Characteristics of Petroleum Product Prices: A Survey†

Louis H. Ederington*, Chitru S. Fernando*, Seth A. Hoelscher**,
Thomas K. Lee***, and Scott C. Linn*

*Price College of Business
University of Oklahoma
307 West Brooks, Norman, OK 73019

**College of Business
Missouri State University
901 S. National Ave., Springfield, MO 65897

***U.S. Energy Information Administration, U.S. Department of Energy
1000 Independence Ave., SW
Washington, DC 20585

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Abstract

We review and synthesize the empirical evidence on several factors related to petroleum product prices: (1) the general distributional characteristics of petroleum product prices; (2) the influence of refinery outages, extreme weather, and similar circumstances on product prices; (3) the way that price discovery occurs for petroleum products; (4) the predictive accuracy of petroleum product futures prices for future spot prices; and (5) the impact of speculation on product prices.

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1. Introduction

This review is the second of a two-part series surveying the extant literature on the behavior and determinants of petroleum product futures prices. Ederington et al. (2018a) focuses on the relation between petroleum product prices and oil prices. In this part, we turn to the general distributional characteristics of petroleum product prices, the influence of fundamental factors such as refinery outages and the weather on product prices, the way that price discovery occurs for petroleum products, and the predictive accuracy of petroleum product futures prices for future spot prices.[1]

Recent years have seen a surge in research devoted to the question of whether fundamental supply and demand factors or excess speculation have influenced movements in crude oil prices. However, little attention has been paid to whether speculation appears to influence petroleum product prices. We also review the research on this topic.

2. Prices and inventories

The theory of storage (Kaldor, 1939; Working, 1949) predicts that price volatility and price level are inversely related to inventory levels. When there are little or no inventories to act as a buffer, imbalances in supply and demand may result in dramatic price changes. In addition, prices and volatility will be positively correlated, as both are negatively related to inventories. A separate argument made by Smith (2009) and others emphasizes that oil price volatility can be high because the underlying demand and supply curves are so price-inelastic that shocks to supply or demand are immediately reflected in the price. Finally, the relation between volatility and inventory can run in the opposite direction as well; that is, volatility can potentially influence inventory levels.

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[1] For a review of the literature focusing on the behavior and determinants of crude oil prices see Ederington et al. (2011), https://www.eia.gov/workingpapers/pdf/factors_influencing_oil_prices.pdf .

For instance, as Pindyck (2004) has suggested, high oil price volatility increases the opportunity cost of producing now in contrast to producing later; that is, waiting to see if future spot prices are greater than current spot prices. Balancing these views, Smith (2009) points out that price volatility provides incentives to hold inventories, but because inventories are costly, they may not be sufficiently large to fully offset the rigidity of demand and supply.

Gorton et al. (2012) study the relation between petroleum product futures' excess returns (what they refer to as the risk premium) and inventories. They find that time-series variation and cross-sectional variation of the risk premium are inversely related to inventory levels of heating oil, gasoline, and crude oil. However, although negative relations are documented for all three commodities, none is statistically different from zero at conventional levels. The authors attribute the weak statistical significance levels to the fact that inventories are measured with error.

A recent study completed by the U.S. Energy Information Administration (U.S. Energy Information Administration, 2014) focuses on the relation between changes in the benchmark prices (Brent and WTI) and gasoline prices. The study also presents results regarding the conditional effects on gasoline prices of changes in deviations of gasoline inventories from prior five-year averages. The authors generally find an inverse and statistically significant relation between inventory deviations and gasoline price change.

Pindyck (2004) develops a structural model of inventories, spot prices, and futures prices that explicitly considers the role of volatility and estimates the model with daily and weekly data on crude oil, heating oil, and gasoline during the period 1984-2001. Weekly volatilities are estimated as sample standard deviations of adjusted daily log changes in prices. Pindyck (2004) finds that spot prices, inventories, and convenience yield do not cause volatility in crude oil and thus concludes that volatility is an exogenous variable. However, he also finds that the model performs poorly for the crude oil market. For heating oil, changes in volatility influence convenience yields and, to a lesser extent, inventories, but the effects are not large. There is no strong evidence of such effects in the crude oil and gasoline markets. Furthermore, although changes in heating oil volatility can help explain changes in the spot-futures spread (convenience yield), it does not explain the spot price itself. Pindyck (2004) concludes that the results fit the theoretical predictions for heating oil but not for crude oil or gasoline. Pindyck conjectures that the mixed results might be an artifact of model misspecifications or that market variables affect production decisions more slowly than can be captured with weekly data. Pindyck also notes that speculation might influence price volatility, which is not considered in the model.

Kaufmann et al. (2009) study the relation between oil prices, gasoline prices, inventory levels for oil and gasoline, refinery utilization rates, and the price of a substitute fuel (natural gas). They are interested in how oil price changes are transmitted horizontally and/or vertically through the energy supply chain. The authors define "horizontal transmissions as changes that are generated by linkages among fuels at a similar stage of processing while vertical transmissions are changes that are generated by upstream/downstream linkages in the oil supply chain" (p. 644). They estimate vector error correction models among the series using both weekly and quarterly observations, concluding from tests of causality that the price of crude oil is an important determinant of behaviors throughout the oil supply chain. Analyzing impulse response functions, they find that shocks to crude oil prices affect inventory behaviors, refinery utilization rates, and the price of motor gasoline, and are transmitted laterally to the natural gas market.

Studies by Kilian (2010) and Bilgin and Ellwanger (2017) both emphasize the role of inventories (both oil inventories and inventories of petroleum products) in the formation of gasoline demand and prices. Kilian (2010) examines the relationship between the global crude oil market and U.S. fuel consumption. He finds significant oil price effects associated with shifts in U.S. gasoline consumption. Bilgin and Ellwanger (2017) develop and estimate a model of the oil and gasoline market that reflects the underlying premise that "demand from crude oil is derived from the demand for oil products that it is converted to" (p. 3). The model includes both oil and petroleum product inventories. The authors find that global fuel demand is inelastic with respect to crude oil prices.[2]

3. Refinery outages, weather-related factors and product prices

Focusing on weekly wholesale gasoline prices in the United States from January 2002 to September 2008, Kendix and Walls (2010) quantify the impact of refinery outages on petroleum product prices. The authors match refinery unit output to specific wholesale gasoline markets, then estimate panel data regressions and quantify the impact of refinery unit outages on wholesale gasoline prices. They control for time-specific effects, city-specific effects, fuel-specific effects, refinery concentration, and other factors that could affect the prices of refined petroleum products. Their results show that refinery outages have a statistically significant positive impact on refined product prices and that the magnitude of this effect is larger for certain fuel blends.

Chesnes (2015) also investigates the relation between refinery outages on current petroleum product prices and future refinery investment. The author studies detailed refinery-level data on planned and unplanned refinery outages for the period 2001-2011. The data are measured at the monthly frequency, which includes the wholesale prices studied. Outages are aggregated to the Petroleum Administration for Defense District (PADD)-month level, and the author controls for

[2] Linn et al. (2018) review the literature on how petroleum product futures prices respond to news about unexpected changes in product as well as crude oil inventories. The evidence indicates that petroleum product futures prices increase in response to unexpected decreases in inventory and decrease in response to unexpected increases. Linn et al. (2018) also present a review of the evidence on product price responses to macroeconomic news, monetary policy changes and in the U.S. Strategic Petroleum Reserve.

such things as stocks and hurricane activity.[3] Similarly to Kendrix and Wall (2010), Chesnes concludes that refinery outages "can have an economically significant effect on product prices" (p. 333). He finds that product prices are positively related to outages.

Fink et al. (2010) study how tropical storms influence petroleum product prices. The authors examine the effect of tropical storm forecasts on the 3-2-1 crack spread—the difference between refined petroleum and crude oil prices focusing on refinery activity in the Gulf Coast region. The authors test the effect of the release of the leading seasonal hurricane forecast in the Atlantic basin, the Gray-Klotzbach forecast from Colorado State University, on the crack spread market and find important economic effects. Prices appear to reflect storm effects at the 24-hour forecast horizon. Further, the magnitude is significant—category 4 hurricanes in this region increase refined petroleum prices relative to crude oil by about 13.5%.

In a follow-up study, Fink and Fink (2014) also find that crack spread prices are affected by seasonal hurricane forecasts. Their approach is to test the effect of the release of the Gray-Klotzbach forecasts in the Atlantic basin (which includes the Gulf of Mexico) on the crack spread market. The authors show that 3-2-1 crack spread prices increase by more than 9% when the June forecast for the upcoming season increases by one standard deviation.

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[3] Report: http://www.eia.gov/petroleum/weekly/archive/2015/150122/includes/analysis_print.cfm. Per information from the website of the EIA (http://www.eia.gov/tools/glossary/index.cfm?id=P#PADD_def),
Petroleum Administration for Defense District (PADD): A geographic aggregation of the 50 states and the District of Columbia into five districts, with PADD 1 further split into three sub-districts. The PADDs include the states listed below:
•PADD 1 (East Coast):
•PADD 1A (New England): Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.
•PADD 1B (Central Atlantic): Delaware, District of Columbia, Maryland, New Jersey, New York, and Pennsylvania.
• PADD 1C (Lower Atlantic): Florida, Georgia, North Carolina, South Carolina, Virginia, and West Virginia.
•PADD 2 (Midwest): Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Wisconsin.
•PADD 3 (Gulf Coast): Alabama, Arkansas, Louisiana, Mississippi, New Mexico, and Texas.
•PADD 4 (Rocky Mountain): Colorado, Idaho, Montana, Utah, and Wyoming.
•PADD 5 (West Coast): Alaska, Arizona, California, Hawaii, Nevada, Oregon, and Washington.

Blair and Rezek (2008) find deviations from historic price pass-through patterns during the immediate post-Hurricane Katrina period. Although gasoline price pass-through patterns have largely returned to their long-term equilibrium, evidence indicates that asymmetry, previously not evident, may now exist.

4. Evidence on international market integration

Studying the question of whether petroleum product prices have become more integrated over time, Zavaleta et al. (2015) point out that, due to changes in the petroleum refining industry, trade in refined petroleum products has become more widespread and global. The authors investigate the convergence of prices for refined products across different international markets. They examine data on refined products from market centers in the United States and Europe and test for convergence of prices using standard time-series techniques. The researchers base their analysis on tests for cointegration between pairs of prices, such as New York Harbor gasoline and Rotterdam-Amsterdam gasoline. They do not examine relations between Brent prices and New York Harbor gasoline prices. The data plainly show that markets for refined petroleum products have become more interrelated as Europe has begun exporting its gasoline surplus and global demand for petroleum products approaches refining capacity. Their results suggest that the U.S. and European markets for oil and refined products are integrated.[4]

5. Reduced form models of petroleum product prices

5.1. Overview

An alternative to modeling spot prices explicitly from fundamentals is to model the price process using a reduced form structure. Models in this class do not directly model fundamental

[4] Ji and Fan (2016) reach similar conclusions from an empirical study of the world market for crude oil.

supply and demand changes but are structured to capture the net effects of these factors without explicitly modeling the underlying forces. These models typically propose one or more sources of underlying uncertainty that contribute to the time series variation in price changes. Examples include general random behavior, mean reversion in the price, price jump activity, random behavior of the convenience yield, stochastic interest rate behavior, and time-varying volatility.

5.2. Model specifications

The genesis of these models can be traced back at least to Black (1976a) in his work on commodity derivatives. Modern thought on the construction of these types of models for oil prices stems from the work of Brennan and Schwartz (1985) and later Schwartz (1997). Numerous extensions of the basic framework by Schwartz and his coauthors as well as others have appeared in the literature.

Reduced form models are designed around a framework in which one or more sources of randomness (commonly referred to as random factors) contribute to the total randomness of spot price change. A single-factor framework is essentially a model with a single source of "net" uncertainty. The fundamental source of the randomness, however, is not explicitly modeled, but it is implied that the factor reflects the net effect of all fundamental sources of uncertainty. Numerous authors have studied the issue of whether excessive speculative trading activity can disrupt or increase the level of prices and the volatility (randomness) of prices. Non-structural models are agnostic on this potential force. If such effects do exist, these models capture those influences along with all other fundamental randomness in a reduced-form manner. This is not to say that one could not construct a structural model built up from fundamentals involving stochastic supply and demand conditions (Seppi, 2002). Such an approach, however, requires assumptions about the functional forms of the demand and supply functions. The benefits of such models are that they permit key parameters to be functionally related to “non-price” data, such as the weather.

The notion of the “convenience yield” plays an important role in many non-structural models and is a fundamental element of the modern theory of storage, so a brief comment is warranted. Brennan and Schwartz (1985) define the convenience yield as follows: “The convenience yield is the flow of services that accrues to an owner of the physical commodity but not to the owner of a contract for future delivery of the commodity” (p. 139). They point out that “competition among potential storers will ensure that the net convenience yield of the marginal unit of inventory will be the same across all individuals who hold positive inventories” (p. 139). Most reduced form models that incorporate a convenience yield actually use the net convenience yield measured as the convenience yield minus the cost of carry, where the cost of carry includes storage costs as well as borrowing costs.

Reduced form models of oil prices are generally couched in terms of the instantaneous dynamics of price changes, not the level of prices. The models are generally variations on geometric Brownian motion, ensuring that, under the usual set of statistical distributional assumptions, prices can never fall below zero. The development of these models has proceeded through various incremental stages with an eye towards identifying a structure that best fits the actual data. Best fit is generally defined not in terms of whether the spot price process fits the spot data, but by whether the implied prices of derivatives (futures and options on futures) on the commodity are priced accurately under a particular set of assumptions about the spot process. However, in a study described in the section 6.4, Nomikos and Andriosopoulos (2012) present a comprehensive analysis of multiple specifications that include mean reversion; jumps as well as stochastic volatility; fit to heating oil, gasoline, and crude oil prices; and focus on best fit relative to actual data.

6. Empirical models of oil prices and statistical behavior

6.1. Overview

The literature examining the properties and stochastic behavior of the prices for the nearby NYMEX futures contracts for gasoline and heating oil reaches several conclusions.[5] First, front month futures prices (as proxies for the spot price) exhibit mean reversion. Second, the volatility is large on an annualized basis and comparable to volatility of oil futures prices, and volatility itself varies over time. Third, volatility at any date is conditionally related to volatility in the recent past. Fourth, there is long-memory in volatility, meaning that, after controlling for the short-term effects in the relation between current and past volatility, there is also a relation between volatility at longer lags. Related to these observations is the conclusion that petroleum product prices exhibit jumps and, as a result, distribution of oil price changes exhibits "fat tails" (i.e., kurtosis). Log price changes of heating oil and gasoline exhibit statistically significant autocorrelation. Unconditional as well as conditional correlations between heating oil or gasoline returns and stock price index returns are small and tend not to be significantly different from zero.

6.2. General distributional characteristics of petroleum product price changes

Kat and Oomen (2007a), Chong and Miffre (2010), Erb and Harvey (2006), and Gorton et al. (2012) have investigated the general distributional characteristics of commodity price changes (returns). Kat and Oomen (2007a), Chong and Miffre (2010), and Gorton et al. (2012) present results on heating oil, unleaded gasoline, and crude oil futures, while Erb and Harvey (2006)

[5] Much has been written about the characteristics of crude oil spot and futures prices, including the volatility of those prices. As such we do not review that literature in this survey.

present results only for heating oil. Kat and Oomen (2007a) study daily futures settlement prices for heating oil and unleaded gasoline, in addition to NYMEX crude oil. In total, they study 142 different commodities (including different trading locations for the same commodity), covering the period January 1987 to 2005. They examine the following questions:

1. Do commodities offer a risk premium?
2. Are commodity returns excessively volatile?
3. Are commodity returns positively or negatively skewed?
4. Do commodity returns exhibit "fat tails?"
5. Are commodity returns autocorrelated?

Kat and Oomen's results for heating oil and unleaded gasoline can be summarized as follows:

1. They find that heating oil and unleaded gasoline futures exhibit sizeable and statistically significant annualized positive excess returns, relative to the risk-free return. On average, energy performs well during the start of a recession but poorly during the end of a recession. Erb and Harvey (2006) also find a positive average excess return for heating oil for the period December 1982 to May 2004, but they do not study unleaded gasoline. Finally, Gorton et al. (2012) document average positive excess returns for heating oil (1979-2010) and gasoline (1985-2010), finding an annualized average excess return of 17.87% for gasoline and 8.90% for heating oil, as compared with 12.59% for crude oil.
2. The authors show that heating oil and unleaded gasoline futures exhibit annualized daily standard deviations of return of 33.8% and 35.8%, as compared with light sweet crude oil at 36.2%. By comparison, the average of the annual standard deviations of returns on the components of the DJIA was 29.5%. KO also estimate

GARCH(1,1) models for the series they study and find that volatility shocks for heating oil and unleaded gasoline exhibit persistency. Volatility also varies with the business cycle (increasing during recessionary periods and decreasing during expansions) as well as with the monetary regime (increasing during monetary expansion periods but decreasing during periods of stable policy actions). For heating oil, gasoline, and crude oil, Gorton et al. (2012) report annualized standard deviations similar to those listed above.

3. Using the traditional unbiased measure of skewness, Kat and Oomen find negative and statistically significant skewness for unleaded gasoline but not heating oil. Gorton et al. (2012) find similar results. They also fit a GARCH(1,1) model with errors assumed to exhibit a skewed *t*-distribution. The results show that, given the GARCH framework, unleaded gasoline futures exhibit significant error skewness. However, the returns exhibit no statistically significant skewness after dropping one extreme event day, the U.S. invasion of Iraq on January 17, 1991 ("Operation Desert Storm").

4. Kat and Oomen find that heating oil and unleaded gasoline futures returns exhibit significant kurtosis. Gorton et al. (2012) find similar results. The results hold even after accounting for GARCH effects.

5. Finally, the authors find that heating oil exhibits no autocorrelation at the one-day lag but significant and negative autocorrelation at the two- and three-day lag periods. Unleaded gasoline exhibits negative and statistically significant autocorrelation at the one- and three-day lag periods. Finally, the Box-Ljung test with 10 lags soundly rejects white noise for both commodities.

Chong and Miffre (2010) examine weekly data for the period January 1, 1981 to December 27, 2006, and find results consistent with those presented by Kat and Oomen.

6.3. Price volatility and maturity

Suenaga and Smith (2011) explore the volatility and correlation patterns of crude oil, heating oil, and gasoline futures contracts by time to maturity and delivery month by estimating a "partially overlapping time series" model for times-to-delivery of 1 to 12 months and 12 delivery months: January to December. Their findings include the following. First, volatility is low in the longer time-to-delivery months, and returns on the three energy futures contracts are largely explained by a common factor implying high correlation. Second, as maturity approaches, volatility increases sharply, and both a short-term factor and idiosyncratic terms become more important. Correlations among the three short-term factors are positive but much lower than those for the longer-term factors, indicating that prices of short-term contracts are more influenced by commodity-specific supply and demand developments. Consistent with this evidence, much of the same pattern is observed for crack spreads; that is, volatility is low (but not zero in far-from-maturity contracts) and increases sharply as maturity approaches. Third, for heating oil, volatility is highest and the proportion of volatility explained by common factors is lowest for contracts expiring in the winter months. For gasoline, volatility is highest and the proportion of volatility explained by common factors is the lowest for contracts expiring in the fall. These two seasonal patterns are most prominent when time to expiration is short. Fourth, there is evidence that volatility in heating oil is transmitted to gasoline and vice versa. For instance, volatility in gasoline is slightly elevated for contracts maturing in the winter, and volatility for heating oil is slightly elevated for contracts maturing in the fall.

6.4. *Stochastic volatility, mean reversion, jumps, and volatility spillover*

Researchers generally agree that crude oil prices exhibit stochastic or conditionally stochastic volatility (among others, Duffie et al., 2004; Fong and See, 2002; Sadorsky, 2006; Lee and Zyren, 2007; Agnolucci, 2009), as well as mean reversion (Bessembinder et al., 1995; Schwartz, 1997; Pindyck, 1999; Geman, 2007; Geman and Ohana, 2008; Dvir and Rogoff, 2009). "Mean reversion" generally indicates that price deviations from a long-term equilibrium value for the oil price tend to be corrected over time.[6] It would be suspected that petroleum products should inherit these traits, but they also exhibit others, such as seasonal patterns. As mentioned earlier, Kat and Oomen (2007a) identify significant excess kurtosis in the distribution of oil price changes, which suggests the presence of jumps in oil prices (Das and Sundaram, 1999). Comprehensive models of the stochastic processes for petroleum products have been studied that capture time-varying volatility, mean reversion, seasonal effects, and jump behavior.

Nomikos and Andriosopoulos (2012) present a comprehensive study of how well mean-reverting jump diffusion type models, with and without conditional time-varying variance, fit petroleum product prices. Specifically, they study heating oil (New York Harbor No. 2 Fuel Oil), gasoline (New York Harbor Reformulated Blend stock for Oxygen Blending (RBOB)), and crude oil (West Texas Intermediate (WTI)). They study log daily closing prices of the nearby futures contracts from NYMEX for the period December 9, 2000 to January 12, 2010, using data from Thomson DataStream.

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[6] Statistical models of time-varying volatility have largely focused on specifying the oil price change process as an ARMA-GARCH process or a variant. The consensus is that oil price changes exhibit conditional heteroskedasticity (Fong and See, 2002; Sadorsky, 2006; Agnolucci, 2009, Kang et al., 2009). Agnolucci concludes that a model popularly known as the Component GARCH (CGARCH, Engle and Lee, 1999) fits the data best. Developments in the literature have extended the menu of possible models to a number too large to review here (see Bollerslev, 2009).

The authors specify the following general underlying structure for the models they estimate, expressed in continuous time form as

$$ln S_t = g(t) + Y_t \tag{1}$$

where S_t is the futures price observed at time *t*, $g(t)$ is a deterministic component that depends upon time (potentially due to seasonalities) and Y_t is a stochastic component.. This translates into

$$S_t = G(t) e^{Y_t} \tag{2}$$

where $G(t) \equiv e^{g(t)}$ represents the predictable or deterministic part of the price, such as seasonal effects. Y_t is defined by the following general stochastic process

$$d Y_t = a_i (\mu - Y_t) d t + \sigma_t d Z_t + k d q_t \tag{3}$$

where a_i is the mean reversion rate, μ is the long-term mean in the absence of jumps, σ_t is the volatility of the log price process (which can be time-varying), $d Z_t$ is a Weiner process, *k* is a proportional jump size, and $d q_t$ is a Poisson process. The authors discretize the model and estimate a variety of optional structures, which are listed in Table 1. The results indicate that all three commodity price series exhibit *mean reversion* and *jump behavior* and that heating oil and crude oil exhibit asymmetric variance behavior fit best by an exponential GARCH (EGARCH) specification.[7] In the case of the EGARCH model, the authors find that, for heating oil, negative

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[7] For a description of the EGARCH model, see Bollerslev (2009). The EGARCH model allows for differential (asymmetric) behavior of volatility in response to log price change shocks that are either positive or negative (potentially larger impacts on volatility from negative shocks).

error shocks have a greater impact on volatility than do positive shocks. The reverse is true for gasoline.

Table 1: Empirical models estimated by Nomikos and Andriosopoulos.
(Nomikos and Andriosopoulos, 2012, p. 1156)

Model	Name
1	GBM
2	MR-OLS
3	MR-GARCH(1,1)
4	MR-EGARCH(1,1)
5	MRJD-OLS
6	MRJD-GARCH(1,1)
7	MRJD-EGARCH(1,1)

"GBM" stands for geometric Brownian motion; "MR" for mean reversion; "MRJD" for mean reversion with jump diffusion, "OLS" for ordinary least squares (constant volatility), "GARCH" for generalized autoregressive conditional heteroskedasticity, "EGARCH" for exponential GARCH.

Nomikos and Andriosopoulos (2012) perform several diagnostic tests on the estimated models. The first is a simulation exercise in which sample moments from simulations of the estimated models are compared with the moments from the actual data and computation of the Kolmogorov–Smirnov test of distributional equivalence. The second is an in-sample analysis of root mean squared error values of actual prices versus predictions from the models and computation of Theils U. The authors conclude that MRJD-EGARCH(1,1) fits best and has the best predictive power for crude oil, heating oil, and gasoline. In sum, the data exhibit mean reversion, jumps, and EGARCH variance behavior.

The period studied by the authors essentially runs through the end of 2009. Interestingly, the authors present evidence that prices of oil and heating oil exhibit an EGARCH parameter that implies a leverage effect (Black, 1976a) in the sense that positive price change shocks are associated with decreases in volatility. However, this is not true for gasoline, which exhibits what Geman (2005) refers to as "inverse leverage," meaning that positive shocks result in increased volatility because both prices and volatility are negatively related to inventory. Evidence suggests that not finding an inverse leverage effect for oil and heating oil may be a feature of the time period that Nomikos and Andriosopoulos (2012) study. We return to this point in Section 6.7.

Liu and Tu (2012) also estimate jump-diffusion models for crude oil, heating oil, and unleaded gasoline. In addition to testing for whether jumps are present, the authors examine the simultaneous jump intensities of pairs of energy futures and the probabilities that jumps in crude oil cause jumps or unusually large returns in heating oil and unleaded gasoline futures. In all cases, they find significant evidence that the diffusion-jump process is a better characterization for energy futures prices.

Ng and Pirrong (1995) study daily spot and futures price data for heating oil and gasoline from 1984 to 1990 through the lens of a nonlinear error-correction model (ECM) with time-varying volatility. The authors show that spreads between spot and futures prices explain virtually all spot return volatility innovations for these two commodities, and spot returns are more volatile when spot prices exceed futures prices than when the reverse is true. Furthermore, they find that there are volatility spillovers from futures to spot markets (but not the reverse), that futures volatility shocks are more persistent than spot volatility shocks, and that the convergence of spot and futures prices is asymmetric and nonlinear.

Lee and Zyren (2007) study volatility behavior for weekly crude oil prices as well as gasoline and heating oil spot and futures prices during the period January 1, 1990 to May 20, 2005. The authors present evidence that volatility in these markets increased around April 1999 when OPEC changed its production policies. The authors also generally find that, although GARCH-type models fit most of the series well, heating oil price behavior is better explained by a TARCH model (which permits asymmetric responses to good and bad news). Finally, the authors find that volatility of the petroleum product prices is greater than volatility of crude prices and that volatility persistence is low.

Pindyck (2004) examines the role of volatility in short-term commodity market dynamics and the determinants of volatility itself. He develops a structural model of inventories, spot prices, and futures prices that explicitly accounts for volatility, and estimates the model using daily and weekly data for the petroleum complex: crude oil, heating oil, and gasoline. He estimates volatility by the sample standard deviations of adjusted daily log changes in spot and futures prices using weekly data for January 1, 1984 to January 31, 2001 for crude and heating oil, and January 1, 1985 to January 31, 2001, for gasoline. Estimating vector autoregression models to test whether price, inventories, and the convenience yield influence volatility, Pindyck finds for crude oil and heating oil that the spot price, inventories, and the convenience yield have no predictive power with respect to price volatility. However, for gasoline, he finds that the spot price and convenience yield are significant predictors of volatility. He suggests that this latter result could arise because past values of the spot price affect past values of volatility, which in turn affect current values of volatility.[8]

6.5. Long memory in volatility

Several authors, including Cunado et al. (2010), Kang et al. (2009) and Chkili et al. (2014) have studied long-memory persistence in price changes and volatility for oil. Generally, these authors find that volatility exhibits long-memory behavior, whereas price changes do not.

[8] See Linn et al. (2018) for a review of the literature and new empirical evidence on the response of petroleum product futures prices to unexpected news, such as unexpected changes in product inventories and unexpected macroeconomic news including monetary policy changes.

The general consensus in the literature is that asset returns do not exhibit long memory but that it is present in volatility or variables that proxy for volatility, such as squared returns and absolute returns. Choi and Hammoudeh (2009) test for the presence of long memory in daily oil (WTI) and refined products prices' absolute returns, squared returns, and conditional volatilities. The authors present evidence that long memory is present in the daily absolute and squared spot and futures returns for gasoline (NYMEX) and heating oil (NYMEX), but not to the same degree. They find that crude oil futures have stronger long memory than gasoline and heating oil futures. The authors also state that they find weak evidence of long memory in the actual futures returns (in contrast to the absolute or squared returns) but do not report those results or tests. The authors report finding weak evidence that the simple returns exhibit long memory, but they do not report their results. The study utilizes daily data for the period January 2, 1986 to July 19, 2005. Several extant tests for long memory are employed, including the modified rescaled range statistic of Lo (1991). The authors also estimate fractionally integrated GARCH (FIGARCH) models.[9] The FIGARCH structure permits inferences about the degree to which long memory is present in the variance. The FIGARCH estimation results support the earlier conclusions that long memory is present in volatility.

Using a variety of techniques based on non-parametric, semi-parametric, and parametric methods, Cunado et al. (2010) test for long-memory dependence in log price changes as well as volatility. They study futures prices for gasoline, propane, oil, and heating oil at different maturities and find little or no evidence of long memory in log price changes. However, they do find evidence of long memory in absolute returns (a proxy for volatility) for all the commodities

[9] For a description of the FIGARCH model, see Bollerslev (2009).

and contracts. They study daily closing prices from NYMEX for the nearby contract as well as the next three (i.e., 2nd through 4th) maturing contracts. The sample period varies by contract, but all series end in September 2008, and every series exceeds 3,650 observations.

6.6. Volatility spillover

A volatility spillover occurs when changes in price volatility in one market spill over to another market with a lag. Manera et al. (2013) estimate multivariate GARCH models using crude oil, heating oil, gasoline, and natural gas prices. The multivariate GARCH model allows the elements of the covariance (correlation) matrix of the system to follow a GARCH-type process.[10] This permits one to test whether the error variance in one variable in the system influences the error variance in another variable in the system, indicating the strength of any spillover. The authors examine weekly averages of daily futures prices for roughly the period 1986-2010 for futures on light sweet crude oil, heating oil, gasoline, and natural gas sourced from NYMEX, finding that volatility spillovers between commodities are present.

Barunik et al. (2015) examine transaction level data for crude oil, heating oil and gasoline futures traded on the New York Mercantile Exchange (NYMEX). The period studied begins September 1, 1987 and ends February 12, 2014. The authors study 5-minute logarithmic returns and implement statistical methods proposed by Diebold and Yilmaz (2012) for the study of directional volatility spillover. Barunik et al. (2015) find evidence of asymmetries in volatility spillovers and that there was an increase in volatility spillovers between petroleum products following 2001 but this was reversed after 2008.

[10] See Bollerslev (2009).

Hammoudeh et al. (2003) examine volatility spillover in daily spot and futures prices for crude oil, heating oil and gasoline using a GARCH model. The authors study prices at five commodity centers within and outside the United States. Hammoudeh et al. (2003) find evidence of spillover effects in crude oil, gasoline and heating oil markets in nearby futures contract prices and spot prices. The authors study volatility spillover within the context of a vector error correction model accounting for GARCH effects in errors. In particular, they study spot prices for crude oil, heating oil, and gasoline.

As mentioned earlier, Ng and Pirrong (1995) study daily spot and futures price data for heating oil and gasoline from 1984 to 1990 through the lens of a nonlinear ECM with time-varying volatility. The authors find evidence of volatility spillovers from futures to spot markets (but not the reverse).[11]

6.7. Implied volatility of petroleum product futures prices

Implied volatility for a commodity such as heating oil is a market-based measure of forward-looking expectations of price volatility. The process of calculating an implied volatility begins by first assuming a particular model for the pricing of options on futures for the commodity (in this case a petroleum product). A crucial parameter for the valuation of options is the expected price volatility of the underlying asset or security over the life of the option. The second step in the process is to numerically recover the implied value of volatility that makes the current observed price of the option equal to the "formula" price based on the assumed model, usually Black's (1976a) model, for valuing options on commodity futures. Indeed, this is the model employed by

[11] Examples of research on volatility spillover between crude oil markets (but not petroleum products) and separately oil markets and stock markets include Lin and Tamvakis (2001), Chang et al. (2010) and Awartani and Maghyerch (2012), Jin et al. (2012) and Maghyereh et al. (2016).

the EIA (U.S. Energy Information Administration, 2009) for computing confidence intervals for oil price forecasts.[12]

Szakmary et al. (2003) study the predictive content of implied volatility of heating oil and unleaded gasoline futures for future realized volatility for the period January 11, 1989 to February 5, 2001. The authors find that implied volatility computed using the Black (1976a) model is a better predictor of future realized volatility than historical volatility computed from past price history. For the heating oil market, the authors find that historical volatility contains no economically significant predictive information beyond what is already incorporated in implied volatility, regardless of whether volatility is modeled as a simple moving average or in a GARCH framework. However, for unleaded gasoline, the authors find that historical volatility has some explanatory power beyond implied volatility. The results for heating oil are consistent with the view that futures options markets for that commodity are efficient.

Geman and Nguyen (2003) also study implied volatility for heating oil and unleaded gasoline based upon futures options data. In particular, they are interested in the "volatility smile," how implied volatility varies across strike prices for a given commodity futures option on a given date.[13] They find that the smile for both commodities tends to be skewed to the right for their period of examination. In graphical terms, this means that implied volatility tends to rise as the strike price increases. The authors interpret these results as indicating that the market exhibits

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[12] Available at http://www.eia.gov/forecasts/steo/special/pdf/2009_sp_05.pdf). Britten-Jones and Neuberger (2000) developed a "model free" for calculating implied volatility, which does not require the assumption that option prices follow an assumed model, such as Black-Scholes. In 2003, the Chicago Board Options Exchange switched its calculation of the well-known VIX index to this procedure. However, this procedure requires active trading over a very wide range of out-of-the-money options, which are not present in most option markets, so most other implied volatility calculations continue to use Black-Scholes.

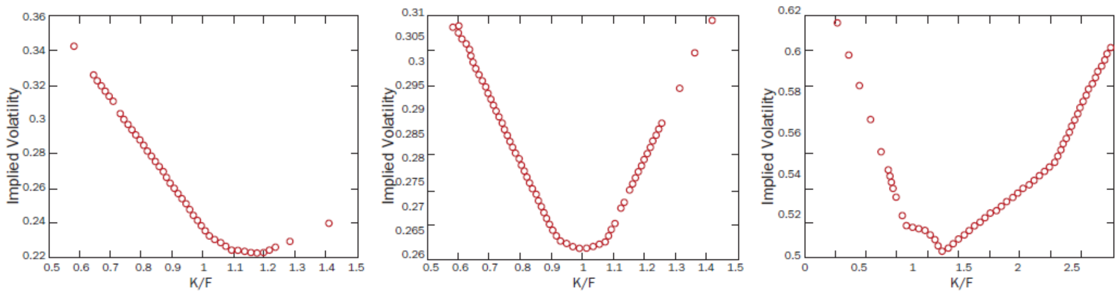
[13] See Hull (2018) for a discussion of implied volatility.

greater risk aversion to a rise in prices. A right skew in implied volatility would in principle be consistent with an inverse leverage effect in an EGARCH model.

However, Geman (2011) argues that market participants became more averse to commodity price decreases and were prepared to pay more for out-of-the-money put options following 2003, when billions of dollars were poured into commodity indexes, ETFs, and other vehicles treating commodities as long investments. She contends that this aversion caused a shift in the implied volatility curve in energy commodities, as illustrated by her three graphs (reproduced below) of the smile for crude oil computed at three dates: (left) September 21, 2007; (middle) February 22, 2008; (right) February 23, 2009. Crude oil implied volatility was skewed to the left in September 2007 and February 2008. By contrast, following the 2008 collapse of Lehman Brothers and a decline in crude oil prices, there was a return to a right skew. However, Geman does not present evidence for gasoline. A right skew in implied volatility would, in principle, be consistent with an inverse leverage effect in an EGARCH model and with the results of Baumeister and Peersman (2013), who find that positive net demand shocks have a greater impact on oil price volatility than negative shocks. Geman (2005) labels this the “inverse leverage” effect, which occurs because commodity prices and commodity price volatility are positively correlated, in contrast to the “leverage” effect for common stocks, which arises because stock prices and volatility are negatively correlated (Black, 1976b). Although the evidence presented by Nomikos and Andriosopoulos (2012) indicates no inverse leverage effect for oil and heating oil, the data examined by those authors ends in 2007, which suggests that the “inverse leverage” relation may have varied over time.

Figure 1

Implied Volatility Smile for Crude Oil



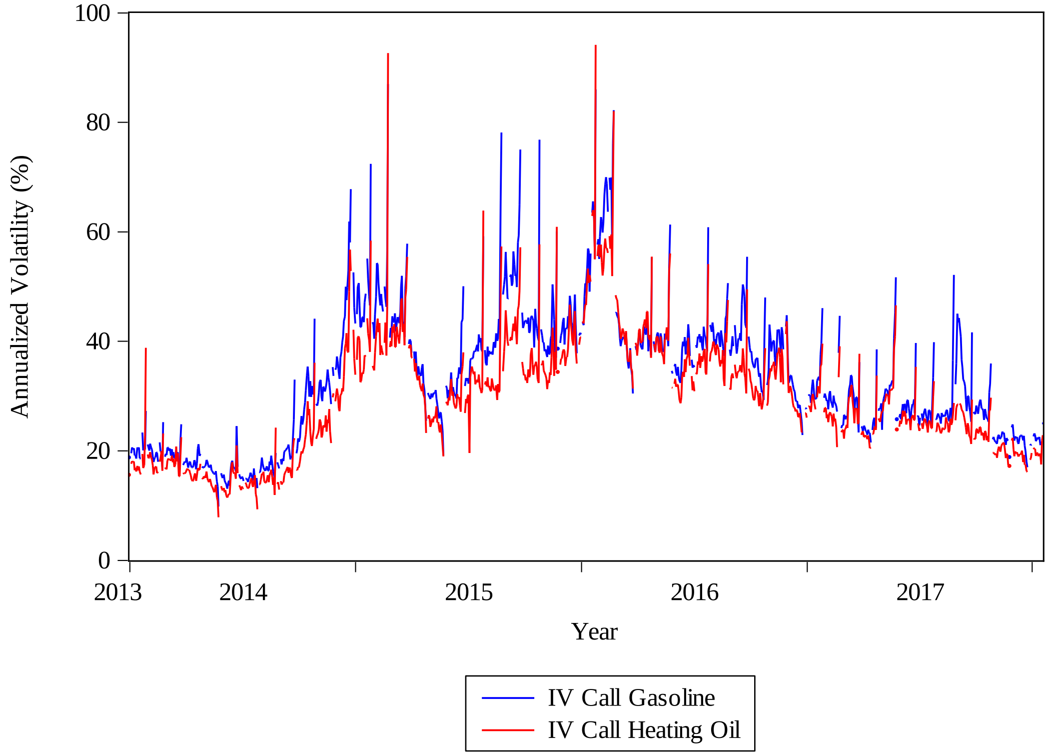
Left: September 21, 2007. Middle: February 22, 2008. Right: February 23, 2009.

Source: Geman, H. (2011). Price volatility in storable commodity markets: Speculation or scarcity? *Swiss Derivatives Review* 46, 16-19.

Although the implied volatilities of RBOB unleaded gasoline and heating oil have varied over time, the academic literature has paid little attention to this behavior. Figure 2 shows the daily implied volatilities of at-the-money call options on futures using data from Bloomberg.[14] It is clear that implied volatility for RBOB has generally exceeded that of heating oil. Furthermore, implied volatility for the both gasoline and heating oil options has been on a downward trend since mid-2015. The correlation between the implied volatility of gasoline (heating oil) and the implied volatility of oil (WTI) is roughly 87% for both petroleum products.

[14] Bloomberg indicates that the implied volatilities are for the first listed expiry that is at least 20 business days out.

Figure 2
Implied Volatility
Implied Volatilities Computed from At-the-Money Call Options on Futures Prices, Daily Observations



Source: Bloomberg

6.8. Heating oil prices and natural gas prices

According to the EIA, residual fuel oil is:

"A general classification for the heavier oils, known as No. 5 and No. 6 fuel oils, that remain after the distillate fuel oils and lighter hydrocarbons are distilled away in refinery operations. It conforms to ASTM Specifications D 396 and D 975 and Federal Specification VV-F-815C. No. 5, a residual fuel oil of medium viscosity, is also known as Navy Special and is defined in Military Specification MIL-F-859E, including Amendment 2 (NATO Symbol F-770). It is used in steam-powered vessels in government service and inshore power plants. No. 6 fuel oil includes Bunker C fuel oil and is used for the production of electric power, space heating, vessel bunkering, and various industrial purposes."

A potentially natural connection exists between natural gas prices and the prices of petroleum products that can be substituted for natural gas, and vice versa. In a study of monthly prices, Hartley et al. (2008) conclude that oil prices influence fuel oil prices, which in turn influence natural gas prices, but that natural gas prices do not influence oil prices. The authors also present evidence that technology is critical to the long-term relationship between fuel prices, and that short-term departures from the long-term equilibrium are influenced by product inventories, weather, and supply shocks, such as hurricanes.

6.9. Contemporaneous correlations

Evidence for the years examined by Kat and Oomen (2007b) and Chong and Miffre (2010) indicates that unconditional as well as conditional contemporaneous correlations, computed using a GARCH-based model of dynamic conditional correlation, between stock returns (as well as bond returns) and both gasoil and unleaded gasoline futures returns are small but negative, on the order of -5%.

6.10. Evidence on speculation, product price changes and volatility

In recent years, considerable research has been devoted to the role of fundamentals versus excess speculation in the movement of oil prices. Papers arguing that at least some oil price movements in recent years have been due to speculation include U.S. Senate (2006); Masters (2008); Einloth (2009); Kaufmann and Ullman (2009); Sornette et al. (2009); Phillips and Yu (2011); Parsons (2010); and Singleton (2013). Papers arguing that excess speculation has had little or no impact on oil prices include Interagency Task Force on Commodity Markets (2008); Gilbert (2010); International Energy Agency (2008); International Monetary Fund (2008); Brunetti and

Büyükşahin (2009); Büyükşahin and Harris (2011); Hamilton (2009); Irwin et al. (2009); Ederington et al. (2011); Irwin and Sanders (2012); Fattouh et al. (2013); Brunetti et al. (2013); Kilian and Murphy (2014); Kilian and Lee (2014); Hamilton and Wu (2015). Clearly, because of the close link between petroleum product prices and crude oil prices, the answer to the question has bearing for product prices. A companion question, of course, is whether there is a separate effect in the market for gasoline beyond the effect arising through the connection to the crude oil market. This is an under-researched issue.

Although considerable attention has been given to the potential impact of speculation on oil prices, as mentioned above, there is a dearth of research on whether or how speculation affects or has affected petroleum product prices. Exceptions are the studies by Till (2009) and Manera et al. (2013, 2016), which examine whether the volatility of petroleum product prices has been influenced by speculation.

In a study utilizing three years of data from the U.S. Commodity Futures Trading Commission's "Disaggregated Commitments of Traders" reports, Till (2009) computes the time series of Working's speculative T index for NYMEX heating oil and gasoline, following methods outlined in Sanders et al. (2010).[15] Till (2009) supplies graphs of the computed statistics but reports not formal tests. The author concludes: "For the NYMEX heating oil and gasoline futures markets, the T indices are within range of what had not been considered excessive for the agricultural futures markets" (p. 14).

[15] Quoting from Sanders et al. (2010, p. 86): "Peck (1980, p. 1037) notes that the speculative index . . . reflects the extent by which the level of speculation exceeds the minimum necessary to absorb long and short hedging, recognizing that long and short hedging positions could not always be expected to offset each other even in markets where these positions were of comparable magnitudes." Working (1960, p. 197) is careful to point out that what may be "technically an 'excess' of speculation is economically necessary" for a well-functioning market.

Manera et al. (2016) test whether speculation increases or decreases energy futures *price volatility* by introducing speculation measures into univariate GARCH-type models of energy futures price volatility. The GARCH models are estimated for four energy futures markets (crude oil, heating oil, gasoline, and natural gas) with three speculation measures: non-commercial's share of total open interest, Working's T, and non-commercial's net long position as a percent of total open interest. Except for the net long measure (whose coefficient is also negative and significant in the crude oil estimation), all speculation variables enter the GARCH equations negatively for all four energy futures, indicating that higher speculation is associated with lower volatility, and most are significant at least at the 10% level. Their GARCH specification presumes that the impact of speculation on volatility persists over time with a gradual decay. Results are robust to different GARCH specifications. In other words, the authors conclude that speculation, as they measure it, benefits these markets in the sense of reducing volatility.

In a companion study, Manera et al. (2013) study the impact of speculation on the levels of returns (in contrast to volatility). The authors estimate multivariate GARCH models using crude oil, heating oil, gasoline, and natural gas prices. They seek to answer four questions: 1) Are macroeconomic factors relevant in explaining returns of energy and non-energy commodities? 2) Is financial speculation significantly related to returns in futures markets? 3) Are there significant relationships among returns, in either their mean or their variance, across different markets? 4) Does speculation in one market affect returns in other markets? They find that financial speculation, proxied by Working's T index, is *not* a significant factor in modelling the level of returns of energy commodities. Therefore, Manera et al. (2013) conclude that the level of returns is unaffected by speculation, but Manera et al. (2016) conclude that an increase in speculative activity is associated with a *reduction* in return volatility.

Gorton et al. (2012) study the relation between petroleum product futures excess returns (what they refer to as the risk premium) and hedging pressure, finding no evidence that hedging pressure from changes in the positions of commercial and non-commercial traders (as defined using U.S. Commodity Futures Trading Commission guidelines) is related to excess returns (the risk premium).

Ederington et al. (2018b) present evidence indicating that a causal relation running from oil futures prices to product futures prices is present both before the time that oil futures began to be viewed as an important portfolio investment asset and following that shift, which they approximate as the end of 2005. Although the evidence is limited, the conclusion from these results is that speculation did not increase volatility in petroleum product prices nor the excess returns on such products during the periods studied.

There is potentially room for additional tests of whether speculation beyond that associated with oil has an impact on petroleum product prices. One potential point of departure for investigating this issue is the recent structural model developed in Knittel and Pindyck (2016). They develop a simple model of supply and demand in the cash and storage markets for a commodity. The model's structure allows the authors to test whether speculation is the main determinant of price changes given data on production, consumption, inventory changes, and spot and futures prices, and reasonable assumptions about elasticities of supply and demand. The model is general and could be applied to any commodity. As a footnote, Knittel and Pindyck conclude that for the period they studied, oil prices were not driven by speculative activity.

7. Price discovery and transparency in petroleum product markets

7.1. Overview

The overarching theme of this section is the relationship between information and prices (i.e., how changes in information manifest in prices). We begin by focusing on the relation between spot prices and the information contained in futures prices (Sections 7.2 and 7.3). First, we focus on where price discovery occurs for petroleum products, in the spot market or in the futures market. The evidence indicates that price discovery generally occurs in the futures market; however, there are important issues that remain unclear, such as the influence of futures contract liquidity and the interrelation between prices of different commodities and oil. The second question focuses on the predictive ability of futures prices; that is, how accurate are the futures prices of petroleum products in predicting future spot prices? The empirical evidence generally suggests that shorter maturity futures prices are unbiased predictors of future spot prices for gasoline and heating oil.

7.2. Where does price discovery occur?

Futures markets are considered important aggregators of information about commodity prices, ultimately contributing to the efficient allocation of commodity resources. Black (1976a) goes so far as to argue that the price discovery role of futures markets dominates its role as a facilitator of risk sharing. The theory of efficient price formation argues that true and accurate prices are most likely to arise in unfettered marketplaces. Price discovery is the process of uncovering an asset's full information or permanent value. The issue of where price discovery occurs, in the spot or in the futures market, is important in the crude oil market, as it has direct implications for whether excessive speculative activity in the futures market can influence spot market prices. Early works on the subject were devoted to tests of causality between futures price changes and spot prices changes. Several subsequent measures of price discovery have been proposed in the literature and have survived over time. These measures attempt to parse out the relative contributions to price discovery of multiple markets on which assets or derivatives of those assets are traded. The foundation for these models is the condition that a true underlying but unobservable value exists for the asset in question.[16] Here, we review several studies that focus on the relation between spot and futures prices for petroleum products.

7.3. *Spot and futures prices of petroleum products*

Although much research has been published regarding price discovery in the crude oil market, this is not the case for petroleum products. In a study of data for the period January 1, 1984 to May 15, 1991, Schwarz and Szakarmy (1994) present results on price discovery for daily spot and futures prices for heating oil and unleaded gasoline, based on linear causality tests for a bivariate model accounting for cointegration. The results indicate that futures price changes lead spot price changes for both heating oil and gasoline, but spot price changes do not influence futures price changes**.**

Hammoudeh et al. (2003) present evidence that spot and futures prices for gasoline and separately for heating oil are cointegrated. Zhang and Wang (2013) also present evidence that gasoline futures and spot prices are cointegrated and use this as a basis for tests of where price discovery occurs in the gasoline market. The usual test for price discovery makes use of a bivariate autoregressive model allowing for cointegration. A test to show that gasoline futures do not cause gasoline spot prices utilizes an equation in which the change in the spot price appears on the left-hand side and has two parts. The first part tests whether the appropriate adjustment coefficient is

[16] The most popular measures are due to Garbade and Silber (1983), Hasbrouck (1995), Gonzalo and Granger (1995), and Harris et al. (1995), who utilize developments in Gonzalo and Granger (1995) and Yan and Zivot (2010) and are reviewed in Baillie et al. (2002). Figuerola-Ferretti and Gonzalo (2010) present a theoretical justification for the Gonzalo-and-Granger-based measure within the context of an equilibrium model of commodity spot and futures prices.

equal to zero (a long-term effect), and the second tests whether the coefficients on the lagged differences of the futures price are jointly equal to zero (a short-term effect). Studying daily data for the period October 3, 2005 to October 25, 2011, Zhang and Wang reject the null hypothesis in both cases, although the short-term test is rejected only at the 10% level. The authors also study crude oil spot and futures prices and test for causality between those prices and gasoline prices, again accounting for cointegration. They reject the null hypothesis that crude oil futures prices do not cause gasoline futures prices, but only in the short-term; interestingly, they find that gasoline futures cause crude oil futures in the long-term. The latter is somewhat consistent with the hypothesis that petroleum product prices determine crude oil prices. Such a view is consistent with the idea that the price of oil is based on derived demand for petroleum products (Verleger, 1982). Verleger (1982) argues that spot market prices for petroleum products are the primary determinants of crude oil prices. In separate tests based on a model of commodity futures and spot market equilibrium developed by Garbade and Silber (1983), Zhang and Wang present corroborating evidence that price discovery in gasoline markets occurs in the futures market.

Few studies examine the influence of speculators on price discovery in petroleum product markets. Zhang and Wang do, however, split their sample into two subperiods (essentially before and after 2007) and conclude: “The financial crisis since 2007 does not strongly influence the price discovery and risk transfer mechanisms of crude oil and gasoline futures markets” (p. 227). Some might view the latter subperiod as being a period of greater speculative activity, which would lead to the conclusion that such activity had no impact on price discovery regarding petroleum product prices, consistent with what others have found for the oil market (such as Haigh et al., 2007; Ederington et al., 2018c).[17]

Ewing et al. (2006) examine whether there is differential (asymmetric) adjustment to a new equilibrium if the deviation (error) from equilibrium is above or below some threshold level, based on daily crude oil, heating oil, and gasoline prices for the period June 1986 to January 2004. The model, popularly referred to as the momentum-threshold autoregressive model or M-TAR (Enders and Siklos, 2001), allows two different adjustment coefficients (α, a 2 x 1 vector): one adjustment coefficient multiplies errors falling below the threshold, and the other multiplies errors falling above the threshold. The threshold is established using a heuristic algorithm, but the authors report no tests of how robust the results are to the threshold identification model. Given the thresholds identified, the authors conclude that for the bivariate pairs of futures and spot prices for heating oil and gasoline, 1) each pair exhibits cointegration, 2) the responses to errors above and below the threshold are not equal, and 3) there is faster convergence back to equilibrium for errors above the threshold than for errors below the threshold. They interpret this as evidence that arbitrageurs are faster to exploit positive profit opportunities. The authors, however, do not take the next step to infer in which market prices are discovered.

7.4. Predictive accuracy of futures prices and tests of unbiasedness

A companion issue regarding the relation between futures prices and spot prices is that of whether futures prices are accurate predictors of future spot prices and whether they are unbiased

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[17] Ederington et al. (2018c) study price discovery in the oil spot and futures market using daily price data and examine both WTI prices and Brent prices. The authors conclude that price discovery occurs in the futures market. The authors separate the analysis of the WTI market into two time periods: pre-2005 (January 2, 1986 to Dec ember 31, 20014) and post-2005 (January 2, 2005 to December 31, 2017). They conclude that price discovery occurs in the futures market and was unaffected by the change in thinking about commodity futures as assets to be included in active portfolios, a shift that occurred around 2005. An analysis of Brent spot and futures prices yields similar conclusions.

predictors. Chinn and Coibion (2014) examine whether futures prices are (1) unbiased and/or (2) accurate predictors of subsequent prices in several commodity markets, but particularly in the markets for gasoline and heating oil. The authors study monthly data for the three-, six-, and 12-month futures contracts over the period 1990-2012.

Chinn and Coibion define S_{t+h} as the spot rate at date *t+h* and $F_f^{(h)}$ the futures price at time *t* for delivery at *t+h*. If the cost of carry relation holds, then a linear (in logs) relation will exist between the futures price and today's spot price, allowing for the (log) of the sum of storage costs minus convenience yield, plus interest costs and any risk premium. The traditional test is based upon the model $s_{t+h} - s_t = \alpha + \beta\left(f_t^{(h)} - s_t\right) + \varepsilon_{t+h}$ where lower-case letters denote natural log transforms, and ε_{t+h} is a mean zero error. Unbiasedness is implied by the null hypothesis $\beta = 1$, while market efficiency implies $\alpha = 0,\ \beta = 1$. The authors document that for the three-month futures contracts, energy futures for heating oil and gasoline can be characterized as unbiased predictors of future spot prices, which Chin and Coibion measure using the nearby futures price, and that the null of $\alpha = 0,\ \beta = 1$ is not rejected. These conclusions are not always true using the six- and 12-month contracts. In comparison, the results for oil futures are that unbiasedness cannot be rejected for any of the contract horizons and that the test of the second hypothesis is never rejected at the 1% level. Furthermore, the forecasting ability of futures for these products relative to a random walk fares well in terms of squared forecast errors or when predicting the sign of subsequent price changes. Gasoline futures show the greatest ability to predict subsequent spot prices, whereas crude oil and heating oil do relatively worse. The poor results for crude oil are consistent with the results reported by Alquist and Kilian (2010) (examining data from March 1983 to February 2007). They conclude that the current spot price generally is a better predictor of the future spot price at the one-, three-, six-, nine-, and 12-month forecast horizons when compared with the predictive accuracy of the futures price on a mean squared prediction error basis.

Bastianin et al. (2014), on the other hand, study the forecasting performance of a menu of alternative error correction models that account for asymmetric price transmission considering point, sign, and probability forecasts. The authors study U.S. spot and retail prices of gasoline and diesel, using the WTI spot price as the oil benchmark price, but using the Brent price to test the robustness of their conclusions. The results indicate that accounting for asymmetries improves predictions of the sign of the change in product prices or when forecasting the probability of a change, but do not lead to more accurate point forecasts than the ECM model, which assumes symmetric response to increases and decreases in oil prices. Overall, they find that the results are robust to using the Brent price in place of the WTI price.

8. Summary

We identify, describe, and assess the factors influencing petroleum product prices, including those pertaining to price formation, volatility of prices, and speculative activity. We also review evidence regarding the general behavior of spot and futures prices for petroleum products, the way that price dicovery occurs for petroleum products, the predictive accuracy of petroleum product futures prices, and whether those futures prices are ubiased estimates of future spot prices. Furthermore, we highlight the question of whether speculative activity has influenced the markets for petroleum products. The following is a summary of our findings.

The recent behavior of crude oil prices has attracted considerable attention and debate about whether this behavior can be attributed to fundamental supply and demand factors or to excess speculation and possibly manipulation. However, very little attention has been given to this question regarding petroleum product prices. The empirical evidence, although limited and focused on futures prices, shows that speculation does not increase volatility in petroleum product prices or excess returns, compared to risk-free returns on such products during the periods studied.

Studies of inventory effects typically find an inverse and generally statistically significant relation between gasoline inventory deviations from some norm and gasoline price changes.

We review the evidence showing that refinery outages have a statistically significant and positive impact on refined product wholesale prices. Somewhat related to this, evidence shows that crack spreads exhibit positive and significant revisions to forecasts of tropical storm activity in the Gulf of Mexico, suggesting reactions to anticipated supply effects.

Studies of the general characteristics of nearby futures contract price changes find that heating oil and gasoline futures exhibit sizeable annualized excess returns, relative to the risk-free return, and that the annualized standard deviation of returns is comparable with crude oil futures returns. These same returns exhibit significant kurtosis and daily autocorrelation but not skewness.

Reduced-form stochastic processes for energy prices have become standard for purposes of risk management and derivative valuation. These models have several common features, including mean reversion, jumps in prices, and stochastic volatility. Empirical evidence regarding the prices of the nearby NYMEX futures contracts for gasoline, fuel oil, and heating oil indicates that (1) prices exhibit mean reversion; (2) prices exhibit jump diffusion behavior; (3) volatility at any date is conditionally related to volatility in the recent past, although support for different variations on the volatility process has been documented; (4) there is long memory in volatility for both gasoline futures prices and heating oil futures prices; and (5) volatility spillover occurs between spot and futures prices for oil, gasoline, and heating oil. These conclusions are drawn generally without any formal attempt to explain the findings.

The existing evidence indicates that gasoline and heating oil futures are not contemporaneously correlated with stock and bond returns. However, this body of research is based on pre-2007 data. A study of more recent data would fill a gap and provide clues about whether product markets and prices have become more integrated with general capital markets.

The U.S. evidence on the link between the market prices of petroleum product futures contracts and spot prices tends to indicate that most price discovery occurs in the futures market. Currently, there is no evidence that excess speculative activity influences price discovery for petroleum products. Interestingly, there is limited evidence that gasoline futures prices influence crude oil futures prices.

Petroleum product futures prices (gasoline and heating oil) are generally found to be unbiased predictors of future spot prices three months out, but not for the six- and 12-month contract horizons. In examinations of predictive ability, gasoline futures prices perform better (i.e., generate fewer mean-squared errors) than a simple random walk, and perform better than the forecast ability of oil and heating oil futures.

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