Order Flows and Retail Investor Impacts in Commodity Futures Markets

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Abstract: We examine signed order flows and price formation in six commodity futures markets and find that trading in futures markets plays an important role in price discovery. We then use these results to investigate the impacts of retail investors in these markets. We find strong evidence of order flows and price impacts in agricultural futures markets associated with changes in the positions of commodity index traders reported by the CFTC. These effects are concentrated in the minutes just prior to daily futures settlement, when the price impact of trades is generally lowest. In contrast, we find no impact in oil futures markets from retail flows to the largest oil ETF, although we do find evidence that retail investors react to changes in futures prices. Finally, we confirm the positive returns around the issuance of commodity-linked notes documented by Henderson, Pearson, and Wang (2014), but we find no evidence that these returns are driven by abnormal order flows. We also find that these returns are too large to be explained by uninformed price pressure from hedging trades in futures markets.

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1 Introduction

Increasing retail investment in commodity futures over the last decade has generated substantial interest in the impact of this investment on commodity markets. While theoretical work provides mechanisms through which trading from uninformed retail investors can create price impacts in futures markets, the empirical evidence for these effects is mixed. However, most of this empirical work focuses on daily returns to futures and thus ignores a basic question: How large must a trade be to materially impact the futures market?

In this paper we contribute to this discussion by examining the impact in commodity futures of retail order flows from three different sources: changes in the positions of commodity index traders in as documented by the Commodity Futures Trading Commission (CFTC), retail investor order flows to the United States Oil Fund (USO), and issuances of commodity-linked notes (CLNs). However, rather than focusing on returns at the daily frequency, we examine minute-by-minute signed trading volume (we refer to this as "order flow imbalance", or simply "imbalance") and returns for six major commodity futures markets from January 2007 to April of 2014: WTI Crude, Brent Crude, Gold, Copper, Wheat, and Corn. The commodities are respectively the largest and most liquid markets in the four major commodity classes: energy, precious metals, industrials, and agricultural commodities.

We find that imbalance in futures markets has a large explanatory power for futures returns, indicating that these markets play a central role in price discovery. We also find substantial heterogeneity across the trading day. In particular, in the minutes prior to the determination of the daily futures settlement price, we see large increases in volume and a substantial decrease in the price impact of order flow. This finding is particularly relevant for retail investment vehicles, such as commodity mutual funds and CLNs, which rely on daily settlement prices, as they may be able to trade in these minutes and reduce the impacts of their trades.

Our primary goal is understand the impact of trades by participants who are likely to be trading for portfolio reasons, as opposed to traders who may possess superior information. We use the term "retail" to refer to these investors, but for much of our analysis we are also thinking of institutional investors who are managing index strategies and are responding to the demands of their clients. For example, our first set of tests examines the impact of retail order flow coming from weekly changes in the positions of commodity-index traders. The CFTC provides these data only for agricultural futures, so we restrict this analysis to corn and wheat futures. Here we find evidence largely consistent with theoretical models of retail investment. When positions of index traders increase (decrease), we see high levels of buy (sell) volume and positive (negative) returns. Both the volume and return impacts are highly concentrated in the minutes prior to the daily settlement.

The economic magnitude of this effect is small relative to the overall price variance in these futures, but large enough to generate potentially significant impacts on the level of prices. As an illustration, we find that a one standard deviation increase in the positions of wheat index traders is associated with a strongly statistically significant positive return of 45 basis points accumulating in the 30 minutes prior to the daily settlement over the week. While this effect explains 9% of the weekly return variation in those minutes, it explains less than 1% of the overall weekly variation in wheat returns.

Though these trades are unlikely to explain a large amount of volatility, their effect could potentially accumulate over time to create a larger effect on the level of prices. For instance, from January 2009 to January 2010 the net long position in futures contracts held by wheat index investors nearly doubled. Using our estimates, this buying by index traders would lead to a cumulative increase of approximately 10% in the price of wheat. While this illustrates the potential impact of these retail investors, this estimate should be viewed cautiously, as it assumes no reversal of the price impact. While we do not see any price reversal in our estimates, we have very little statistical power to test for reversals if they occur slowly. Therefore, these estimates might be viewed as an upper bound of potential impact.

The order flows from index traders in wheat and corn are large relative to the overall size of the futures market, so it is not surprising that we find significant price impacts. Again, using wheat as an illustration, we find that the standard deviation of weekly index flows is approximately $140 Million/week. For comparison, the standard deviation of a single minute's imbalance in wheat futures is approximately $4 Million, which rises to approximately $20 Million in the minute prior to futures settlement. This suggests that a $140 Million flow, even when spread over 5 days in the trading week, would need to be executed carefully if it was traded near the daily settlement.

Our second set of tests examines flows to the United States Oil ETF (USO). This fund has been studied in several other papers including Bessembinder, Carrion, Tuttle, and Venkataraman (2016) who study the impact of the fund rolling its futures positions from the front month contract to the next month contract, and Irwin and Sanders (2012) who find no impact of fund share creation or redemption on oil futures returns. The USO is very liquid, and may be used by informed traders to trade on oil news, so we proceed by first isolating order flow imbalance from retail investors using the algorithm proposed by Boehmer, Jones, and Zhang (2017).

While there is substantial retail volume in the USO, we find that these volumes are small when compared to the volume in WTI futures. The one-mnute standard deviation of daily imbalance from retail traders in the USO is $0.2 Million, compared to $15.2 Million for WTI futures across all minutes ($36.6 Million in the settlement minute). This suggests that futures trades driven by uninformed volume from USO retail traders should have a relatively small effect on futures markets.

When we test for price impact of this volume at a daily frequency, we obtain a puzzling result. Days with buying (selling) by retail investors in the USO tend to be days with negative (positive) return. However, when we examine the relation of retail imbalance and returns at higher frequencies, we see that this result is an artifact of retail investors pursuing contrarian strategies. Retail investors tend to buy after drops in prices, and aggregating up to daily frequencies leads to a spurious contemporaneous correlation. When we move to a one-minute frequency, the finding reverses, and we find a small positive association between retail order flow and price changes, but this association disappears when we examine data at the one-second frequency.

To further illustrate the reaction of retail traders to changes in prices, we also examine returns around inventory announcements. These are periods of time when we know that sophisticated investors will be trading in oil markets. We find, that on low- (high-)inventory announcements, we see very fast positive (negative) imbalance in both WTI futures and the USO corresponding with the price increases (decreases). This result indicates that sophisticated investors are trading in both the WTI and the USO. In contrast, retail investors in the USO respond asymmetrically to different announcements. We find no response of these investors following a price-decreasing announcement, but we find that they buy in the minute following a price-increasing announcement. We also find that this positive response is considerably slower than the response by the sophisticated investors.[1]

Our results highlight the potential issues with examining returns at daily frequencies. If retail demand is dependent on prices, aggregating up to lower frequencies can lead to the appearance of a price impact when none exists. This is a potential explanation for the results we obtain when we examine the findings of Henderson, Pearson and Wang (2014) (henceforth HPW), who show that issuances of Commodity-Linked Notes (CLNs) are

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[1] This asymmetric response is similar to the result in Lee (1992) who found small traders buying primarily in response to positive earnings announcements.

associated with positive price changes on the day the notes are priced. Their primary analysis considers 486 CLNs with a notional of greater than $2 Million across various commodities. The average notional value of these notes is approximately $15 million, and they find an associated price increase of approximately 30 basis points on the pricing day of the notes. They attribute these changes to the price impact of the hedging trades in futures markets made by the issuers of these notes, and suggest that this result supports the theory that uninformed retail investors can have a strong impact on commodity prices.

Our intraday data allow us to examine whether the size of these notes is large enough for hedging trades to generate the observed price changes. Here we find that the observed price impacts are too large. We examine the trading activity associated with the largest notes issued in the six commodities for which we have data, restricting our analysis to those which have greater than $10 Million of notional, giving us approximately 200 notes with an average notional of approximately $30 Million. Consistent with HPW, we find a significantly positive daily return on the pricing days for these notes, with an average daily return of approximately 30 basis points. However, our estimates suggest that if the full value of these notes were traded in the minute of settlement, the average impact would be approximately five basis points. We also find no evidence that there is any signed trading volume associated with these notes, either throughout the day or in the period around the daily settlement, or that the largest notes create a larger impact. Moreover, nearly all of the positive return occurs before the final 30 minutes prior to settlement, with more than half of the effect accumulating between the prior day's settlement and the open of the market. This is surprising, because the CLNs are priced using the daily close, so any hedging trades should occur very close to the settlement minute.

Taken together, our results suggest that CLN issuance may be reacting to changes in prices, as opposed to causing them. CLN issuers have flexibility to determine the specific date that the notes are priced and issued, so association between issue and return prior to settlement suggests that CLN issuers prefer days with rising prices, or that demand for these notes is high on days in which prices are rising.

1.1 Related Literature

To our knowledge, our paper is one of the first to systematically examine trade imbalances in several commodity futures markets, and thus the first to document price impacts of order flows, as well as to examine the intraday behavior of signed order flow across several markets.

The study of the impact of retail investors on commodity markets is motivated by a growing theoretical literature. Hamilton and Wu (2015), Sockin and Xiong (2015), Baker (2014), Basak and Pavlova (2016), Goldstein and Yang (2017) and others derive theoretical models by which uninformed retail investors can create price impacts in commodity futures markets.

Our work is mostly closely related to the empirical studies of "financialization" in commodity prices. For instance, Irwin and Sanders (2012) examine retail investor flows coming from daily purchases of futures contracts by the United States Oil Fund (USO) and find no impact on the prices or returns of oil futures, and Hamilton and Wu (2015) find no evidence that index-fund investment can predict the returns to commodity futures. In contrast, HPW examine issuances of commodity-linked notes (CLNs) and find evidence of sizeable positive price impacts on the pricing days of these notes. Some of this work finds additional evidence supporting the impacts of retail traders including Buyuksahin and Robe (2011), Tang and Xiong (2012), and Singleton (2013), Cheng, Kirilenko, and Xiong (2015) while others find no evidence of impacts of retail investors, including, Silvennoinen and Thorp (2012), Fattouh, Kilian, and Mahadeva (2013), Aliquist and Gervais (2013), and Chari and Christiano (2017).

While the above empirical work studies prices at daily or longer frequencies, there is a small set of papers that study intraday trading and liquidity in commodity markets. Bessembinder, Carrion, Tuttle, and Venkataraman (2016) study liquidity around the predictable roll of the futures in the United States Oil Fund, and Bessembinder (2015) reviews the empirical and theoretical framework for understanding predictable roll trades. However, these papers are focused on predictable calendar spread trades, and are therefore distinct from the price level effects we study here. Raman, Robe, and Yadav (2017) examine price impacts and liquidity in WTI oil futures markets, and examine the impact of retail traders on liquidity, but do not examine price impacts for retail flows.

Other related work includes Elder, Miao, and Ramchander (2012), who study intraday price patterns in Brent and WTI futures, Marshall, Nguyen, and Visaltanachoti (2012), who study liquidity proxies in commodity prices, and Halova, Kurov, and Kucher (2014), who study price reactions to inventory announcements. However, these papers do not study signed volume and price formation in futures markets.

2 Data

Our data sources include:

- Intraday futures data from Thomson Reuters Tick History from January of 2007 through March of 2014 (we exclude data for the Brent contract prior to January 1, 2008 due to issues in the reported timing of trades).
- A sample of commodity-linked notes obtained from 424b filings obtained from the SEC's EDGAR database.
- Positions of index traders in corn and wheat futures from the CFTC "Supplementary Positions of Traders" reports
- Intraday trade and quote data in the USO from the NYSE TAQ database

Our data cover six major exchange-traded futures contracts. We include two energy contracts, both the West Texas Intermediate (WTI) contract traded on the NYMEX (now owned by the CME) and the Brent contract traded on the ICE. We also include the gold, corn, wheat, and copper contracts from the CME. In terms of open interest and volume, these contracts are generally largest in their respective commodity classes. Moreover, the gold, corn and wheat contracts on the CME are the dominant futures markets for each commodity. The copper contract on the CME rivals the contract traded on the London Metal Exchange, but generally has slightly lower volume. Nevertheless, even in copper, we find that CME volume plays an important role in price discovery.

Our primary analysis uses 1-minute returns and order imbalance for the nearest-to-maturity high volume contracts in each market. When we study activity surrounding the oil inventory announcements, we aggregate the data in 1-second intervals. As an illustration for how we construct these measures, we first describe them in detail for the WTI crude oil futures.

2.1 Volume Patterns for WTI

WTI futures contracts are available for every month going out five years and for June and December delivery months going out an additional four years. Unlike stock index futures, where nearly all of the trading is in the contract with the nearest delivery dates, there is substantial trading and open interest in longer-dated WTI futures contracts. However, most of this trading in the longer-dated contracts is through calendar spread trades, wherein traders agree to simultaneously buy one maturity and sell another. Most of the trading in a single contract is concentrated in the nearer months.

We use data starting in January 2007 and we calculate our imbalance measures using trades and quotes from the Globex platform that are obtained from Thomson Reuters. The NYMEX adopted the CME Globex platform for electronic trading of the WTI contracts in June of 2006 (the CME announced its acquisition of the NYMEX in March of 2008). The Thompson Reuters data include some floor trades over the earlier part of our sample, and evidently includes most or all of the floor trades starting in March of 2013. Starting in March of 2013, the data also include calendar spread trades, but we are able to identify them separately. In order to illustrate the typical pattern in trading volumes, Table 1 shows the WTI contract volumes (in thousands of contracts, each for 1,000 barrels of oil) for the trading days in June 2013.

Table 1 shows that the July 2013 contract last traded on June 20, but most of the trading volume had moved to the August 2013 contract the day before that. The table also shows that calendar spread trading makes up a fairly substantial portion of the front and next month volume, and it constitutes the vast majority of trading in the remaining months. Finally, the table shows that floor trading volume is much smaller than Globex volume, which is a feature common to most futures contracts. In fact, the NYMEX suspended floor trading in WTI futures and many other futures products in July of 2015.

We exclude floor trades because they are executed manually, making it impossible to accurately align them in time with the GLOBEX quotes, and therefore impossible to assign trade direction. We also exclude calendar spread trades from our imbalance measure, motivated in part by results from supplemental tests where we found that the imbalance in the calendar spread trades has little impact on the level of front and next month futures prices.

We classify each Globex single-month trade as a buy or sell by comparing the price to the current quote for that contract, and we aggregate buying and selling volume by minute. We also measure the (logged) return over each minute using quote midpoints as of the end of each minute.

Globex trading in WTI futures runs from Sunday night at 6:00 p.m. to Friday night at 5:00 p.m. with one-hour breaks at 5:00 p.m. each day. The bulk of the trading occurs during the day, so we limit our analysis to the time periods from 7:30 a.m. to 4:00 p.m. each day. This time window captures 88% of the total WTI volume in the front and next month contracts.

2.3 Definition of Near Month Imbalance

Most of the trading activity in the contracts that we consider takes place in contracts that have only a few months to expiration. Many users of commodity futures maintain positions in these high volume contracts and roll their positions into later contract months as their contracts near expiration. While this general description applies to all six of our commodities, the specific trading patterns differ.

The WTI and Brent contracts are the easiest to understand. Contracts are available for every calendar month out through 5 years. Trading continues until three business days before the 25th calendar day of the month before the delivery month. As illustrated in Table 1, the nearest contract to expiration, which called the front month contract, has the highest trading volume until a few days prior to expiration. The contract expiring in the next calendar month has the next highest volume across all contracts, and it becomes the highest volume contract as the front month contract nears expiration.

The CME procedures for determining daily settlement prices begin by focusing the contract that generally has the highest volume. This is called the "Active Month" for WTI, gold and copper, and is called the "Lead Month" for corn and wheat. We measure returns using the quote midpoints for the Active/Lead Month contracts. We measure imbalances using the difference between buy and sell volume for trades in all months from the front month through the month that is currently the Active/Lead month or is within three weeks of becoming the Active/Lead month. Although we exclude trades that are part of explicit calendar spreads, we recognize that some traders may roll their position using separate individual trades in the two contract months. Our definition of imbalance effectively nets out any trades that are a result of a trader rolling between contract months. For example, if a WTI trader uses market orders to sell the front month and buy the next month (within three weeks of the front month expiration), our measure will reflect zero net imbalance for those trades. As a robustness check, we also repeat some of our tests using imbalance based on just the trades in the Active/Lead month.

The Active Month in the WTI futures is the nearest month contract, except for the last two trading days prior to expiration, at which point the next month contract becomes the Active Month. Thus, referring back to Table 1, our return data on June 18, 2013 use the July 2013 contract and our return data on June 19, 2013 use the August 2013 contract.

Our imbalance data include both the July 2013 and August 2013 through June 20, 2013, and reflect just the August 2013 contract starting June 21, 2013.

The volume patterns in the other commodities are more complex. Gold futures contracts are available for the nearest three calendar months and for all even calendar months (February, April, June, etc.) for the next two years. Although some trading occurs in odd calendar months that are close to expiration, the volume in odd expiration months is much lower than in the nearby even calendar months. In addition, volume for October tends to be lower that for the other even months. The Active Months in gold are the even months, except for October. The current Active Month is the nearest of these contracts that is not in the final calendar month of trade. For example, on February 1 the April contract becomes the Active Month. The active months in copper are March, May, July, September and December, and the current active month works the same way it does in gold. So for example, on March 1 the May contract becomes the Active Month.

Corn and wheat futures contracts are available for expirations March, May, July, September and December. Trading occurs through the business day prior to the 15th calendar day of the expiration month. For wheat, each of these months is the Lead month until the 12th business day of the calendar month prior to expiration. For example, on the 12th business day of November, the lead month changes from December to March. Corn is very similar to wheat, except September is never considered the Lead month in corn.

3 The Price Impact of Trade Imbalances

As a first step to understanding the impact of order flows in this market, we follow the Vector Autoregression approach developed in Hasbrouck (1991). Specifically, assume that the (log) quote midpoint for the commodity evolves according to:

$$q_t = m_t + s_t$$

Where m_t is the "efficient price" based on all relevant information, including public announcements and order flow up to time *t*, and the s_t component captures transient market microstructure effects. The efficient price evolves according to:

$$m_t = m_{t-1} + w_t$$

where the increments w_t are mean zero, have variance σ_w^2, and are serially independent at all lags. The s_t process has zero unconditional mean and is jointly covariance stationary with w_t.

We observe the evolution of quote midpoints, $r_t = q_t - q_{t-1}$, and the signed order flow x_t, and following Hasbrouck (1991) we assume these evolve according to the following VAR:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \cdots + b_0 x_t + b_1 x_{t-1} + b_2 x_{t-2} + \cdots + v_{1,t} \\ x_t &= c r_{t-1} + c_2 r_{t-2} + \cdots \qquad + d_1 x_{t-1} + d_2 x_{t-2} + \cdots + v_{2,t} \end{aligned} \tag{1}$$

In the above VAR, $v_{1,t}$ denotes the impact of public announcements in period t and $v_{2,t}$ denotes the surprise in current period order flow, and these have variances σ_1^2 and σ_2^2, respectively. The assumption that the current period order flow does not depend on the current period public announcement allows the above VAR to be recast in the following VMA representation:

$$\begin{aligned} r_t &= v_{1,t} + \boldsymbol{a}_1^* v_{1,t-1} + \boldsymbol{a}_2^* v_{1,t-2} + \cdots + \boldsymbol{b}_0^* v_{2,t} + \boldsymbol{b}_1^* v_{2,t-1} + \boldsymbol{b}_2^* v_{2,t-2} + \cdots \\ x_t &= \qquad \boldsymbol{c}_1^* v_{1,t-1} + \boldsymbol{c}_2^* v_{1,t-2} + \cdots + \quad v_{2,t} + \boldsymbol{d}_1^* v_{2,t-1} + \boldsymbol{d}_2^* v_{2,t-2} + \cdots \end{aligned} \tag{2}$$

The system in (1) is estimated using OLS, giving the coefficients as well as estimates for σ_1^2 and σ_2^2. Then a Cholesky decomposition recovers the coefficients in (2). This VMA representation allows for the calculation of impulse response functions. Hasbrouck shows that the fraction of the variance of the efficient price innovations w_t that is due to the innovations in the order flow is given by:

$$R_w^2 = (\sum_{t=0}^{\infty} \boldsymbol{b}_t^*)^2 \sigma_2^2 / \{(\sum_{t=0}^{\infty} \boldsymbol{b}_t^*)^2 \sigma_2^2 + (1 + \sum_{t=1}^{\infty} \boldsymbol{a}_t^*)^2 \sigma_1^2\}$$

When examining equity data, Hasbrouck applies the approach to trade-by-trade data, although trades within 5 seconds of each other are aggregated into a single observation. In contrast, we aggregate data into one-minute time intervals. As in Hasbrouck (1991), we set the lagged values returns and imbalances to zero at the start of each trading day.

We examine three primary dimensions of liquidity based on the VAR, including:

$\boldsymbol{b}_0^*$, the initial price impact of the innovation in order flow (higher values suggest either a higher fraction of trades come from the informed or the information held by informed traders is more valuable)

$\sum \boldsymbol{b}_t^*$, the permanent price impact of an innovation in order flow. We illustrate this with impulse response functions to test if the impact of order flow is reversed in subsequent minutes.

R_w^2, the fraction of the efficient price variance explained by order flow innovations (as with $\boldsymbol{b}_0^*$, a higher value implies more informed trades, but this measure is relative to the amount of information that arrives through public announcements).

3.1 Summary of Near Month Volume Imbalance and Returns

Table 2 shows summary statistics for our six futures contracts. We measure returns in percent, and express both volumes and imbalances as the number of contracts and as millions of dollars of futures notional. Oil futures contracts are for 1,000 barrels, and the average oil price over our sample was approximately \$100 per barrel. Gold futures contracts are for 100 troy ounces and the average gold price was a bit more than \$1,000 per ounce. Copper futures are for 25,000 pounds and the average copper price was about \$3 per pound. Accordingly, for oil, gold and copper, a single contract roughly corresponds to \$100 thousand notional value (gold notional value a bit higher and copper notional value a bit lower).

Corn and wheat futures contracts are for 5,000 bushels. The average prices for corn was around \$5 per bushel, and wheat was just a bit higher, so one contract corresponds to approximately \$25 thousand of notional value. As the table shows, trade volumes are large and, trade volumes, imbalances, and returns are quite volatile over the period. Average one-minute volume ranges from approximately \$32 Million of notional for WTI to approximately \$3.7 Million of notional for Copper. Average imbalances are near zero, but they are quite volatile with standard deviations of near \$20 Million per minute for gold, Brent, and the WTI, and close to \$3 and \$7 Million per minute for copper and corn respectively.

3.2 Full Sample Price Impact VAR

Table 3 shows the results of the regressions shown in equation (1) for the full sample. Imbalance is measured in 100s of contracts, and return is expressed in percentage to facilitate interpretation. Again, for most of the commodities, 100 contracts translates into roughly \$10 million of notional (with the exception of Corn and Wheat, which translates into approximately \$2.5 Million of notional over the sample).

The parameter b_0 from equation (1) is shown in the first row of each of the return columns in Table 3. This is the estimated response of the futures price to the order imbalance in the current minute. When the regressions from Table 3 are converted to the VMA representation from equation (2) (results not shown), we find that the values of b_0 from equation (1) are very close to the values of $\boldsymbol{b}_0^*$ from equation (2). This is not surprising, because as shown in the remaining rows of Table 3, current returns are not sensitive to past imbalances and there is only modest persistence in imbalances. The low R^2 values in the imbalance regressions indicates that most of the current minute imbalance is unpredictable.

The b_0 value of 0.032 for WTI futures shows that a minute with 100 contracts of buy (sell) imbalance will create a same-minute price increase (decrease) of 3.22 basis points. A roughly \$10 Million dollar flow yields an impact of approximately 3 basis points for gold, similar to the WTI, but a similar size trade will move copper and corn prices approximately 10 basis points. For all four of these commodities, the R^2 of these return regressions is relatively large, and results in a correspondingly high value of R_w^2 from the VMA representation, both results suggesting that order flow imbalance in these markets is playing a major role in price discovery.

To ascertain whether or not these price impacts from order flow reverse in subsequent minutes. We use the VMA representation to calculate impulse response functions. The graphs of these functions are shown in Figure 1. This figure plots impulse response functions for returns in response to a one standard deviation innovation in order flow and in public price news for the six commodities. The primary takeaway from these plots is that the price impacts of both order flow and public return news are mostly permanent at one-minute horizons. For oil, gold, and copper there is essentially no reversal or continued trend in prices. For corn, wheat, and Brent there is a small reversal after a movement in prices unrelated to order flow, but for a price move corresponding to order flow we see very little reversal.

3.3 Intraday Patterns in Volume and Trade Impact

The results from the VAR suggest that trade in financial futures markets plays a major role in price discovery. Moreover, we find that the impacts from trade are largely permanent, and do not substantially reverse at 1-minute horizons. However, performing these regressions on the full sample obscures substantial variation in intraday trading patterns. These intraday patterns are important to understanding how a sophisticated investor might implement hedging positions associated with a retail investment. Since many retail products are benchmarked to the daily futures settlement price, it is intuitive that the hedging trades would take place near the settlement, which occurs at various times for the different contracts.

To estimate how trading impacts change through the day, we rely on the insight from our VAR analysis that price impacts are mostly permanent, and simply estimate a univariate

OLS regression of current minute return on current period imbalance. To facilitate comparison across commodities, we also use imbalance measured in of millions of dollars of notional rather than the number of contracts as the independent variable in this regression. We perform this univariate regression for each minute of the trading day. For each contract we consider the interval from 7:30 a.m. through 5:15 p.m. (with the exception of corn and wheat, which stop trading at 2:15 p.m.) New York time, which is a total of 511 minutes. Thus, there are 511 regression estimates, each with approximately 1800 observations (the number of days in the sample). Figure 2 shows the results for these regressions, along with average volume, for each of the six commodities.

The first panel shows the minute-by-minute average volume and trade impacts throughout the trading day for the WTI futures. The volume rises on the open of pit-trading at 9 AM, and then spikes at times of various announcements, including the EIAs weekly energy outlook published each Wednesday at 10:30 AM. The largest spike however occurs at 2:30 PM in New York when the daily futures settlement price is set.

The fall in price impact immediately before the WTI settlement suggests these trades have lower information content. The average impact throughout the day is relatively stable around 0.3 basis points per million dollars of imbalance, but this drops drastically in the minutes just around the settlement to roughly 0.12 basis points per million dollars of imbalance.

The implication of this finding is that even for reasonably large trades, say one necessary to hedge a $30 Million CLN, would only have an impact of roughly 3.6 basis points if traded with a market order in the last minute before settlement. Note that a trade of this size would be smaller than a single standard deviation of imbalance for the settlement minute and less than 20% of the average settlement minute volume (see Table 2).

This pattern is repeated for each of the six commodities. For all of the commodities volume spikes and trade impacts fall around the futures settlement, which occurs respectively at 2:30 PM, 1:00 PM, 1:30 PM, and 2:15 PM New York time for Brent[2], copper, gold, and both corn and wheat respectively[3]. The drop in price impact is most notable for the WTI and gold, but is apparent in all six commodities. While impacts do vary during the day, the high amount of volume at the settlement means that the impacts in these minutes are estimated with high levels of statistical accuracy. Table 4 illustrates this and presents the univariate regressions estimated for the whole sample and for the settlement minute. In all cases, the settlement minute has significantly lower price impact than the full sample estimate.

The regressions shown in Figure 2 and Table 4 assume a linear impact of imbalance on returns. Given that we are concerned with potentially large trades, we also examine the settlement minute imbalance and returns for evidence of a nonlinear relation. Figure 3 shows scatter plots of imbalance and returns in minute prior to futures settlement for each of the six commodities. Also presented are the linear regression line, and fitted non-parametric LOESS smoother. For all six of the commodities, large flows generally lead to smaller impacts per dollar.

Having established that futures markets appear important for price discovery, and that volumes rise and trade impacts fall prior to futures closing times, we now examine how potential sources of retail order flow impact prices and trading in commodity futures markets.

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[2] Brent settles at 7:30 PM London time, which is 2:30 PM New York time for much of the year.

[3]Corn and wheat had their settlements delayed to 3:00 PM New York time from 5/22/2012 to 4/5/2013. We therefore omit this period for the analysis in Figure 1, and for most subsequent analysis presenting results across the trading day. We include this data when presenting analysis related to impacts prior to the daily settlement.

4 Retail Investor Flows and Futures Trading

In this section we investigate the futures market impacts of three sources of retail investor flows. First, using data from the CFTC's Index Investor Data report, we calculate the change in index-fund holdings for corn and wheat futures. These data, provided by the CFTC for agricultural futures only, have been studied extensively in the literature and are generally considered the best indication of retail investor holdings in commodity futures.

Second, using the NYSE TAQ database we collect order flows and returns for the USO. Irwin and Sanders (2012) examine the impact of this fund by looking at share creation and redemption, and find no impact on returns. However, ETFs are highly liquid instruments and are therefore likely to be used by highly sophisticated investors, including arbitrageurs. Moreover, share creation is not necessarily a good indicator of investor purchases in the fund. An investor may buy from a market maker who then creates a short position in the fund, while directly hedging their exposure in the futures market. The market maker may then create a share in the ETF by delivering the future at a later date. For instance, Brown, Davies, and Ringgenberg (2018) use share creation and redemption as a proxy for arbitrage opportunity rather than an indication of retail investment.

To avoid these issues we take a different approach. We first collect data from the NYSE TAQ database, and then follow Lee and Ready (1991) to sign trades as buy or sell. This gives us an indication of overall imbalance in the USO, but is likely to include sophisticated traders. To isolate the retail buys and sells, we follow the technique of Boehmer, Jones, and Zhang (2017), and use the fact that internalizing broker-dealers are required to give price improvement to retail investors, and that this price improvement typically occurs at sub-penny prices.

Finally, we follow the procedure of HPW and collect and process the universe of 424b filings for issuers of CLNs from the SEC's Edgar website to identify CLNs in our six commodities with notional values of larger than $10 Million.

While we generally follow HPW in our collection of CLNs, there are some differences. HPW use a larger set of CLNs, because they use a $2 Million notional value cutoff and consider a broader set of commodities. We restrict our set to the largest notes to increase the possibility of identifying trade impacts, and restrict it to the six commodities in which we have data. We follow HPW and omit CLNs indexed to multiple commodities. We find 200 notes linked solely to five our six commodities (we find no notes linked to wheat) with face values of greater than $10 Million, and the average size of these notes is approximately $30 Million. Our sample of large notes appears to closely track the set captured by HPW in terms of number and notional size, and our commodities are the ones most commonly used for CLNs, so we have more than 90% of the total notes in excess of $10 million used by HPW.

Table 5 presents the summary data for each of the sources of retail investor flow. While our 200 CLNs represent the very largest in the sample of HPW they are considerably smaller in magnitude and frequency than weekly changes in index-fund positions from the CFTC data, while on a similar scale to the retail flows in the USO. While this can be seen from Table 5, it is perhaps easier to see visually, so we plot these flows in Figures 4 and 5. Figure 4 plots the weekly changes in positions of index traders, the daily retail imbalance in the USO, and the notional values of the CLNs in Millions of dollars. To illustrate the size of the flows relative to the corresponding futures market, Figure 5 plots the absolute values of the flows to index traders as a percentage of weekly futures volume, the USO retail imbalance as a fraction of daily WTI futures volume, and CLN notional as a fraction of daily volume in the corresponding future. All of the plots are on the same scale to illustrate that the variations in the relative flows from the wheat and corn index-funds are generally an order of magnitude larger than those from the USO and the CLNs. Some CLNs are large outliers though, in particular in Copper. It is worth noting here however, that the CME Copper future does not represent the whole futures market, as the LME future has equal or larger volume over the period.

4.1 Index Trader Positions

The first source of retail investor flow we examine is the weekly change in positions of index traders in corn and wheat identified in by the CTFC. Unlike our other two sources of retail flow, these data allow us to directly observe the futures holdings of funds trading on the behalf of retail investors. We therefore know that these investors are trading in the futures market. However, we cannot identify traders in our high frequency data, so we will investigate whether or not we can associate changes in index trader positions with changes in aggregate order flow, and whether or not this order flow is concentrated at any point of the day. We also want to investigate whether this buying is associated with returns. To this end, we will estimate regressions of the form

$$FuturesImbalance_t = \alpha + \beta \, \Delta Index\ Positions_t$$

$$FuturesReturn_t = \alpha + \beta \, \Delta \, \overline{Index\ Positions_t}$$

When performing regressions of imbalance, we regress weekly imbalance on the total change in index trader positions measured in contracts. Therefore, the slope coefficient can be interpreted as the percentage of the change in index trader position reflected in abnormal trade imbalance. For the return regressions, we standardize the index flow so it has a standard deviation of one, so that the slope can be interpreted as the weekly return impact of a one standard deviation change in index trade positions. The overbar denotes this standardized variable.

The index trader positions are available weekly, so we sum the dependent variable across the trading days in a week to create each observation. We are still interested in intraday patterns however, so we also estimate our regressions use various portions of the trading day (aggregated across days in the week) as our dependent variable. Table 6 shows the results.

Columns (1) and (4) of both panels show the full day's returns and imbalance summed across the week. The coefficients of 0.309 for corn and 0.489 in column (1) for wheat indicate that we are picking up approximately 31% and 49% of the total changes in positions of index traders as imbalance. However, looking at column (4), we see that the relation to returns, while positive, is not statistically significant at the 5% level.

For both wheat and corn, the results are particularly strong in the minutes prior to the daily futures settlement. Column (2) shows that in the 30 minutes prior to settlement we see imbalance equal to approximately 28% and 24% of the total change in index positions for corn and wheat respectively. Column (5) shows that these imbalances are translating into a return impact. A one standard deviation increase in index traders' positions is translating into a 13.5 basis point price increase across the weak over these minutes for corn, and a 45.4 basis point increase for wheat. Columns (3) and (6) show that a large portion of this impact is concentrated in the single minute prior to settlement. All of the results near the settlement have strong statistical significance.

To visualize these patterns, Figure 6 plots the regression slopes from expanding windows of cumulative returns and trading imbalance across the trading day, and Figure 7 repeats this exercise using the 30 minutes prior to settlement.

Panel A of Figure 6 shows slope estimates where the dependent variable is the cumulative return up to each minute in the trading day. For example, the 12:00 PM point on the plot shows the estimated slope and 95% confidence interval for a regression where the dependent variable is the cumulative return (including the overnight return from the previous days settlement at 2:15 PM) through 12:00 PM, summed across the days of the week. The plot ends at the settlement time, and excludes the 11-month period beginning in May of 2012 when the settlement was delayed until 3:00 PM.

Figure 6 shows positive return and imbalance association with increases in index fund traders slowly increases across the day, and then spikes at the closing minute. The confidence intervals show that the result is not statistically significant for return until the settlement minute is included, and even then the result is only marginally significant when excluding the period of delayed settlement. Including this period leads to the results in Table 6 where the full day return impacts are not significant. However, the relation with imbalance is strongly significant.

Figure 7 focuses on the 30 minutes prior to the daily settlement (here we include the period when the settlement was delayed). Again the plots show regression coefficients for expanding windows. So for the 15-minute point on the plot, the dependent variable is the cumulative return from 30 minutes before to 15 minutes before the daily settle, summed across the days in the week. Here we see a much stronger statistical relation for both imbalance and returns, and again the large spike is evident at the closing minute.

These results suggest that index traders are taking positions prior to the close. This potentially allows them to reduce tracking error if the fund is targeting daily changes in price, and also reduces the impact of trades. However, there does seem to be an impact, and looking at Figure 6, the lack of negative overnight return suggests that this impact is not reversing over short horizons. However, the insignificance of the full day return suggests that we do not have enough statistical power to rule out that these returns are in fact reversing over longer horizons.

To understand the economic magnitude of the return impacts prior to the close, one can look first at the R-squared values in the return regressions of Table 6. The R-squared in column (5) shows that this return impact explains roughly 5% and 9% of the price variation in the 30 minutes prior to close for corn and wheat respectively. Although the coefficients are similar in column (4), the R-squared falls to less than 1% when considering the full weeks return, suggesting that index funds are not contributing a large portion of the weekly variance in futures prices.

Despite the fact that these returns do not contribute significantly to the overall variance of prices, it is possible that cumulatively they could add up to larger distortions in the level of price. To illustrate this, Figure 8 plots cumulative changes in the positions of index traders and estimated impacts. For this analysis, we use the return impact coefficient from the 30 minutes prior to settlement in Table 6, and assume that there is no reversal. This should therefore be viewed as an upper bound on the overall impact.

Panels A and B of Figure 8 show the positions of index traders in corn and wheat respectively over our sample. There are some large changes over the period. For both corn and wheat the positions fall by roughly 40% over 2008, while full rebounding to above previous levels in 2010. As shown in Panels C and D, these large changes in positions, when multiplied by our impact estimates, would lead to price impacts of roughly 6% for corn and 8% for wheat. Panel E and Panel F plot observed prices of corn and wheat, and the but-for price in the absence of the observed impacts. Note that this is not intended to be a true measure of a "fundamental" price, as we do not include changes in prices prior to 2007 due to the fact we do not have the data to estimate price impacts over this period. Instead, this is to illustrate that these changes, while potentially economically meaningful in level, are again small compared to the overall volatility in corn and wheat.

4.2 Retail Traders in the United States Oil Fund

Having established that index traders in agricultural futures appear to trade around the settlement of futures, and that this trading does seem to create price impacts, we now turn to a retail trading in the United States Oil Fund. As shown by Table 5 and Figure 5, this flow is quite small relative to the size of the WTI futures market. Therefore, we might expect to see little or no impact of these trades in futures markets, and we will see that this is the case. More interestingly, our results will show a strong response of this flow to prices, and demonstrate how aggregating data up to lower frequencies can lead to misleading results when running regressions of return on retail flow.

As mentioned above, we identify retail trades and imbalances using the procedure suggested by Boehmer, Jones, and Zhang (2017). Specifically, any trade that is reported through the FINRA TRF (TAQ market code="D") with a trade price that is not in whole cents per share and not near a half cent (which may be midpoint trades from dark pools) is assumed to be a retail trade sent to an internalizing broker. Price improvements are generally small, so a trade with a price below the nearest full cent is assumed to be a retail buy order and a trade with a price above the nearest full cent is assumed to be a retail sell order. Note that, at best, this procedure identifies only the subset of retail trades that are sent through internalizing brokers.

As a first test, we perform the following regressions similar to those in Table 6 :

$$FuturesImbalance_t = \alpha + \beta \; USO\ Retail\ Imbalance_t$$

$$FuturesReturn_t = \alpha + \beta \; \overline{USO\ Retail\ Imbalance_t}$$

Here WTI futures imbalance and USO retail imbalance are measured in millions of dollars. We aggregate USO retail imbalance up to the trading day, and consider the impacts of this daily retail imbalance on futures imbalance and return at various times in the trading day. The overbar again represents a standardization so that the standard deviation is equal to one. Table 7 shows the results.

Column (1) shows the regression of the full day's WTI imbalance on the same day retail imbalance, while column (4) repeats this regression with the full day's WTI returns as the dependent variable. Column (1) shows no significant relation with imbalance, while Column (4) shows the puzzling result that on days when retail investors are buying, prices tend to be falling. We see similar negative patterns in the 30 minutes prior to settle, with no significant result in the settlement minute itself. The most plausible interpretation of these results is that retail investors are responding to changes in the futures return, and we will show that this is indeed the case.

In order to see if past futures returns are driving imbalance, we estimate regressions in the spirit of the VAR approach of Hasbrouck (1991) and Hasbrouck (1995).

$$Imbalance_t = \alpha + \beta_1 \; LagFuturesReturn + \beta_2 \; LagImbalance$$

$$FuturesReturn_t = \alpha + \beta_o Imbalance_{\,t} + \beta_1 \; LagWTIReturn + \beta_2 \; LagImbalance$$

The first regression is a predictive regression of imbalance on lag of imbalance and returns. The source of the imbalance differs across various specifications. We examine imbalance in WTI futures, imbalance from all USO investors, and imbalance from USO retail investors, but we always be focus on returns in the futures market. Hasbrouck (1995) emphasizes that high-frequency data is needed to correctly assign impact, so as to avoid classifying trading imbalance that responds to prices as having a causal impact. Therefore we change the time horizon to see how the inference changes at different frequencies. Table 8 presents results for these regressions at both the daily and one-minute frequency over the full sample.

Panel A shows the results at the daily frequency. In columns (2) and (4) we see that for both WTI Imbalance and full USO Imbalance there is a positive relation between imbalance and WTI futures. What is interesting is that the impact of imbalance in the USO is roughly eight times as large as that in the WTI, but the R-squared is much lower. The low R-squared for USO imbalance suggests that this is not price discovery, but more likely the result of arbitrage activity in the USO. In column (6) we see again the negative relation between USO retail imbalance and WTI futures returns, but column (5) suggests a reason, namely that USO retail investors are contrarian. The previous days return to futures negatively predicts USO retail investment, suggesting that USO Retail investors are contrarian at daily frequencies.

Panel B repeats these regressions at the one-minute frequency, with the lagged imbalance and returns representing the sum over the previous five minutes. The results are largely the same, except that in column (6) we see that USO retail imbalance has a marginally positive relation with WTI futures. Note that this reaction is the same in magnitude as trade in the futures market. It is therefore possible that retail trades do move prices, but that the retail trades in the USO simply aren't numerous enough to create a perceptible impact. To see if this is the case, we now move to a higher frequency.

Unfortunately the length of our sample makes analyzing one-second data for the whole sample somewhat difficult. We therefore focus on a period when we know new information reaching the market. To do this, we collect data in the 20-minute window centered on 10:30 AM Wednesday release of the Weekly Petroleum Status Report by the Energy Information Association. This closely watched report contains information on U.S. inventories, and Halova, Kurov, and Kucher (2014) show that the inventory surprise creates significant movement in prices on release.

Table 9 repeats the regressions of Table 8, with Panel A corresponding to the same one-minute specification as Panel B in Table 8, except restricted to the 20 minutes around announcements. In these periods we see that the positive relation between USO Retail imbalance and WTI returns is strongly significant and larger than the impact of WTI imbalance at one-minute horizons. However, when we move to the one-second frequency in Panel B, this positive relation completely disappears, again suggesting that USO investors are reacting to futures returns and not the other way round.

To further emphasize this, we focus further on the minute following inventory announcements. Following Halova, Kurov, and Kucher (2014), we compare inventory announcements to the median forecast from Bloomberg. We group days with positive or negative inventory surprises, and examine returns and imbalances in the minute following the announcement. Figure 9 shows the results. Panel A shows, consistent with the finding of Halova, Kurov, and Kucher (2014), that announcements of low inventory lead to positive returns. This is also associated with nearly instantaneous buying in WTI futures and the USO. However, for retail investors in the USO the pattern is quite different. They respond asymmetrically over the minute after the announcement, and buy towards the end of the minute on price increasing announcements, but show no buying or selling on price decreases.

Overall these results suggest that the correlations between futures returns and retail investment in the USO are an artifact of aggregating up to lower frequencies the endogenous response of retail investors to returns. Notably this response may be asymmetric and may change sign depending on the horizon.

4.3 Commodity-Linked Notes

HPW find that days with the issuance of Commodity-Linked Notes generally have positive returns. They attribute this to the price impact of hedging trades made in the futures market. These notes take different forms, but they typically consist of a bond with payments linked to the change in the price of a commodity. The price change is usually measured as the change in the futures settlement price on an initial “pricing day” to a final “measurement day” near the maturity of the note. Therefore, these types of notes create exposure to the underlying commodity starting at the daily settlement on the pricing day, so this is where we would expect to see the hedging trades and their associated price impact. However, when we examine these notes, we find no abnormal trading activity in the futures market. Moreover, although we find average price impacts similar to those from HPW, we see that most of the price impact occurs earlier in the trading day, and none of the impact occurs near the settlement. Finally, we show that these notes are very small in relation to the return impact they generate, and therefore it seems a more likely case that either demand or supply of the notes is reacting to commodity returns rather than the hedging trades creating a price impact.

To test for the impacts of CLNs we follow we follow HPW and exclude notes issued during the “Goldman Roll” described by Mou (2013), which occurs from the fifth to the ninth trading day of each month. This leaves us with 169 CLNs from our original set of 200.[4] We also follow their analysis and rely on observing average returns and imbalances on the pricing days of CLNs rather than relying on regressions.

Table 10 shows the average returns and imbalances on CLN pricing days. Column (1) of Panel A confirms the main result of HPW We find that on pricing days of CLNs, there is on average a 30 basis point positive return to the underlying commodity. However, as

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[4] Including the remaining notes reduces the magnitudes of the return effect, but does not change the results’ implications.

columns (2) and (3) show, most of this return occurs in the first part of the trading day. By 10:30 AM, which is the earliest time when all of our commodities are on the floor, we see that the overnight return from the previous settlement is already 17 basis points, which is more than half of the total effect. By 1:00 PM, when the first contracts (copper) settle, 29 of the 30 basis point return has been realized. Moreover, as columns (4) and (5) show, there is no return impact on or before the settlement minute, in contrast with the findings for index investors in corn and wheat. Panel B shows that there is no evidence these abnormal returns are driven by trade flows in the futures market. Figure 10 shows these results graphically. Panel A shows that the return is already significant on the open of the market, and that the full effect has been realized prior to any of the commodities closing. Panel B shows the lack of trade imbalance effect, and Panel's C and D show the absence of any significant effect around the futures settlement.

To see if we should anticipate these notes creating a price impact through their hedging trades, we use our estimates from Table 4 to see what type of return impact we would expect if the notes were hedged in the minute prior to settlement. To approximate the size of the hedging trade, we use the notional of the note. Table 11 shows this calculation. Using our estimates of impact we calculate that for these 169 notes, we would expect so see on average an impact of approximately 5 basis points rather than the 30 basis points observed. We note again that this is quite conservative, as HPW find this magnitude of impact even including smaller notes (average of approx $10 mil), and this is assuming that the trades are put on in a very naive way. Put simply, these notes appear to be too small to generate this type of impact.

While these notes on average are small, there is the possibility that some of the large outlier notes are driving the results. Figure 11 plots the notional of each note, scaled by the futures volume, against its pricing day return. We find that larger notes do not seem to have larger impacts on prices, and in fact for most commodities the relation is slighly negative. This finding again suggests that the decision to issue the note is related to the days return, rather than hedging trades impacting the futures price.

5 Conclusion

In this paper we construct trade imbalances for six major commodity futures markets. We find that order flows in these futures markets play a large role in price discovery. We also document substantial intraday variation in price impacts, with high volumes and low price impact around futures settlements.

We use our findings on trade impacts to examine the potential impacts of retail investors in this market. We examine the impact from changing positions in index-fund investment for corn and wheat futures from the CFTC. We find strong evidence for trade imbalances and price impacts associated with these flows, concentrated in the minute prior to the daily futures settlement.

We also examine retail order flows to the United States Oil Fund and find that these flows appear to correlate with prices at daily and one-minute frequencies, but that this correlation disappears at one-second frequencies. This pattern appears to be driven by the response of these retail investors to price changes in futures markets.

Finally, we find that the positive returns associated with the issuance Commodity-Linked Notes are quite large relative to their size, occur primarily early in the trading day, and are not associated with abnormal trade imbalance. These findings suggest that the positive returns are potentially the result of CLN issuers or purchases favouring days with increasing commodity prices, rather than evidence of impacts from associated hedging trades.

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Table 1: Daily WTI futures volumes for June 2013

The table shows volume for the days June of 2013 (in thousands of contracts) of the July 2013 and August 2013 delivery futures contracts.

	July 2013 Contract			August 2013 Contract			All other contracts		
	Globex			Globex			Globex		
Trade Date	Single Month	Cal. Spread	Floor	Single Month	Cal. Spread	Floor	Single Month	Cal. Spread	Floor
20130603	214.2	55.4	2.0	13.6	61.2	4.1	15.9	235.8	17.2
20130604	226.7	56.7	8.4	13.2	58.5	7.5	18.2	269.1	37.3
20130605	189.4	56.7	12.3	11.7	40.5	3.0	13.2	219.7	23.0
20130606	178.4	68.3	5.8	15.3	71.7	3.6	21.8	277.4	20.6
20130607	219.4	75.3	17.8	19.2	76.6	9.4	31.4	366.1	26.4
20130610	124.9	67.9	18.1	14.7	69.6	10.7	12.3	214.5	25.1
20130611	174.0	59.4	6.7	23.5	57.7	5.7	14.7	191.0	20.6
20130612	170.0	53.1	9.2	26.7	71.4	9.3	14.3	177.1	6.2
20130613	144.6	57.7	8.3	38.7	61.6	6.0	18.0	186.5	18.7
20130614	161.8	51.1	14.3	48.8	66.5	5.3	42.4	307.5	34.0
20130617	150.1	71.7	7.0	54.0	78.7	6.7	26.2	186.5	21.1
20130618	81.9	50.6	6.7	65.7	75.5	4.9	15.3	191.9	12.1
20130619	31.7	45.8	11.3	144.8	92.1	4.0	26.9	271.1	15.8
20130620	7.1	13.9	0.1	282.9	81.5	3.3	45.5	343.9	19.0
20130621	-	-	-	267.4	52.6	-	93.6	261.7	-
20130624	-	-	-	223.9	75.5	4.9	39.5	336.2	31.4
20130625	-	-	-	176.4	78.9	5.1	29.5	445.8	43.6
20130626	-	-	-	221.1	59.4	1.7	33.0	255.7	12.2
20130627	-	-	-	188.4	67.5	2.4	33.5	255.3	16.0
20130628	-	-	-	177.4	52.7	1.8	36.1	257.4	18.5

Table 2: Summary Data for Near Month Futures by Minute

The table shows means and standard deviations for minute-by-minute returns, trading volume, and signed trading volume (imbalance). Statistics for volume and imbalance are reported in both number of contracts and millions of dollars of notional value. The sample is January 1st, 2018 to April 1st 2014 for Brent Crude, and January 1st, 2017 to April 1st 2014, for all other commodities. The settlement minute for WTI is the minute prior to daily settlement of the active month.

CME WTI Crude Oil (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	38,852	-2.0	33.8	-0.2
St. Dev.	0.09	46,926	172.2	42.7	15.2
# of Min			920,396		

CME WTI Crude Oil (Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	-0.01	220,622	-51.4	191.5	-4.2
St. Dev.	0.11	89,670	418.2	89.1	36.6
# of Min				1,822	

ICE Brent Crude Oil (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	29,211	1.2	28.4	0.1
St. Dev.	0.08	44,411	217.9	46.2	21.8
# of Min			796,869		

ICE Brent Crude Oil (WTI Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	-0.01	75,549	-2.7	74.6	-0.3
St. Dev.	0.11	58,834	231.3	66.5	24.1
# of Min				1,560	

CME Gold (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	20,654	-1.5	24.8	-0.2
St. Dev.	0.05	146,112	125.6	180.2	15.4
# of Min			934,832		

CME Gold (Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	66,494	18.0	83.3	2.0
St. Dev.	0.06	42,180	189.5	63.4	23.9
# of Min				1,825	

CME Copper (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	4,687	-0.2	3.4	0.0
St. Dev.	0.09	36,122	35.9	27.3	2.8
# of Min			891,977		

CME Copper (Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	32,386	10.2	23.2	0.7
St. Dev.	0.12	27,388	116.9	24.5	9.2
# of Min				1,867	

CBOT Corn (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	30,588	-7.1	8.7	-0.2
St. Dev.	0.12	63,963	262.1	17.6	7.3
# of Min			514,404		

CBOT Corn (Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.01	434,837	119.7	120.2	4.3
St. Dev.	0.25	298,308	1,030.5	96.6	29.9
# of Min				1,810	

CBOT Wheat (All Minutes)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	0.00	13,012	-2.7	4.7	-0.1
St. Dev.	0.15	29,807	108.3	9.7	3.9
# of Min			487,299		

CBOT Wheat (Settlement Minute)	Ret. (%)	Vol. (# Contracts)	Imb. (# Contracts)	Vol. (Mil $)	Imb. (Mil $)
Mean	-0.04	214,641	-60.8	74.5	-1.9
St. Dev.	0.36	167,621	583.6	64.3	20.8
# of Min				1,808	

Table 3: Full Sample Price Impact VARs

The table shows the results from vector autoregressions of the form described in equation (1) in the text. The R_w^2 shown in the final row is the percentage of variation in returns explained by unexpected innovations in order flow, calculated from a vector moving average representation of the VAR. Return is measured in percent, while imbalance is measured in 100s of contracts.

	WTI Crude		Brent Crude		Gold		Copper		Corn		Wheat	
	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance
Imb. (t)	0.032***		0.032***		0.032***		0.098***		0.020***		0.053***	
	[782.300]		[378.648]		[772.039]		[447.557]		[402.498]		[312.588]	
Imb (t-1)	-0.003***	0.088***	-0.004***	0.126***	-0.002***	0.065***	-0.006***	0.079***	-0.000	0.104***	-0.001***	0.085***
	[-62.293]	[65.726]	[-40.125]	[103.079]	[-39.762]	[52.981]	[-23.049]	[70.137]	[-0.386]	[65.756]	[-6.365]	[53.927]
Imb (t-2)	-0.001***	0.029***	-0.002***	0.048***	-0.001***	0.034***	-0.005***	0.040***	-0.001***	0.051***	-0.002***	0.038***
	[-25.054]	[21.482]	[-19.514]	[39.231]	[-20.500]	[27.696]	[-19.333]	[35.715]	[-14.671]	[31.946]	[-9.278]	[23.248]
Imb (t-3)	-0.001***	0.029***	-0.002***	0.043***	-0.000***	0.011***	-0.002***	0.019***	-0.001***	0.035***	-0.002***	0.027***
	[-22.489]	[22.264]	[-19.367]	[37.712]	[-11.030]	[12.257]	[-10.881]	[21.983]	[-16.023]	[23.184]	[-8.237]	[16.871]
Ret (t-1)	-0.058***	1.699***	-0.039***	0.484***	-0.060***	1.825***	-0.036***	0.167***	-0.110***	1.500***	-0.063***	0.295***
	[-55.861]	[64.821]	[-33.764]	[31.407]	[-61.457]	[78.042]	[-34.596]	[34.532]	[-81.796]	[39.598]	[-43.864]	[24.406]
Ret (t-2)	-0.015***	0.457***	-0.014***	0.150***	-0.024***	0.615***	-0.002	0.073***	-0.028***	0.473***	-0.020***	0.107***
	[-13.932]	[17.392]	[-12.555]	[9.731]	[-24.780]	[26.269]	[-1.487]	[15.193]	[-20.617]	[12.494]	[-13.145]	[8.281]
Ret (t-3)	-0.007***	0.123***	-0.004***	0.019**	-0.010***	0.251***	-0.001	0.017***	-0.013***	0.129***	-0.011***	0.028**
	[-6.896]	[4.728]	[-6.439]	[2.324]	[-12.224]	[12.372]	[-0.651]	[4.396]	[-11.165]	[3.905]	[-7.432]	[2.238]
Cons	0.001***	-0.017***	0.000	-0.004***	0.000***	-0.010***	0.000***	-0.001***	0.001***	-0.058***	0.001***	-0.022***
	[7.329]	[-9.424]	[0.190]	[-3.234]	[9.683]	[-11.808]	[4.680]	[-3.684]	[10.188]	[-15.944]	[5.246]	[-15.174]
Obs	924,383	924,383	795,580	795,580	1,046,882	1,046,882	943,241	943,241	511,861	511,861	480,168	480,168
R^2	0.399	0.030	0.153	0.029	0.363	0.026	0.175	0.015	0.245	0.030	0.171	0.016
R^2_w	0.382		0.135		0.314		0.161		0.228		0.161	

T-stats in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Univariate Price Impact Regressions

The table shows the results from univariate regressions of one-minute returns on one-minute imbalances for each of the six commodities. Return is measured in percentage and imbalance is measured in millions of dollars. The left column for each commodity shows the results using all minutes in the sample, while the right columns shows results using only returns and imbalances in the settlement minute for each day. Standard errors are shown in parentheses and T-statistics are shown in brackets. The sample is 1/1/2007 to 4/1/2014. We exclude data prior to 2008 for Brent.

	WTI Crude		Brent Crude		Gold	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imb.	0.0033***	0.0012***	0.0028***	0.0010***	0.0022***	0.0012***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
	[279.5]	[19.3]	[155.1]	[13.3]	[99.8]	[11.1]
Cons	0.001***	0.000	0.000	-0.005**	0.000***	-0.000
	(0.0001)	(0.0022)	(0.0001)	(0.0026)	(0.0000)	(0.0013)
	[7.3]	[0.0]	[0.5]	[-2.0]	[8.9]	[-0.2]
Obs	926,570	1,813	790,606	1,559	926,426	1,825
R_sq	0.340	0.180	0.125	0.055	0.305	0.224

	Copper		Corn		Wheat	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imb.	0.0113***	0.0042***	0.0064***	0.0045***	0.0143***	0.0086***
	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0005)	(0.0008)
	[112.7]	[12.3]	[35.4]	[19.1]	[30.5]	[11.1]
Cons	0.000***	-0.002	0.001***	-0.007	0.001***	-0.019**
	(0.0001)	(0.0026)	(0.0001)	(0.0050)	(0.0002)	(0.0076)
	[5.3]	[-0.9]	[8.1]	[-1.3]	[5.4]	[-2.5]
Obs	902,187	1,867	517,009	1,810	493,377	1,808
R_sq	0.147	0.113	0.188	0.297	0.148	0.254

Robust standard errors in parentheses, t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Summary Statistics for Sources of Retail Investor Flow

The table shows summary statistics for weekly changes in position of commodity index traders from the CFTC, daily USO imbalance from all investors and retail investors identified using the algorithm of Boehmer, Jones, and Zhang (2017), and CLNs collected from the SEC's Edgar Database. The sample is 1/1/2007 to 4/1/2014. All summary statistics are in Millions of $

Panel A: Changes in Positions of Commodity Index Traders

Commodity	Number of Weeks	(Millions of $) Mean	Std. Dev.	Min	Max
Corn	382	-6.8	220.3	-958.6	1306.0
Wheat	382	-7.7	140.7	-1308.6	437.1

Panel B: Trade Imbalance in USO

Investor Type	Number	(Millions of $) Mean	Std. Dev.	Min	Max
By Minute					
All	663,630	0.0	1.2	-75.6	204.8
Retail	663,630	0.0	0.2	-97.5	36.5
By Day					
All	1,824	-2.0	36.7	-359.6	373.7
Retail	1,824	0.2	6.1	-92.2	69.9

Panel C: Notional of Commodity Linked Notes

Commodity	Number of Notes	(Millions of $) Mean	Std. Dev.	Min	Max
Gold	91	33.0	23.2	10	143.2
Copper	12	42.7	46.9	10	155.5
WTI	39	27.9	17.7	10	75.9
Brent	38	23.7	19.4	10	103.8
Corn	20	28.8	20.8	10.5	81.6

Table 6: Regressions of Return and Imbalance on Index Trader Flows

The table shows the results from the regression of weekly imbalance and changes in the positions in index traders. For the imbalance regressions (columns (1) – (3)), futures imbalance and changes in index trader positions are measured in number of contracts. For the return regressions (columns (4) – (6)), returns are measured in percent and changes in index positions are standardized to have a standard deviation of one. In columns (1) and (4) , the dependent variable is the imbalance or return for the entire trading day summed across the trading days in the week. For columns (2) and (5), the dependent variable is the total return or imbalance in the 30 minutes prior to futures settlement summed across the trading days in the week. In columns (3) and (6) the return and imbalance in the single settlement minute is summed across the trading days in the week. Data are 1/1/2007 to 4/1/2014.

Panel A: Changes in Corn Index Positions

	Futures Imbalance				Futures Return		
		30 Minutes	Settlement			30 Minutes	Settlement
	Full Day	Prior to Settle	Minute		Full Day	Prior to Settle	Minute
	(1)	(2)	(3)		(4)	(5)	(6)
				Standardized			
Δ Corn Index	0.309**	0.283***	0.091***	Δ Corn Index	0.361	0.135***	0.049***
Positions	[2.232]	[4.765]	[3.958]	Positions	[1.545]	[3.700]	[4.792]
Constant	-97.930***	-8.470***	3.140***	Constant	-0.233	0.073	0.104***
	[-10.006]	[-2.949]	[3.363]		[-1.119]	[1.209]	[4.758]
Obs	382	382	382	Obs	382	382	382
R-sq	0.019	0.041	0.050	R-sq	0.008	0.054	0.042

Panel B: Changes in Wheat Index Positions

	Futures Imbalance				Futures Return		
		30 Minutes	Settlement			30 Minutes	Settlement
	Full Day	Prior to Settle	Minute		Full Day	Prior to Settle	Minute
	(1)	(2)	(3)		(4)	(5)	(6)
				Standardized			
Δ Wheat Index	0.489***	0.238***	0.114***	Δ Wheat Index	0.399	0.454***	0.237***
Positions	[4.375]	[5.627]	[4.404]	Positions	[1.363]	[4.900]	[4.213]
Constant	-34.788***	-5.818***	-2.595***	Constant	-0.288	-0.263***	-0.168***
	[-9.507]	[-4.405]	[-4.067]		[-1.236]	[-3.459]	[-4.230]
Obs	382	382	382	Obs	382	382	382
R-sq	0.068	0.118	0.116	R-sq	0.008	0.089	0.089

Robust t-statistics in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regressions of Daily WTI Futures Returns on USO Order Flow

The table shows the result of regressions of WTI Futures imbalance and returns on retail imbalance in the USO. There is one observation for each trading day from 1/1/2007 to 4/1/2014.

	Futures Imbalance ($ Millions)				Futures Return (Percent)		
		30 Minutes	Settlement			30 Minutes	Settlement
	Full Day	Prior to Settle	Minute		Full Day	Prior to Settle	Minute
	(1)	(2)	(3)		(4)	(5)	(6)
USO Retail				Standardized			
Imbalance	-1.248	-2.069***	-0.089	USO Retail	-0.062***	-0.017***	0.000
($ Millions)	[-0.662]	[-2.991]	[-0.530]	Imbalance	[-9.000]	[-6.848]	[0.196]
Constant	-75.917***	11.045***	-3.837***	Constant	0.010	0.040***	-0.005**
	[-7.004]	[3.111]	[-4.858]		[0.265]	[2.763]	[-2.105]
Obs	1,824	1,824	1,824	Obs	1,824	1,824	1,824
R-sq	0.000	0.006	0.000	R-sq	0.039	0.023	0.000

Robust t-statistics in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 8: WTI Returns and USO Imbalance at different frequencies

The table examines three different sources of order flows: WTI futures trades, all USO trades, and USO trades from retail investors. Columns (1), (3) and (5) show the results of regressions of these flows on lagged WTI futures return and the lagged value of the respective order flow. Columns (2), (4) and (6) show the results of price impact regressions, where WTI futures returns are regressed on lagged WTI futures return and the current and lagged values of the respective order flow. In Panel A, lagged returns and imbalance are the sum over the previous trading day, and in Panel B they are the sum over the previous five minutes. All returns are in (%) and imbalances are in millions of dollars. Data are from 1/1/2007 to 4/1/2014.

Panel A: One-Day Frequency

Imbalance source:	WTI trades		All USO trades		USO retail trades	
	Imbalance	WTI Return	Imbalance	WTI Return	Imbalance	WTI Return
	(1)	(2)	(3)	(4)	(5)	(6)
Imbalance		0.002***		0.017***		-0.064***
		[37.131]		[8.079]		[-3.057]
Lag WTI Return	-32.884***	0.042	-1.275**	-0.030	-0.311***	-0.054
	[-4.936]	[0.784]	[-2.573]	[-0.729]	[-3.103]	[-1.374]
Lag Imbalance	0.140***	-0.000**	0.095***	0.002*	0.256***	0.005
	[4.307]	[-2.287]	[3.721]	[1.655]	[5.672]	[0.471]
R-sq	0.014	0.365	0.009	0.113	0.084	0.043
N	1,823	1,823	1,823	1,823	1,823	1,823

Panel B: One-Minute Frequency

Imbalance source:	WTI trades		All USO trades		USO retail trades	
	Imbalance	WTI Return	Imbalance	WTI Return	Imbalance	WTI Return
	(1)	(2)	(3)	(4)	(5)	(6)
Imbalance		0.003***		0.026***		0.003*
		[238.439]		[19.423]		[1.931]
Lag WTI Return	38.342***	-0.122***	2.087***	-0.066***	-0.241***	-0.020
	[21.895]	[-6.285]	[7.827]	[-3.921]	[-7.260]	[-1.244]
Lag Imbalance	0.171***	-0.001***	0.088***	-0.003***	0.060***	0.000
	[19.639]	[-16.548]	[2.803]	[-3.870]	[3.825]	[0.108]
R-sq	0.006	0.344	0.002	0.122	0.001	0.000
N	663,630	663,630	663,630	663,630	663,630	663,630

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 9: WTI Returns and USO Imbalance around Wednesday Inventory Announcements

The table examines the 20-minute window around Wednesday 10:30 AM inventory announcements, and examines three different sources of order flows: WTI futures trades, all USO trades, and USO trades from retail investors. Columns (1), (3) and (5) show the results of regressions of these flows on lagged WTI futures return and the lagged value of the respective order flow. Columns (2), (4) and (6) show the results of price impact regressions, where WTI futures returns are regressed on lagged WTI futures return and the current and lagged values of the respective order flow. In Panel A, lagged returns and imbalance are the sum over the previous five minutes, and in Panel B the previous five seconds. All returns are in (%) and imbalances are in millions of dollars. Data are from 1/1/2007 to 4/1/2014.

Panel A: One-Minute Frequency

Imbalance source:	WTI trades		All USO trades		USO retail trades	
	Imbalance	WTI Return	Imbalance	WTI Return	Imbalance	WTI Return
	(1)	(2)	(3)	(4)	(5)	(6)
Imbalance		0.005***		0.052***		0.207***
		[17.632]		[11.731]		[3.987]
Lag WTI Return	0.387	-0.058	0.184	-0.05	0.001	-0.036
	[0.089]	[-1.466]	[0.610]	[-1.529]	[0.033]	[-1.060]
Lag Imbalance	0.187**	-0.001**	0.084**	-0.002	0.324**	-0.001
	[2.405]	[-2.473]	[2.287]	[-0.602]	[2.166]	[-0.023]
R-sq	0.035	0.41	0.008	0.284	0.088	0.028
N	2,850	2,850	2,850	2,850	2,850	2,850

Panel B: One-Second Frequency

Imbalance source:	WTI trades		All USO trades		USO retail trades	
	Imbalance	WTI Return	Imbalance	WTI Return	Imbalance	WTI Return
	(1)	(2)	(3)	(4)	(5)	(6)
Imbalance		0.005***		0.030***		-0.001
		[20.451]		[11.619]		[-1.090]
Lag WTI Return	0.203	-0.011*	0.141***	-0.008*	0.004***	0.000
	[1.008]	[-1.819]	[6.564]	[-1.724]	[3.534]	[-0.052]
Lag Imbalance	0.049***	-0.000**	0.011***	0.001***	0.001***	0.001
	[11.344]	[-2.353]	[2.955]	[3.427]	[3.565]	[1.175]
R-sq	0.017	0.192	0.003	0.072	0.000	0.000
N	180,399	180,399	180,399	180,399	180,399	180,399

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Intraday Returns and Imbalances on CLN Days

The table shows the average returns and imbalances over various subperiods of the trading day for the underlying commodity on days with CLN issuance. Returns are measured in percent and imbalance in millions of dollars. Columns (1) – (3) measure return and imbalance from the previous days settlement price. We exclude notes issued during the 5th to 9th trading days of the month.

Panel A: Average Returns on CLN Days

	Full Day (1)	Prior to 10:30 AM (2)	Prior to 1:00 PM (3)	Last 30 Minutes Prior to Settle (4)	Settlement Minute (5)
Average Return	0.309*** [3.156]	0.171** [2.272]	0.289*** [3.073]	0.032 [0.896]	0.003 [0.543]
Observations	169	169	169	169	169

Panel B: Average Imbalance on CLN Days

	Full Day (1)	Prior to 10:30 AM (2)	Prior to 1:00 PM (3)	Last 30 Minutes Prior to Settle (4)	Settlement Minute (5)
Average Imbalance	-0.071 [-0.230]	-0.089 [-0.409]	-0.181 [-0.602]	0.097 [1.119]	0.006 [0.269]
Observations	169	169	169	169	169

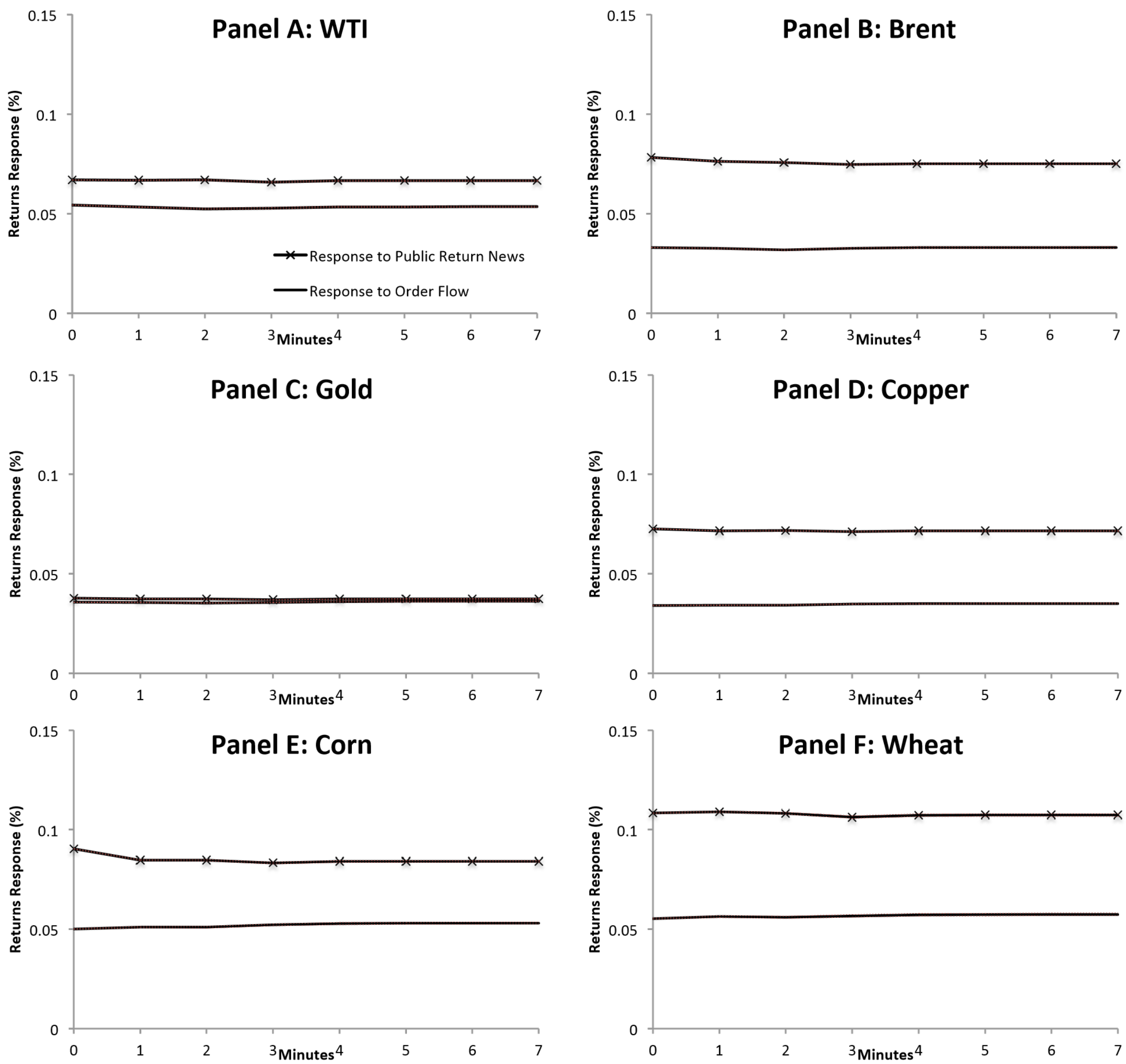
Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Daily Returns and Predicted Daily Returns around CLN Issuance

The table shows the mean notional and daily returns on days with CLN Issuance. The predicted impact is the slope from the settlement minute regression described in Table 3. The mean predicted return for each commodity is the predicted impact multiplied times the average CLN notional. The total mean predicted return is the number-of-note-weighted average of the predicted return for each commodity. We exclude notes issued during the 5th to 9th trading days of the month.

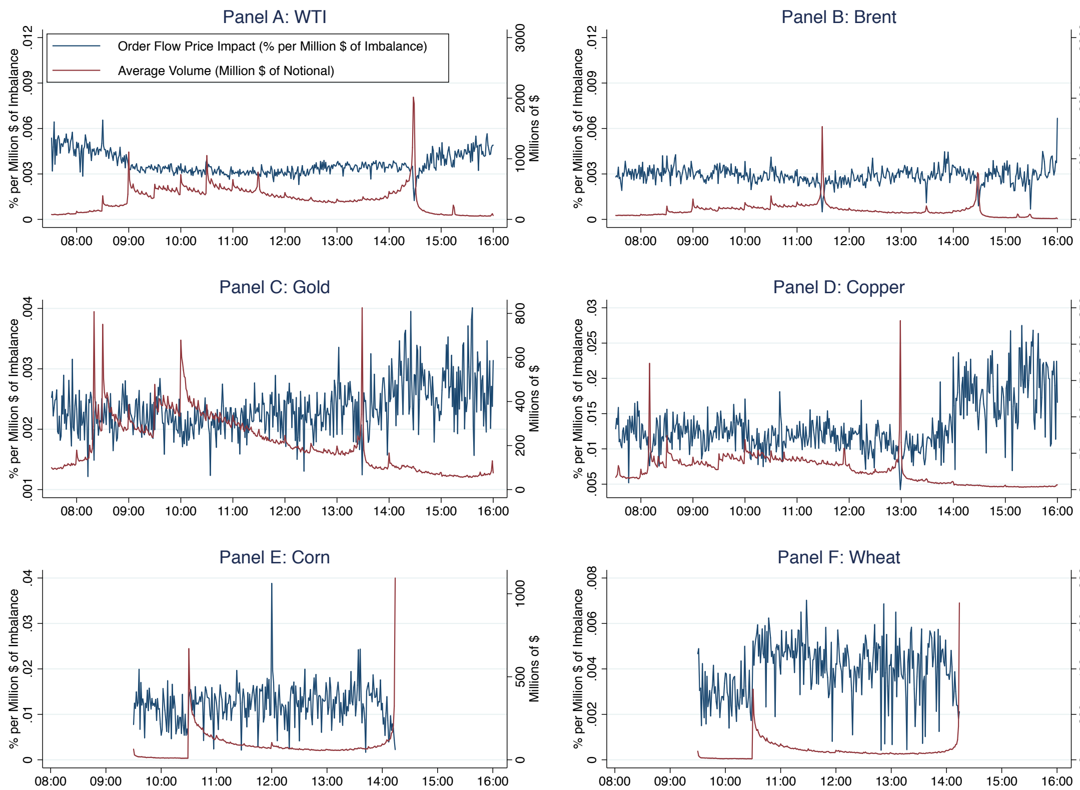
Commodity	# of Notes	Mean Notional ($ Mil)	Mean Daily Return (%)	Predicted Impact (%) /($ Mil)	Mean Predicted Return (%)
Gold	79	33.6	0.245	0.0012	0.040
Copper	11	45.6	0.721	0.0042	0.192
WTI	31	26.0	-0.159	0.0012	0.031
Brent	31	21.3	0.810	0.0010	0.021
Corn	17	26.1	0.292	0.0045	0.117
Total	169	30.4	0.309		0.053

Figure 1: Return Impulse Response Functions for VARs



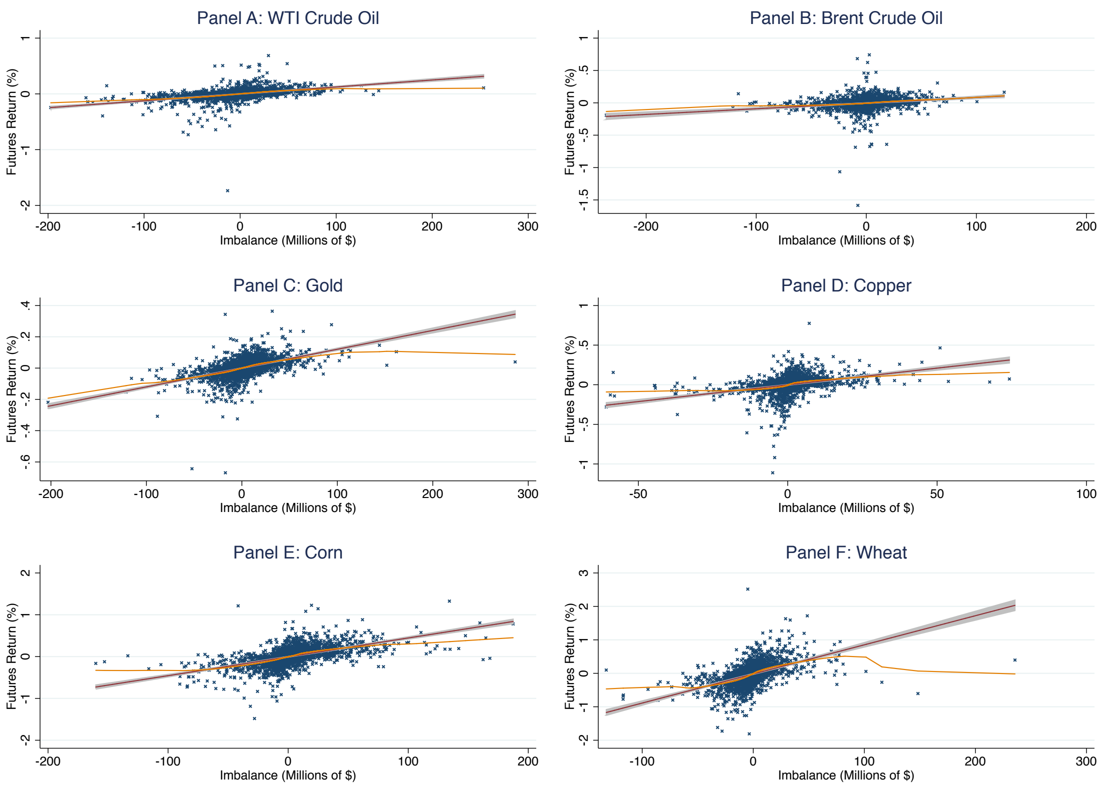
The figure shows the impulse response of returns to innovations in order flow and public news from the vector autoregression specification estimated in Table 3. Plots show return responses to one standard deviation innovations in public return news and unanticipated order flow.

Figure 2: Intraday Volume and Trade Impacts



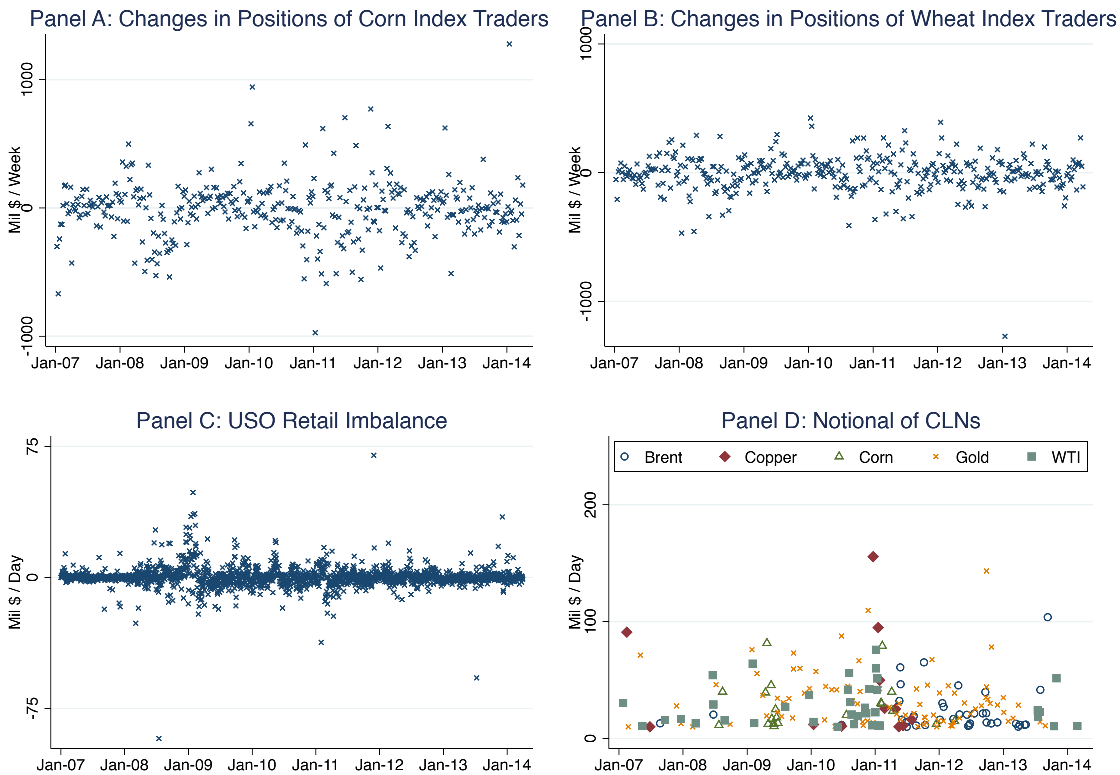
The figure shows the average intraday volume by minute for each commodity as well as the minute-by-minute trade impact. The trade impact is measured as the slope in a univariate regression of return (%) on trade imbalance (Millions of $) estimated using imbalance and returns in each minute of the day. For instance, the 12:00 average volume we calculate the total volume from 12:00:00 to 12:00:59 for each day, and take the average of this value across all trading days. Similarly, to calculate the 12:00 imbalance, we calculate the total return and imbalance from 12:00:00 to 12:00:59 for each day, and then run a univariate regression of return on imbalance for this minute across all trading days. The sample is 1/1/2007 to 4/1/2014. We exclude data prior to 1/1/2008 for Brent, and we exclude the period for Corn and Wheat in which the future settlement was delayed until 15:00 EST (5/22/2012 to 4/5/2013) .

Figure 3: Imbalance and Return in Minute Prior to Futures Settlement



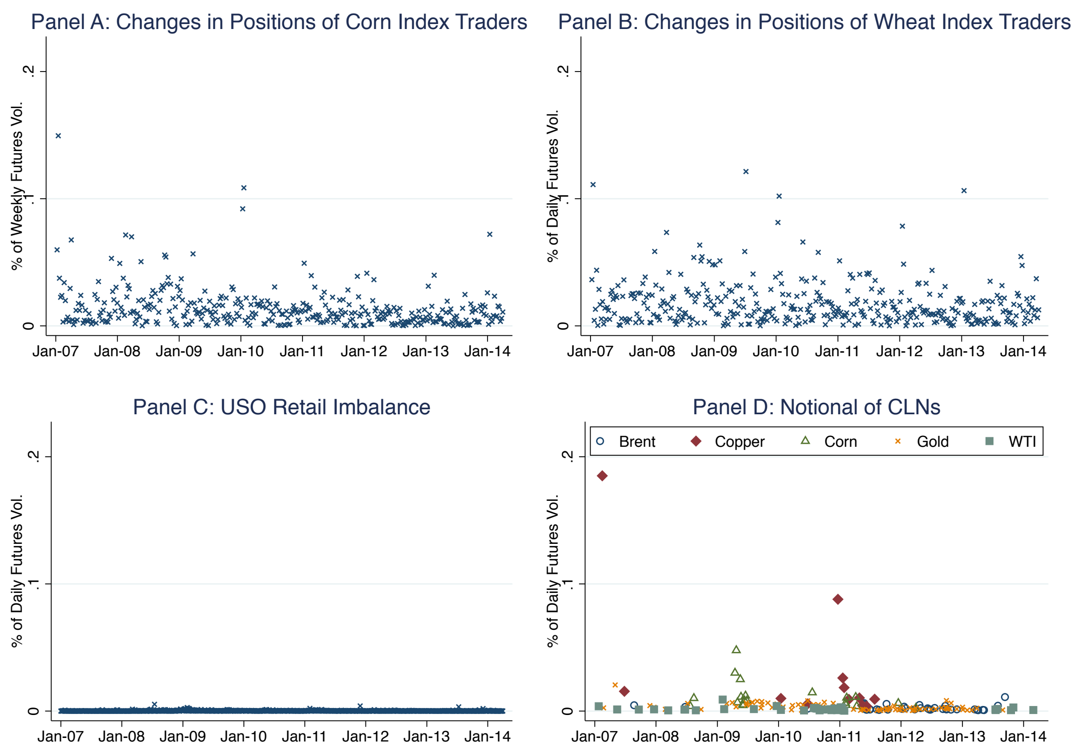
The figure shows scatter plots of order imbalance (in Millions of $) and return (in %) in the minute prior to settlement for each day across the sample. The shaded line shows linear fit and confidence interval. The single line shows a second-order LOESS smoother calculated using a tricube kernel with α=0.8. Data are 1/1/2007 to 4/1/2014. We exclude data prior to 1/1/2008 for Brent

Figure 4: Sources of Retail Investor Flow in Millions of Dollars



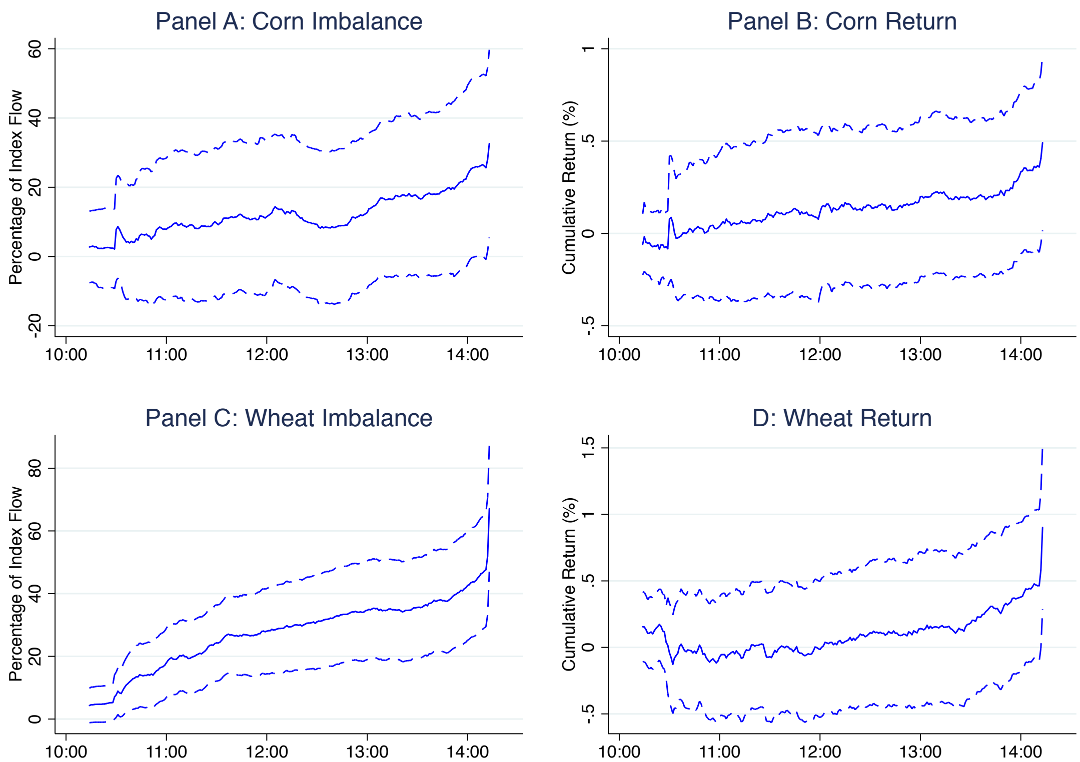
The figure shows plots of sources of retail order flow in commodity markets. Panels A and B show weekly changes in position of commodity index traders for corn and wheat from the CFTC. Panel C shows daily USO imbalance from retail investors identified using the algorithm of Boehmer, Jones, and Zhang (2017). Panel D shows notional of CLNs collected from the SEC's Edgar Database.

Figure 5: Magnitude of Retail Investor Flows as a Percentage of Volume



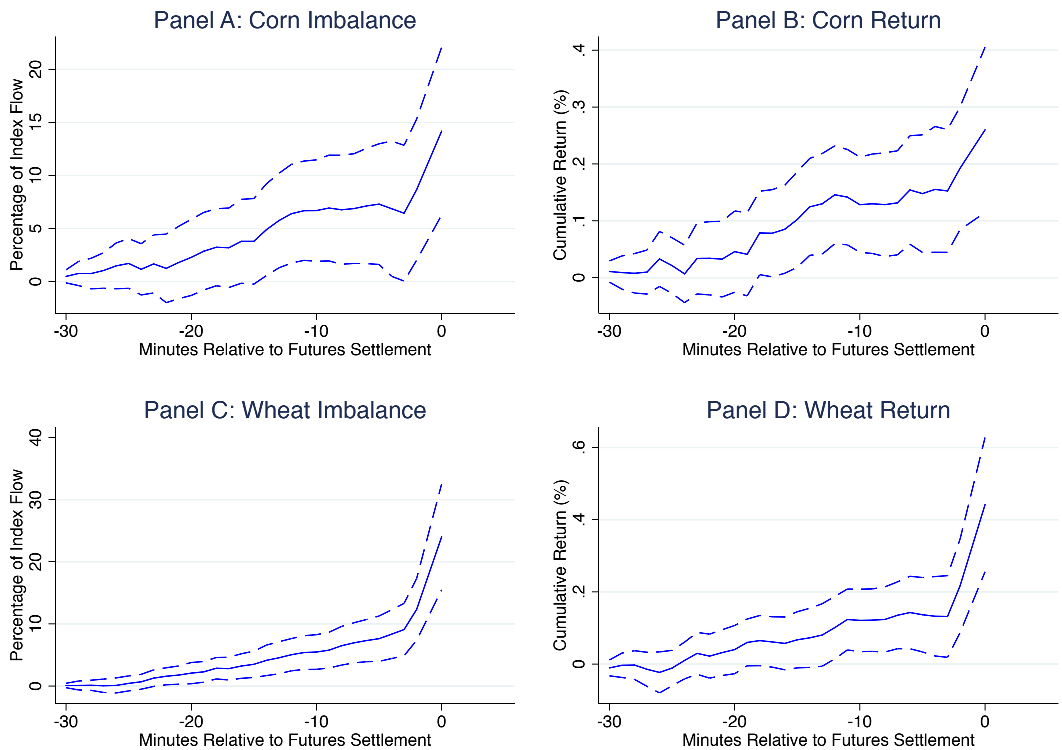
The figure shows plots of sources of retail order flow in commodity markets. Each panel shows the absolute value of the retail flow divided by volume in the corresponding futures market over the relevant period. Panels A and B show weekly changes in position of commodity index traders from the CFTC for corn and wheat relative to weekly volume in corn and wheat futures markets. Panel C shows daily USO imbalance from retail investors identified using the algorithm of Boehmer, Jones, and Zhang (2017) divided by the daily volume in WTI futures. Panel D shows notional of CLNs collected from the SEC's Edgar Database divided by the daily volume in the corresponding future.

Figure 6: Intraday Impact of Index Trader Flows



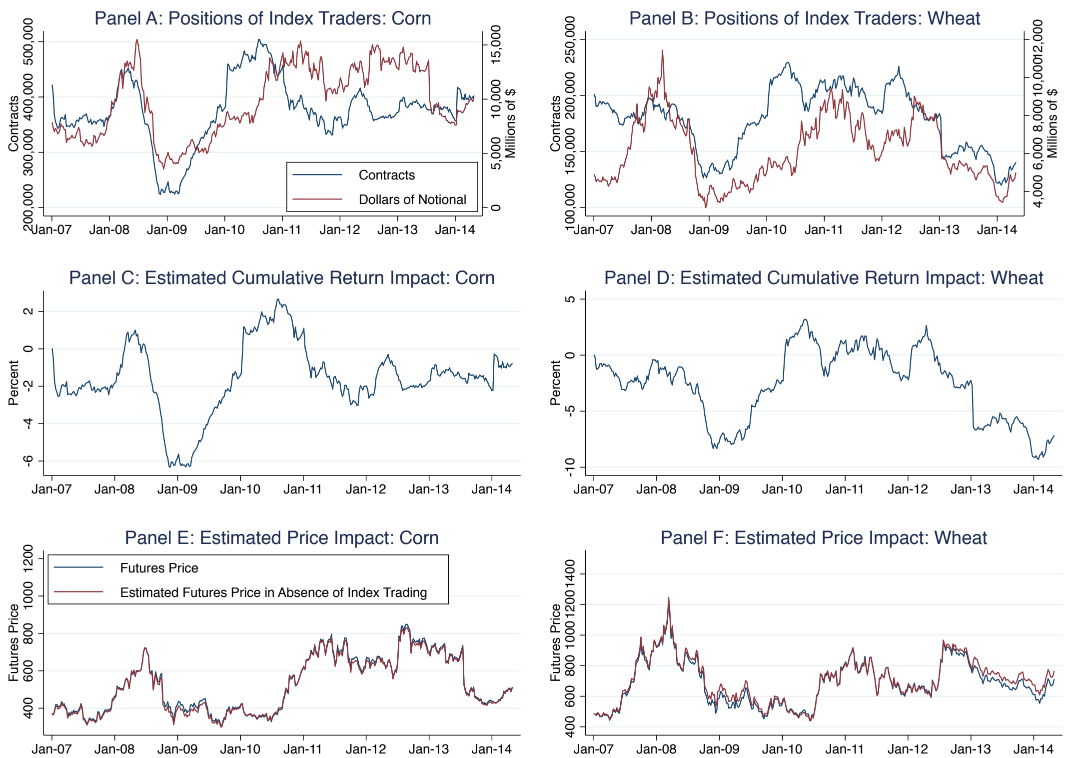
The figure plots the slope coefficient and 95% confidence interval from regressions where the dependent variables are cumulative futures returns for expanding windows across the trading day, and the independent variables are weekly changes in the positions of index traders for corn and wheat. In Panels A and C the independent and dependent variable are measured in number of contracts. In Panels B and D the dependent variable is returns in percent and the independent variable (index flows) is standardized to have a standard deviation of one. For each minute, the dependent variable is the cumulative return or imbalance measured from the previous day's settlement summed across the trading days in the week. Data are 1/1/2007 to 4/1/2014.

Figure 7: Impacts of Index Trader Flows in 30 Minutes Prior to Futures Settlement



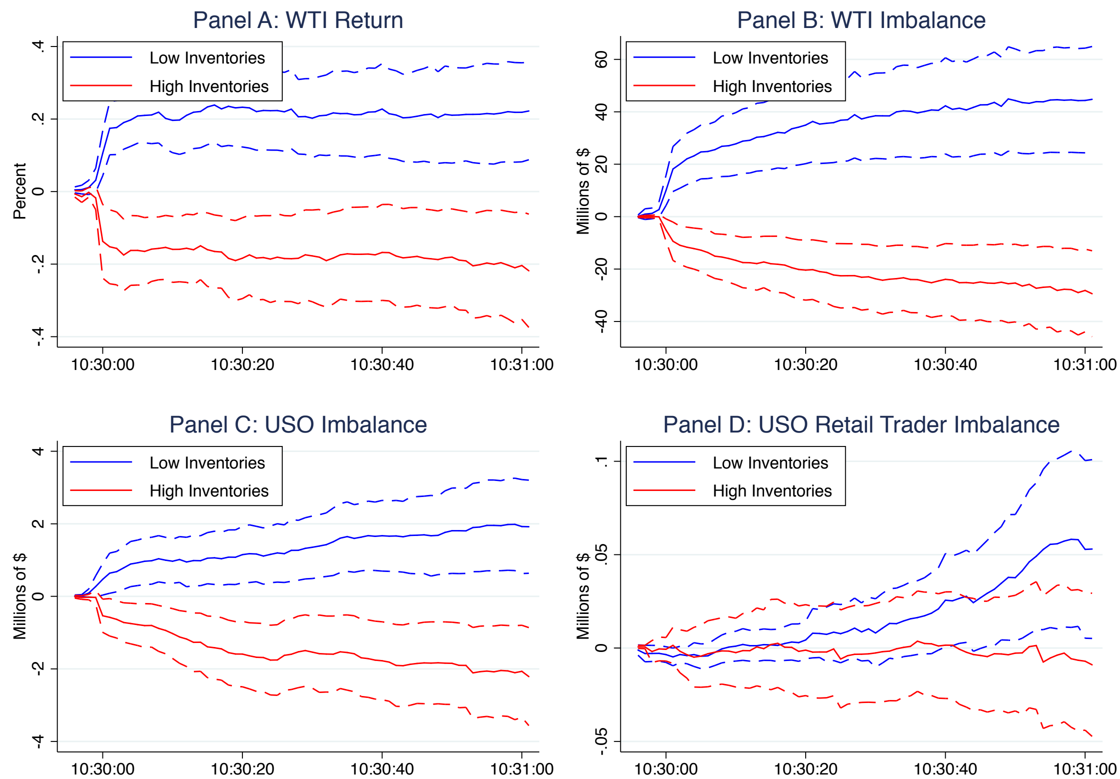
The figure plots the slope coefficient and 95% confidence interval from regressions where the dependent variables are cumulative futures returns for expanding windows across the 30 minutes prior to futures settlement and the independent variables are weekly changes in the positions of index traders for corn and wheat. In Panels A and C the independent and dependent variable are measured in number of contracts. In Panels B and D the dependent variable is returns in percent and the independent variable (index flows) is standardized to have a standard deviation of one. For each minute, the dependent variable is the cumulative return or imbalance measured from 30 minutes prior to settlement summed across the trading days in the week. Data are 1/1/2007 to 4/1/2014.

Figure 8: Estimated Cumulative Impact of Index Trader Flows



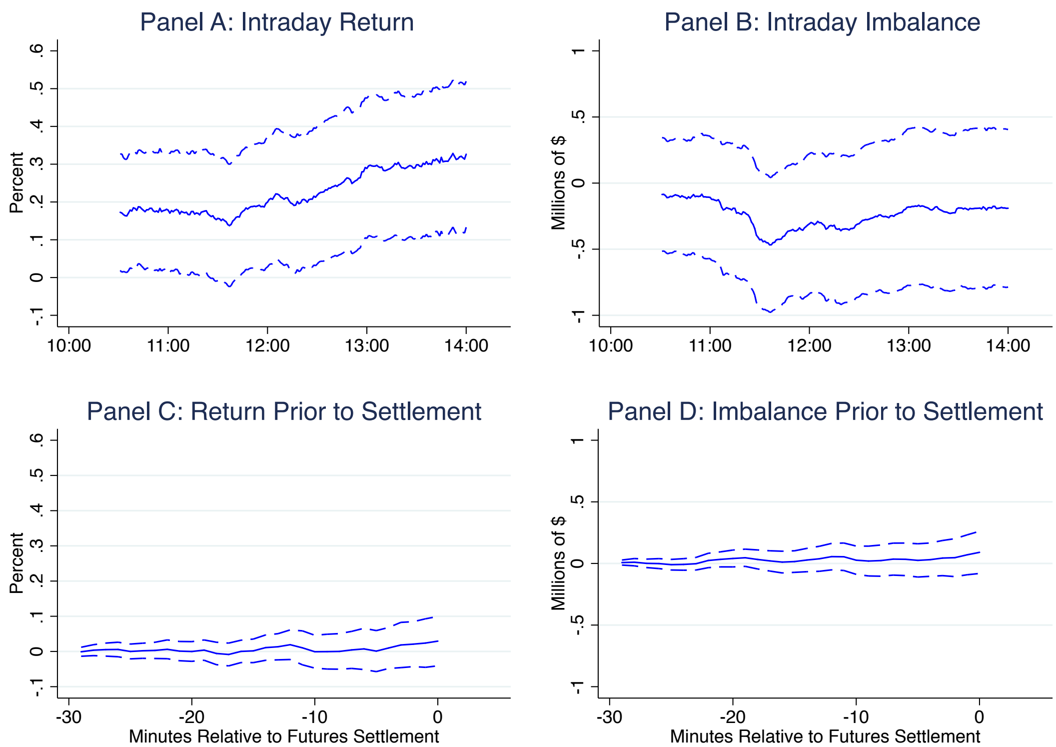
The figure shows the positions of index traders from the CFTC in corn and wheat along with the estimated imapcts of these trade flows using our estimates of price impact in the 30 minutes prior to futures mettlement.(Table 6 column (6)). Panels A and B show the positions of index traders in futures contracts and millions of dollars. Panels C and D show the cumulative estimated impact calculated by multiplying each week's standardized change in index trader positions mutliplied by the estimate of impact from Table 6. Panels E and F show the observed futures price and the futures price adjusting for the cumulative impact shown in Panels C and D.

Figure 9: Order Flows and WTI Returns around Wednesday 10:30 Inventory Announcements



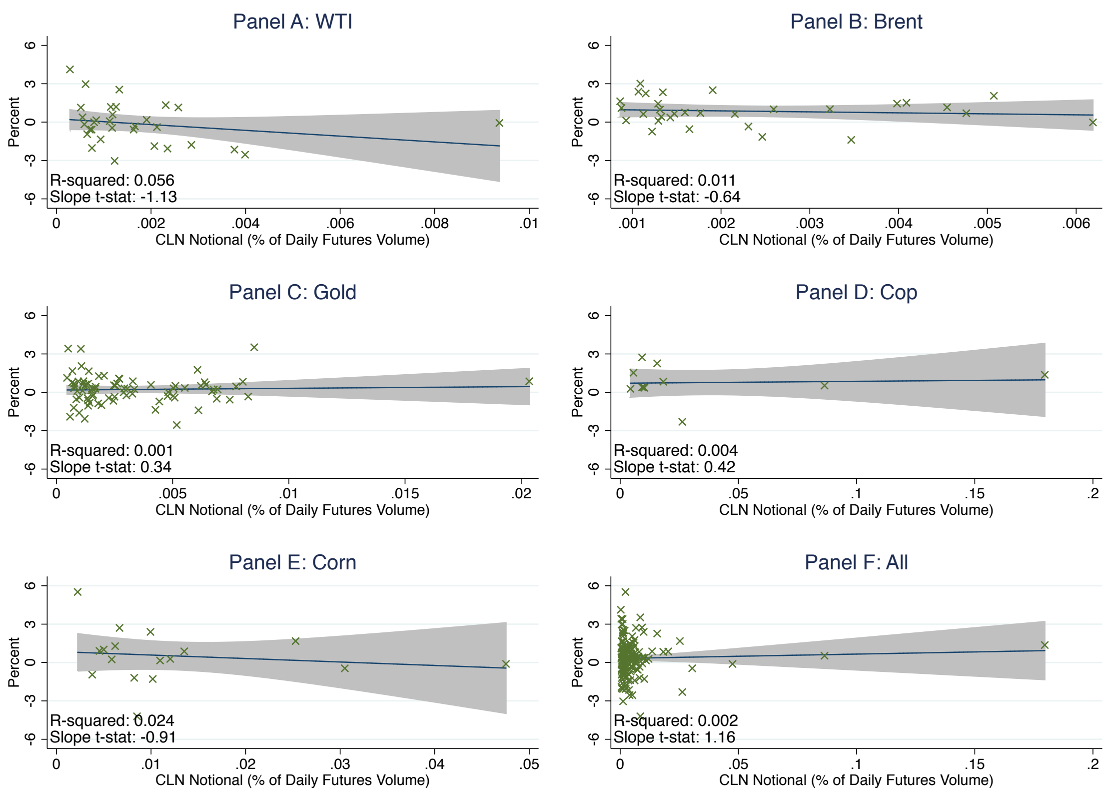
The figure shows the cumulative returns and imbalances with 95% confidence intervals over the 10 minutes following inventory announcements by the Energy Information Assoociation. The blue lines show returns and imbalances on days with the announcement of low inventory relative to the median forecast. The red lines show returns and imbalance on days with high inventory.

Figure 10: Intraday Returns and Imbalances on CLN Days



The figure shows the average returns and imbalances over various expanding windows of the trading day for the underlying commodity on days with CLN issuance. Returns are measured in percent and imbalance in millions of dollars. Panels A and B measure cumulative return and imbalance from the previous day's settlement. Panels C and D show cumulative returna nd imbalance in the 30 mintues prior to the daily settlement. We exclude notes issued during the 5th to 9th trading days of the month.

Figure 11: CLN Notional Value and Daily Returns



The figure shows plots of daily returns to commodity futures on CLN issuance days against the relative size of the notes. The relative size of the note is calculatd as the note's notional divided by the futures volume of the underlying commodity on the issuance day. We exclude notes issued during the 5th to 9th trading days of the month.