

Investor Flows and the 2008 Boom/Bust in Oil Prices

Kenneth J. Singleton¹

April 27, 2012

¹Graduate School of Business, Stanford University, kenneths@stanford.edu. This research is the outgrowth of a survey paper I prepared for the Air Transport Association of America. Helpful comments from Bahattin Buyuksahin, Jim Hamilton, Pete Kyle, Kristoffer Laursen, Stefan Nagel, and participants at conferences at the Department of Energy and CFTC are greatly appreciated, as is the research assistance of Kristoffer Laursen and Sebastian Infante.

Abstract

This paper explores the impact of investor flows and financial market conditions on returns in crude-oil futures markets. I argue that informational frictions and the associated speculative activity may induce prices to drift away from “fundamental” values, and may result in booms and busts in prices. Particular attention is given to the interplay between imperfect information about real economic activity, including supply, demand, and inventory accumulation, and speculative activity in oil markets. Further, I present new evidence that there were economically and statistically significant effects of investor flows on futures prices, after controlling for returns in US and emerging-economy stock markets, a measure of the balance-sheet flexibility of large financial institutions, open interest, the futures/spot basis, and lagged returns on oil futures. The largest impacts on futures prices were from intermediate-term growth rates of index positions and managed-money spread positions. Moreover, my findings suggest that these effects were through risk or informational channels distinct from changes in convenience yield. Finally, the evidence suggests that hedge fund trading in spread positions in futures impacted the shape of term structure of oil futures prices.

1 Introduction

The dramatic rise and subsequent sharp decline in crude oil prices during 2008 has been a catalyst for extensive debate about the roles of speculative trading activity in price determination in energy markets.¹ Many attribute these swings to changes in fundamentals of supply and demand with the price effects and volatility actually moderated by the participation of non-user speculators and passive investors in oil futures markets and other energy-related derivatives.² At the same time there is mounting evidence that the “financialization” of commodity markets and the associated flows of funds into these markets from various categories of investors have had substantial impacts on the drifts and volatilities of commodity prices.³ This paper builds upon the latter literature and undertakes an in depth analysis of the impact of investor flows and financial market conditions on returns in crude-oil futures markets.

The prototypical dynamic models referenced in discussions of the oil boom (e.g., [Hamilton \(2009a\)](#), [Pirrong \(2009\)](#)) have representative agent-types (producer, storage operator, commercial consumer, etc.) and simplified forms of demand/supply uncertainty. Moreover, these models, as well as the price-setting environment underlying [Irwin and Sanders \(2010\)](#)’s case against a role for speculative trading, do not allow for learning under imperfect information, heterogeneity of beliefs, and capital market and agency-related frictions that limit arbitrage activity. As such, they abstract entirely from the consequent rational motives for many categories of market participants to speculate in commodity markets based on their individual circumstances and views about fundamental economic factors.

Detailed information about the origins of most of the open interest in OTC commodity derivatives that could in principle shed light on the historical contributions of information- and learning-based speculative activity is not publicly available. However, indirect inferences suggest that traders’ investment strategies did impact prices. [Tang and Xiong \(2011\)](#) show that, after 2004, agricultural commodities that are part of the GSCI and DJ-AIG indices became much more responsive to shocks to a world equity index, changes in the U.S. dollar exchange rate, and oil prices. These trends are stronger for those commodities that are part of a major index than for other commodities. Tang and Xiong attribute their findings to “spillover effects brought on by the increasing presence of index investors to individual commodities (page 17).” Using proprietary data from the Commodity Futures Trading

¹This debate is surely stimulated in part by the large costs that oil price booms and busts potentially impose on the real economy. See, for example, [Hooker \(1996\)](#), [Rotemberg and Woodford \(1996\)](#), [Hamilton \(2003\)](#), and the survey by [Sauter and Awerbuch \(2003\)](#).

²The conceptual arguments and empirical evidence favoring this view are summarized in a recent Organization of Economic Cooperation and Development report by [Irwin and Sanders \(2010\)](#).

³See, for example, [Tang and Xiong \(2011\)](#), [Masters \(2009\)](#), and [Mou \(2011\)](#).

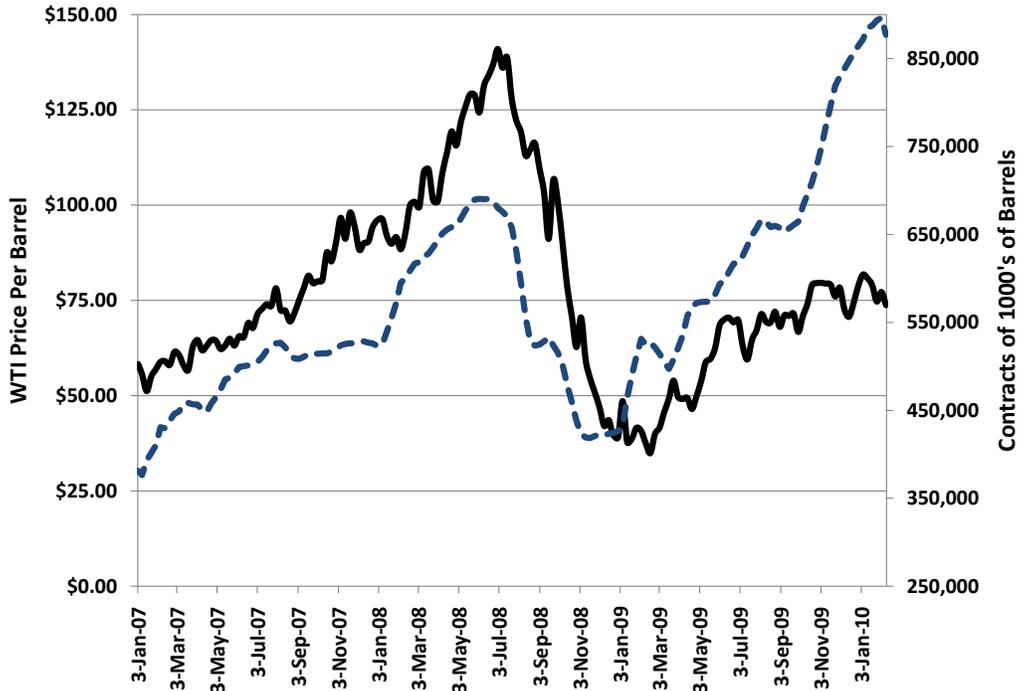


Figure 1: Commodity index long positions inferred from the CIT reports (dashed line, right sale) plotted against the front-month NYMEX WTI futures price (solid line, left scale).

Commission (CFTC), [Buyuksahin and Robe \(2011\)](#) link increased high-frequency correlations among equity and commodity returns to trading patterns of hedge funds. Less formally, [Masters \(2009\)](#) imputes flows into crude oil positions by index investors using the CFTC’s commodity index trader (CIT) reports. The imputed index long positions based on his methodology ([Figure 1](#)), displayed against the near-contract forward price of WTI crude oil, shows a strikingly high degree of comovement. Additionally, [Mou \(2011\)](#) documents substantial impacts on futures prices of the “roll strategies” employed by index funds, and finds a link between the implicit transactions costs born by index investors and the level of speculative capital deployed to “front run” these rolls.

To interpret these as well as my own empirical findings, I argue in [Section 2](#) that informational frictions (and the associated speculative activity) that can lead prices to drift away from “fundamental” values, were likely to have been present in commodity markets. [Section 3](#) discusses the interplay between imperfect information about real economic activity, including supply, demand, and inventory accumulation, and speculative activity. [Section 4](#) describes in detail the measures of index flows underlying my empirical analysis and reviews

what is known about their impacts on commodity prices. [Section 5](#) presents new evidence that, even after controlling for many of the other conditioning variables in recent studies of price behavior and risk premiums in oil futures markets, there were economically and statistically significant effects of investor flows on futures prices. Concluding remarks are presented in [Section 6](#).

2 Speculation and Booms/Busts in Commodity Prices

Virtually all classes of participants in commodity markets are, at one time or another, taking speculative positions.⁴ Certainly in this category are the large financial institutions that make markets in commodity-related instruments; those who hold unhedged inventory positions (producers, shippers, sovereign energy agencies); hedge funds and investment management companies; and commodity index investors.

Absent near stock-out conditions in a commodity market, equilibrium in the market for storing oil implies the cost-of-carry relation:⁵

$$S_t = E_t^{\mathbb{Q}} \left[e^{-\int_t^T (r_s - C_s) ds} S_T \right], \quad (1)$$

where S_t is the spot price of the commodity, C_t denotes the instantaneous convenience yield net of storage costs, r_t is the instantaneous, continuously compounded short rate, and $E_t^{\mathbb{Q}}$ denotes the expectation under the risk-neutral pricing distribution conditional on date t information. This expression is a consequence of S_t drifting at the rate $(r_t - C_t)S_t dt$ for a stand-in risk-neutral market participant. Additionally, the futures price for delivery of a commodity at date $T > t$ is related to S_T according to $F_t^T = E_t^{\mathbb{Q}} [S_T]$.

Rearranging these expressions, it follows that

$$\frac{F_t^T}{S_t} = \frac{1 - Cov_t^{\mathbb{Q}} \left(e^{\int_t^T C_s ds}, e^{-\int_t^T r_s ds} \frac{S_T}{S_t} \right)}{B_t^T E_t^{\mathbb{Q}} \left[e^{\int_t^T C_s ds} \right]} - \frac{1}{B_t^T} \times Cov_t^{\mathbb{Q}} \left(e^{-\int_t^T r_s ds}, \frac{S_T}{S_t} \right), \quad (2)$$

where B_t^T denotes the price of a zero coupon bond issued at date t that matures at date T .

⁴The primary exception would be participants that hold futures or options positions that precisely offset their current spot exposures and who adjust their derivative positions frequently enough to rebalance as new exposures arrive and old exposures dissipate.

⁵See, for examples, equation (1) of [Miltersen and Schwartz \(1998\)](#) or equation (4) of [Casassus and Collin-Dufresne \(2005\)](#), and related discussions in [Hamilton \(2009b\)](#) and [Alquist and Kilian \(2010\)](#).

If the covariance terms are negligible, then (2) can be rewritten approximately as

$$\frac{F_t^T - S_t}{S_t} \approx y_t^T (T - t) - \ln E_t^{\mathbb{Q}} \left[e^{\int_t^T C_s ds} \right], \quad (3)$$

where y_t^T is the continuously compounded yield on a zero-coupon bond with maturity of $(T - t)$ periods. This is the multi-period counterpart to the standard expression of the futures basis in terms of foregone interest and convenience yield. In the presence of stochastic interest rates and convenience yields, the multiperiod covariances between r and \mathcal{C} impact the relationship between F_t^T and S_t according to (2).

Most of the extant model-based interpretations of the oil price boom focus on representative risk-neutral producers and refiners and arrive at a similar expression with the expectation $E_t^{\mathbb{Q}}$ replaced by $E_t^{\mathbb{P}}$, the expectation of market participants under the historical distribution. The perfect-foresight model of [Hamilton \(2009a\)](#), for instance, leads to a special case of (1) without the expectation operator (since there is no uncertainty about future oil prices, inventory accumulations, or supply). If refiners and investors are risk averse, or if they face capital constraints that lead them to behave effectively as if they are risk averse, then (1) is the appropriate starting point for discussing speculation.

Implicit in (1) is the risk premium that market participants demand when trading commodities in futures and spot markets. Define the market risk premium as $RP_t^T \equiv (E_t^{\mathbb{P}}[S_T/S_t] - E_t^{\mathbb{Q}}[S_T/S_t])$, for $T > t$. Further, consider a short time interval $[t, \tau]$ over which r and \mathcal{C} are approximately constant. Then (2) implies that

$$\frac{E_t^{\mathbb{P}}[S_\tau] - S_t}{S_t} - y_t^\tau (\tau - t) \approx RP_t^\tau - \mathcal{C}_t (\tau - t). \quad (4)$$

Thus, expected excess returns in the spot commodity market depend on both convenience yields and risk premiums. The same will in general be true of expected excess returns in the futures market, which are percentage changes in the price of a future contract, adjusted for roll dates (see the Appendix for details).

While a time-varying convenience yield has been a widely acknowledged feature of oil markets, there has evidently been less agreement about the importance time-varying risk premiums. Many of the structural supply/demand models of oil price determination presume that risk premiums are zero. This is true of much of the large literature builds on the competitive storage model of [Deaton and Laroque \(1996\)](#).⁶ The findings in [Alquist and Kilian \(2010\)](#) have been cited as evidence in support of risk neutrality, but their analysis focuses on

⁶This includes [Hamilton \(2009a\)](#), [Dvir and Rogoff \(2010\)](#), and [Cafiero, Bobenrieth H., Bobenrieth H., and Wright \(2011\)](#), among others.

the “unbiasedness” of the futures price as a predictor of future spot prices and, in particular, ignores all conditioning information. Contrary to their assessment and the presumption in many storage models, the evidence for time-varying risks premiums in oil markets from the finance literature seems compelling.⁷

To sustain the pricing relation (2) and its approximate simplification (4) in equilibrium, it is not necessary that participants in the spot and futures markets, or those refining or holding inventories of crude oil, be one and the same individual.⁸ It follows that: (i) Spot prices are influenced not only by current oil market and macroeconomic conditions, but also by investors’ expectations about future economic activity. (ii) Supply and demand pressures in the futures and commodity swap markets will in general affect prices in the spot market. Indeed, these relationships are fully consistent with price discovery taking place in either the futures, the cash, or the commodity swap markets, or in all three. (iii) Risk premiums will typically change over time as investors’ willingness to bear risk changes. As I discuss in more depth below, the capacity of financial institutions to bear risk also changes over time, and this also may affect equilibrium futures and spot prices. (iv) Higher-order moments of prices and yields in financial markets also affect spot, futures, and swap prices through risk premiums and precautionary demands.

Virtually the entire literature on commodity price determination has abstracted away from differences in beliefs across investors. More plausibly, there is likely to be investor disagreement about virtually every source of fundamental risk, including the future of global demands, the prospects for supply, future financing costs, etc. Saporta, Trott, and Tudela (2009) document large errors in forecasting demand for oil, typically on the side of under estimation of demand and mostly related to the non-OECD Asia and the Middle East regions. Additionally, they document substantial revisions to forecasts of market tightness, based on data reported by the U.S. Energy Information Administration (EIA), especially during 2007.⁹ The International Energy Agency (IEA (2009)) reports substantial revisions to their monthly estimates of demands for the U.S., and emphasizes that poor information is available

⁷See, for examples, Fama and French (1987), Gorton, Hayashi, and Rouwenhorst (2007), Basu and Miffre (2011), and Hong and Yogo (2011).

⁸In particular, the claim that “index fund investors ... only participated in futures markets... In order to impact the equilibrium price of commodities in the cash market, index investors would have to take delivery and/or buy quantities in the cash market and hold these inventories off of the market. (ISOECD, page 8)” is not true in the economic environment considered here.

⁹Market tightness is defined as total consumption (excluding stocks) minus the sum of non-OPEC and OPEC production. After comparing news about, and revisions in forecasts of, supply and demand for oil during 2008, these authors conclude that “Based on the news about the balance of demand and supply in 2008 ... it seems that one can justify neither the rise in prices in the first half of 2008, nor the fall in prices in the second half (page 222).”

on non-OECD inventories.¹⁰ [Sornette, Woodard, and Zhou \(2008\)](#) document significant differences in the total world supplies for liquid fuels published by the IEA and the EIA, particularly from 2006 until 2008. The timeliness of non-OECD data is highly variable (IEA), and OPEC quotas and measured production levels are quite vague ([Hamilton \(2009b\)](#)).

The implications of informational frictions in commodity markets for pricing depends on the nature of these frictions. It is instructive to consider separately cases where investors have heterogeneous beliefs about economic fundamentals and where investors are learning about what other investors believe about these fundamentals from market prices. Several different approaches to introducing heterogeneity in beliefs in both static and dynamic settings have been explored in equity and bond markets. In a typical “rational expectations” equilibrium (*REE*) the source of different views across investors is private information. Investors share common priors and they do not disagree about public information. In contrast, in a “differences of opinion” equilibrium (*DOE*) investors can disagree even when their views are common knowledge. Accordingly, in a *DOE* investors can agree to disagree even when they share common information— they disagree about the interpretation of public information. Under a *REE* it is difficult to generate the volume of trade observed in commodity markets, because investors share common beliefs (see the “no-trade” theorems of [Milgrom and Stokey \(1982\)](#) and [Tirole \(1982\)](#)). In contrast in a *DOE*, because investors may disagree about the interpretation of public information, it is possible to generate rich patterns of comovement among asset returns, trading volume, and market price volatility (e.g., [Cao and Ou-Yang \(2009\)](#) and [Banerjee and Kremer \(2010\)](#)).

Of particular relevance to my analysis is whether differences in beliefs can generate price drift, in the sense of past changes in prices forecasting future changes in the same direction, and thereby booms and busts in prices.¹¹ When market participants have different information sets, behavior in the spirit of Keynes’ “beauty contest” may arise naturally in a *REE*. It is typically optimal for each participant to forecast the forecasts of others ([Townsend \(1983\)](#), [Singleton \(1987\)](#)): participants guess the beliefs of other participants and adjust their investment strategies accordingly. [Allen, Morris, and Shin \(2006\)](#) argue that this heterogeneity leads investors to overweight public opinion and this, in turn, exacerbates volatility in financial markets and induces level drift. However, [Banerjee, Kaniel, and Kremer \(2009\)](#) show that, in fact, market participants in a *REE* learn from the price and eliminate price drift at the aggregate level.

¹⁰[IEA \(2008a\)](#) observes that “detailed inventory data [for China] continues to test observers’ powers of deduction. As we have repeatedly stressed in this report, these data are key to any assessment of underlying demand trends... (page 15)”

¹¹There is extensive empirical evidence that announcements of public information lead post-announcement drift and momentum in common stock markets; see, for instance, [Zhang \(2006\)](#) and [Verardo \(2009\)](#).

Much of the recent literature on dynamic asset pricing models has focused on *DOE*. [Xiong and Yan \(2009\)](#), [Ehling, Gallmeyer, Heyerdahl-Larsen, and Illeditsch \(2012\)](#), and [Buraschi and Whelan \(2012\)](#) develop dynamic term structure models in which classes of investors differ in their beliefs about fundamental economic factors. By introducing a commodity with log-price process depending on the same economic factors g_t , $\log S_t = \rho_0 + \rho_g \cdot g_t$, we are led to pricing relations involving investors' beliefs. Specifically, suppose g is not observed and that the j^{th} group of investors observes the signals dI_t^j ,

$$dI_t^j = (\phi^j g_t^j + (1 - \phi^j) \epsilon_t) dt + \sigma_t^j dB_t^{I^j}, \quad (5)$$

that depend on g_t , where $d\epsilon_t = dB_t^\epsilon$, (dB^{I^j}, dB^ϵ) are standard Brownian motions. Investors compute their posterior views by conditioning on the aggregate endowment and their signals, but not on prices. This is because in a *DOE* each investor presumes that other investors' signals have no informational value, as in [Detemple and Murthy \(1994\)](#).

Assuming an endowment economy in which investors have constant relative risk averse preferences, The equilibrium short-rate is given by ([Buraschi and Whelan \(2012\)](#)):

$$r_t = \gamma_0 + \gamma'_g (w_1(t) \hat{g}_t^1 + w_2(t) \hat{g}_t^2) + \gamma_\Psi w_1(t) w_2(t) \Psi'_t \Psi_t, \quad (6)$$

where $w_i(t)$ is the wealth of the i^{th} class of investors with forecast \hat{g}_t^j of g_t and Ψ_t is the vector of differences in the subjective posterior beliefs about the state across the investors. In this setting with subjective beliefs about future spot prices, no arbitrage gives rise to subjective assessments of the “convenience services” provided by holding inventories, \mathcal{C}_t^j . Given (6), the \mathcal{C}_t^j also inherit dependence on the dispersion of beliefs of investors. It follows that futures prices depend on the wealth-weighted consensus views about the fundamental factors in the commodity market. Risk premiums, and hence excess returns, will change with the commitments of capital to commodity markets, and as investors' views change.

Importantly, it is not just that the wealth-weight consensus beliefs may differ from those that would be obtained in the counterpart homogeneous economy, but also that commodity spot and futures prices may depend directly on the dispersion of beliefs across investors. Changes in differences in beliefs will be a source of variation in risk premiums, independent of actual changes in the underlying fundamentals driving supply and demand in the commodity market, and will in general contribute to heightened volatility in commodity markets.

Direct evidence on the extent of disagreement about future oil prices on the part of professional market participants comes from comparing the patterns in the cross-sectional standard deviations of the one-year ahead forecasts of oil prices by the professionals surveyed

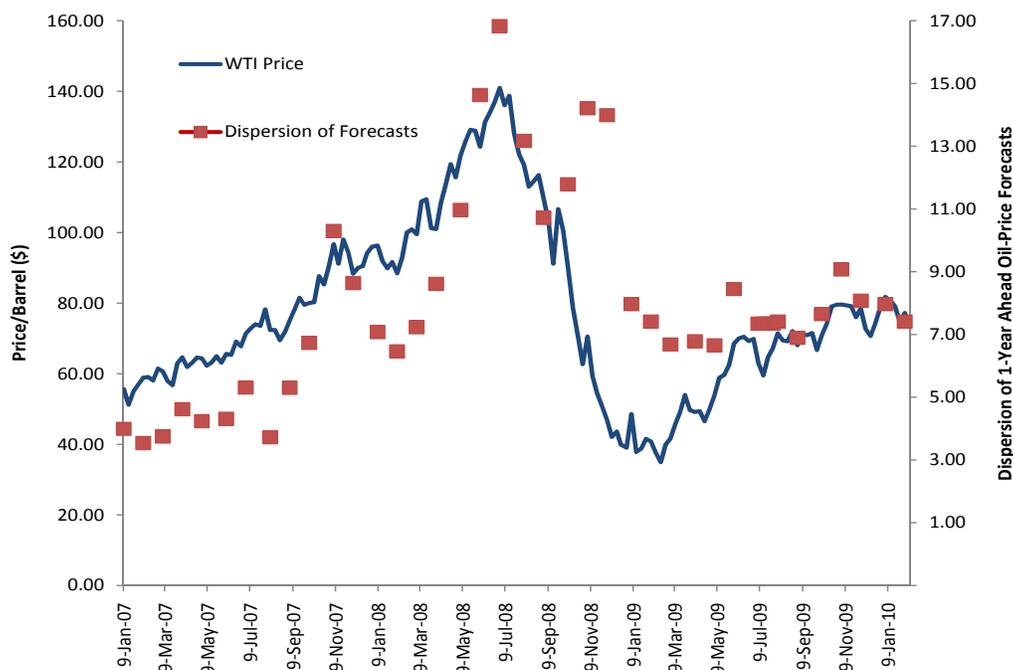


Figure 2: The front-month NYMEX WTI futures price (solid line, left scale) plotted against the cross-sectional dispersion of forecasts of oil prices one-year ahead by the professionals surveyed by Consensus Economics (squares, right scale).

by Consensus Economics.¹² Larger values of this dispersion measure correspond to greater disagreement among the professional forecasters surveyed. Figure 2 shows a strong positive correlation between the degree of disagreement among forecasters and the level of the WTI oil price. This comovement is consistent with the positive relationship between price drift and dispersion in investors' opinions found in theory and documented in equity markets.

Additionally, higher dispersion of forecasts is positively correlated with future increases in futures price volatility, again consistent with *DOE*. Using daily data on the generic near futures contract from Bloomberg, I computed a rolling monthly (20 trading day) series of volatilities using the Garman and Klass (1980) and Yang and Zhang (2000) estimators based on open/close/high/low price information. Predictive regressions were then estimated with forecast dispersion on the right-hand side for the sample period January, 2000 through January, 2010. For both volatility estimates the coefficients on forecast dispersion were statistically significant and the adjusted R^2 s were 11% and 7%, respectively.

¹²Consensus Economics surveys over thirty of (in their words) “the world’s most prominent commodity forecasters” and asks for their forecasts of oil prices in the future. The series plotted in Figure 2 is the cross-forecaster standard deviation for each month of their reported forecasts. I am grateful to the IMF for providing this series, as reported in their *World Economic Forum*.

Explaining this coincidence of a high dispersion in forecasts and a high oil price within a Bayesian *REE* seems challenging. As in many asset markets, a high level of the spot price is often accompanied by high conditional volatility of this price. Yet if (real) prices are mean reverting, then at exceptionally high price levels one might anticipate a strengthening consensus that prices will fall towards their long-run mean. Consistent with this intuition, the theoretical model in [Banerjee, Kaniel, and Kremer \(2009\)](#) implies price reversals in a *REE*. The pattern in [Figure 2](#) seems more symptomatic of an economic environment with learning that has prices drifting away from the (hypothetical) *REE* price.

There are several additional, complementary economic mechanisms through which informational frictions may affect commodity prices. In particular, [Adam and Marcet \(2010a\)](#) examine a framework in which investors are “internally” rational in the sense of [Adam and Marcet \(2010b\)](#)– they make fully optimal dynamic decisions given their subjective beliefs about variables that impact prices and are beyond their control. However investors may not agree on how public information about fundamentals translate into a specific price level. Nor do investors know the utility weights that other investors assign to specific economic events, a requirement of *REE* that seems implausible. For both of these reasons internally rational investors try to infer information about fundamental economic variables from market prices. They show that a model of stock price formation embodying these features produces boom/bust cycles in prices that match those experienced historically.

Finally, of relevance to my subsequent discussion is whether the patterns in dispersion of opinion in oil markets in [Figure 2](#) coincided with the dispersion of views on world economic growth. [Figure 3](#) plots the ratio of the forecast dispersion for the price of oil to the corresponding dispersion of forecasts of growth for the world economy.¹³ At least relative to views about economic growth, there was something special about oil markets during 2008. Dispersion in views about economic growth did not rise substantially from its mid-2008 value until the spring of 2009 when the financial crisis was more pronounced.

Several implications of this research, particularly as it relates to the roles of speculation in commodity markets, warrant emphasis. First, it is not necessary for investors with heterogeneous beliefs to have private information in order for their actions to impact commodity prices. Rather, so long as they have differences of opinion about the interpretation of public information and find it useful to learn from past prices, then their actions can induce higher volatility, price drift, and booms and busts in prices. Investors typically do not condition on past prices when they “agree to disagree” in a *DOE*. However, if each other’s opinions are not common knowledge (as seems likely) so there is uncertainty about consensus beliefs, then

¹³For the purpose of these calculations the world is considered to be the G7 plus Brazil, China, India, Mexico, and Russia. I am grateful to the IMF for providing me with these dispersion measures.

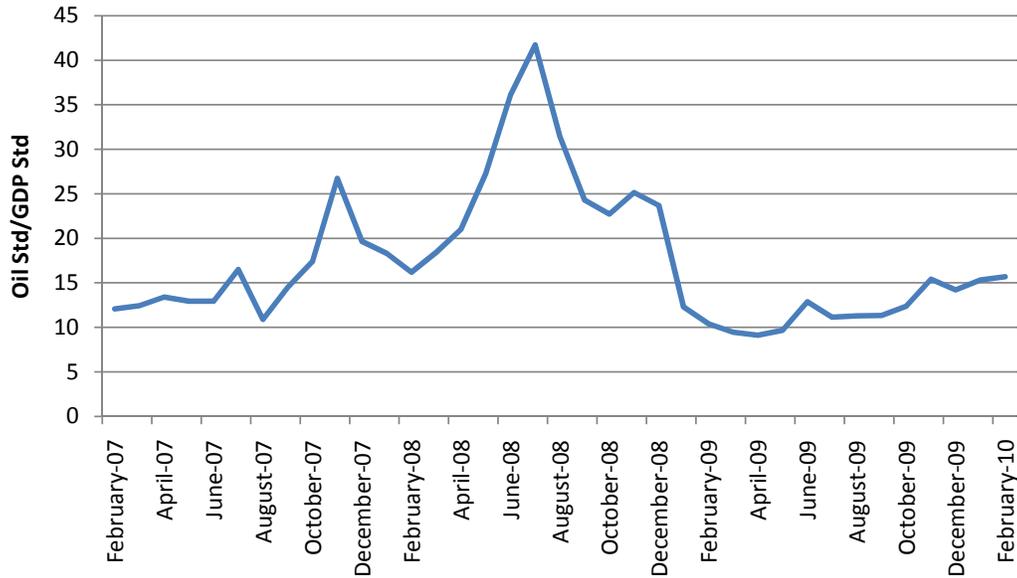


Figure 3: Ratio of the dispersions in forecasts for the price of oil and world economic growth (real GDP growth).

learning from prices arises in a *DOE* (Banerjee, Kaniel, and Kremer (2009)).

Second, the documented comovement among futures prices on commodities that are and are not in an index, or among spot prices across markets with and without associated futures contracts, is not evidence against an important role for speculation underlying this comovement.¹⁴ Participants in all commodity markets should find it optimal to condition on prices in other markets when drawing inferences about future spot prices, and this includes wholesalers and speculators.¹⁵ Third, commodity prices and market risk premiums may well depend the degree of differences of opinion about economic fundamentals and the nature of learning mechanisms.

Fourth, the fact that investors are learning about both fundamentals and what other investors know or believe about future commodity prices may mean that the release of a seemingly small amount of new information about supply or demand has large effects on

¹⁴It follows that the presence of heterogeneous beliefs and learning could invalidate both of the following claims in Irwin and Sanders (2010): (i) for index investors to have had a material affect on commodity prices “would have required a large number of sophisticated and experienced traders in commodity futures markets to reach a conclusion that index fund investors possessed valuable information that they themselves did not possess (page 8).” and (ii) “if index buying drove commodity prices higher then markets without index fund investment should not have seen prices advance (page 9).”

¹⁵The perception that there are links between flows into index funds and agricultural commodity prices is evident from Corkery and Cui (2010) who cite concerns about pension fund investments in commodities exacerbating fluctuation in food prices and, thereby, food shortages in poorer nations.

prices. Indeed, it is possible that prices change owing to changes in investors perceptions or risk appetite and absent the release of any new information.¹⁶ Finally, in many economic environments, the informational heterogeneity discussed above will, at certain times, have first-order effects on the levels of prices in addition to increasing trading volumes.

In any market setting where there are limits to the amount of capital investors are willing to commit to an asset class— that is, where there are limits to arbitrage— large increases in desired long or short positions by any class of investors can potentially impact prices in the futures and spot markets. [Acharya, Lochstoer, and Ramadorai \(2009\)](#) and [Etula \(2010\)](#) document significant connections between the risk-bearing capacity of broker-dealers and risk premiums in commodity markets. [Hong and Yogo \(2011\)](#) rely on similar reasoning in referencing inelastic demand for futures positions as an explanation for their finding that open interest predicts changes in futures prices. [Cheng, Kirilenko, and Xiong \(2012\)](#) document significant changes in the risk-bearing capacity of hedge funds trading in commodities after the onset of the current financial crisis. Price impacts of investor flows may also arise owing to inelastic supply of short positions in futures markets. Similar frictions underlie the documented impacts on bond prices of the supply and demand shocks examined by [Vayanos and Villa \(2009\)](#) and [Greenwood and Vayanos \(2010\)](#).

3 Demand/Supply, Inventories, and Speculation

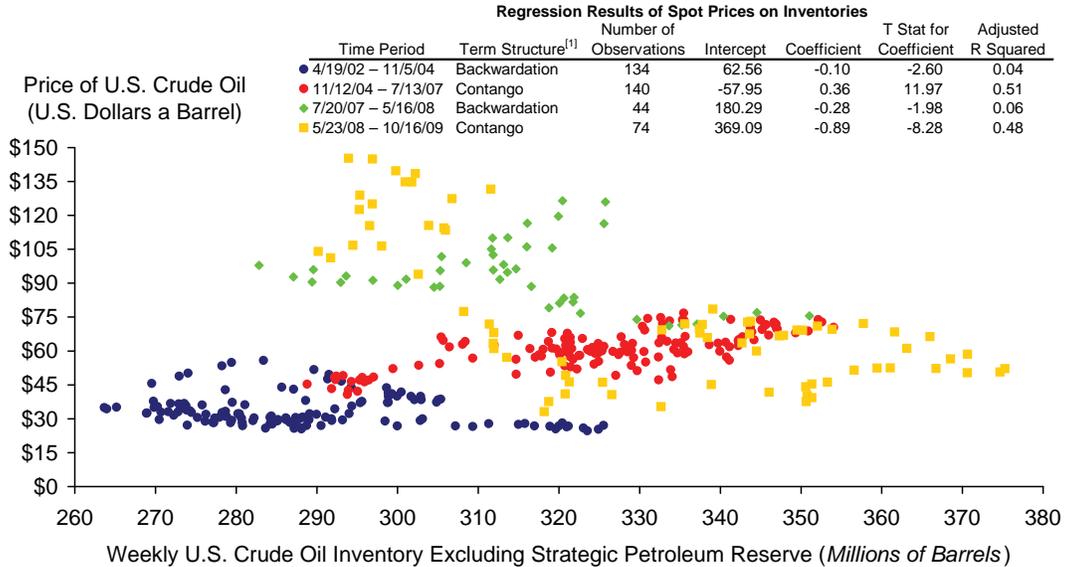
Many of the arguments against a significant role for speculative trading in the recent boom/bust in oil prices highlight the historical linkages between supply/demand and inventory accumulation. Specifically, a widely held view is that speculative trading that distorts prices on the upside must be accompanied by increases in inventories.¹⁷ From [Figure 4](#) it is seen that prior to 2003 there was a strong negative relationship between the price of oil and the amount of oil stored in the U.S. for commercial use (net of strategic petroleum reserves). This relationship turned significantly positive from 2004 to 2007. It weakened in 2007 and turned negative, and then was weakly positive again during the first half of 2008. Of course the price of oil is set in global markets, and during this period several major emerging economies where stockpiling crude oil in strategic reserves. These reserves are omitted from [Figure 4](#) and, even if one wanted to include them, the inventory data for emerging economies has been much less reliable than for the G7. So this figure can, at best, only give a partial picture of

¹⁶[Tang and Xiong \(2011\)](#) conclude that “the price of an individual commodity is no longer simply determined by its supply and demand. Instead, prices are also determined by ... the risk appetite for financial assets, and investment behavior of diversified commodity index investors (page 30).”

¹⁷For instance, the IEA expresses the view that “if speculators are driving spot oil prices, an imbalance in the form of higher stocks should be apparent ([IEA \(2008b\)](#)).”

Crude Oil Spot Price vs. U.S. Stocks 4/19/02 – 10/16/09

Source: Energy Information Administration; *Bloomberg*



Note 1: Contango and Backwardation are defined using the spot price and the three-month futures price.

Figure 4: U.S. commercial inventories of crude oil plotted against the spot price of oil, for various recent subperiods.

the historical inventory/price relationship.

Conceptually, the links between speculative trading– dynamic strategies based on the shapes of conditional distributions of future spot prices– and spot commodity prices are surely more complex than what emerges from models with static (non-forward looking or strategic) demands on the part of a homogenous class of agents. In a dynamic uncertain environment, time-varying expectations and volatility influence optimal inventory behavior. For instance, [Pirrong \(2009\)](#) shows that in a model with time-varying volatility, but otherwise similar features to Hamilton’s framework, there is not a stable relationship between inventories and prices. In particular, a positive inventory–price relationship may arise as a consequence of increased demand- or supply-side uncertainty. Thus, there is not an unambiguously positive theoretical relationship between changes in prices and inventories.

Equally importantly, the impact of inventory adjustments on the volatility of prices depends critically on what one assumes about the nature of uncertainty about supply and demand. Many storage models (e.g., [Deaton and Laroque \(1996\)](#)) assume that, subsequent to a surprise change in inventories induced by a shock to demand, inventories revert to a

long-run mean. It is this response pattern that led Verleger (2010), among others, to expect inventory adjustments to have a stabilizing effect on oil prices. However, these models of storage cannot simultaneously explain the high degree of persistence in oil prices and the high level of oil price volatility over the past 30 years (Dvir and Rogoff (2010)).

Arbitrageurs (those who store to make a profit from price changes) are confronted with two opposing implications of a positive income or demand shock. The price of oil increases and there is a drop in effective availability, both of which encourage a reduction in optimal storage. On the other hand, the persistent nature of aggregate demand means that both income and prices are expected to be higher in the future. Dvir and Rogoff (2010) show that when growth has a trend component, the expectation that prices will be higher in the future encourages an *increase* in inventories and this effect dominates the reduction in storage induced by the immediate post-shock increase in prices. On balance, storage (by arbitrageurs, refiners or consumers) may amplify the effects of demand shocks on prices.¹⁸ Aguiar and Gopinath (2007) argue that shocks to growth contribute more to variability in output in emerging than in developed economies.

At the core of many demand-based explanations for oil prices is the view that inelastic demand, combined with a relatively steeply sloped supply curve, implied that small changes in demand translated into large changes in prices, both on the upside and downside of the boom/bust. This same reasoning implies that small changes in strategic inventory positions can also have large changes in prices. Once expectations-based behavior is introduced, optimal inventory management can potentially further amplify the effects of differences of opinion and learning on commodity prices.

Figure 5 plots the level of non-strategic U.S. crude oil inventories against the spread between the futures prices for two- and four-month contracts ($M2 - M4$, inverted scale). Spreads that are above the zero line occur when the futures market is in contango, and spreads below this line indicate backwardation. There is a clear tendency throughout the period of 2004 through 2009 for inventories to increase when the futures market is in contango.¹⁹ A notable feature of Figure 5 that seems consistent with the an amplification effect of strategic behavior based on expected future prices is that, at least from 2007 onwards, steepening and flattening of the forward curve preceded changes in inventories: a steeper forward curve anticipated accumulations of inventories.

Teasing out the relative contributions of the risks associated with fundamental factors in

¹⁸While this amplification mechanism has some characteristics of the precautionary demand studied by Pirrong, the economic mechanism underlying it is not driven by uncertainty about demand, but rather by expectations of rising prices.

¹⁹These patterns are even stronger when inventory levels from Cushing or Padd2 are used.

U.S. Crude Inventory Level excl. SPR vs. WTI Contango 1/5/04 – 10/23/09

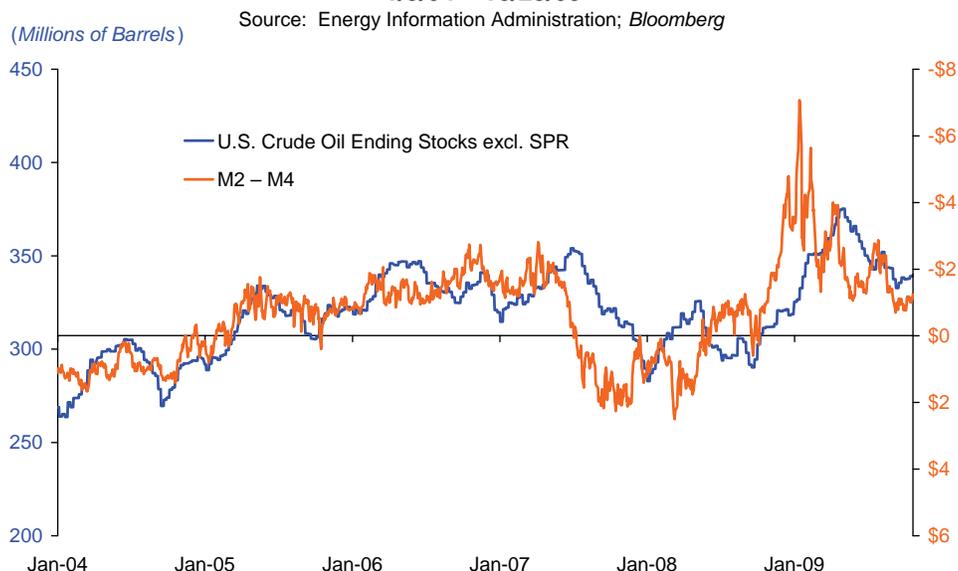


Figure 5: U.S. Commercial Inventories of Crude Oil Plotted Against the Spread Between Two-Month and Four-Month Futures Prices

demand and supply through the channels encompassed in models such those of [Hamilton \(2009a\)](#) and [Pirrong \(2009\)](#) from the effects of price drift owing to learning and speculation based on differences of opinion will require much richer structural models than have heretofore been examined. In an attempt to provide some guidance to such endeavors, the remainder of this paper explores the historical correlations between trader flows and excess returns in oil markets, particularly for the 2008/09 boom and bust.

4 What Is Known About Investor Flows?

When exploring the impact of speculative activity on the prices of oil a natural focal point is the trading patterns of participants in the commodity markets. While futures markets are zero-sum markets, this fact *per se* does not rule out the possibility that trading patterns have significant effects on prices. Under the presumption that the demand and supply of futures positions are not infinitely elastic, the dynamic interactions among the various classes of traders will induce pressure on prices, up and down.

Of particular interest to policy makers and academics alike is the question of whether the growth in index investing—exposure to commodities through index-linked products—affected

the distribution of oil prices. It seems reasonable to presume that the growth in index investing affected the trading strategies of at least some other large investors. [Buyuksahin, Haigh, Harris, Overdahl, and Robe \(2008\)](#), for instance, argue that, since the middle of 2004, there has been a significant change in the degree of cointegration of the one- and two-year futures with the nearby contract. This, as well as the higher degrees of comovement between oil futures and equity market returns, are attributable in part to the increased participation of hedge funds in oil futures markets ([Buyuksahin and Robe \(2011\)](#)). Hedge fund trading strategies also impacted oil futures prices around the rolls of index funds ([Mou \(2011\)](#)).

My subsequent empirical work focuses specifically on the question of whether the growth of investors in commodity index funds and the concurrent rapid growth of spread trades by hedge funds induced pressure on future prices in the same direction of the flows. Measuring the positions of these classes of traders is not straightforward. Prior to 2009 the Commitment of Traders Report (COT) from the CFTC only reported information for the broad categories of “commercial” and “non-commercial” traders. The CFTC now releases position reports for traditional commercial (commodity wholesalers, producers, etc.), managed money (hedge funds), commodity swap dealers, and “other.” This Disaggregated Commitment of Traders Report (DCOT) splits out swap dealers from the COT commercial category. However, the futures positions of swap dealers cover *all* of their activities while excluding positions that are netted across dealers. Moreover, this DCOT category ignores index positions held in the managed money category. Therefore, it may be only weakly related to the object of my interest, the futures positions related to index investing.

Most relevant for my purposes is the Commodity Index Traders (CIT) report that is available weekly and provides the positions of the index traders for twelve agricultural markets. The CFTC identifies index traders from filed forms and through confidential interviews with traders. Though the CIT reports include only agricultural commodities, approximate flows into oil futures associated with index investors can be inferred from this data using the known compositions of the S&P GSCI and Dow Jones UBSCI commodity indices. I follow the methods of [Verleger \(2007\)](#) and [Masters \(2008\)](#) to impute oil futures positions of commodity index investments from the CIT data.

These indices include both agricultural and energy contracts and, therefore, futures positions of index funds in agricultural positions are associated with matching positions in energy contracts based on the known weights of the indices. Some reassurance that the imputed flows are broadly consistent with the rapid growth in index positions in oil leading up to the boom/bust in oil prices comes from comparing the standardized, barrels-equivalent quarterly positions of all index investors imputed from the CIT data to the positions imputed

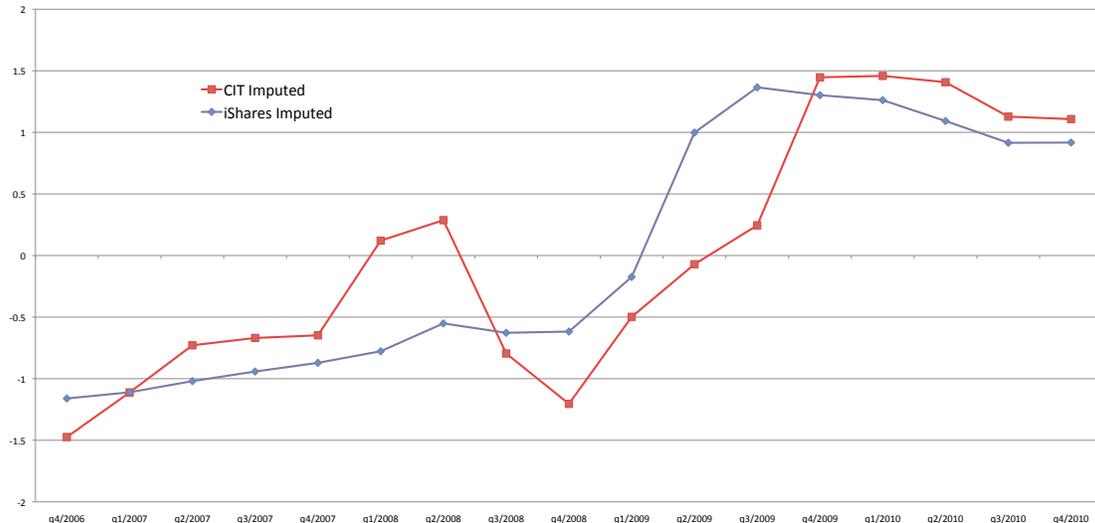


Figure 6: Oil-barrel-equivalent positions of index funds imputed from the CIT data (for all index investors) and the iShares S&P GSCI Commodity-Indexed Trust, standardized.

from the iShares S&P GSCI Commodity-Indexed Trust.²⁰ Figure 6 shows that that broad trends in these two imputed positions are similar; the sample correlation is 0.85. The CIT-imputed series declines more during the 2008 bust, and its increase during 2009 lags the increase in the iShares positions.

What is key for my purposes is not that the CIT-imputed index positions perfectly measure the positions of all index investors, but rather that changes in this series are highly correlated with the oil futures positions of institutional, retail, and hedge-fund investors taking positions through index-based instruments. There is widespread agreement that the CIT reported index positions in agricultural products are reliable measures of the actual positions of index investors (Verleger (2007), Commodity Futures Trading Commission (2008)). A major source of mismeasurement in imputing index positions in oil futures is that the CFTC extracts information from swap dealer positions.²¹ If these are netted positions, then the reported futures positions will *understate* actual levels of index investment (Irwin and Sanders (2011)).

Many have characterized index traders as “passive investors.”²² As noted by Stoll and

²⁰I am grateful to Jim Hamilton for suggesting this comparison. The imputed barrel-equivalent positions of the iShares Commodity-Indexed Trust are computed using the number of futures contracts reported in the quarterly SEC filings of this Trust and its weights on oil.

²¹There are other potential limitations to this imputation method. If the proportion of each index made up of any one agricultural product is small, mismeasurement is likely to be amplified through the process of scaling up to impute oil positions. Also, valuation is at the near-contract futures price (as in Tang and Xiong (2011)). Support for this choice is provided by Buyuksahin, Haigh, Harris, Overdahl, and Robe (2008) who find, based on proprietary CFTC data, that the net positions of commodity swap dealers were primarily in short-dated futures contracts (three months or under).

²²For instance, Stoll and Whaley (2009) express the view that commodity index investors “do not take a directional view on commodity prices. They simply buy-and-hold futures contracts to take advantage of the

Whaley (2009), patterns similar to Figure 1 (in their case for agricultural commodities) reflect the fact that a portion of the imputed position of index traders in any given commodity is driven by the movement in the underlying commodity price, as opposed to changes in the sizes of the positions of index traders. Nevertheless, overall position sizes did change. Even under the conservative estimates of position sizes by index investors in Stoll and Whaley, they doubled between 2006 and the middle of 2008, and then declined rapidly by nearly one half as of early 2009.

In addition to imputed index positions in oil, I examine the predictive content of spread positions in futures by “managed money” investors (hedge funds), also reported weekly as part of the CIT positions. I focus on spread trades— simultaneous long and short positions at different points of the futures term structure— because of the high level of hedge-fund activity in this type of trade. Erb and Harvey (2006) and Fuertes, Miffre, and Rallis (2008) document that simple spread trades led to large historical returns. Buyuksahin and Robe (2011) argue that increased positions of hedge funds in commodity futures affected the correlations between energy futures and returns on the *S&P500* index, and thereby the distribution of oil futures prices. Spread positions were the largest component of open interest during my sample period (Buyuksahin, Haigh, Harris, Overdahl, and Robe (2008)), and the CIT reports show that managed money accounts showed substantial growth in spread positions.

Perhaps the most compelling evidence to date that index flows and limits-to-arbitrage have, together, had economically important effects on futures prices is provided by Mou (2011)’s analysis of excess returns around the dates of the rolls of the futures positions in the GSCI index. He argues that speculators made substantial profits effectively at the expense of index investors, particularly for energy-related contracts. Moreover, the profitability of the trading strategies Mou examines were decreasing in the amount of arbitrage capital deployed in the futures markets and increasing in the proportion of futures positions attributable to index fund investments.²³

Most of the other evidence in the literature is based on predictive lead or lag regressions of futures returns on position changes over short horizons (a few days),²⁴ and prior research has not considered imputed flow data from the weekly CIT reports. The influence on prices within a day or two of changes in traders’ positions is relevant for analyses of market manipulation, the focus of much of the research by the CFTC.

In contrast, the preceding discussion motivates my focus on the impact of trader flows on risk-reducing properties they provide (Stoll and Whaley (2009), page 17).”

²³While the profitability of such positions declined leading up to the boom of 2008, they remained positive suggesting that there were limits to the amount of speculative capital investors were willing to deploy.

²⁴See, for example, Boyd, Buyuksahin, Harris, and Haigh (2009), Buyuksahin and Robe (2009), Buyuksahin and Harris (2009), and Brunetti and Buyuksahin (2009).

prices over the intermediate horizons of a week to a month. Whether through changes in allocations of capital to commodities, revisions in beliefs about future fundamental factors that drive commodity prices, or updating of beliefs based on inferences drawn from past changes in commodity prices, the impacts of the changes in positions of commodity investors on prices is more likely to manifest itself over a time frame of weeks. Furthermore, changes in index investor or hedge fund commitments of capital or beliefs may well be influenced by their perceptions about economic developments over the coming weeks and months (or their perceptions about the beliefs of other investors about these developments). New information about many of the fundamental factors determining prices in oil markets is released at monthly or quarterly intervals, leaving price changes as a central signal about the future during intervening periods.

5 Evidence on the Impact of Trader Flows on Oil Prices

Motivated by these considerations, I project weekly and monthly excess returns on positions in futures contracts onto the thirteen-week (roughly quarterly) changes in flows into long positions by index investors and spread positions by managed money (hedge funds). I focus on these flows because of their rapid growth over the sample period and their prominence in recent debates about the impact of investor flows on prices.

Flows from the CIT reports could be informative about changes in futures prices for at least three reasons: (i) flows will induce changes in prices in order to balance supply and demand in the futures markets, (ii) investors' risk premiums may depend on information that is correlated with these flows, and (iii) some financial institutions may base trade strategy on proprietary order-flow information.²⁵ Regarding (iii), the International Swaps and Derivatives Association, a financial industry trade organization, was opposed to the CFTC releasing the information in the CIT reports that I use in my empirical work, out of concern that traders could reverse engineer their competitors' positions in oil futures.²⁶

To explore empirically whether the flows of index and managed-money investors had predictive power for returns in futures markets I project realized returns onto these flows and several other control variables that have been found previously to predict futures prices. Time-series of excess returns over one- and four-week holding periods are computed for futures

²⁵For evidence that order-flow information is valuable in currency markets see [Evans and Lyons \(2009\)](#).

²⁶In their comments to the CFTC about the desirability of releasing the CIT reports [ISDA \(2006\)](#) states: "Because the index weightings are publicly available, knowledge of a dealer's position in a particular commodity would allow another market participant to calculate the dealer's position in all of the index commodities. ... In a dispersed market, the risk of reverse engineering would be low, but the non-traditional commercial category is highly concentrated..."

contracts with maturities of 1, 3, 6, 12, and 24 months. The sample period is September 12, 2006 through January 12, 2010.²⁷

I estimate the forecasting equations

$$ERmM_{t+n}(n) = \mu_{nm} + \Pi_{nm}X_t(n) + \Psi_{nm}ERmM_t(n) + \varepsilon_{m,t+n}(n), \quad (7)$$

where $ERmM_t(n)$ is the realized excess return for an n -week investment horizon on a futures position that expires in m months, X_t is the set of predictor variables, and the data were sampled at weekly intervals. Included in $X_t(n)$ are the following conditioning variables:

RSPn and REMn: the n -week returns on the S&P500 and the MSCI Emerging Asia indices, respectively (not annualized). These returns control for the possibility that investors were pursuing trading strategies in oil futures that conditioned on developments in global equity markets, or that investors were engaged in cross-market trade strategies.

REPOn: the n -week change in overnight repo positions on Treasury bonds by primary dealers (trillions of dollars). This is an indicator of the balance-sheet flexibility of large financial institutions.²⁸

IIP13: the thirteen-week change in the imputed positions of index investors, measured in millions of contracts, computed using the algorithm described in [Section 4](#).

MMS13: the thirteen-week change in managed-money spread positions, measured in millions of contracts, as reported by the CFTC. Spread trades are not signed: trades that are long or short the long-dated futures are treated symmetrically.

OI13: the thirteen-week change in aggregate open interest, measured in millions of contracts, as reported by the CFTC.

AVBn: the n -week change in average basis. Defining the basis at time t of a futures contract with maturity $T_i(t)$ to be²⁹

$$B_i(t) = \left(\frac{F_t^{T_i}}{S_t} \right)^{1/(T_i(t)-t)} - 1, \quad (8)$$

²⁷Details of the excess return calculations are presented in the Appendix.

²⁸[Etula \(2010\)](#) in the context of futures trading, and [Adrian, Moench, and Shin \(2010\)](#) more generally, argue that the balance sheets of financial institutions affect their willingness to commit capital to risky investments. This in turn implies that risk premiums may depend on the costs to these institutions of financing their trading activities.

²⁹Note that this measure of the basis has the opposite sign of the basis in [Figure 5](#).

as in [Hong and Yogo \(2011\)](#), then *AVBAS1* is the average of these values for maturities $i \in \{1, 3, 6, 9, 12, 15, 18, 21, 24\}$. In computing (8) I account for the time-varying maturity of the futures contracts.

The fitted values from these regressions are typically interpreted as expected excess returns or risk premiums. This is a natural interpretation when $X_t(n)$ represents information that was available to at least some market participants at the time the forecasts were formed. *IIP13* and *MMS13* are constructed using information available at the time of the forecast. However this data was released by the CFTC starting in 2007 and, as such, was not readily available to market participants during my sample period. Therefore, a finding of economically significant predictive power for these variables would be suggestive of an impact of trading patterns on futures prices (controlling for other variables in $X_t(n)$), but not necessarily evidence that investors conditioned on these variables in forecasting future oil prices.

These projections of $ERmM_{t+n}(n)$ onto *IIP13* and *MMS13* have two equivalent interpretations. First, they lead to tests of the null hypotheses of predictable short-horizon (weekly or monthly) returns. Second, assuming that futures returns and the predictor variables are covariance stationary, these null hypotheses have the same economic content as the hypotheses that weekly or monthly investor flows impact futures prices over thirteen week horizons ([Hodrick \(1992\)](#), [Singleton \(2006\)](#)).³⁰

AVBASn is a proxy for the net convenience yield in commodity markets.³¹ Recall from (4) that expected excess returns in commodity markets are in general influenced by variation in convenience yields, changes in market risk premiums, and factors related to agents' learning from market prices or differences of opinions. To the extent that *AVBASn* is a reasonable proxy for the convenience yield in oil markets, conditioning on *AVBASn* allows me to highlight the effects of other conditioning variables on risk premiums or other factors related to limits to arbitrage or speculative behavior.³²

³⁰Consistent with most prior studies, weekly changes in index positions have little predictive content for the weekly or monthly excess returns. Such high frequency correlations between futures prices and investor flows are likely to be dominated by noise that obscures the presence of any lower frequency comovement.

³¹Another motivation for controlling for the basis is that it might capture effects of hedging pressures on subsequent returns to futures positions ([Hong and Yogo \(2011\)](#)). There is an extensive literature examining links between net positions of hedgers and the forecastability of commodity returns—the “hedging pressure” hypothesis ([Keynes \(1930\)](#), [Hicks \(1939\)](#)). In two recent explorations of this issue [Gorton, Hayashi, and Rouwenhorst \(2007\)](#) find no support for the hedging pressure hypothesis, while [Basu and Miffre \(2011\)](#) argue that systematic hedging pressure is an important determinant of risk premiums. Both use the aggregated CFTC data on commercial and non-commercial traders in futures markets which is not reliably informative about the trading activities of such classes of investors as index investors or hedge funds.

³²[Gorton, Hayashi, and Rouwenhorst \(2007\)](#) extend the model of [Deaton and Laroque \(1996\)](#) to allow for risk averse speculators (maintaining mean reverting demand) and show that inventories are negatively related to expected excess returns in futures markets. They also establish a link between the futures basis

Variable	RSP1	REM1	REPO1	IIP13	MMS13	OI13	AVB1
Contemporaneous Predictors							
ER1M(1)	0.35	0.40	0.10	0.21	0.16	0.12	-0.40
ER3M(1)	0.43	0.48	0.08	0.24	0.19	0.15	-0.24
ER6M(1)	0.45	0.50	0.06	0.25	0.17	0.15	-0.20
ER12M(1)	0.44	0.51	0.04	0.25	0.15	0.14	-0.17
ER24M(1)	0.41	0.48	0.04	0.25	0.12	0.13	-0.13
Lagged Predictors							
ER1M(1)	0.03	-0.17	-0.21	0.25	0.18	0.12	-0.24
ER3M(1)	0.11	-0.10	-0.20	0.26	0.19	0.13	-0.29
ER6M(1)	0.13	-0.09	-0.19	0.26	0.18	0.13	-0.27
ER12M(1)	0.16	-0.10	-0.19	0.26	0.16	0.12	-0.22
ER24M(1)	0.15	-0.11	-0.17	0.25	0.13	0.11	-0.16

Table 1: Correlations among the one-week excess returns on futures positions and the contemporaneous and lagged values of the predictor variables.

For a broad set of commodities, [Hong and Yogo \(2011\)](#) find a very strong positive relationship between open interest and subsequent returns on futures positions. They view this pattern as arising from a downward sloping demand curve for futures positions induced by limits to arbitrage. However, just as demand may be less than perfectly elastic, so might the supply of futures. Particularly during periods of substantial increases in long positions in futures associated with index flows, changes in futures prices may be necessary to induce other market participants to take the short side of futures positions. Additionally, their study of open interest does not condition on the flows of index investors or managed money. The sample correlation between *IIP13* (*MMS13*) and *OI13* was 0.56 (0.45), so inclusion of flows and *OI13* may well affect how open interest affects returns in futures markets.

I also include the lagged value of the realized n -week excess return on oil futures positions. [Stoll and Whaley \(2009\)](#) find that, once lagged returns on futures positions are included in predictive regressions, there is no incremental predictive power for flows into commodity index investment. In contrast, Hong and Yogo found that open interest effectively drives out the forecasting power of lagged returns.

The correlations among the $ERmM(1)$ and contemporaneous and first-lagged values of $X(1)$ are displayed in [Table 1](#). The contemporaneous correlations between the $ERmM(1)$ and the predictor variables have signs that are consistent with previous findings in the and inventories. These authors and [Hong and Yogo \(2011\)](#), among others, present empirical evidence that a high basis (high $M2 - M4$ in [Figure 5](#)) predicts high excess returns on futures positions, consistent with the theory of normal backwardation and compatible with the theory of storage.

Predictors			One-Week Returns			One-Month Returns		
Variable	Mean	Std	Maturity	Mean	Std	Maturity	Mean	Std
RSP1	-0.04	2.94	1	0.03	6.49	1	0.00	12.7
RSP4	-0.15	5.80	3	0.02	5.51	3	-0.01	11.1
REM1	0.27	4.82	6	0.09	5.13	6	0.29	10.4
REM4	1.01	9.16	9	0.11	4.93	9	0.39	9.97
REPO1	-0.35	8.03	12	0.13	4.76	12	0.46	9.62
REPO4	-1.55	12.13	18	0.16	4.50	18	0.56	9.05
IIP13	3.81	8.42	24	0.17	4.32	24	0.63	8.63
MMS13	0.14	4.44	36	0.20	4.14	36	0.74	8.11
OI13	0.96	9.98						
AVB1	0.00	0.65						
AVB4	0.00	0.76						

Table 2: Sample means and standard deviations of the excess returns and predictor variables for the projection (7), expressed in percent for return-related variables.

literature. Yet, notably, the correlations of the $ERmM(1)$ with emerging market stock returns ($REM1$) and the growth in repo positions by primary dealers ($REPO1$) change sign when these conditioning variables are lagged one period. Moreover, the investor flows $IIP13$ and $MMS13$ have sizable positive correlations with excess returns. For the signed index positions, this is consistent momentum-style trading. Also, though the correlations between $OI13$ and the $ERmM(1)$ are relatively small, their signs are consistent with [Hong and Yogo \(2011\)](#)’s evidence based on monthly data over a much longer sample period.

To explore these comovements more systematically and jointly, I estimated the parameters in (7) using linear least-squares projection. For ease of interpretation, all of the predictor variables are standardized by dividing by their respective sample standard deviations. With this convention, each element of the coefficient matrix Π represents the impact on the left-hand excess return of a one-standard deviation change in the predictor. The sample means and standard deviations of the left- and right-hand side variables are reported in [Table 2](#).

The null hypotheses are that the elements of Π are zero: excess returns on futures positions are not predictable by the variables in X_t , after conditioning on lagged excess returns. Economic theory accommodates other transformations of the conditioning information (more lags or nonlinear transformations) have incremental predictive content for excess returns. Accordingly, following [Hansen \(1982\)](#) and [Hansen and Singleton \(1982\)](#), robust standard errors are computed allowing for serial correlation and conditional heteroskedasticity in ε_{t+n} .³³

Estimates of Π along with their asymptotic “t-statistics” are displayed in [Tables 3](#) and

³³Specifically, I use the [Newey and West \(1987\)](#) construction allowing for five lags.

Contract	RSP1	REM1	REPO1	IIP13	MMS13	OI13	AVB1	R_{Lag}	AdjR ²
1	0.96 (1.39)	-1.69 (-2.42)	-1.69 (-2.92)	2.32 (3.60)	1.62 (4.46)	-1.00 (-2.12)	-2.10 (-6.86)	-1.34 (-2.03)	0.27
3	1.06 (1.95)	-1.22 (-2.03)	-1.42 (-2.79)	1.86 (3.70)	1.29 (4.54)	-0.79 (-1.79)	-1.76 (-4.43)	-0.75 (-2.00)	0.26
6	1.15 (2.33)	-1.30 (-2.25)	-1.25 (-2.69)	1.68 (3.48)	1.11 (4.23)	-0.69 (-1.67)	-1.44 (-3.84)	-0.50 (-1.57)	0.24
12	1.29 (2.82)	-1.39 (-2.56)	-1.10 (-2.54)	1.53 (3.41)	0.92 (3.90)	-0.62 (-1.67)	-1.02 (-2.90)	-0.34 (-1.14)	0.22
24	1.22 (2.97)	-1.39 (-2.82)	-0.88 (-2.25)	1.33 (3.44)	0.72 (3.45)	-0.52 (-1.64)	-0.63 (-2.49)	-0.20 (-0.610)	0.18
$\overline{ER}(1)$	1.15 (2.21)	-1.38 (-2.41)	-1.33 (-2.75)	1.80 (3.79)	1.180 (4.37)	-0.75 (-1.86)	-1.48 (-4.21)	-0.65 (-1.82)	0.25
$\overline{ER}(1)$	1.30 (2.37)	-1.24 (-2.10)				0.59 (1.08)	-1.24 (-3.38)	-0.36 (-0.697)	0.10

Table 3: Estimates of standardized coefficients for the futures excess return forecasting model over the horizon of one week. $ERmM(1)$ is the dependent variable for the individual contract returns, expressed in percent of return, and $\overline{ER}(1)$ denotes the average excess return for the 1, 3, 6, 9, and 12 month contracts.

Contract	RSP4	REM4	REPO4	IIP13	MMS13	OI13	AVB4	R_{Lag}	Adj R^2
1	0.13 (.056)	2.17 (1.14)	1.31 (1.46)	8.27 (4.32)	4.29 (6.89)	-4.34 (-3.79)	-0.38 (-.334)	-2.59 (-21.80)	0.38
3	-0.79 (-.520)	3.14 (2.35)	0.45 (.539)	7.81 (4.55)	4.15 (7.02)	-3.73 (-3.36)	0.05 (.063)	-3.10 (-2.60)	0.41
6	-1.15 (-.781)	3.21 (2.56)	0.16 (.197)	7.40 (4.31)	3.70 (6.69)	-3.38 (-3.22)	0.28 (.374)	-2.85 (-2.48)	0.39
12	-1.27 (-.884)	2.85 (2.45)	0.17 (.238)	6.80 (4.23)	3.05 (6.08)	-3.06 (-3.12)	0.42 (.590)	-2.32 (-1.92)	0.36
24	-1.22 (-.916)	2.27 (2.26)	0.31 (.501)	5.75 (4.12)	2.35 (5.31)	-2.55 (-2.81)	0.37 (.578)	-1.65 (-1.48)	0.30
$\overline{ER}(4)$	-0.87 (-.552)	2.90 (2.21)	0.44 (.572)	7.52 (4.35)	3.72 (6.77)	-3.59 (-3.44)	0.10 (.127)	-2.72 (-2.29)	0.40
$\overline{ER}(4)$	-0.04 (-.020)	2.97 (1.61)				1.54 (1.14)	-0.02 (-.021)	.083 (.687)	0.12

Table 4: Estimates and robust test statistics for the futures excess return forecasting model over the horizon of four weeks. $ERmM(4)$ is the dependent variable for the individual contract returns, and $\overline{ER}(4)$ denotes the average excess return for the 1, 3, 6, 9, and 12 month contracts.

4 for $n = 1$ and 4 weeks, respectively. The adjusted R^2 's provide compelling evidence that there was substantial predictability of changes in futures prices in oil markets during this period. From Table 2 it is seen that the volatilities of the one-week excess returns decline, and the mean excess returns are increasing, in the contract month. Thus, the lower adjusted R^2 's for the longer maturity contracts in Table 3 imply that the predictor variables explain smaller percentages of relatively less volatile, but larger on average, returns.

The last two rows of these tables display the projection coefficients for the cross-sectional average of the excess returns for the 1, 3, 6, 9, and 12 month contracts, with and without the conditioning variables ($REPO_4$, $IIP13$, $MMS13$). For both horizons there is a substantial drop in the adjusted R^2 s from omitting these variables. Particularly for the case of $n = 4$, where the coefficients on $REPO_4$ are all insignificant, this finding points to ($IIP13$, $MMS13$) having had substantial predictive power for excess returns during this sample period.

Elaborating, perhaps the most striking findings in Tables 3 and 4 are the statistically significant predictive powers of changes in the index investor ($IIP13$) and managed money spread ($MMS13$) positions on excess returns in crude oil futures markets. Increases in flows into index funds over the preceding three months predict higher subsequent futures prices. The significant positive relationship between futures excess returns and index investor flows is seen visually from a comparison of $IIP13$, the four-week moving average of $ER1M(1)$, and the price of the one-month futures contract (Figure 7).³⁴ Other notable features of this figure are: (i) both the futures returns and $IIP13$ start to decline in the spring of 2008 prior to the peak in oil prices, (ii) the thirteen-week growth in index positions turns sharply negative shortly after the peak in prices, and (iii) the return to positive growth in index positions during late 2008 appears to lead the recovery in futures returns.

There is also a significantly positive effect of flows into managed money spread positions on future oil prices. The weekly excess returns embody the roll returns once per month. Therefore, the predictive power of $MMS13$ might in part reflect the growth in spread trading by hedge funds in anticipation of the Goldman roll for index funds (Mou (2011)). Alternatively, Boyd, Buyuksahin, Harris, and Haigh (2010) present evidence of herding behavior by hedge funds during this sample period. Whatever the motives of the professionals categorized as “managed money” traders, their net effect on excess returns was positive: increases in spread positions were associated with future increases in oil contract prices.

Consider next the coefficients on the growth in open interest ($OI13$). Its coefficients are negative for both horizons, though they are small relative to their standard deviations for the one-week horizon. For the case of the four-week returns $ERmM(4)$ (Table 4) the negative effect declines monotonically with the maturities of the futures contracts, the opposite of the

³⁴This series is the price of the generic one-month futures contract, $CL1$, from Bloomberg.

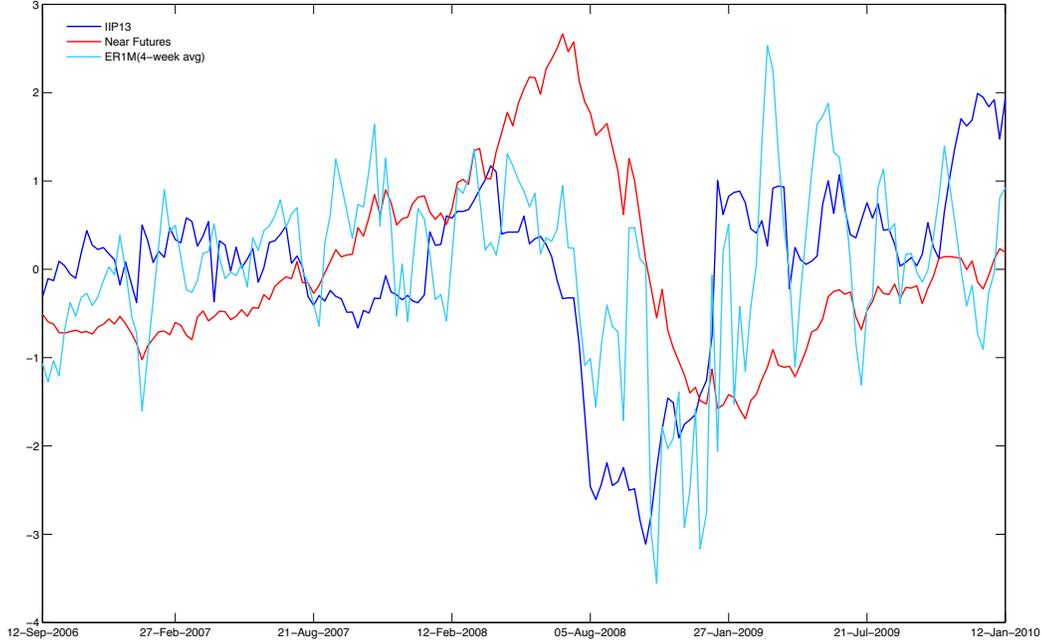


Figure 7: Investor flows ($IIP13$) and the four-week moving-average of the one-week futures return ($ER1M$) plotted against the price of the one-month futures contract.

findings in [Hong and Yogo \(2011\)](#). This difference seems to arise as a consequence of having controlled for the investor flows $IIP13$ or $MMS13$. These can be seen from the last rows of the tables where, when the flow variables ($IIP13$, $MMS13$) are omitted, the coefficient on $OII3$ is positive (though statistically insignificant).

With $n = 1$ the coefficients on the lagged futures returns for the one- and three-month contracts are marginally significant, but for all other contracts they are statistically insignificant. Additionally, the absolute values of the estimates decline rapidly with the maturity of the futures contract. Thus, there is weak evidence of reversals in the prices of the short-dated futures contracts, after accounting for the other conditioning information. Increasing the holding period to $n = 4$ weeks does not alter the signs of these coefficients, though they remain statistically significant for contracts out to about one year in length. More generally, and importantly for interpreting the evidence regarding the boom and bust in oil prices, these findings suggest that the significant predictive content of the conditioning variables X_t is fully robust to inclusion of the lagged return (see also below). This stands in contrast to the results from focusing on returns and conditioning variables over daily intervals as, for instance, in [Buyuksahin and Harris \(2009\)](#) and [Stoll and Whaley \(2009\)](#).

Taken together, and viewed through the lens of the economic environments discussed in [Section 2](#), this evidence on investor positions points to an economically large and statistically significant effect of flows into index funds and spread trades by hedge funds on excess returns

in futures markets. These flow variables could well be proxies for position changes associated with investor learning rules about fundamental determinants of oil prices, or for trading patterns associated with differences of opinion within or across investor categories.

The coefficients in Tables 3 and 4 measure the impact on futures returns (in percent) of one standard-deviation changes in the predictors. So the impacts of changes in (*REM1*, *REPO1*, *IIP13*, *MMS13*, *AVB1*), for examples, on the one-week return on the one-month futures contract are $(-1.69, -1.69, 2.32, 1.62, -2.10)$ percent, and these responses should be viewed relative to the weekly standard deviation in *ER1M(1)* of 6.49% (Table 2). The absolute responses tend to decline with the maturity of the futures contract, but (*REM1*, *IIP13*, *MMS13*) maintain their statistical significance for all maturities.

Differences among the impacts become more sizable when the holding period is extended to four weeks. The largest percentage changes in futures returns are induced by one-standard-deviation shocks to the flow related variables (*IIP13*, *MMS13*, *OI13*): for instance, for *ER1M(4)* these responses are $(8.27, 4.29, -4.34)$ percent, relative to its standard deviation of 12.7%. The large impacts of these variables tend to be preserved as the maturity of the futures contract increases.

The standard deviations of the trader flow variables were large during the period around the 2008 boom/bust in oil prices. For instance, the standard deviations of *IIP13* and *MMS13* were 8.42 and 4.44 million contracts, respectively. Using these values we can translate the reported responses in futures returns into basis points per million of barrels as follows. For *IIP13* over the one-week (four-week) horizon, an increase in index positions of one million barrels led (*ceteris paribus*) to changes in raw futures returns on the three-month contract of 2.2bp (9.3bp), and 1.8bp (8.1bp) on the twelve month contract.

The coefficients in Table 3 on the lagged returns on emerging market equity positions (*REM1*) are negative and statistically significant. In contrast, the signs on the coefficients on *REM4* in the projections for four-week excess returns *ERmM(4)* are positive, as are the contemporaneous correlations between the *ERmM(1)* and *REM1*. To explore this change of sign in more depth, I project $ERmM_{t+j}(1)$ onto X_t (for the case of $n = 1$) and $ERmM(1)_t$, for $j = 1, 2, 3, 4$. The coefficients on $REM1_t$ in these projections effectively trace out the conditional impulse response function of *ERmM(1)* to an innovation in *REM1*. They start negative, turn positive in week two and peak at a larger positive number at week three.

This pattern suggests that, after controlling for the other variables in X_t , positive innovations in (favorable news about) emerging market growth predicted reversals in futures prices in the subsequent week, perhaps as a consequence of limits to capital market intermediation or learning mechanisms that lead to short-term over-shooting of prices. Then, over somewhat longer horizons, such news predicts positive futures returns. Again, these responses can be

translated into responses of futures returns per say 1% change in $REM1$ or $REM4$ using their standard deviations in [Table 2](#). A one-percent increase in $REM1$ leads (*ceteris paribus*) to a $-26bp$ ($-30bp$) change in the weekly return on the three- (twelve-) month contract, and a $34bp$ ($31bp$) change in the four-week return on the same contracts.

The negative and statistically significant effects of $REPO1$ on excess returns are consistent with the model of [Etula \(2010\)](#) in which risk limits and funding pressures faced by broker-dealers impact risk premiums in commodity markets. The *OTC* commodity derivatives market is substantially larger than the markets for exchange traded products and servicing the *OTC* markets requires a substantial commitment of capital by broker-dealers. As funding conditions improve—reflected here through an increase in the repo positions of primary dealers—the effective risk aversion of broker-dealers declines and, hence, so should the expected excess returns in commodity futures markets. This effect of funding liquidity on excess returns declines (in absolute value) with contract maturity, while remaining statistically significant. The statistically insignificant effects on $ERmM(4)$ in [Table 4](#) indicate that the effects of funding liquidity on trader positions were short-lived.

Finally, increases in the average basis ($AVBAS1$) are associated with declines in excess returns, particularly for the short-maturity contracts. Notably, $AVBAS1$ shows small correlations with the other conditioning variables. For instance, its correlations with ($REPO1$, $IIP13$, $MMS13$, $OI13$) are $(-0.15, -0.05, -0.05, -0.08)$ so the weekly average basis represents distinct information about future returns. Over monthly horizons the effect of $AVBAS4$ is not statistically significant. This finding aligns with those in studies of earlier sample periods (e.g., [Fama and French \(1987\)](#) and [Hong and Yogo \(2011\)](#)).

The reported findings are robust to inclusion of several other conditioning variables. In preliminary regressions I also included the one-week change in the Cushing, OK inventory of crude oil in millions, as reported on Bloomberg. There is a statistically weak negative effect of inventory information on the excess return for the one-month contract. Beyond one month, the coefficients are all small relative to their estimated standard errors. Additionally, I estimated the predictive regressions with additional lags of excess returns included as predictor variables and the pattern of results in [Table 3](#) remained qualitatively the same. Their inclusion did not affect the predictive content of the investor flow variables.

Finally, some argue that the trading patterns of index and managed-money investors are linked to speculation about global economic growth. A relevant question then is whether measures of global economic growth also had predictive power for excess returns on futures. As a proxy for aggregate demand, I follow [Kilian \(2009\)](#) and [Pirrong \(2009\)](#), as well as many oil-market practitioners, and use shipping rates based on the Baltic Exchange Dry Index (BEDI). The growth rate of the BEDI over the previous three months does explain

an additional 2 – 3% of the variation in excess returns, and its coefficients are marginally statistically significant. However, BEDI has little effect on the explanatory power of my X_t which continues to account for most of the predictable variation in futures returns.

6 Concluding Remarks

The trading patterns of investors who are learning about economic fundamentals, both from public announcements and market prices, may contribute to drift in commodity prices that looks like a boom followed by a bust. This phenomenon is entirely absent, essentially by assumption, from many of the models of oil price determination that focus on representative suppliers, consumers, and hedgers. My empirical evidence suggests that growth in positions of index investors and managed-money accounts had significant positive effects on returns in oil futures markets around the time 2008 boom/bust in oil prices, after accounting for stock returns in the U.S. and emerging economies, open interest, and lagged futures returns. These findings will hopefully serve as motivation for further development of dynamic models of commodity price determination with informational frictions.

Two issues central to the modeling background in [Section 2](#) warrant further comment. First, some insight into whether my results are documenting changes in informational factors, risk premiums, or convenience yields on excess returns can be gleaned from examining the errors from forecasting future spots prices using futures prices. Toward this end I projected $S_{t+4} - F_t^{t+4}$ (the spot price one month ahead minus the one-month futures price) onto the conditioning variables X_t (for the monthly horizon).³⁵ The adjusted R^2 in this projection is 0.39, similar to the result for *ER1M* in [Table 4](#). Only the investor flow variables *IIP13* and *MMS13* enter with statistically significant coefficients; in particular, the average basis (*AVBAS1*), a proxy for convenience yield, does not have predictive content for $S_{t+4} - F_t^{t+4}$. Similarly, neither *OI13* nor *REM4* enter significantly. It seems that, for this horizon, traders’ reactions to news about emerging market equity returns and open interest helped shaped the futures curve, but not so much spot market risk premiums. These findings are consistent with preferred maturity habitats for certain investors in futures markets combined with arbitrageurs trading along the futures curve, and they seem less easily explained by supply/demand pressures in the spot market for commodities.

Second, the significant impact of spread positions by managed money on excess returns in the futures market raises the question of whether hedge-fund trading affected the shape

³⁵Based on the three shortest maturity futures contracts, a cubic spline was used to interpolate for the one-month futures price. Two different interpolations schemes were examined and they gave qualitatively identical results.

of the futures curve during the 2008 boom/bust in oil prices.³⁶ To explore this question I computed returns on spread positions as the return over n weeks of a long position in the long-dated futures contract and a short position in the short-dated futures contract. These returns were then projected onto the same set of predictor variables as before. The results for $n = 1$ and 4 and three different spreads along the futures curve are displayed in [Table 5](#), standardized to represent responses to one-standard deviation shocks to the X 's.

Interestingly, returns on spread positions are relatively more predictable for positions involving futures beyond the six-month maturity point. Moreover, between the two flow variables $IIP13$ and $MMS13$, the coefficients on the latter are by far the more precisely estimated (relative to the estimates). For the one-week holding period $IIP13$ has (mostly) a statistically insignificant impact on slope returns, whereas the loadings on $MMS13$ are large relative to their standard errors, especially for the longer segments of the futures curve. Evidently the increased hedge-fund trading in futures that strengthened the cointegration of long- and short-maturity futures contracts ([Buyuksahin, Haigh, Harris, Overdahl, and Robe \(2008\)](#)) also affected the predictable variation in returns on spread positions.

The negative loading on $MMS13$ indicates that, *ceteris paribus*, increases in spread positions by managed money were associated with larger returns on the near futures contracts relative to the far futures contracts. As discussed by [Mou \(2011\)](#), there was a substantial increase in spread trading by hedge-funds after 2004 in part as a consequence of the profits to be made by trading in anticipation of the “Goldman roll.” As he documents, investment strategies that anticipated undervalued near and overvalued far contracts earned large risk-adjusted returns (Sharpe ratios). The results in [Table 5](#) are consistent with managed money attempting to take advantage of these or similar opportunities, though $MMS13$ has a statistically significant effect well out the forward curve (on the six- to twelve-month spread) and far beyond where the roll is taking place. When the spread trade is shortened to $3m - 1m$, all of the predictor variables are statistically insignificant *except* for $MMS13$ which has a loading of 0.28% and the adjusted R^2 is 0.06. Thus, spread trading along the futures curve seems to have had an impact on returns on slope positions extending all along the curve.³⁷

Also notable about these results for spread returns is the forecast power of the average basis $AVBn$. Over a one-week horizon, $AVB1$ is a statistically significant predictor for all three spread returns, after conditioning on the flow variables. On the other hand, $AVB4$ has no incremental predictive power for the four-week returns. Since the basis shows very weak correlation with the investor flow variables, its role in predicting spread returns represents

³⁶I am grateful to an anonymous referee for suggesting this exercise.

³⁷ $MMS13$ also has significant predictive content for the returns on the slope segment $24m - 12m$ over both investment horizons (not displayed).

Horizon	Spread	RSPn	REMn	REPOn	IIP13	MMS13	OII3	AVBn	R_{Lag}	AdjR ²
$n = 1$	6m - 1m	0.30 (.845)	0.60 (1.43)	0.48 (2.14)	-0.53 (-1.19)	-0.45 (-2.68)	0.27 (1.18)	0.54 (3.97)	-0.52 (-1.67)	0.10
	12m - 6m	0.15 (1.37)	-0.06 (-.833)	0.14 (1.87)	-0.14 (-2.22)	-0.21 (-4.73)	0.07 (.959)	0.43 (9.78)	-0.22 (-2.87)	0.26
	12m - 1m	0.46 (1.12)	0.52 (1.19)	0.61 (2.41)	-0.68 (-1.46)	-0.68 (-3.43)	0.35 (1.38)	1.12 (8.53)	-0.94 (-2.35)	0.16
$n = 4$	6m - 1m	-1.53 (-1.27)	0.99 (1.00)	-1.11 (-2.42)	-1.22 (-1.17)	-0.63 (-1.74)	0.93 (1.63)	0.29 (.593)	-0.22 (-.430)	0.10
	12m - 6m	-0.06 (-.309)	-0.34 (-1.55)	0.01 (.046)	-0.43 (-2.79)	-0.62 (-7.77)	0.23 (1.24)	0.11 (.995)	-0.50 (-4.05)	0.27
	12m - 1m	-1.63 (-1.23)	0.76 (.671)	-1.13 (-2.31)	-1.53 (-1.46)	-1.18 (-2.82)	1.21 (1.70)	0.44 (.750)	-0.61 (-.895)	0.13

Table 5: Estimates of standardized coefficients for the returns on futures spread positions for investors who are long the long-dated contract and short the short-dated contract. Maturities are measured in months (e.g., “1m” is one month).

information in the convenience yield that is relevant for changes in the shape of the futures curve over short (weekly) horizons.

Assessing the welfare costs of trading based on limits to arbitrage or imperfect information in commodity markets is a challenging task. Any such costs are potentially amplified by the fact that the costs to individual investors of near-rational behavior – following slightly suboptimal investment or consumption plans– is negligible (Lucas (1987) and Cochrane (1989)).³⁸ When investors make small correlated errors around their optimal investment policies, financial markets amplify these errors and generate price changes that are unrelated to fundamental supply/demand information (Hassan and Mertens (2010)). If market participants are just slightly too optimistic (in market rallies) or pessimistic (in market downturns) relative to the true state of the world then their errors, while inconsequential for their own welfare, may be material for society as a whole.³⁹ Frictions associated with multi-period contracting over labor and physical capital will likely exacerbate the social costs of any price drift.

Finally, much of the literature on commodity pricing abstracts from the impact of the extensive array of derivatives contracts in commodity markets (e.g., commodity swaps) on market-price dynamics. Adding derivatives markets may improve price discovery and mitigate some of the informational problems highlighted above. A key step towards a better understanding of the effects of interactions among various market participants on price behavior is the collection and dissemination of more detailed information about the trading patterns in *OTC* commodity derivatives, as well as exchange traded futures.

³⁸Such suboptimal plans may arise out of misinterpretations of public information say about future economic growth in developing countries, because of small costs to sorting through the complexity of global economic developments and their implications for commodity prices, or because of over-confidence about future economic growth as in Dumas, Kurshev, and Uppal (2006).

³⁹Recent research by Qiu and Wang (2010) shows that when market participants have heterogeneous information, and so asset prices depend on the expectations of the expectations of others, prices tend to be more volatile and the overall welfare of society is lowered. Additionally, if index traders impart noise to market prices through their trading activities, then this could also reduce the efficiency with which futures and spot markets perform their roles in price discovery.

Appendix: Construction of Excess Returns

Let $F_t^{T_i(t)}$ denote the futures contract with expiration $T_i(t)$. The futures-price-term-structure consists of points $F_t^{T_1(t)}, \dots, F_t^{T_N(t)}$. Let $D(s) > s$ denote the first time after s that the generic futures curve switches contracts. Then, for all $i = 1, \dots, N - 1$, and all s ,

$$T_{i+1}(D(s) - 1) = T_i(D(s))$$

The excess rolling return in generic contract i , between s and t is given by

$$\begin{aligned} & \frac{F_t^{T_i(t)}}{F_s^{T_i(s)}} - 1 && \text{if } t < D(s) \\ & \frac{F_{D(s)-1}^{T_i(D(s)-1)}}{F_s^{T_i(s)}} \cdot \frac{F_t^{T_i(t)}}{F_{D(s)-1}^{T_{i+1}(D(s)-1)}} - 1 && \text{if } D(s) \leq t < D^{(2)}(s) \\ & \frac{F_{D(s)-1}^{T_i(D(s)-1)}}{F_s^{T_i(s)}} \cdot \frac{F_{D^{(2)}(s)-1}^{T_i(D^{(2)}(s)-1)}}{F_{D(s)-1}^{T_{i+1}(D(s)-1)}} \cdot \frac{F_t^{T_i(t)}}{F_{D^{(2)}(s)-1}^{T_{i+1}(D^{(2)}(s)-1)}} - 1 && \text{if } D^{(2)}(s) \leq t < D^{(3)}(s) \end{aligned}$$

and so forth.

By construction these are the net returns from holding one long position in the generic i -month contract, liquidating the position the day before the generic curve “moves the contracts one month down,” and going long one unit in the following month $i + 1$ (which the day after, by definition will be generic contract i). This strategy is followed from s until t .

The riskfree rate does not enter these calculations. The rationale is (following, for instance, [Etula \(2010\)](#)) that investing in a futures position, does not require an initial capital injection. In practice, however, the futures trading strategies are met with margin calls. For this reason [Hong and Yogo \(2011\)](#) consider a fully collateralized return of the form (say if $t < D(s)$)

$$\frac{F_t^{T_i(t)}}{F_s^{T_i(s)}} R_{s,t}^f$$

My calculations omit the multiplying factor $R_{s,t}^f$ from the construction of excess returns.

References

- Acharya, V., L. Lochstoer, and T. Ramadorai, 2009, “Limits to Arbitrage and Hedging: Evidence from Commodity Markets,” working paper, New York University.
- Adam, K., and A. Marcet, 2010a, “Booms and Busts in Asset Markets,” working paper, IMES Discussion Paper 2010-E-2, Bank of Japan.
- , 2010b, “Internal Rationality, Imperfect Market Knowledge and Asset Prices,” working paper, forthcoming, *Journal of Economic Theory*.
- Adrian, T., E. Moench, and H. Shin, 2010, “Financial Intermediation, Asset Prices, and Macroeconomic Dynamics,” working paper, Federal Reserve Bank of New York Staff Report 422.
- Aguiar, M., and G. Gopinath, 2007, “Emerging Market Business Cycles: The Cycle is the Trend,” *Journal of Political Economy*, 115, 69–102.
- Allen, F., S. Morris, and H. Shin, 2006, “Beauty Contests and Iterated Expectations in Asset Markets,” *Review of Financial Studies*, 19, 719–752.
- Alquist, R., and L. Kilian, 2010, “What Do We Learn From the Price of Crude Oil Futures?,” *Journal of Applied Econometrics*, 25, 539–573.
- Banerjee, S., R. Kaniel, and I. Kremer, 2009, “Price Drift as an Outcome of Differences in Higher-Order Beliefs,” *Review of Financial Studies*, 22, 3707–3734.
- Banerjee, S., and I. Kremer, 2010, “Disagreement and Learning: Dynamic Patterns of Trade,” *Journal of Finance*, LXV, 1269–1302.
- Basu, D., and J. Miffre, 2011, “Capturing the Risk Premium of Commodity Futures: The Role of Hedging Pressure,” working paper.
- Boyd, N., B. Buyuksahin, J. Harris, and M. Haigh, 2009, “The Impact of Hedging on Futures Prices,” working paper, U.S. Commodity Futures Trading Commission.
- , 2010, “The Prevalence, Sources and Effects of Herding,” working paper, U.S. Commodity Futures Trading Commission.
- Brunetti, C., and B. Buyuksahin, 2009, “Is Speculation Destabilizing?,” working paper, Commodity Futures Trading Commission.

- Buraschi, A., and P. Whelan, 2012, “Term Structure Models and Differences in Beliefs,” working paper, Imperial College.
- Buyuksahin, B., M. Haigh, J. Harris, J. Overdahl, and M. Robe, 2008, “Fundamentals, Trader Activity and Derivative Pricing,” working paper, Commodity Futures Trading Commission.
- Buyuksahin, B., and J. Harris, 2009, “The Role of Speculators in the Crude Oil Futures Market,” working paper, Commodity Futures Trading Commission.
- Buyuksahin, B., and M. Robe, 2009, “Commodity Traders’ Positions and Energy Prices: Evidence from the Recent Boom-Bust Cycle,” working paper, U.S. Commodity Futures Trading Commission.
- , 2011, “Does “Paper Oil” Matter? Energy Markets’ Financialization and Equity-Commodity Co-Movements,” working paper, International Energy Agency.
- Cafiero, C., E. Bobenrieth H., J. Bobenrieth H., and B. Wright, 2011, “The Empirical Relevance of the Competitive Storage Model,” *Journal of Econometrics*, 162, 44–54.
- Cao, H., and Ou-Yang, 2009, “Differences in Opinion of Public Information and Speculative Trading in Stocks and Options,” *Review of Financial Studies*, 22, 299–335.
- Casassus, J., and P. Collin-Dufresne, 2005, “Stochastic Convenience Yield Implied from Commodity Futures and Interest Rates,” *Journal of Finance*, LX, 2283–2331.
- Cheng, I., A. Kirilenko, and W. Xiong, 2012, “Convective Risk Flows in Commodity Futures Markets,” working paper, Princeton University.
- Cochrane, J., 1989, “The Sensitivity of Tests of the Intertemporal Allocation of Consumption to Near-Rational Alternatives,” *American Economic Review*, 79, 319–337.
- Commodity Futures Trading Commission, 2008, “Commodity Swap Dealers and Index Traders,” working paper, Commodity Futures Trading Commission.
- Corkery, M., and C. Cui, 2010, “Calstrs Reins in Plans for a Big Bet,” *Wall Street Journal*, November 12, 2010.
- Deaton, A., and G. Laroque, 1996, “Competitive Storage and Commodity Price Dynamics,” *Journal of Political Economy*, 104, 896–923.
- Detemple, J., and S. Murthy, 1994, “Intertemporal Asset Pricing with Heterogeneous Beliefs,” *Journal of Economic Theory*, 62, 294–320.

- Dumas, B., A. Kurshev, and R. Uppal, 2006, “What Can Rational Investors Do About Excessive Volatility and Sentiment Fluctuations?,” working paper, Swiss Finance Institute Research Paper No. 06-19.
- Dvir, E., and K. Rogoff, 2010, “The Three Epochs of Oil,” working paper, Harvard University.
- Ehling, P., M. Gallmeyer, C. Heyerdahl-Larsen, and P. Illeditsch, 2012, “Beliefs about Inflation and the Term Structure of Interest Rates,” working paper, University of Virginia.
- Erb, C., and C. Harvey, 2006, “The Strategic and Tactical Value of Commodity Futures,” *Financial Analysts Journal*, 62, 69–97.
- Etula, E., 2010, “Broker-Dealer Risk Appetite and Commodity Returns,” working paper, Federal Reserve Bank of New York.
- Evans, M., and R. Lyons, 2009, “Forecasting Exchange Rate Fundamentals with Order Flow,” working paper, University of California, Berkeley.
- Fama, E., and K. French, 1987, “Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage,” *Journal of Business*, 60, 55–73.
- Fuertes, A., J. Miffre, and G. Rallis, 2008, “Tactical Allocation in Commodity Futures Markets: Combining Momentum and Term Structure Signals,” working paper, EDHEC.
- Garman, M., and M. Klass, 1980, “On the Estimation of Security Price Volatilities from Historical Data,” *Journal of Business*, 53, 67–78.
- Gorton, G., F. Hayashi, and K. Rouwenhorst, 2007, “The Fundamentals of Commodity Futures Returns,” working paper, Yale University.
- Greenwood, R., and D. Vayanos, 2010, “Bond Supply and Excess Bond Returns,” working paper, LSE.
- Hamilton, J., 2003, “What is An Oil Shock?,” *Journal of Econometrics*, 113, 363–398.
- , 2009a, “Causes and Consequences of the Oil Shock of 2007-08,” *Brookings Papers on Economic Activity*.
- , 2009b, “Understanding Crude Oil Prices,” *Energy Journal*, 30, 179–206.
- Hansen, L., 1982, “Large Sample Properties of Generalized Method of Moments Estimators,” *Econometrica*, 50, 1029–1054.

- Hansen, L., and K. Singleton, 1982, “Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models,” *Econometrica*, 50, 1269–1286.
- Hassan, T., and T. Mertens, 2010, “The Social Cost of Near-Rational Investment: Why we Should Worry about Volatile Stock Markets,” working paper, University of Chicago.
- Hicks, J., 1939, *Value and Capital*. Oxford University Press.
- Hodrick, R., 1992, “Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement,” *Review of Financial Studies*, 5, 357–386.
- Hong, H., and M. Yogo, 2011, “What Does Futures Interest Tell Us About the Macroeconomy and Asset Prices?,” working paper, forthcoming, *Journal of Financial Economics*.
- Hooker, M., 1996, “What Happened to the Oil Price-Macroeconomy Relationship?,” *Journal of Monetary Economics*, 38, 195–213.
- IEA, 2008a, “Medium-Term Oil Market Report,” October, International Energy Agency.
- , 2008b, “Medium-Term Oil Market Report,” July, International Energy Agency.
- , 2009, “Oil Market Report,” December, International Energy Agency.
- Irwin, S., and D. Sanders, 2010, “The Impact of Index Swap Funds on Commodity Futures Markets,” working paper, OECD Food, Agriculture and Fisheries Working Papers No. 27.
- , 2011, “Testing the Masters Hypothesis in Commodity Futures Markets,” working paper, University of Illinois at Urbana-Champaign.
- ISDA, 2006, “Letter to the CFTC Commenting on the Commitments of Traders Reports,” International Swap and Derivatives Association.
- Keynes, J., 1930, *Treatise on Money*. Macmillan, London.
- Kilian, L., 2009, “Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market,” *American Economic Review*, 99, 1053–1069.
- Lucas, R., 1987, *Models of Business Cycles*. Basil Blackwell.
- Masters, M., 2008, “Testimony Before the Committee on Homeland Security and Governmental Affairs,” working paper, US Senate.

- , 2009, “Testimony Before the Commodity Futures Trading Commission,” working paper, Commodity Futures Trading Commission.
- Milgrom, P., and N. Stokey, 1982, “Information, Trade, and Common Knowledge,” *Journal of Economic Theory*, 26, 11–21.
- Miltersen, K., and E. Schwartz, 1998, “Pricing of Options on Commodity Futures with Stochastic Term Structures of Convenience Yields and Interest Rates,” *Journal of Financial and Quantitative Analysis*, 33, 33–59.
- Mou, Y., 2011, “Limits to Arbitrage and Commodity Index Investments: Front-Running the Goldman Roll,” working paper, Columbia Business School.
- Newey, W., and K. D. West, 1987, “Hypothesis Testing with Efficient Method of Moment Estimation,” *International Economic Review*, 28, 777–787.
- Pirrong, C., 2009, “Stochastic Fundamental Volatility, Speculation, and Commodity Storage,” working paper, University of Houston.
- Qiu, W., and J. Wang, 2010, “Asset Pricing Under Heterogeneous Information,” working paper, MIT.
- Rotemberg, J., and M. Woodford, 1996, “Imperfect Competition and the Effects of Energy Price Increases on Economic Activity,” *Journal of Money, Credit, and Banking*, 28, 550–577.
- Saporta, V., M. Trott, and M. Tudela, 2009, “What Can Be Said About the Rise and Fall in Oil Prices?,” *Bank of England Quarterly Bulletin*, 49, 215–225.
- Sauter, R., and S. Awerbuch, 2003, “Oil Price Volatility and Economic Activity: A Survey and Literature Review,” working paper, IEA Research Paper.
- Singleton, K., 1987, “Asset Prices in a Time Series Model with Disparately Informed, Competitive Traders,” in *New Approaches to Monetary Economics*, ed. by W. Burnett, and K. Singleton. Cambridge University Press.
- , 2006, *Empirical Dynamic Asset Pricing*. Princeton University Press.
- Sornette, D., R. Woodard, and W. Zhou, 2008, “The 2006-2008 Oil Bubble and Beyond,” working paper, ETH Zurich.
- Stoll, H., and R. Whaley, 2009, “Commodity Index Investing and Commodity Futures Prices,” working paper, Vanderbilt University.

- Tang, K., and W. Xiong, 2011, “Index Investing and the Financialization of Commodities,” working paper, Princeton University.
- Tirole, J., 1982, “On the Possibility of Speculation under Rational Expectations,” *Econometrica*, 50, 1163–1181.
- Townsend, R., 1983, “Forecasting the Forecasts of Others,” *Journal of Political Economy*, 91, 546–588.
- Vayanos, D., and J. Villa, 2009, “A Preferred Habit Model of the Term Structure of Interest Rates,” working paper, London School of Economics.
- Verardo, M., 2009, “Heterogeneous Beliefs and Momentum Profits,” *Journal of Financial and Quantitative Analysis*, 44, 795–822.
- Verleger, P., 2007, “Prepared Testimony to the Subcommittee on Energy and the U.S. Senate Committee on Energy and Natural Resources,” PKVerleger LLC.
- , 2010, “Comments on Federal Speculative Position Limits for Referenced Energy Contracts and Associated Regulations,” Federal Register 4144.
- Xiong, W., and H. Yan, 2009, “Heterogeneous Expectations and Bond Markets,” *Review of Financial Studies*.
- Yang, D., and Q. Zhang, 2000, “Drift Independent Volatility Estimation Based on High, Low, Open and Close Prices,” *Journal of Business*, 73, 477–491.
- Zhang, F., 2006, “Information Uncertainty and Stock Returns,” *Journal of Finance*, LXI, 105–36.