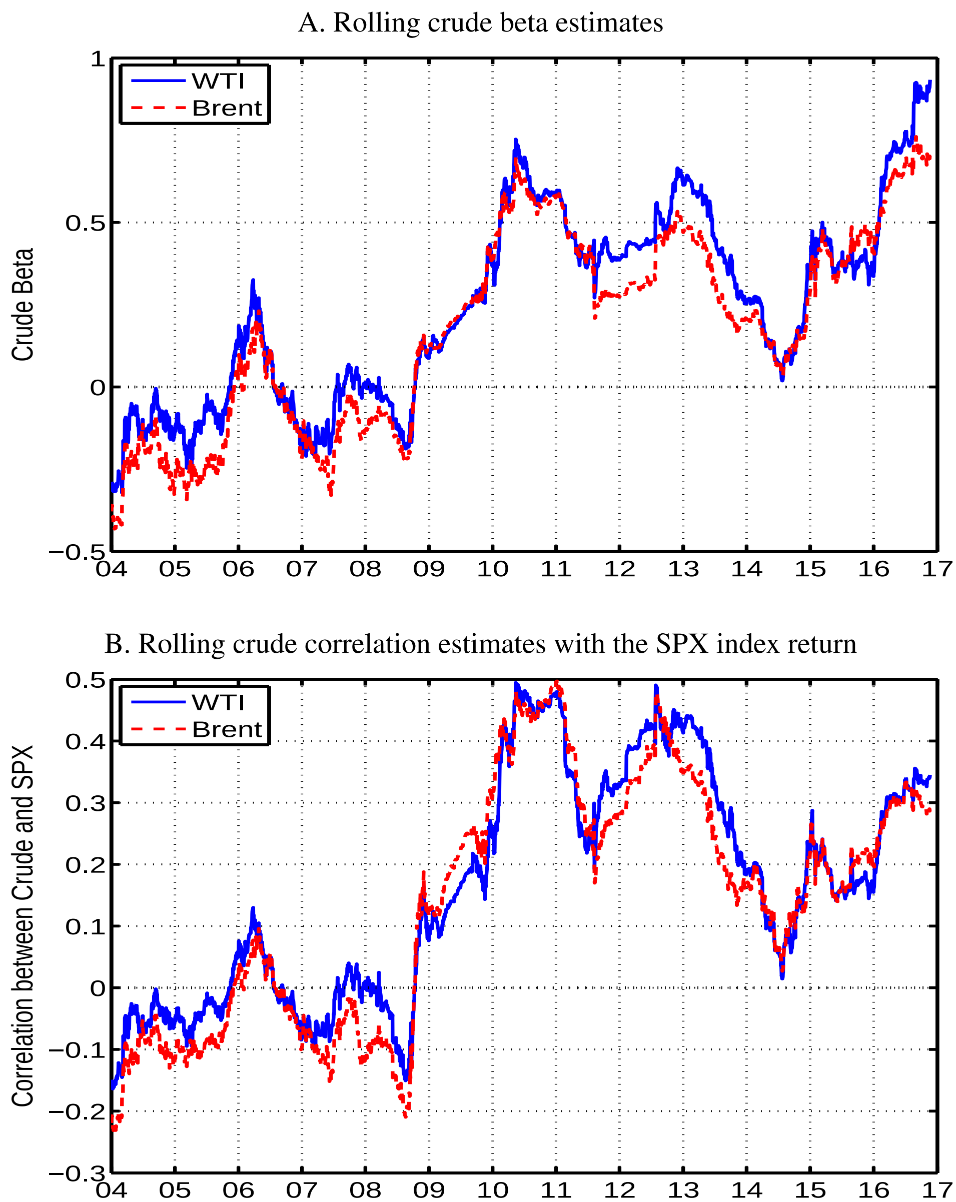

Figure 7
Rolling crude beta and correlation estimates on the SPX index
Lines in Panel A plot the rolling beta estimates of the two crude futures on the SPX index, estimated with daily returns with a one-year rolling window, with the solid line denoting the rolling beta for WTI front-month futures and dashed line denoting the rolling beta for Brent front-month futures. Panel B plots the corresponding one-year rolling correlation estimates between returns on the two crude futures and SPX index returns.

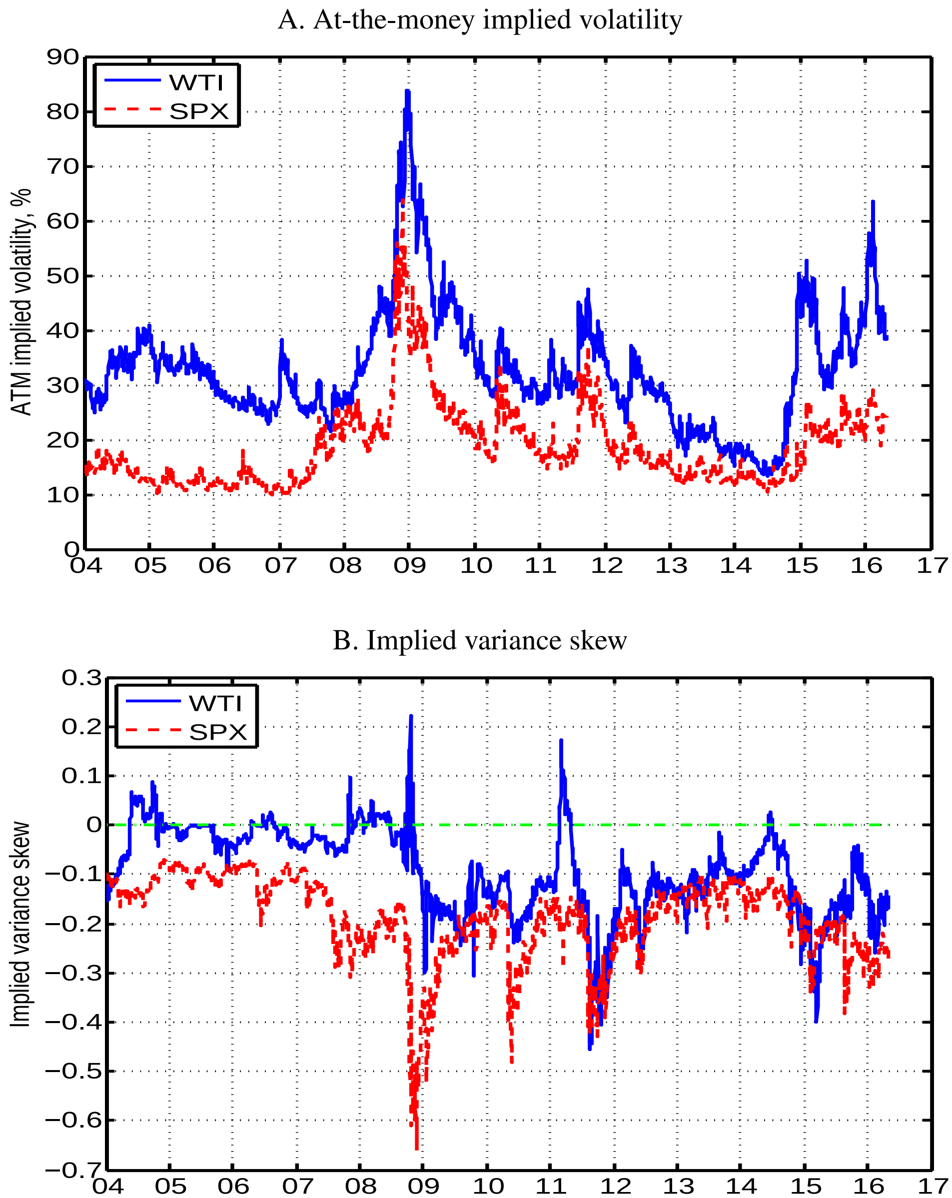

Figure 8

Comparing the movements in implied volatility and implied variance skew on crude futures options and SPX 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 WTI crude futures options (solid lines) and the SPX stock index (dashed lines). The floating series are estimated via smoothing and interpolation of the exchange-listed option implied volatilities with fixed strikes and expiry dates.

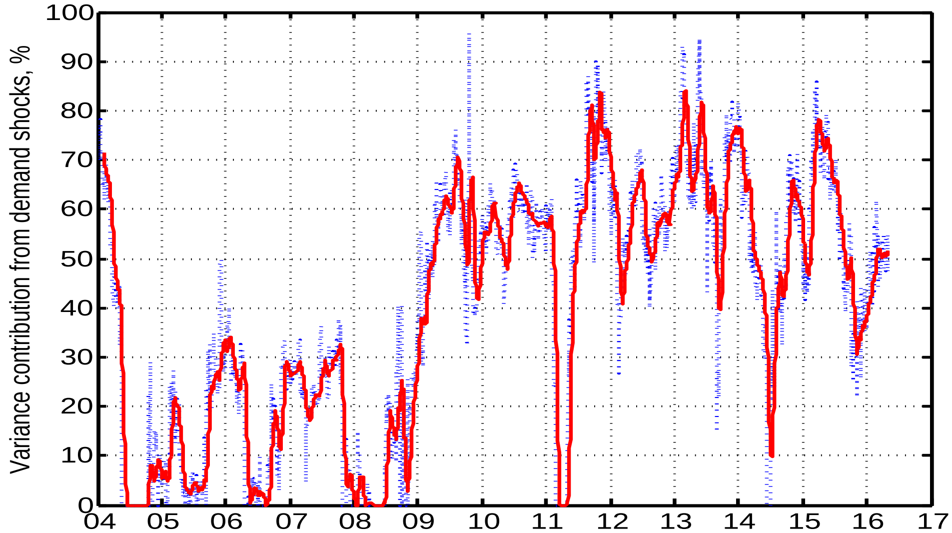

Figure 9
Time-varying demand shock contribution to crude futures movements
The dotted line represents the daily estimates of the variance contribution from demand shocks to crude futures movements, estimated based on interpolated three-month at-the-money implied variance and implied variance skew on the WTI crude futures options and the SPX index options. The solid line represents the monthly moving average of the daily estimates.

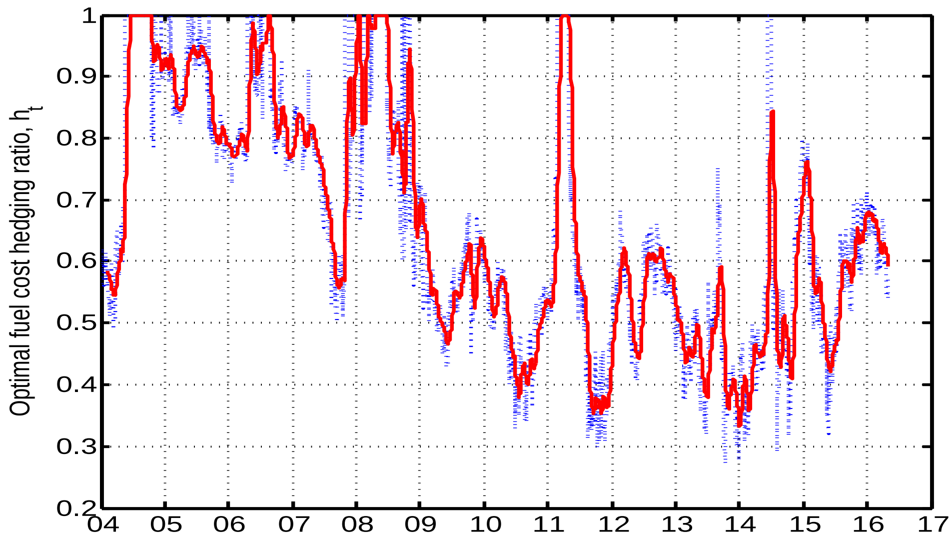

Figure 10
Time variation in the optimal jet fuel cost hedging ratio
The dotted line represents the daily estimates of the optimal fuel cost hedging ratio for a company with unit revenue exposure to the SPX movements and unit cost exposure to the WTI crude futures. The estimates are based on interpolated three-month at-the-money implied variance and implied variance skew on the crude futures options and the SPX index options. The solid line represents a monthly moving average of the daily estimates.