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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 price booms and busts. 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. Furthermore, I present new evidence that there were economically and statistically significant effects of investor flows on futures prices, after controlling for returns in the United States 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.

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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 the fundamentals of supply and demand with the price effects and volatility moderated by participation of nonuser 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. This paper builds on 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.

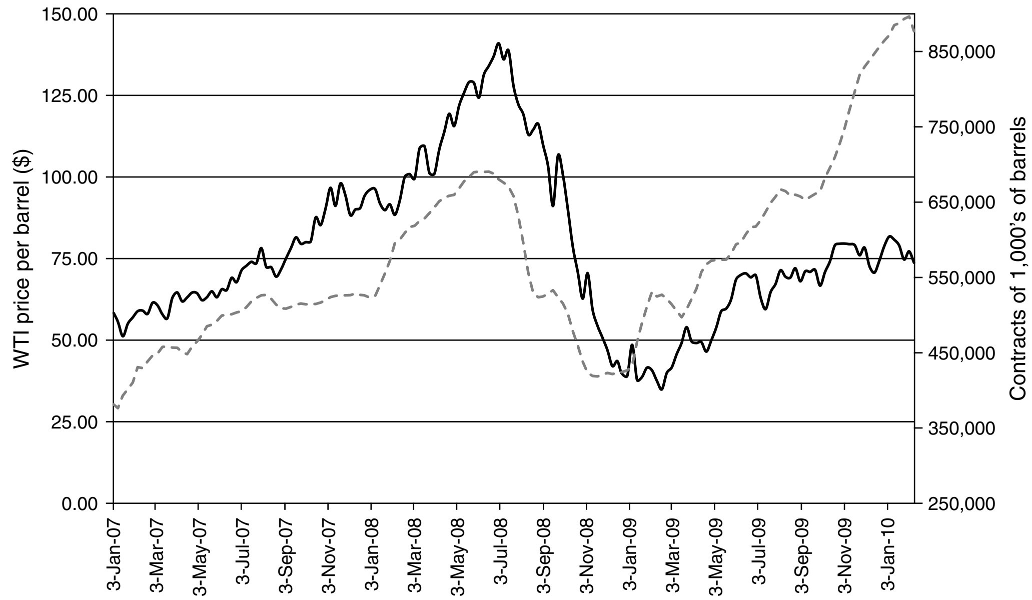
Detailed information about the origins of most of the open interest in over-the-counter (OTC) commodity derivatives that could in principle shed light on the historical contributions of information- and learning-based speculative activity is not publicly available. However, indirect inferences suggest that traders' investment strategies did impact prices. Tang and Xiong (2011) show that, after 2004, agricultural commodities that are part of the Goldman Sachs Commodity Index (GSCI) and the Dow Jones (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. They attribute their findings to "spillover effects brought on by the increasing presence of index investors to individual commodities" (p. 17). Using proprietary data from the U.S. Commodity Futures Trading 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 Traders (CIT) reports. The imputed index long positions based on his methodology (Figure 1), displayed against the near-contract forward price of West Texas Intermediate (WTI) crude oil, shows a strikingly high degree of comovement. Additionally, Mou (2011) documents substantial impacts on futures prices of the "roll strategies" used 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 that informational frictions (and the

[1] This debate is stimulated in part by the large costs that oil price booms and busts potentially impose on the real economy. For a recent survey on the effects of oil prices on the real economy, see Kilian (2008).

[2] The conceptual arguments and empirical evidence favoring this view are summarized in a recent Organisation for Economic Co-operation and Development (OECD) report by Irwin and Sanders (2010).

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)**



associated speculative activity) can lead prices to drift away from "fundamental" values. These economic mechanisms are absent from the prototypical dynamic models referenced in discussions of the oil boom (e.g., Hamilton 2009a, Pirrong 2009). Yet learning under imperfect information, heterogeneity of beliefs, and capital market and agency-related frictions that limit arbitrage activity are plausibly present in commodity markets. Consistent with this view, my empirical evidence suggests that, even after controlling for many of the other conditioning variables in recent studies of price behavior in oil futures markets, there were economically and statistically significant effects of investor flows on futures prices.

2. Speculation and Booms/Busts in Commodity Prices

Most of the extant model-based interpretations of the oil price boom focus on representative risk-neutral producers and refiners. In contrast, I focus on frameworks that accommodate risk aversion and heterogeneity among market participants. Specifically, absent near stockout conditions, equilibrium in the market for storing oil implies the cost-of-carry relation:[3]

$$S_t = E_t^{\mathbb{Q}}[e^{-\int_t^T (r_s - \mathscr{C}_s)\,ds} S_T], \tag{1}$$

where S_t is the spot price of the commodity, $\mathscr{C}_t$ 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 $(r_t - \mathscr{C}_t)S_t\,dt$ 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

$$\frac{F_t^T}{S_t} = \frac{1 - \mathrm{Cov}_t^{\mathbb{Q}}(e^{\int_t^T \mathscr{C}_s\,ds}, e^{-\int_t^T r_s\,ds}(S_T/S_t))}{B_t^T E_t^{\mathbb{Q}}[e^{\int_t^T \mathscr{C}_s\,ds}]} - \frac{1}{B_t^T} \times \mathrm{Cov}_t^{\mathbb{Q}}\left(e^{-\int_t^T r_s\,ds}, \frac{S_T}{S_t}\right), \tag{2}$$

where B_t^T denotes the price of a zero coupon bond issued at date t that matures at date T. If the covariance terms are negligible, then Equation (2) can be rewritten approximately as

$$\frac{F_t^T - S_t}{S_t} \approx y_t^T(T-t) - \ln E_t^{\mathbb{Q}}[e^{\int_t^T \mathscr{C}_s\,ds}], \tag{3}$$

where y_t^T is the continuously compounded yield on a zero-coupon bond with maturity of $(T-t)$ periods. This is the multiperiod 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 $\mathscr{C}$ impact the relationship between F_t^T and S_t according to Equation (2).

Implicit in Equation (1) is the risk premium that market participants demand when trading commodities in futures and spot markets. Define the market risk premium as $RP_t^T \equiv (E_t^{\mathbb{P}}[S_T/S_t] - E_t^{\mathbb{Q}}[S_T/S_t])$,

[3] For example, see 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).

for $T > t$. Furthermore, consider a short time interval $[t, \tau]$ over which r and $\mathscr{C}$ are approximately constant. Then Equation (2) implies that

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

Thus, expected excess returns in the spot commodity market depend on 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). To sustain Equation (2) as an equilibrium condition, 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.[4]

While a time-varying convenience yield has been a widely acknowledged feature of oil markets, there is less agreement about the importance of time-varying risk premiums. Many of the structural supply/demand models of oil price determination presume that risk premiums are zero, including many of the papers that build on the competitive storage model of Deaton and Laroque (1996).[5] The findings in Alquist and Kilian (2010) have been cited as evidence in support of risk neutrality, but their analysis focuses on the "unbiasedness" of the futures price as a predictor of future spot prices and 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.[6]

Though Equation (2) accommodates risk aversion, it presumes common beliefs across investors about fundamental risks. Saporta et al. (2009) document large errors in forecasting demand for oil, typically on the side of underestimation 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.[7] The International Energy Agency (IEA 2009) reports substantial revisions to their monthly estimates of consumptions for the United States, and emphasizes that poor information is available on non-OECD inventories.[8] Sornette et al. (2008) document significant differences in the total world supplies for liquid fuels published by the IEA and the EIA, particularly from 2006 to 2008. The timeliness of non-OECD data is highly variable (IEA 2009), and Organization of the Petroleum Exporting Countries (OPEC) quotas and measured production levels are quite vague (Hamilton 2009b). Given this degree of imperfect information, one might expect substantial disagreement among market participants.

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. 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 agree to disagree even when they share common information–they disagree about the interpretation of public information. Under an 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, a DOE can generate rich patterns of comovement among asset returns, trading volume, and market-price volatility because investors may disagree about the interpretation of public information (e.g., Cao and Ou-Yang 2009, 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. Xiong and Yan (2010), Ehling et al. (2012), and Buraschi and Whelan (2012) develop dynamic term structure models in which classes of

[4] In 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" (Irwin and Sanders 2010, p. 8) is not true in the economic environment considered here.

[5] See Routledge et al. (2000), Hamilton (2009a), Dvir and Rogoff (2010), and Cafiero et al. (2011).

[6] For example, see Fama and French (1987), Gorton et al. (2007), Hong and Yogo (2012), and Basu and Miffre (2013).

[7] Market 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, Saporta et al. (2009, p. 222) 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."

[8] IEA (2008a, p. 15) 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 . . . ."

investors differ in their beliefs about fundamental economic factors g_t. Specifically, suppose g is not observed and that the jth group of investors observes the signals dI_t^j,

$$dI_t^j = (\phi^j g_t^j + (1-\phi^j)\epsilon_t)\,dt + \sigma_I^j dB_t^{I^j}, \quad j=1,2, \tag{5}$$

that depend on g_t, where $d\epsilon_t = dB_t^\epsilon$ and (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):

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

where $w_j(t)$ is the wealth of the jth 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 investors.

Now suppose that there is a commodity with log-price process depending on the same economic factors, $\log S_t = \rho_0 + \rho_g \cdot g_t$. 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, $\mathscr{C}_t^j$. Given Equation (6), the $\mathscr{C}_t^j$ 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 change with the allocations of wealth to commodity markets, and as investors' views change.

Importantly, it is not just that the wealth-weighted 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.

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 by Consensus Economics.[9] 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.

Explaining concurrent high dispersion in forecasts and high oil prices within a Bayesian REE seems challenging. A high level is often accompanied by high conditional volatility of an asset price. Yet if (real) prices are mean reverting, then at exceptionally high price levels one might anticipate a strengthening consensus that prices will fall toward their long-run mean. Consistent with this intuition, the theoretical model in Banerjee et al. (2009) implies price reversals in an 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.

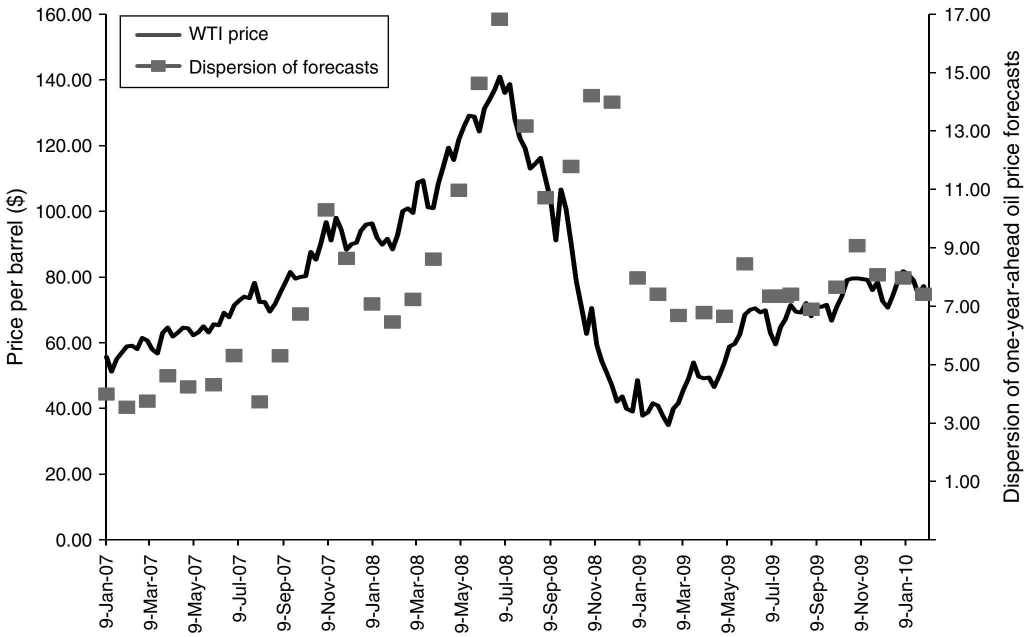
In at least one important respect, it seems that neither standard REE nor DOE are likely to be adequate characterizations of the learning problems faced by market participants. Specifically, these models assume that agents know the mapping between the exogenous (fundamental) state variables and oil prices. Perhaps more plausible is the assumption that participants in the oil markets learn about the true mapping between changes in fundamentals and prices by conditioning on past fundamentals and prices.[10]

Adam and Marcet (2010, 2011) examine a framework in which investors are "internally rational"—they make fully optimal dynamic decisions given their subjective beliefs about variables that impact prices and are beyond their control—but they may not agree on how public information about fundamentals translates into a specific price level. Nor do investors know the utility weights that other investors assign to specific economic events, a requirement of an 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

[9] Consensus Economics surveys over 30 of (in their words) "the world's most prominent commodity forecasters" and asks for their forecasts of oil prices in the future (http://www.consensuseconomics.com/download/Energy_and_Metals_Price_Forecasts.htm, accessed July 15, 2012). The series plotted in Figure 2 is the cross-forecaster standard deviation for each month of their reported forecasts. I am grateful to the International Monetary Fund for providing this series, as reported in their *World Economic Forum*.

[10] Investors typically do not condition on past prices when they "agree to disagree" in a DOE. However, if individual opinions are not common knowledge (as seems likely) so there is uncertainty about consensus beliefs, then learning from prices arises in a DOE (Banerjee et al. 2009).

Figure 2 **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)**



boom/bust cycles in prices that match those experienced historically.

Summarizing, it is not necessary for investors to have private information for their actions to impact commodity prices. As long as they have different interpretations of public information and find it useful to learn from past prices, their actions can induce higher volatility and booms and busts in prices. Furthermore, 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.[11] Participants in all commodity markets should find it optimal to condition on prices in other markets when drawing inferences about future spot prices.[12] As a consequence, commodity prices and market risk premiums may depend on the degree of differences of opinion about economic fundamentals and the nature of agents' learning mechanisms.

[11] It follows that the presence of heterogeneous beliefs and learning could invalidate the claims in Irwin and Sanders (2010) that (i) for index investors to have had a material affect on commodity prices they would have to have had valuable information, and (ii) "if index fund buying drove commodity prices higher then markets without index fund investment should not have seen prices advance" (p. 9).

[12] The 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.

Finally, when 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 may impact prices in the futures and spot markets. Acharya et al. (2009) and Etula (2010) document significant connections between the risk-bearing capacity of broker dealers and risk premiums in commodity markets. Hong and Yogo (2012) 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 et al. (2012) argue that there were significant changes in the risk-bearing capacity of financial institutions with positions in commodities after the onset of the current financial crisis. Price impacts of investor flows may also arise as a result of 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).

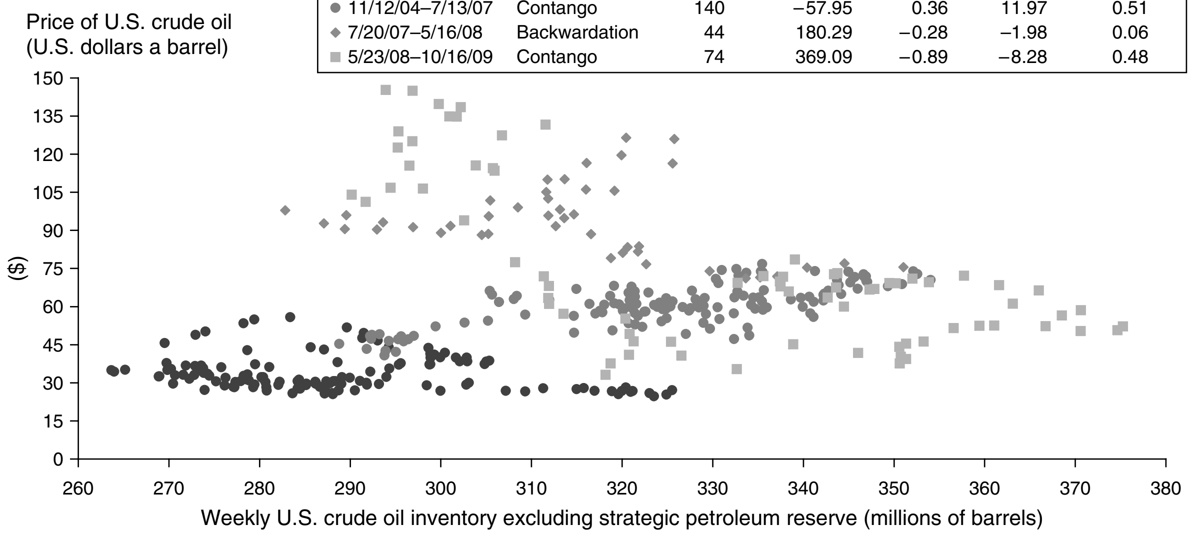
3. Demand/Supply, Inventories, and Speculation

Many of the arguments against a significant role for speculative trading in the recent boom/bust in oil prices highlight the historical links between supply/demand and inventory accumulation. A widely held view is that speculative trading that distorts prices on the upside must be accompanied by

Figure 3 U.S. Commercial Inventories of Crude Oil Plotted Against the Spot Price of Oil for Various Recent Subperiods

Regression results of spot prices on inventories

Time period	Term structure[a]	Number of observations	Intercept	Coefficient	*t*-stat. for coefficient	Adjusted R^2
● 4/19/02–11/5/04	Backwardation	134	62.56	−0.10	−2.60	0.04
● 11/12/04–7/13/07	Contango	140	−57.95	0.36	11.97	0.51
◆ 7/20/07–5/16/08	Backwardation	44	180.29	−0.28	−1.98	0.06
■ 5/23/08–10/16/09	Contango	74	369.09	−0.89	−8.28	0.48



Sources. Energy Information Administration; Bloomberg.

[a]Contango and backwardation are defined using the spot price and the three-month futures price.

increases in inventories.[13] Figure 3 shows that prior to 2003, there was a strong negative relationship between the price of oil and the amount of oil stored in the United States 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. The price of oil is set in global markets, and during this period several major emerging economies where stockpiling crude oil in strategic reserves. Because these reserves are omitted from Figure 3, at best, it can only give a partial picture of the historical inventory/price relationship.

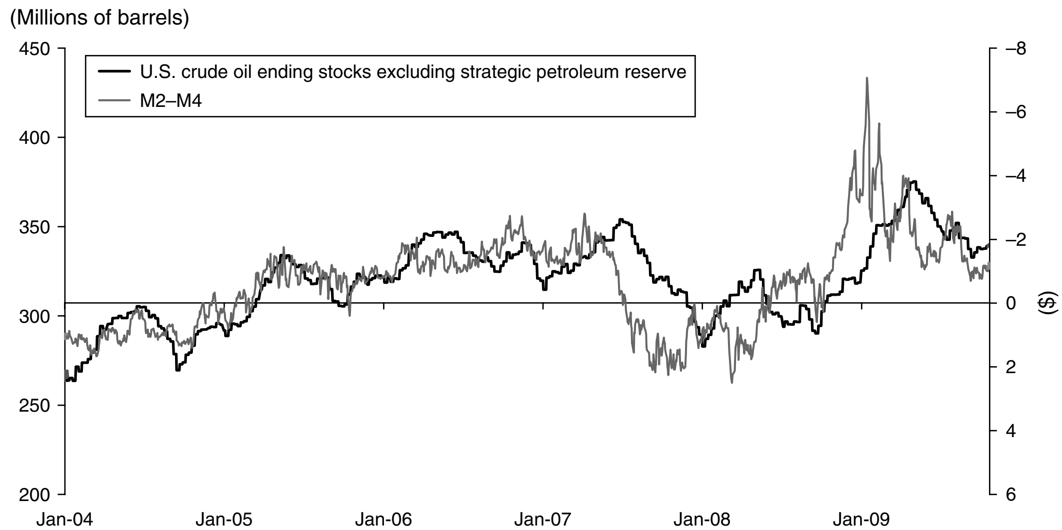
Conceptually, the links between speculative trading and spot commodity prices are more complex than what emerges from models with static (nonforward looking or strategic) demands on the part of a homogeneous class of agents. In a dynamic uncertain environment, time-varying expectations and volatility 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 no 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 no unambiguously positive theoretical relationship between changes in prices and inventories.

Equally important, the impact of inventory adjustments on the volatility of prices depends crucially on what one assumes about the nature of supply and demand uncertainty. 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 has led many to associate inventory adjustments with a stabilizing effect on oil prices. However, these models 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 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; this effect dominates the reduction in storage induced by the immediate post-shock increase in prices. Aguiar and Gopinath (2007) argue that shocks to growth contribute more to variability in output in emerging

[13] For instance, the IEA (2008b, p. 12) expresses the view that "if speculators are driving spot oil prices, an imbalance in the form of higher stocks should be apparent."

Figure 4 U.S. Commercial Inventories of Crude Oil Plotted Against the Spread Between Two- and Four-Month Futures Prices



Sources. Energy Information Administration; Bloomberg.

than in developed economies. Because a substantial portion of global demand for oil during the recent boom/bust was from emerging economies, on balance, storage (by arbitrageurs, refiners or consumers) may have amplified the effects of demand shocks on prices.

Figure 4 plots the level of nonstrategic 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 2004–2009 for inventories to increase when the futures market is in contango.[14] A notable feature of Figure 4 that seems consistent with an amplification effect of strategic behavior based on expected future prices is that, at least from 2007 onward, steepening and flattening of the futures curve preceded changes in inventories: a steeper futures curve anticipated accumulations of inventories.

Teasing out the relative contributions of the risks associated with the direct effects of shocks to demand and supply from the effects of price drift due to learning and speculation based on differences of interpretation of these shocks will require much richer structural models than have heretofore been examined. Structural vector autoregressions as typically formulated (e.g., Kilian and Murphy 2013) are unlikely to be sufficient for this purpose. In an attempt to provide some guidance for structural analysis, the remainder of this paper explores the historical correlations between trader flows and excess returns in oil markets, particularly for the 2008/2009 boom and bust.

[14] These patterns are even stronger when inventory levels from Cushing, Oklahoma, or PADD2 (Petroleum Administration for Defense Districts, Midwest District) are used.

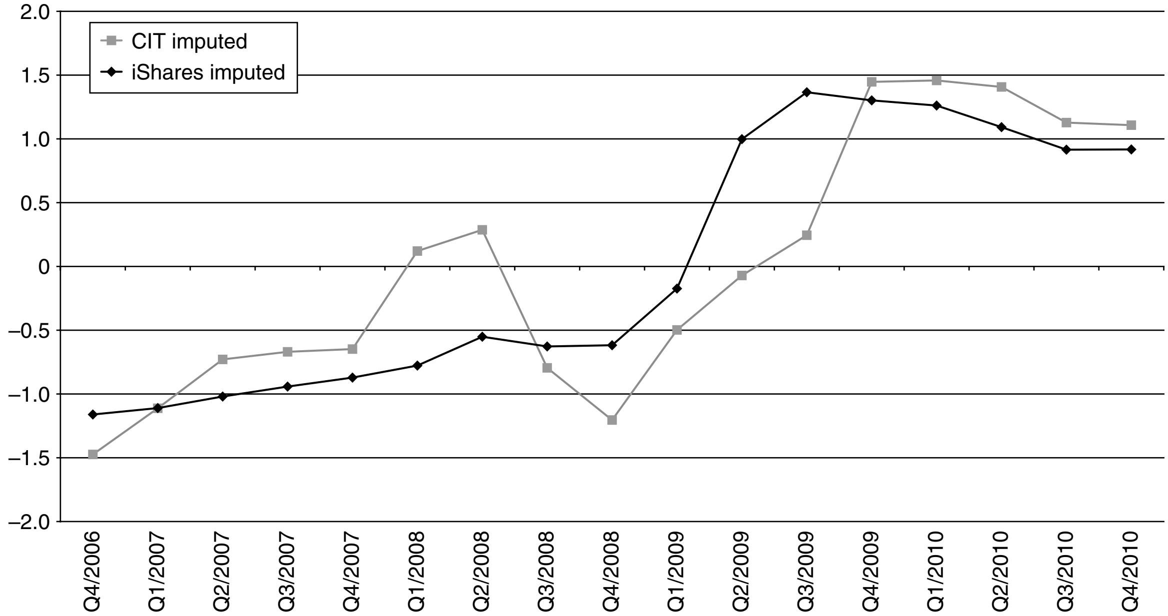
4. What Is Known About Investor Flows?

When exploring the impact of speculative activity on the prices of oil, it is natural to focus on 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 is the question of whether the growth in index investing—exposure to commodities through index-linked products—affected the distribution of oil prices.

That the growth in index investing affected the trading strategies of at least some large investors is suggested, for instance, by Buyuksahin et al. (2008). They 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

Figure 5 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



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 Commitments of Traders (COT) report from the CFTC only reported information for the broad categories of commercial and noncommercial 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 COT report 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 Disaggregated COT 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 of index investors.

Most relevant for my purposes is the weekly CIT report that provides the positions of the index traders for 12 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 these data using the known compositions of the S&P GSCI and the Dow Jones–UBS Commodity Index. I follow the methods of Verleger (2007) and Masters (2008) to impute oil futures positions of commodity index investments from the CIT data.

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 from the iShares S&P GSCI Commodity-Indexed Trust.[15] Figure 5 shows that broad trends in these two imputed positions are similar; the sample correlation is 0.85. Note also that the positions of index investors changed substantially over this period; they were not simply passive investors. Even under the conservative estimates of position sizes by index investors in Stoll and Whaley (2009), they doubled between 2006 and the middle of 2008, and then declined rapidly by nearly one half as of early 2009.

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

[15] I 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.

that the CFTC extracts information from swap dealer positions.[16] If these are netted positions, the reported futures positions will *understate* actual levels of index investment (Irwin and Sanders 2012).

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 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. 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&P 500 index, and thereby the distribution of oil futures prices. Spread positions were the largest component of open interest during my sample period (Buyuksahin et al. 2008), and the CIT reports show that managed-money accounts showed substantial growth in spread positions.

Perhaps the most compelling evidence that index flows and limits to arbitrage have, together, had economically important effects on futures prices is provided by the Mou (2011) analysis of excess returns around the dates of the rolls of the futures positions in the GSCI index (the "Goldman roll"). 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 that Mou (2011) examines was 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.[17]

Motivated by the discussions in §§2 and 3, I focus on the impact of trader flows on prices over the intermediate horizons of a week to a month.[18] 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 timeframe of weeks than days. 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

I project weekly and monthly excess returns on positions in futures contracts onto the 13-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 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.[19] Regarding (iii), the International Swaps and Derivatives Association (ISDA), 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.[20]

To explore empirically whether the flows of index and managed-money investors had predictive power

[16] There are other potential limitations to this imputation method. If the proportion of each index made up of any one agricultural product is small, mismeasurement may 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 et al. (2008), who find, using proprietary CFTC data, that the net positions of commodity swap dealers were primarily in short-dated futures contracts (three months or fewer).

[17] While 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.

[18] Much of the evidence in the literature is based on predictive lead or lag regressions of futures returns on position changes over short horizons (a few days); see, for example, Boyd et al. (2009), Buyuksahin and Robe (2009), Buyuksahin and Harris (2009), and Brunetti and Buyuksahin (2009). 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.

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

[20] In their comments to the CFTC about the desirability of releasing the CIT reports, ISDA (2006, p. 2) 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 ... ."

for returns in futures markets, I project realized returns onto these flows and several other control variables that have previously been found to predict futures prices. Time-series of excess returns over one- and four-week holding periods are computed for futures contracts with maturities of 1, 3, 6, 12, and 24 months. The sample period is from September 12, 2006, through January 12, 2010.

I estimate the forecasting equations:

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

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. In computing the realized excess returns, $ERmM_{t+n}(n)$, one must contend with the roll of the near liquid contract into the new liquid contract, a change that happens prior to the expiration of the shortest maturity futures. Mindful of the issues associated with the Goldman roll highlighted by Mou (2011), for all of the subsequent calculations using oil futures, I assumed that the roll took place on the 10th calendar day of the month. The index roll is typically between the 5th and 10th business day, so this choice represents a reasonable compromise.[21]

Included in $X_t(n)$ are the following conditioning variables:

RSPn and *REMn*: These variables denote the n-week returns on the S&P 500 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: This variable denotes 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.[22]

IIP13: This variable denotes the 13-week change in the imputed positions of index investors, measured in millions of contracts, computed using the algorithm described in §4.

MMS13: This variable denotes the 13-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: This variable denotes the 13-week change in aggregate open interest, measured in millions of contracts, as reported by the CFTC.

AVBn: This variable denotes the n-week change in average basis. Defining the basis at time t of a futures contract with maturity $T_i(t)$ to be[23]

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

as in Hong and Yogo (2012), then *AVBAS1* is the average of these values for maturities $i \in \{1, 3, 6, 9, 12, 15, 18, 21, 24\}$. In computing Equation (8), I account for the time-varying maturity of the futures contracts.[24]

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. The variables *IIP13* and *MMS13* are constructed using information available at the time of the forecast. However, these data were released by the CFTC starting in 2007 and, as such, were not readily available to market participants during my sample period. Therefore, a finding of economically significant predictive power for these variables would suggest an impact of trading patterns on futures prices (controlling for other variables in $X_t(n)$), but not necessarily provide evidence that investors conditioned on these variables in forecasting future oil prices. These projections of $ERmM_{t+n}(n)$ onto *IIP13* and *MMS13* address the predictability of short-horizon (weekly or monthly) returns. Assuming that futures returns and the predictor variables are covariance stationary, these null hypotheses also have similar economic content to the hypotheses that weekly or monthly investor flows impact futures prices over 13-week horizons (Hodrick 1992, Singleton 2006).[25]

[21] The Bloomberg generic oil futures contract is rolled at the expiration date of the contract, which is often well after the index roll date. When I repeat the subsequent projections using the Bloomberg default roll dates, the results are qualitatively the same but with lower adjusted R^2. This is consistent with the default roll date introducing noise associated with periods when the nearest contract was not the most liquid among the short-term futures.

[22] Etula (2010) in the context of futures trading, and Adrian et al. (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 to finance their trading activities.

[23] Note that this measure of the basis has the opposite sign of the basis in Figure 4.

[24] Replacing this expression with $B_i(t) = (F_t^{T_i}/S_t)^{1/(T_i(t)-1)} - 1$ gives virtually identical results.

[25] The analogy is not perfect because of the presence of the other conditioning variables. Also, consistent 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.

AVBASn is a proxy for the net convenience yield in commodity markets.[26] Recall from Equation (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.[27]

For a broad set of commodities, Hong and Yogo (2012) find a 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 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 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,

[26] Another motivation for controlling for the basis is that it might capture effects of hedging pressures on subsequent returns to futures positions (Hong and Yogo 2012). 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 et al. (2007) find no support for the hedging pressure hypothesis, whereas Basu and Miffre (2013) argue that systematic hedging pressure is an important determinant of risk premiums. Both use the aggregated CFTC data on commercial and noncommercial traders in futures markets, which are not reliably informative about the trading activities of such classes of investors as index investors or hedge funds.

[27] Gorton et al. (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 and inventories. These authors and Hong and Yogo (2012), among others, present empirical evidence that a high basis (high M2–M4 in Figure 4) predicts high excess returns on futures positions, consistent with the theory of normal backwardation and compatible with the theory of storage.

Table 1 Correlations Among the One-Week Excess Returns on Futures Positions and the Contemporaneous and Lagged Values of the Predictor Variables

Variable	*RSP1*	*REM1*	*REPO1*	*IIP13*	*MMS13*	*OI13*	*AVB1*
			Contemporaneous predictors				
ER1M(1)	0.40	0.43	0.09	0.23	0.19	0.14	−0.29
ER3M(1)	0.44	0.48	0.08	0.25	0.18	0.15	−0.21
ER6M(1)	0.45	0.50	0.06	0.25	0.17	0.15	−0.16
ER12M(1)	0.44	0.51	0.04	0.25	0.14	0.14	−0.14
ER24M(1)	0.41	0.48	0.03	0.25	0.12	0.13	−0.10
			Lagged predictors				
ER1M(1)	0.09	−0.11	−0.21	0.26	0.19	0.11	−0.35
ER3M(1)	0.11	−0.09	−0.20	0.26	0.18	0.13	−0.35
ER6M(1)	0.13	−0.09	−0.19	0.26	0.17	0.13	−0.33
ER12M(1)	0.16	−0.10	−0.19	0.26	0.16	0.12	−0.27
ER24M(1)	0.15	−0.11	−0.17	0.25	0.13	0.11	−0.20

Hong and Yogo (2012) 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 have signs that are consistent with previous findings in the 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 the Hong and Yogo (2012) evidence based on monthly data over a much longer sample period.

To explore these comovements more systematically and jointly, I estimated the parameters in Equation (7) using linear least-squares projection. For ease of interpretation, all of the predictor variables are standardized by dividing by their respective sample standard

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

Predictors			One-week returns			One-month returns		
Variable	Mean	SD	Maturity	Mean	SD	Maturity	Mean	SD
RSP1	−0.04	2.94	1	−0.14	5.91	1	−0.62	12.21
RSP4	−0.15	5.80	3	0.04	5.47	3	0.10	11.06
REM1	0.27	4.82	6	0.10	5.11	6	0.34	10.38
REM4	1.01	9.16	9	0.13	4.92	9	0.44	9.95
REPO1	−0.35	8.03	12	0.14	4.74	12	0.50	9.58
REPO4	−1.55	12.13	18	0.16	4.48	18	0.59	9.01
IIP13	0.038	0.084	24	0.18	4.31	24	0.66	8.60
MMS13	0.14	4.44						
OI13	0.96	9.98						
AVB1	0.00	0.77						
AVB4	0.00	0.85						

Table 3 Estimates of Standardized Coefficients for the Futures Excess Return Forecasting Model over the Horizon of One Week

Contract	*RSP1*	*REM1*	*REPO1*	*IIP13*	*MMS13*	*OI13*	*AVB1*	R_{Lag}	Adj. R^2
1	1.013	−1.190	−1.400	2.136	1.548	−1.153	−2.277	−0.961	0.31
	(1.61)	(−1.89)	(−2.86)	(4.10)	(4.95)	(−2.48)	(−9.14)	(−1.81)	
3	1.012	−1.062	−1.247	1.892	1.252	−0.840	−1.979	−0.780	0.29
	(1.89)	(−1.76)	(−2.74)	(3.81)	(4.54)	(−1.99)	(−8.37)	(−2.05)	
6	1.111	−1.177	−1.113	1.725	1.082	−0.750	−1.647	−0.523	0.26
	(2.27)	(−2.05)	(−2.60)	(3.64)	(4.19)	(−1.89)	(−7.41)	(−1.63)	
12	1.246	−1.299	−1.003	1.560	0.895	−0.661	−1.201	−0.369	0.23
	(2.74)	(−2.42)	(−2.46)	(3.54)	(3.87)	(−1.83)	(−5.56)	(−1.21)	
24	1.183	−1.336	−0.821	1.353	0.705	−0.551	−0.759	−0.219	0.19
	(2.87)	(−2.73)	(−2.17)	(3.54)	(3.44)	(−1.74)	(−3.67)	(−0.64)	
$\overline{ER}(1)$	1.115	−1.201	−1.169	1.788	1.145	−0.818	−1.690	−0.588	0.27
	(2.20)	(−2.09)	(−2.67)	(3.82)	(4.44)	(−2.07)	(−7.65)	(−1.73)	
$\overline{ER}(1)$	1.239	−1.048				0.508	−1.560	−0.317	0.13
	(2.30)	(−1.75)				(0.95)	(−6.74)	(−0.66)	

Note. The dependent variable for the individual contract returns is denoted by *ERmM*(1), expressed in percent of return; $\overline{ER}(1)$ denotes the average excess return for the 1-, 3-, 6-, 9-, and 12-month contracts.

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) having 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}.

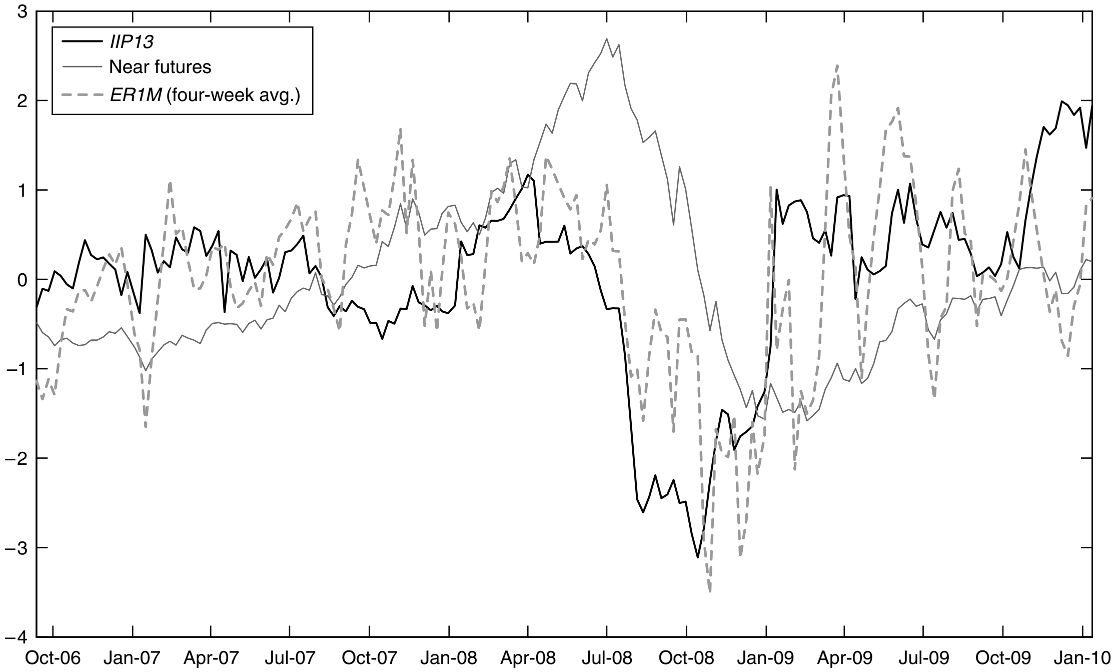
Estimates of Π along with their asymptotic t-statistics are displayed in Tables 3 and 4 for $n = 1$ and 4 weeks, respectively. The adjusted R^2's provide compelling evidence that there was substantial predictability of changes in futures prices in oil markets during this period. Table 2 shows that the 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.

Table 4 Estimates and Robust Test Statistics for the Futures Excess Return Forecasting Model over the Horizon of Four Weeks

Contract	*RSP4*	*REM4*	*REPO4*	*IIP13*	*MMS13*	*OI13*	*AVB4*	R_{Lag}	Adj. R^2
1	−0.007	2.968	0.645	8.346	4.554	−4.799	−0.932	−3.464	0.40
	(0.00)	(1.90)	(0.69)	(4.73)	(7.21)	(−3.77)	(−1.02)	(−2.59)	
3	−0.903	3.371	0.253	7.876	4.028	−3.718	−0.415	−3.406	0.40
	(−0.60)	(2.52)	(0.30)	(4.47)	(6.75)	(−3.32)	(−0.52)	(−2.70)	
6	−1.197	3.312	0.026	7.436	3.559	−3.390	−0.163	−2.998	0.39
	(−0.83)	(2.64)	(0.03)	(4.33)	(6.39)	(−3.18)	(−0.21)	(−2.40)	
12	−1.286	2.906	0.047	6.776	2.934	−3.062	−0.052	−2.424	0.35
	(−0.92)	(2.51)	(0.07)	(4.23)	(5.79)	(−3.07)	(−0.07)	(−1.96)	
24	−1.210	2.310	0.204	5.709	2.279	−2.560	−0.071	−1.723	0.30
	(−0.95)	(2.34)	(0.33)	(4.15)	(5.11)	(−2.76)	(−0.10)	(−1.52)	
$\overline{ER}(4)$	−0.922	3.149	0.193	7.558	3.669	−3.665	−0.345	−3.050	0.39
	(−0.62)	(2.48)	(0.24)	(4.45)	(6.52)	(−3.39)	(−0.44)	(−2.45)	
$\overline{ER}(4)$	−0.199	3.300				1.407	−0.424	0.484	0.12
	(−0.10)	(1.83)				(1.03)	(−0.49)	(0.40)	
$\overline{ER}(4)_N$	−3.892	6.571	0.162	9.079	3.799	−4.599	0.346	−5.145	0.31
	(−1.90)	(2.35)	(0.190)	(5.08)	(8.07)	(−3.24)	(0.42)	(−2.53)	
$\overline{ER}(4)_N$	−3.573	7.104				1.062	1.153	0.094	0.05
	(−1.94)	(2.56)				(0.770)	(1.11)	(0.04)	

Note. The dependent variable for the individual contract returns is denoted by *ERmM*(4); $\overline{ER}(4)$ denotes the average excess return for the 1-, 3-, 6-, 9-, and 12-month contracts, with the subscript "*N*" indicating nonoverlapping (monthly) data.

Figure 6 **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**



The rows for $\overline{ER}(n)$, $n = 1, 4$, 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 (*REPO4, 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 *REPO4* are all insignificant, this finding points to (*IIP13, MMS13*) having had substantial predictive power for excess returns during this sample period.

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. This significant positive relationship 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 6).[28] Other notable features of this figure are as follows: (i) both the futures returns and *IIP13* start to decline in the spring of 2008 prior to the peak in oil prices; (ii) the 13-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.

[28] This series is the price of the generic one-month futures contract, CL1, from Bloomberg.

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 et al. (2010) present evidence of herding behavior by hedge funds during this sample period. Whatever the motives of the managed-money traders, their net effect on excess returns was positive: increases in spread positions were associated with future increases in futures 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 findings in Hong and Yogo (2012). This difference seems to arise as a consequence of having controlled for the investor flows *IIP13* or *MMS13*: When the flow variables (*IIP13, MMS13*) are omitted (see the rows for $\overline{ER}(1)$ and $\overline{ER}(4)$), the coefficient on *OI13* is positive (though statistically insignificant). These observations remain qualitatively intact when monthly (instead of overlapping weekly) data are used in the last two rows of Table 4.

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. More generally, and as important, for interpreting the evidence on 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 §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*, and *AVB1*, for example, on the one-week return on the one-month futures contract are -1.19%, -1.40%, 2.14%, 1.55%, and -2.27%, respectively, and these responses should be viewed relative to the weekly standard deviation in *ER1M*(1) of 5.91% (Table 2). The absolute responses tend to decline with the maturity of the futures contract, but *REM1*, *IIP13*, and *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 8.35%, 4.55%, and -4.80%, relative to its standard deviation of 12.2%. 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 0.0842 and 0.0444 million contracts, respectively. Using these values we can translate the reported responses in futures returns into basis points per million 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 3-month contract of 2.2 bp (9.4 bp), and 1.9 bp (8.0 bp) on the 12-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 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 2, and peak at a larger positive number in week 3.

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 overshooting 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 1% increase in *REM1* leads (ceteris paribus) to a -26 bp (-30 bp) change in the weekly return on the 3- (12)-month contract, and a 34 bp (31 bp) 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 Etula (2010) model 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. Servicing the OTC markets requires a substantial commitment of capital by broker dealers. As funding conditions improve—reflected here by 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 where short-lived.

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*, and *OI13* are −0.15, −0.05, −0.05, and −0.08, respectively, 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, Hong and Yogo 2012).

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, Oklahoma, inventory of crude oil in millions, as reported by 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; the pattern of results in Table 3 remained qualitatively the same. Their inclusion did not affect the predictive content of the investor flow variables.

An alternative explanation of my findings of predictable excess returns is that commercial hedgers took increasingly large short positions during my volatile sample period. To examine this potential connection between trading patterns and excess returns, I reestimated Equation (7) with the 13-week growth rate in either the short or net long-short futures positions of producers from the Disaggregated COT report in place of *IIP13*. For producer short positions, the coefficients are negative, consistent with this alternative view, but they are all statistically insignificant. Also, particularly for the case of $n = 4$, the adjusted R^2's fall substantially when *IIP13* is not included. With producer net futures positions replacing *IIP13*, the coefficients are always *positive*, contrary to this hedging explanation. Again, the R^2's fall substantially, though with $n = 4$, the coefficients are statistically significant at conventional levels for the longer-maturity contracts.

Finally, some argue that the trading patterns of index and managed-money investors are linked to speculation about global economic growth. A relevant question is whether measures of global economic growth also had predictive power for excess returns on futures. I follow Kilian (2009) and Pirrong (2009), as well as many oil-market practitioners, and use a proxy for global real activity derived from shipping rates based on the BalticExchange 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 the conditioning variables in X_t, which continue to account for most of the predictable variation in futures returns.

6. Investor Flows and the Slope of the Futures Curve

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 of the futures curve during the 2008 boom/bust in oil prices.[29] 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 used earlier. 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 6-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 et al. 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. Interpreting the sign of this effect is compromised by the fact that these spread trades are unsigned; we do not know which leg of the trade was long versus short. Data on the actual positions of market participants are needed to say more about interactions between managed money and index trading, and their effects on the shape of the futures curve.[30] Additionally, while the results in Table 5 are

[29] I am grateful to an anonymous referee for suggesting this exercise.

[30] Cheng et al. (2012) compile such proprietary data for a complementary project on the links between changes in the VIX and commodity returns. It would be interesting to explore these shape issues using comparable data.

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

Horizon	Spread	*RSPn*	*REMn*	*REPOn*	*IIP13*	*MMS13*	*OI13*	*AVBn*	R_{Lag}	Adj. R^2
$n=1$	6m–1m	0.151	0.130	0.285	−0.363	−0.471	0.407	0.666	−0.477	0.15
		(0.70)	(0.66)	(1.87)	(−1.72)	(−3.35)	(1.82)	(8.86)	(−2.77)	
	12m–6m	0.144	−0.093	0.103	−0.148	−0.200	0.083	0.452	−0.210	0.30
		(1.36)	(−1.25)	(1.58)	(−2.46)	(−4.68)	(1.34)	(10.28)	(−2.29)	
	12m–1m	0.287	0.032	0.372	−0.517	−0.693	0.501	1.168	−0.756	0.24
		(0.92)	(0.13)	(2.02)	(−2.27)	(−4.14)	(1.97)	(11.35)	(−2.56)	
$n=4$	6m–1m	−1.097	0.363	−0.651	−0.970	−0.661	1.092	0.016	0.280	0.17
		(−1.74)	(0.52)	(−2.04)	(−1.90)	(−2.33)	(2.11)	(0.04)	(0.37)	
	12m–6m	−0.019	−0.380	0.003	−0.474	−0.605	0.230	0.082	−0.528	0.28
		(−0.10)	(−1.76)	(0.03)	(−3.11)	(−7.86)	(1.32)	(0.64)	(−4.09)	
	12m–1m	−1.269	0.147	−0.646	−1.378	−1.311	1.433	0.256	−0.399	0.19
		(−1.66)	(0.17)	(−1.65)	(−2.24)	(−3.98)	(2.12)	(0.48)	(−0.50)	

Note. Maturities are measured in months (e.g., "1m" is one month).

consistent with managed money attempting to take advantage of the Goldman roll or similar opportunities, as discussed by Mou (2011), the phenomenon I document in Table 5 takes place on the 6- to 12-month spread. Thus, these correlations relate to price-pressure effects well outside the roll segment of the futures curve. The fact that they appear along a wide portion of the maturity spectrum suggests that the effects of *MMS13* are distinct from the direct responses of hedge funds to trading opportunities associated with index rolls at the beginning of the month in very short-dated futures.

When $n=1$ and the spread trade is shortened to 3m–1m, all of the predictor variables are statistically insignificant (*except* for *IIP13*, *MMS13*, and *AVB1*, which have loadings of −0.22%, −0.28%, and 0.26%, respectively) and the adjusted R^2 is 0.06. On the other end, for the slope segment 24m–12m, *REPO1*, *MMS13*, and *AVB1* all enter with significant loadings and the adjusted R^2 is 0.26. Spread trading seems to have had an impact on returns on slope positions extending all along the curve.

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 the other hand, *AVB4* has no incremental predictive power for the four-week returns. Because the basis shows very weak correlation with the investor flow variables, its role in predicting spread returns represents information in the convenience yield that is relevant for changes in the shape of the futures curve over short (weekly) horizons.

7. 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 2008 boom/bust in oil prices, after accounting for stock returns in the United States 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. Additional empirical work with longer and more detailed data is also likely to be informative about the economic circumstances associated with boom/bust patterns like the experience of the past few years. My sample period is necessarily short because of the limited amount of data provided to date by the CFTC on investor positions.

Some insight into whether my results document 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).[31] The adjusted R^2 in this projection is 0.42, similar to the result for *ER1M* in Table 4. The investor flow variables *IIP13* and *MMS13* enter with statistically significant coefficients. However, the average basis

[31] Based 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.

(*AVB4*), a proxy for convenience yield, does not have predictive content for $S_{t+4} - F_t^{t+4}$, nor do *OI13* or *RSP4*. There is relatively weak evidence of predictive content for *REM4* and *REPO4*. It seems that, for this horizon, traders' reactions to news about 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.

Looking ahead, one should not necessarily expect to find substantial or even clearly detectable impacts of index and managed-money flows on prices in commodity futures markets in all economic environments and at all times. Booms and busts are infrequent. Furthermore, particularly during crises, there may be significant deterioration in the risk-bearing capacity of large participants in commodity futures markets that disrupts the typical roles of suppliers and demanders of risk and liquidity. These considerations may well explain the changes in signs of the effects of the VIX index on futures positions of hedge funds and index investors for the recent crisis period (Cheng et al. 2012). They also reinforce the importance of accommodating financial frictions and limits to arbitrage in models of commodity futures pricing.

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 toward 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.

Finally, assessing the welfare costs of trading based on limits to arbitrage or imperfect information in commodity markets is challenging. 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, Cochrane 1989).[32] 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, their errors, while inconsequential for their own welfare, may be material for society as a whole.[33] Frictions associated with multiperiod contracting over labor and physical capital will likely exacerbate the social costs of any price drift.

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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 $F_t^{T_1(t)}, \ldots, F_t^{T_N(t)}$. Let $D(s) > s$ denote the first time after s (in days) that the generic futures curve switches contracts. Then, for all $i = 1, \ldots, N-1$, 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

$$\frac{F_t^{T_i(t)}}{F_s^{T_i(s)}} - 1 \quad \text{if } t < D(s)$$

$$\frac{F_{D(s)-1}^{T_i(D(s)-1)}}{F_s^{T_i(s)}} \cdot \frac{F_t^{T_i(t)}}{F_{D(s)-1}^{T_{i+1}(D(s)-1)}} - 1 \quad \text{if } D(s) \le t < D^{(2)}(s)$$

$$\frac{F_{D(s)-1}^{T_i(D(s)-1)}}{F_s^{T_i(s)}} \cdot \frac{F_{D^{(2)}(s)-1}^{T_i(D^{(2)}(s)-1)}}{F_{D(s)-1}^{T_{i+1}(D(s)-1)}} \cdot \frac{F_t^{T_i(t)}}{F_{D^{(2)}(s)-1}^{T_{i+1}(D^{(2)}(s)-1)}} - 1 \quad \text{if } D^{(2)}(s) \le t < D^{(3)}(s)$$

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 risk-free 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

[32] Such suboptimal plans may arise out of misinterpretations of public information, perhaps 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 overconfidence about future economic growth, as in Dumas et al. (2006).

[33] See Xiong (2012) for a survey of recent research on the welfare implications of heterogeneous beliefs.

are met with margin calls. For this reason, Hong and Yogo (2012) 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.

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