Order Flows and Financial Investor Impacts in Commodity Futures Markets*

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Abstract

We examine signed order flows and returns 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 financial 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 index traders reported by the CFTC. These impacts are consistent in size with the magnitudes of the index positions, and are concentrated in the minutes just prior to daily futures settlement, when the price impact of trades is generally lowest. While we confirm the positive returns around the issuance of commodity-linked notes documented by Henderson, Pearson, and Wang (2015), we find no evidence that these returns are driven by abnormal order flows. We also find that these notes are too small for the price impacts of hedging trades to explain these returns. We are unable to replicate their finding of significant negative returns on the notes' determination dates.

JEL Codes: G12, G13

Keywords: Commodities, Futures, Order flow, Financialization

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1 Introduction

Increasing financial and 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 predicts that the trading of uninformed financial investors can create price impacts in futures markets, the empirical evidence is mixed. Moreover, most prior empirical work focuses solely on futures returns and thus ignores a basic question: Are the trades of financial investors large enough to materially impact the futures market?

To help answer this question, 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 oil, Brent crude oil, gold, copper, wheat, and corn. These data allow us estimate the price impact associated with a given dollar value of buying or selling, which in turn allows us to estimate the magnitude of return we would expect to see in the futures market in response to a given amount of financial investment. Our intraday data also allow us to observe trading at specific times during the trading day, and thereby increase the power of our tests. In particular, we find that volume is highest and price impacts are lowest just prior to the daily futures settlement, so it would be reasonable to expect that uninformed investors may concentrate their trading in this period to reduce the effects of their trades.[1]

The increase in uninformed investment after 2004 is often referred to as the "financialization" of commodity markets, so we use the term "financial investment" as opposed to "retail investment" to refer to participants who are likely to be trading for portfolio reasons, as opposed to traders who may possess superior information. These may be retail 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. We focus on two sources of financial investment studied in the literature: weekly changes in the positions of commodity-index traders from from the CFTC, and commodity-linked notes (CLNs) following Henderson, Pearson, and Wang (2015) (henceforth HPW).[2]

[1]This concentration is consistent with the theoretical predictions of Admati and Pfleiderer (1988).

[2]Other work (e.g. Irwin and Sanders (2012) and Bessembinder, Carrion, Tuttle, and Venkataraman (2016)) studies investment in the United States Oil Fund (USO), the largest energy ETF, but finds little evidence of impacts on the level of prices. We also study retail investment in the USO and find similar results, so we relegate this analysis to the Internet Appendix. See Section IA.5.

Changes in the positions of index traders are only available for agricultural futures, so we restrict this portion of our analysis to corn and wheat futures. Our tests are similar in spirit to those of Irwin and Sanders (2011) and Stoll and Whaley (2010), who find little evidence of significant price impacts using daily data. We find similarly insignificant price impact at the daily frequency, but we are able to extend our analysis using our intraday data. Even at the daily frequency, we find significant evidence of imbalance in futures associated with index traders. Additionally, when we examine imbalance and return near the futures settlement, we find strong evidence largely consistent with theoretical models of financialization. When the net long positions of index traders increase (decrease), we see large buying (selling) volume and positive (negative) returns.

The effect of index traders in corn and wheat is strongly statistically significant, but explains only a small amount of the overall price variation for these futures. As an illustration, we find that a one standard deviation increase in the positions of index traders is associated with a positive return of 45 basis points in wheat futures accumulating in the 30-minute intervals prior to the daily settlement. These variations in index flows can explain 10% of the weekly return variation in these intervals prior to settlement, but 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 have a larger effect on the level of prices. For instance, from January 2009 to January 2010 the net long position in wheat futures held by index investors nearly doubled. Using observed returns around the settlement, we estimate that 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 index investors, this estimate should be viewed cautiously, as it assumes no reversal of the price impact. While we do not see any price reversal, the insignificance of our estimates at the daily frequency implies that we have little statistical power to discern reversals if they occur slowly.

The order flows from index traders in wheat and corn are large relative to the overall size of the futures market, so it may not be 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 \$20 million in the minute prior to futures settlement. This suggests that a \$140 million flow, even when spread over five days in the trading week, would need to be executed carefully if it was traded near the daily settlement. We find that the returns associated with these trades are roughly half the size of what we would predict using our price impact estimates. This suggests that these estimates are an upper bound of potential impact, as sophisticated traders are able to minimize their effect on prices.

In our second set of tests, we follow HPW, who find positive futures returns on CLN pricing days. Their primary analysis focuses on notes of at least $2 million of face value, linked to a single commodity, with pricing days outside of the Goldman Roll Period of Mou (2010). For these notes they find an associated average return of approximately 30 basis points, which rises to 40 basis points when they restrict the sample to notes with a face value of at least $10 million. They attribute these positive returns to the price impact of hedging trades in futures markets made by the issuers of these notes, and suggest that this result supports the theory that uninformed investors can have an impact on commodity prices.

We follow their approach for identifying notes and collect 594 CLNs linked to a single commodity with a face value at least $2 million that were issued before February of 2014, the date when their sample ends. Consistent with HPW, we find a significantly positive average return on the pricing dates outside of the Goldman Roll, with very similar magnitudes. However, when we extend the analysis to explicitly calculate the size of the necessary hedging trades, we find that the notes are far too small for price impacts to explain the positive average returns. For instance, we have intraday futures data for approximately 80% of the notes, and for the subset of these notes with $10+ million of face value we observe an average return of approximately 33 basis points on the pricing dates outside of the Goldman Roll. However, considering the size of the necessary hedging trades and our measures of price impact, we would predict that the average impact of naively executed hedging trades would be only three basis points.[3]

We also report additional results that suggest it is unlikely hedging trade price impacts can explain the observed returns. Looking within the trading day, we find no evidence of abnormal order flow on these pricing dates, or of abnormal returns in the minutes around around the pricing of the notes. Moreover, nearly all of the positive return occurs in the first part of the trading day, with approximately half of the effect accumulating between the prior day's settlement and the open

[3]We also use more readily available daily data to extrapolate our estimates of price impacts to commodities outside of our intraday sample, and consider both the universe of single-commodity CLNs and those for which we have intraday data. We find similar results.

of the market.

In order to understand these results we examine the distribution of notes across the trading month. While HPW argue that notes priced during the Goldman Roll Period should be excluded, it is not clear why this should be the case. Roll trades primarily impact calendar spreads as opposed to the level of the front month future, and, as noted by Mou (2010) and Neuhierl and Thompson (2016), the predictable returns around the roll had disappeared by 2003, when the first notes were issued. Using our intraday data, we find no heterogeneity in the price impact of order flow during the roll period. Accordingly, if the issuance of CLNs causes prices to move as a result of the hedging trades, then there should be similar results during the roll period. Instead, we find that the average returns on CLN pricing dates are near zero during the roll periods.

Outside of the roll periods, we find that the average positive return on CLN pricing dates is entirely explained by notes priced in the five days prior to the last day of the trading month. In this period we also see a substantial increase in the frequency of issuance, particularly for large notes. We refer to this period, which is outside of the Goldman Roll Period, as the "Active Issuance Period". During this period, it is clear that either the demand for or supply of notes increases, so it is notable that these are the notes with the positive average pricing date returns.

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 the 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. HPW acknowledge this potential endogeneity, and address it by looking at returns on the determination dates when the final payoffs of the notes are set and any hedging trades are unwound. They find a significantly negative average return, primarily on 42 determination dates for notes with at least \$10 million of face value. The size of this average return is -42 basis points (t-stat of 2.50), roughly equal in magnitude to the pricing date effect. Since these days are set months or years in advance, this result is not subject to the endogeneity concerns of the pricing dates.

The notes often have complicated embedded optionality, (e.g. call provisions, caps, floors, knock-outs, and buffer regions). Accordingly, many of the notes are either called early or have no sensitivity to the commodity price on the determination date. HPW indicate that they only consider surviving notes with a positive sensitivity to the underlying commodity price on the determination date. We use the contractual terms of each note and the realized price path of the underlying commodity to identify these notes. However, when we attempt to replicate the original HPW result, we find 50 determination dates outside of the Goldman Roll with at least $10 million of face value prior to the end of their sample. On these days we find a statistically insignificant average return of negative nine basis points (t-stat of 0.45).[4] We also extend the analysis to include the Goldman Roll period, and extend the sample to include notes which matured after the original HPW sample. In no case do we find a significantly negative average determination date return.

1.1 Related Literature

To our knowledge, our paper is 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 financial investors on commodity markets is motivated by a growing theoretical literature. Hamilton and Wu (2014), Acharya, Lochstoer, and Ramadorai (2013), Sockin and Xiong (2015), Baker (2014), Basak and Pavlova (2016), Goldstein and Yang (2017) and others derive theoretical models by which uninformed investors can create price impacts in commodity futures markets. In these models sophisticated investors have limited risk-bearing capacity, so investment flow from uninformed traders has impacts on commodity futures prices.

Our goal in this paper is testing this theoretical prediction. Similarly, some previous papers find evidence supporting the impacts of financial traders including Buyuksahin and Robe (2011), Tang and Xiong (2012), Singleton (2013), Cheng, Kirilenko, and Xiong (2014), and HPW while others find no evidence of impacts, including Stoll and Whaley (2010), Irwin and Sanders (2010), Irwin and Sanders (2011), Silvennoinen and Thorp (2013), Fattouh, Kilian, and Mahadeva (2013), Alquist and Gervais (2013), Hamilton and Wu (2015), and Chari and Christiano (2017).[5] More recently, Yan, Irwin, and Sanders (2019) examine index fund rebalancing and find temporary price

[4]We are unsure of the source of this discrepancy. The only difference we can discern in our methodology is that we exclude notes linked to multiple commodities in the same sector, but we find none of these notes where the total portion of the face value linked to a single commodity is greater than or equal to $10 million. Therefore, our understanding is that this result should be identical to HPW. We shared our set of notes with HPW in an attempt to resolve this difference on March 11, 2019, and they have not yet shared their data at the time of this writing.

[5]See Cheng and Xiong (2014) for a review of this literature.

impacts in futures markets consistent with the size of our price impact estimates.

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 et al. (2016) study liquidity around the predictable rolling of index funds, 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 over a one-year period around the electronification of WTI oil futures markets in 2007, but do not examine price impacts of financial investors.

Other related work includes Elder, Miao, and Ramchander (2014), who study intraday price patterns in Brent and WTI futures, Marshall, Nguyen, and Visaltanachoti (2011), 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 covering all notes linked to a single commodity issued prior to February 1, 2014.
- Positions of index traders in corn and wheat futures from the CFTC "Supplementary Positions of Traders" reports from January 2007 to March of 2014.
- Daily futures prices from the Commodity Research Bureau from January of 2003 to January of 2019.
- Various commodity-index values from Bloomberg from January of 2003 to January 2019.

We focus on the period through the first quarter of 2014 to be consistent with the sample of

HPW. The one exception is that we collect more recent data to examine the determination date returns of notes which mature after their sample. Our intraday 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 near-to-maturity high volume contracts in each market (defined below). 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. We are able to separately identify floor and calendar spread trades, and we exclude them from our imbalance measures. 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.

2.2 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 in the WTI nearest month contract 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 the nearest 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.

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 Order Flows

We first use our intraday data to estimate the price impact of order flow imbalance in these markets. One common approach is to use the VAR formulation of Hasbrouck (1991). We perform these VARs and report results in the Internet Appendix.[6] The primary takeaways are that the price impacts of both order flow and public return news are mostly permanent at one-minute horizons, and that most of the imbalance in each minute represents an unpredictable innovation. As a result, the VAR estimates of the long-run price impacts of innovations in imbalance are quite close to the coefficients from simple regressions of price change on current imbalance. Thus the results we report below use the univariate regressions.

3.1 Interpreting the Price Impact Measures

Our primary impact measure is the slope in a regression of one-minute returns on one-minute imbalance. In our exposition, we will often refer to the imbalance driving the return. However, it is also possible that imbalance is reacting to returns within each minute. Additionally, informed traders may use limit orders or complicated trading strategies to mask their order flow. Indeed, there is growing evidence that signed volume and its associated price impact is not an effective measure for understanding the impacts of informed traders (see O'Hara (2015) for a review of some these issues).

In this paper however, we are focused on the potential impacts of *uninformed* traders. We

[6] See section IA.1.

simply wish to understand how markets respond, on average, to a given amount of buying or selling. The values that we estimate should then provide an upper bound for the plausible impact of an uninformed trader acting in a rational manner. While it is possible that certain financial traders behave irrationally and trade in a way that greatly impacts markets, the sophistication of the institutions involved in index trading and the issuance of CLNs makes this seem unlikely.

3.2 Summary of Near Month 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 price of 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 between $10 and $15 million per minute for gold, Brent, and the WTI, and between $2 and $7 million per minute for copper, corn and wheat.

3.3 Price Impacts and Volumes Across the Trading Day

To estimate the price impact of imbalance, we first estimate a univariate regression of futures returns (measured in percentage) on imbalance (measured in millions of dollars). The left column for each commodity in Table 3 shows the results of these regressions. For each commodity, we find that imbalance in futures markets has significant explanatory power for futures prices, suggesting that these markets play an important role in price discovery.[7] The R^2 range from 33% for WTI to 12% for Brent. The slope estimates provide our measure of impact, and range from 0.0022 for gold to 0.0143 for wheat. The interpretation is that a one million dollar buy (sell) will lead to a return in gold markets of positive (negative) 0.0022%, or 0.22 basis points. In contrast, in the smaller wheat market, a one million dollar trade will lead to a return impact of 1.43 basis points.

These full sample regressions reveal differences in impacts across commodities, but they obscure substantial variation within commodities across the trading day. These intraday patterns are important to understanding how a sophisticated investor might implement hedging positions. Since many financial products are benchmarked to the daily futures settlement price, it is likely that the hedging trades would take place near the settlement, which occurs at specific times for the various contracts.

To examine how trading impacts change through the day we estimate our univariate regression for each minute of the trading day (there are approximately 1,800 trading days in the sample, so each regression has approximately 1,800 observations, and approximately 1,500 for Brent since we exclude data prior to 2008). For WTI, Brent, gold, and copper we consider the interval from 7:30 a.m. through 4:00 p.m. Corn and wheat have extremely low volume after their close of floor trading at 2:15 p.m., so we end the analysis here. Corn and wheat also had their settlements delayed to 3:00 PM New York time for the 11-month period from 5/22/2012 to 4/5/2013, so we omit this period for the analysis in Figure 1, and for subsequent figures that present results across the trading day. We include these data when presenting analysis related to periods prior to the daily settlement, and when reporting full day regression results in the tables.

Figure 1 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 WTI futures. The volume rises on the open of pit trading at 9 AM, and then spikes at times of various announcements, including the EIA's 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

[7] Evans and Lyons (2002) find a similar result in currency markets.

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 large trades during this period are unlikely to have a large impact on the market. For instance, a $10 million hedging trade (roughly the size of our average CLN), would only have an impact of 1.2 basis points if traded with a market order in the last minute before settlement. Note that a trade of this size would be less than one third of the standard deviation of imbalance for the settlement minute and less than 10% 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 impact falls around the futures settlement, which occurs at 2:30 PM, 1:00 PM, 1:30 PM, and 2:15 PM New York time for Brent, copper, gold, and both corn and wheat respectively. The reduction in price impact is most notable for the WTI and gold, but is apparent in all six commodities. The high volume and volatility of imbalance at the settlement means that the impacts in these minutes are estimated with high levels of statistical accuracy. The right hand columns of Table 3 illustrates this. In unreported pooled regressions with dummy variables for the settlement minute, we confirm that in all cases, the settlement minute has significantly lower price impact than the full sample estimate.[8]

3.4 Inferring Price Impacts from Daily Data for Other Commodities

Roughly 20% of our CLNs are linked to commodities for which we do not have intraday data. In order to estimate the potential price impacts for these commodities, we regress our observed price impacts on data that is available at the daily frequency and that we can obtain for a larger set of commodities. Intuitively we find that markets with lower volumes and higher volatilities have higher estimates of price impact. To formalize this intuition, we first calculate univariate regressions following the specification in Table 3 for each calendar year and commodity in our intraday data. We then regress these estimates on the average daily volume in millions of dollars across all futures maturities for a commodity market, as well as the daily volatility of returns to the near month

[8]The regressions shown in Table 3 and Figure 1 assume a linear impact of imbalance on returns. The Figure IA.2 in the Internet Appendix examines the settlement minute imbalance and returns for evidence of a nonlinear relation. We find little evidence that the relation is non-linear, but we see some evidence that very large imbalance leads to lower price impact than predicted by our linear estimates.

contract. All variables are in logs. The specification is therefore

$$\text{Log}(Impact_{com,yr}) = \alpha + \beta_1 \text{Log}(AverageDollarVolume_{com,yr}) + \beta_2 \text{Log}(DailyVolatility_{com,yr}) \quad (1)$$

The first column of Panel A in Table 4 shows the regression using impact over all minutes in the calendar year as the dependent variable. The second column shows the same specification but with the dependent impact measured in the settlement minute. The third column shows the results from a pooled specification which adds a dummy variable for the settlement impacts. As the table shows, even with the relatively small sample, both volume and volatility are highly significant predictors of impacts with the expected signs. Moreover, the fit of the regression is extremely strong, with R^2 near 90%. Figure 2 illustrates the fit from the three regression specifications. As the figure shows, the regression performs extremely well in predicting impacts both across commodities and across years.

We then use the pooled regression to estimate impacts for each commodity-year for all of the contracts in our sample of CLNs. Panel B of Table 4 shows the averages for estimates across all years.[9] We find that LME copper, due to its high volume and relatively low volatility has the lowest estimated impact. Palladium contracts on the CME have the highest estimated impact. This high impact is partly a result of their relatively recent introduction in 2003. By the later portion of the sample the volume had risen and the estimated impacts had fallen substantially. While these estimates are likely imperfect, the strong fit shown in Figure 2 suggests that they should provide reasonable estimates for impacts in commodities where we do not have intraday data.

4 Impacts of Financial Investors in Commodity Futures Markets

In this section we investigate the futures market impacts of two sources of financial investor flows: futures trades by indexers and issuances of CLNs. We calculate the change in net long positions of index funds in corn and wheat futures using data from the CFTC's supplementary positions of traders report. These data, provided for agricultural futures only, are generally considered the best measure of uninformed holdings in commodity futures.

[9] See Table IA.3 in the internet appendix for a complete list of all commodity-year estimates.

To construct our sample of CLNs, we follow the procedure of HPW and collect and search the universe of 424b filings for issuers of CLNs from the SEC's Edgar website to identify CLNs linked to a single commodity with face value of at least \$2 million.[10] We find 594 notes, of which approximately 80% are in the commodities for which we have intraday data. Our sample of notes appears to closely track the set captured by HPW in terms of number and size.[11]

We also extend the analysis of HPW by explicitly calculating the hypothetical notional value of the hedge for each note, both at initial issue and on the determination date. We refer to the ratio of this notional value to the face value of the note as delta.

4.1 Calculating CLN Deltas

As mentioned in the introduction, many of the CLNs have complicated features (e.g. call provisions, caps, floors, knock-outs, and buffer regions). In order to accommodate the various structures, we calculate the initial delta via Monte Carlo valuation with 10,000 sample paths of daily returns over the life of the note.[12]

Figure 3 uses a representative note from the sample to illustrate the calculation of the pricing date and determination date deltas. The figure illustrates the \$51,437,000 Capped Market Plus Notes linked to the S&P GSCI® Crude Oil Excess Return Index that were issued on January 24, 2011 by Barclays Bank. This note is typical in that it has no payments prior to maturity and the ending return on the note is a piece-wise linear function of the return on the underlying. The note also has a path-dependent "knock-out", which is another common feature in our sample. The note "priced" based on the closing value of the index on January 14, 2011 and the 424B form was filed with the SEC on January 19, 2011. When calculating the initial delta we follow HPW and assume

[10] HPW also include notes linked to multi-commodity indices if all the indices are in the same sector (ie. energy). We collected these notes but do not include them because they complicate some portions of the analysis. None of these notes have more than \$10 million linked to a single commodity, and so for each of our analyses we report results for this subset of notes. HPW likewise report their results for this subset.

[11] We find some notes that were created and then transferred to a subsidiary for later sale to investors. We do not include these notes in our sample. We also do not include exchange-traded notes following HPW.

[12] We assume that returns are log-normally distributed with daily standard deviation equal to the realized daily standard deviation of the underlying over the month prior to issuance. The simulated risk-neutral drift of the underlying depends on the type of index used to calculate the note payoff. In some cases, the underlying is an excess return index, so the risk-neutral proportional expected return is zero. If the note uses a total return index, then the risk-neutral expected return equals the risk free rate. In many of the notes the underlying is a spot price, in which case we set the drift so that the expected value on the determination date is the futures price for the contract whose maturity is closest to the determination date. Roughly 10% of the notes have a final payoff calculated based on the average price over multiple trading days. We take this into account when calculating our deltas, so the determination date delta for these notes will be smaller.

that the full value of the notes was committed and hedged on January 14.

The notes matured on February 1, 2012. The determination date was January 25, 2012, when the final value of the index was observed and payoff of the note was set. If the notes were hedged, then the hedge should have been removed on the determination date, so we calculate the ending delta on that date. These notes have a knock-out buffer, a contingent minimum return, and a maximum return. A knock-out occurs if the index value falls below 80% of the pricing date value on any day over the life of the notes, and if a knock-out occurs then the contingent minimum of 8% is removed.

Panel A shows the actual return path for the index and three hypothetical return paths.[13] The hypothetical return paths are shown in part to illustrate the 10,000 simulated paths that are used to value the note and calculate the delta on the pricing date, and they are also used to illustrate the possible determination date deltas in Panel B. The initial note value is the average of the risk-neutral present values of the ultimate payments to the note along each simulated path based on the specific terms of the note, including interim interest payments and early calls.[14] The initial delta is then calculated by revaluing the note with a small change in the initial value of the underlying. The pricing date delta for this particular note is 0.89, so the size of the delta hedging trade would be 89% of the face value. Because most of the notes have concave payoffs with maximum slopes less than or equal to 1.0, the average (median) delta for the notes in our sample is only 0.61 (0.63). Accordingly, the face value of a note generally overstates the amount of the hypothetical initial hedge.

As shown in Panel A, the realized path for the underlying index was below the knock-out level during the life of the note, so as shown in Panel B, the return on the note matched the realized return on the index. The final return to the notes was -1% giving a final value of $50.9 million. The payoff function had a slope of 1.0 on the determination date, so the final delta is equal to the final value of $50.9 million divided by the initial issue amount (0.99). The hypothetical price path A for the underlying ends with the same return as the actual price path, but it never falls into the knock-out region so the ending return on the notes would have been the contingent minimum of

[13] For all of the notes, we obtain the values of the specific index or spot price to calculate the actual path. These data are obtained either via Bloomberg or the Commodity Research Bureau.

[14] The underlying index is an excess return, so the simulated risk-neutral paths used in the valuation of this note have zero expected return.

8%. The slope of the payoff is zero in this case, so if this had been the actual path, the ending delta would have been zero. The hypothetical price path B has an ending return for both the notes and the underlying of 15% which would have meant an ending value of $59.2 million for the notes, and since the slope of the payoff is 1.0 the size of the delta hedge would also be $59.2 million, or 115% of the face value, so the delta would be 1.15. The hypothetical price path C has a 40% return on the underlying, which would mean the note return would have been the maximum return of 30.5%. The payoff function has a zero slope at this point, so hypothetical path C would have resulted in an ending delta of zero. In our full sample, 342 of the 594 notes have a delta of zero on the determination date.

4.2 Summary Data for Changes in Index Positions and CLNs

Table 5 presents the summary data for the two sources of financial investment flows. Panel A shows the summary statistics for changes in the positions of index traders for corn and wheat. Both of these flows are quite substantial in magnitude. The standard deviation of flows are $225 million and $140 million for corn and wheat respectively. Interestingly, even though many index funds hold both commodities, the correlation of flows is not high, at only 0.23. To estimate the predicted price impacts from these flows, we apply our regression from column (3) of Panel A in Table 4. We obtain the estimated price impact for trades made at the settlement minute in the relative commodity for the given year, and then multiple this estimate times the change in the positions of traders. This yields a time series of predicted impacts. As the right hand side of Panel A in Table 5 shows, the standard deviation of this impact is approximately 1% for both commodities.

Panel B of Table 5 shows summary statistics for the pricing dates of the CLNs. We follow HPW and combine notes in the same commodity with the same pricing date, and report face value, the size of the delta hedging trades, and the predicted price impacts of these trades. Here, in contrast to the changes in positions of index traders, the notes are very small relative to the size of the futures markets. The average size of the delta hedging trades is approximately $10 million. This yields an average predicted price impact of approximately 4 basis points if the note was traded near the futures settlement. This is the first indication that these hedging trades may not be responsible for the observed price impacts documented by HPW.

Figure 4 shows these results visually. The left hand panels of the figure show the weekly changes in index fund positions and the delta hedging trades associated with the pricing dates in millions of dollars. As the figure shows, the changes to corn and wheat index positions are large in magnitude throughout the sample. Panel E shows the issuance of CLNs. These issuances pick up in both size and frequency around 2008 and remain high through the end of the sample. The right hand side panels plot the price impacts associated with these flows on a common scale. As the figure shows, predicted returns associated with the hedging trades of CLNs are much smaller in magnitude than the changes in positions of index traders.

Finally, Panel C of Table 5 reports summary statistics for the CLN determination date. We start with the sample of notes with determination dates prior to 2019. The next line removes the many notes that have zero delta at the determination. This occurs either because the note is called or because the underlying commodity price is in a region in which the note has no exposure. Then we remove the smaller notes to focus on the larger notes where HPW find their significant determination date results. Finally we restrict the sample to prior to February 2014 to obtain the notes that were available at the time of the original HPW study. While the predicted price impacts are again small, they are larger in magnitude than the pricing impacts as the deltas tend to be higher for those notes which still have exposure to the underlying at the determination date.

4.3 The Impact of Commodity-Index Traders on Futures Markets

Here we explore the impacts of commodity-index traders on futures markets using our intraday data. Since we cannot directly identify these traders in our high-frequency data, we instead 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 investigate whether these changes in positions are associated with returns in the futures market. To this end, we estimate regressions of the form

$$FuturesImbalance_t = \alpha + \beta \Delta IndexPositions_t \tag{2}$$

$$FuturesReturn_t = \alpha + \beta \overline{\Delta IndexPositions_t} \tag{3}$$

When performing regressions of imbalance, we regress weekly imbalance on the total change in index trader positions, where both are 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. Thus, in the return regressions 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. To the extent that index contracts are tied to daily settlement prices, we might expect the impacts of changes in index positions to be concentrated near the daily settlement. Accordingly, we also estimate our regressions using later 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 in Table 6 show the results for total returns and imbalance summed across the week. The coefficients in column (1) of 0.371 for corn and 0.514 for wheat are strongly significant, and indicate that for a given weekly change in index positions we see corresponding weekly imbalances in the same direction that average 37.1% and 51.4% of the changes in index positions. While it may seem puzzling that our estimates are lower than 100% this not surprising. We would expect these traders to utilize both limit orders and floor orders to execute these trades, and if they do so it will not be reflected in our measure of imbalance.

Column (4) in both panels shows that the responses of futures returns across the full day to changes in index positions are not statistically significant at the 5% level. The point estimates are positive for both corn and wheat (0.62 and 0.49) with a magnitude of approximately one half of the predicted impact of 1%. This is what one might expect if the traders are able to execute their orders with some sophistication. However, consistent with the findings of Stoll and Whaley (2010) and Irwin and Sanders (2012), a return of this magnitude is not large enough to discern from the noise of daily price changes.

When we focus the analysis further and examine the period around the futures settlement, we see a striking result. Column (2) shows that in the 30 minutes prior to settlement we see imbalance equal to approximately 14% and 24% of the total change in index positions for corn and wheat respectively. Column (5) shows that these imbalances close to settlement are translating into a return impact. A one standard deviation increase in index traders' positions is translating into a 28.1 basis point price increase across the week over these minutes for corn, and a 48.1 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 (t-stats range from 3.5 to 5.6). This significance is not a result of larger point estimates, as these estimates are lower than the full day estimates, but instead is a result of the increased power from focusing on the period of the day when index traders are most likely to be trading.

To visualize these patterns, Panel A of Figure 5 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 Figure shows that returns and imbalances associated with changes in the positions of index fund traders increase slowly across the day, and then spike just before the settlement.[15]

Figure 6 focuses on the 30 minutes prior to the daily settlement. Again the plots show regression coefficients for expanding windows. For example, looking at the 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 trading 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 just 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. Although these results show price impacts of these trades near the settlement, it is difficult to tell from our data whether and to what degree these impacts are permanent. If the impacts were reversed by the next morning, then that might suggest that overnight returns would be negatively related to the average weekly index flow. The left most portions of Panels B and D of Figure 5 show that overnight returns are essentially unrelated to the weekly index flows, but the wide confidence intervals make it difficult to draw conclusions.[16]

[15] In the figure the full day regression result for returns is significant at the 95% level. This discrepancy with the full day estimates in Table 6 arises due to the fact that the figure excludes the period of time when settlement was delayed until 3:00 PM.

[16] In unreported results we directly test for reversal but find similarly inconclusive results.

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 6% and 10% 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 1-2% when considering the full week's return, suggesting that index funds are not contributing a large portion of the weekly variance in futures prices.

Despite the fact that these daily impacts 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 7 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 (Table 6) as our measure of price impact for index traders, 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 7 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.

4.4 Pricing Date Returns for Commodity-Linked Notes

HPW find that days with the creation of CLNs have significant positive average returns. They attribute this to the price impact of hedging trades made in the futures market. Because the exposure to the underlying commodity starts at the daily settlement on the pricing date, that is where we would expect to see the hedging trades and their associated price impact.[17]

[17]HPW also report results for returns on days after the pricing date and results using abnormal returns controlling for various systematic variables. Since their results are similar using raw returns, and generally the most significant on the actual pricing date, we focus on these specifications for parsimony.

When conducting their analysis, HPW exclude notes pricing during the Goldman Roll documented by Mou (2010). This period includes the 5th to 9th trading days of the month and the five previous business days. They do this to avoid potential returns coming from the price pressure associated with the roll trades. However, it is not clear that this is the correct choice. In particular, as documented by both Mou (2010) and Neuhierl and Thompson (2016), the predictable returns associated with the roll trades no longer occur after 2003, which is the period during which we see the issuance of CLNs. Moreover, we find no difference in the price impacts of order flow in the Goldman Roll period.[18] Accordingly, we would not expect to see differences in the price impacts of hedging trades for notes issued during this period.

Although HPW do not mention it, there are substantial differences in the frequency of CLN pricing days across the trading month. Panel A of Figure 8 plots the number of notes with pricing dates on each of the ten trading days at both the beginning and end of the month, with a single bar representing the total notes issued in the middle day of the month (months have from 20-22 trading days, so for some months there are no days in the middle and for others there are one or two). Panel B repeats this figure for notes with at least $10 million of face value. As the figure shows, issuance, particularly of large notes, is much more common the five days prior to the end of the trading month than on other days.[19] We refer to this five day period as the "Active Issuance Period". This increased level of issuance activity implies a change in the demand or supply of large notes in this period. Perhaps this is due to performance targets for sellers of the notes that lead them to market more aggressively to retail clients, or perhaps there are institutional buyers that have reasons to buy during this period. This period is entirely outside of the Goldman Roll and these notes are therefore included in the main analysis of HPW. For our analysis below, we report our findings for the different portions of the trading month. As we will show, it is only the notes in the Active Issuance Period that have positive average pricing date returns.

We now examine daily futures returns on the pricing dates of the notes. Table 7 shows the realized pricing date returns and the predicted impacts for different subsets of notes and different portions of the trading month. Panel A includes all notes. In column (1) we show the average

[18]See Table IA.2 in the Internet Appendix.

[19]Unreported logit regressions show that days in this period are more than three times more likely to have an issuance of a note with $10+ million of face value, and this difference in issuance frequency is highly statistically significant ($p < 0.001$).

pricing date return for all notes, and find only a marginal positively significant average return. Column (2) of Panel A replicates the finding of HPW for all notes outside of the Goldman Roll period. We find a nearly identical average return of 28 basis points on these days. As column (3) shows, this increase is due to the fact that the notes issued during the Goldman Roll have a slightly negative return. When we cut the sample down further and only include notes in the Active Issuance Period, we see that these are the notes that drive the entire positive pricing date result, as these 201 days (of 532 total) have a positive average return of 44 basis points, while the remaining 331 days have an average return of negative 5 basis points. For all of the subsets with significantly positive returns, the returns are much higher than the predicted impact given the size of the delta hedges.

Panel B repeats Panel A but restricting the sample to days with $10+ million of face value. The findings are qualitatively the same, but the positive returns are even stronger. The notes issued during the Active Issuance Period account for the entire result, and have a positive return on average of 66 basis points (t-stat = [5.03]), while the predicted impact of their hedging trades is only 9 basis points. The average return is thus 7 times larger than would be expected if the delta hedges were naively executed in futures markets. Panels C and D repeat the analysis of Panels A and B for the approximately 80% of the notes for which we have intraday data. Here we find nearly identical patterns in average returns. We note that these commodities have large futures markets, so the predicted impacts are less than 10% of the observed pricing date returns both when excluding the Goldman Roll and when restricting to the Active Issuance Period.[20] Panel E shows similar analysis, but uses the full set of dates in each subset from column (1) in Panels A - D and regresses the return on two dummy variables corresponding to the note being in the Active Issuance Period or outside of the Goldman Roll. In all cases the Active Issuance Period Dummy is highly significant, and both the Non-Goldman Roll dummy and the intercept are insignificant at the 5% level. This again illustrates that the positive returns are only associated with the notes that price in the Active Issuance Period.

[20]HPW also measure of the face value of the note relative to the open interest of the two nearest-month futures and find that larger notes have larger returns. We perform a similar test, but regress pricing day returns on our measure of predicted impact from the hedging trade. We find some evidence that notes with a larger predicted impact have higher pricing day returns. However, the slope of the regression is near one, so the small value of the average predicted returns means that this can explain only a small portion of the total pricing date average return. See Section IA.6 in the Internet Appendix.

Our next set of tests focuses on the notes for which we have intraday data, and looks within the trading day to see if we observe any patterns similar to those we see in the analysis of commodity-index traders.[21] We focus on days greater with $10+ million of face value issued during the Active Issuance Period since this is where we see the largest daily effects. Table 8 and Figure 9 show the results. As both the Figure and the Table show, we see no focused pattern of purchases or positive returns around the futures settlement. In fact, looking at Panel A of the figure we see no evidence of any abnormal imbalance during the pricing date of the note. Instead, approximately half the of the return, as well as what positive imbalance there is, appears to occur prior to 9 AM on the day of the pricing. Nearly all of the return effect has accumulated by 12 PM. While there are reasons that a hedging trade may be delayed, there seems no reason a hedging trade would occur prior to the pricing of the note, which typically occurs at the futures settlement. One possible explanation is that many of the gold notes price on the London PM fix, which occurs at 10 AM or 11 AM in New York depending on the time of year, and most of the copper notes price on the close of the LME which is at 12 PM or 1 PM in New York. We therefore examine the returns and imbalance in a two hour window starting 30 minutes before the pricing of the note, and again find no effect.

Our findings on the pricing date can be summed up as follows:

1. The pricing date returns are between 6 and 10 times too large to be explained by the size of the delta hedging trades.
2. The average positive returns are only present in notes that price in the 5 days prior to the end of the month, a period during which CLN issuance frequency greatly increases.
3. There is no return or imbalance in the minutes near the futures settle or the pricing of the notes, and instead most of the positive return occurs overnight or early in the trading day.

Together, these results suggest that demand or supply of notes is responding to the changing price of the underlying commodity. HPW acknowledge this potential bias, and address this by examining returns on the determination dates when final payoff of the CLN is set. If returns are negative on this date, it would be strong evidence of price impact from the unwinding of hedging trades, and this evidence would not be subject to the concerns of selection bias or endogeneity

[21] Many of our gold notes are linked to the London PM fix and nearly all of our copper notes are linked to the LME spot price. We do not have intraday data for these prices. However, using our intraday data we confirm that the futures prices are highly correlated with the London markets. We therefore use our intraday data for copper and gold when examining notes linked to these commodities.

inherent with the pricing date results.

4.5 Determination Date Returns for Commodity-Linked Notes

Table 9 shows our analysis of futures returns on days with CLN determination. Following HPW, we restrict our analysis to notes which still have positive exposure so the underlying commodity on the determination date. The table shows average determination date returns for various subsets of the sample. In particular, column (2) of Panel D is our attempt to replicate the main finding of HPW. This is the return on determination dates of notes that still have a positive delta on the day of determination, are outside of the Goldman Roll, have at least $10 million of face value, and have a maturity prior to February of 2014. As in HPW we combine notes with the same underlying commodity and the same determination date, but in spite of attempting to match their approach exactly, our sample size is larger (we have 50 observations and they have 42). More notably, while they report a significant average return of -42 basis points (t-stat of 2.50), we find an insignificant average return of only -9 basis points (t-stat of 0.45).[22] Looking at the table, we do not find a negative average return that is significant at the 5% level for any subset of the determination dates, either including the Goldman Roll or extending the sample of determination dates through 2018.

It is also interesting to note that the larger deltas of the notes on the determination dates imply that the predicted impacts are considerably larger than those on the pricing dates. The fact that we do not find negative returns may reflect an ability of sophisticated traders to make large trades without impacting futures markets, but it also could reflect a lack of futures hedging in some cases. Particularly with larger notes, it may be the case that the CLN issuance is triggered when an institutional client enters an over-the-counter contract with the investment bank, who then sells the CLNs to hedge their exposure to that contract.

[22]HPW do not indicate how they handle the roughly 10% of notes whose final value depends on the average commodity price over multiple days. When calculating the average return we only use the return on the final determination date. There are very few of these notes with a positive determination date delta, and in particular there is only one note with greater than $10 million of face value prior to 02/2014. Removing or including this note has no significant impact on any of our results.

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 financial investors in this market. We examine the impact from changes in the positions of commodity-index investors for corn and wheat futures from the CFTC. We find strong evidence for trade imbalances and price impacts associated with these positions, concentrated in the minute prior to the daily futures settlement.

We also find that the positive returns associated with the issuance commodity-linked notes documented by Henderson et al. (2015) are surprisingly large given the notes' size, occur primarily early in the trading day, are not associated with abnormal trade imbalance near the futures settlement or pricing of the note, and are only present in notes issued near the end of the month when issuance frequency is substantially higher. We also find no evidence of significant negative returns on CLN determination dates. These findings suggest that the positive returns are potentially the result of CLN issuers or purchasers favoring days with increasing commodity prices, rather than evidence of impacts from associated hedging trades.

References

Acharya, V. V., L. A. Lochstoer, and T. Ramadorai. 2013. Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics* 109:441–465.

Admati, A. R., and P. Pfleiderer. 1988. A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies* 1:3–40.

Alquist, R., and O. Gervais. 2013. The role of financial speculation in driving the price of crude oil. *The Energy Journal* pp. 35–54.

Baker, S. D. 2014. The financialization of storable commodities. *Finance Down Under 2014 Building on the Best from the Cellars of Finance* .

Basak, S., and A. Pavlova. 2016. A model of financialization of commodities. *The Journal of Finance* 71:1511–1556.

Bessembinder, H. 2015. Predictable ETF Order Flow and Market Quality. *Available at SSRN 2506322* .

Bessembinder, H., A. Carrion, L. Tuttle, and K. Venkataraman. 2016. Liquidity, resiliency and market quality around predictable trades: Theory and evidence. *Journal of Financial Economics* 121:142–166.

Buyuksahin, B., and M. A. Robe. 2011. Does paper oil matter? Energy markets' financialization and equity-commodity co-movements. *Available at SSRN 1855264* .

Chari, V. V., and L. Christiano. 2017. Financialization in commodity markets. Tech. rep., National Bureau of Economic Research.

Cheng, I.-H., A. Kirilenko, and W. Xiong. 2014. Convective risk flows in commodity futures markets. *Review of Finance* 19:1733–1781.

Cheng, I.-H., and W. Xiong. 2014. Financialization of commodity markets. *Annu. Rev. Financ. Econ.* 6:419–441.

Elder, J., H. Miao, and S. Ramchander. 2014. Price discovery in crude oil futures. *Energy Economics* 46:S18–S27.

Evans, M. D., and R. K. Lyons. 2002. Order flow and exchange rate dynamics. *Journal of political economy* 110:170–180.

Fattouh, B., L. Kilian, and L. Mahadeva. 2013. The role of speculation in oil markets: What have we learned so far? *The Energy Journal* pp. 7–33.

Goldstein, I., and L. Yang. 2017. Commodity financialization and information transmission. In *AFA 2016 Annual Meeting*.

Halova, M. W., A. Kurov, and O. Kucher. 2014. Noisy inventory announcements and energy prices. *Journal of Futures Markets* 34:911–933.

Hamilton, J. D., and J. C. Wu. 2014. Risk premia in crude oil futures prices. *Journal of International Money and Finance* 42:9–37.

Hamilton, J. D., and J. C. Wu. 2015. Effects of index-fund investing on commodity futures prices. *International economic review* 56:187–205.

Hasbrouck, J. 1991. The summary informativeness of stock trades: An econometric analysis. *The Review of Financial Studies* 4:571–595.

Henderson, B. J., N. D. Pearson, and L. Wang. 2015. New evidence on the financialization of commodity markets. *The Review of Financial Studies* 28:1285–1311.

Irwin, S. H., and D. R. Sanders. 2010. The impact of index and swap funds on commodity futures markets .

Irwin, S. H., and D. R. Sanders. 2011. Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy* 33:1–31.

Irwin, S. H., and D. R. Sanders. 2012. Testing the Masters Hypothesis in commodity futures markets. *Energy economics* 34:256–269.

Marshall, B. R., N. H. Nguyen, and N. Visaltanachoti. 2011. Commodity liquidity measurement and transaction costs. *The Review of Financial Studies* 25:599–638.

Mou, Y. 2010. Limits to arbitrage and commodity index investment: front-running the Goldman roll. *Available at SSRN 1716841* .

Neuhierl, A., and A. Thompson. 2016. Liquidity Timing in Commodity Markets and the Impact of Financialization. *Available at SSRN 2682698* .

O'Hara, M. 2015. High frequency market microstructure. *Journal of Financial Economics* 116:257–270.

Raman, V., M. A. Robe, and P. K. Yadav. 2017. The Third Dimension of Financialization: Electronification, Intraday Institutional Trading, and Commodity Market Quality. *WBS Finance Group Research Paper* .

Silvennoinen, A., and S. Thorp. 2013. Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money* 24:42–65.

Singleton, K. J. 2013. Investor flows and the 2008 boom/bust in oil prices. *Management Science* 60:300–318.

Sockin, M., and W. Xiong. 2015. Informational frictions and commodity markets. *The Journal of Finance* 70:2063–2098.

Stoll, H. R., and R. E. Whaley. 2010. Commodity index investing and commodity futures prices. *Journal of Applied Finance (Formerly Financial Practice and Education)* 20.

Tang, K., and W. Xiong. 2012. Index investment and the financialization of commodities. *Financial Analysts Journal* 68:54–74.

Yan, L., S. H. Irwin, and D. R. Sanders. 2019. Is the Supply Curve for Commodity Futures Contracts Upward Sloping? *Available at SSRN 3360787* .

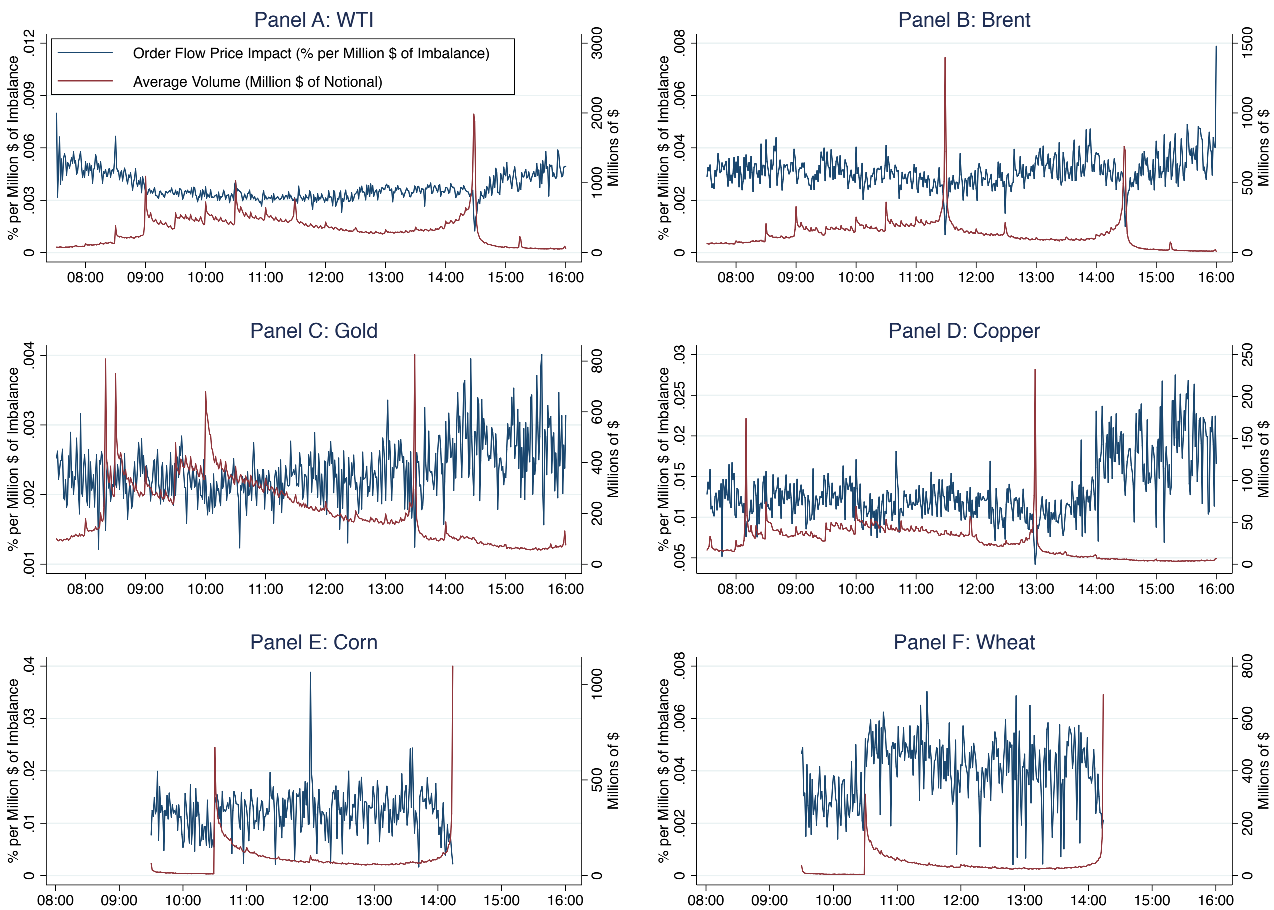

Figure 1. Volume and Price Impact of Order Flow Across the Trading Day
The figure shows the average intraday volume (in red) by minute for each commodity as well as the minute-by-minute trade impact (in blue). The trade impact is measured as the slope in a univariate regression of return (%) on trade imbalance (millions of $) estimated using imbalance and returns in each minute of the day. For instance, for 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).

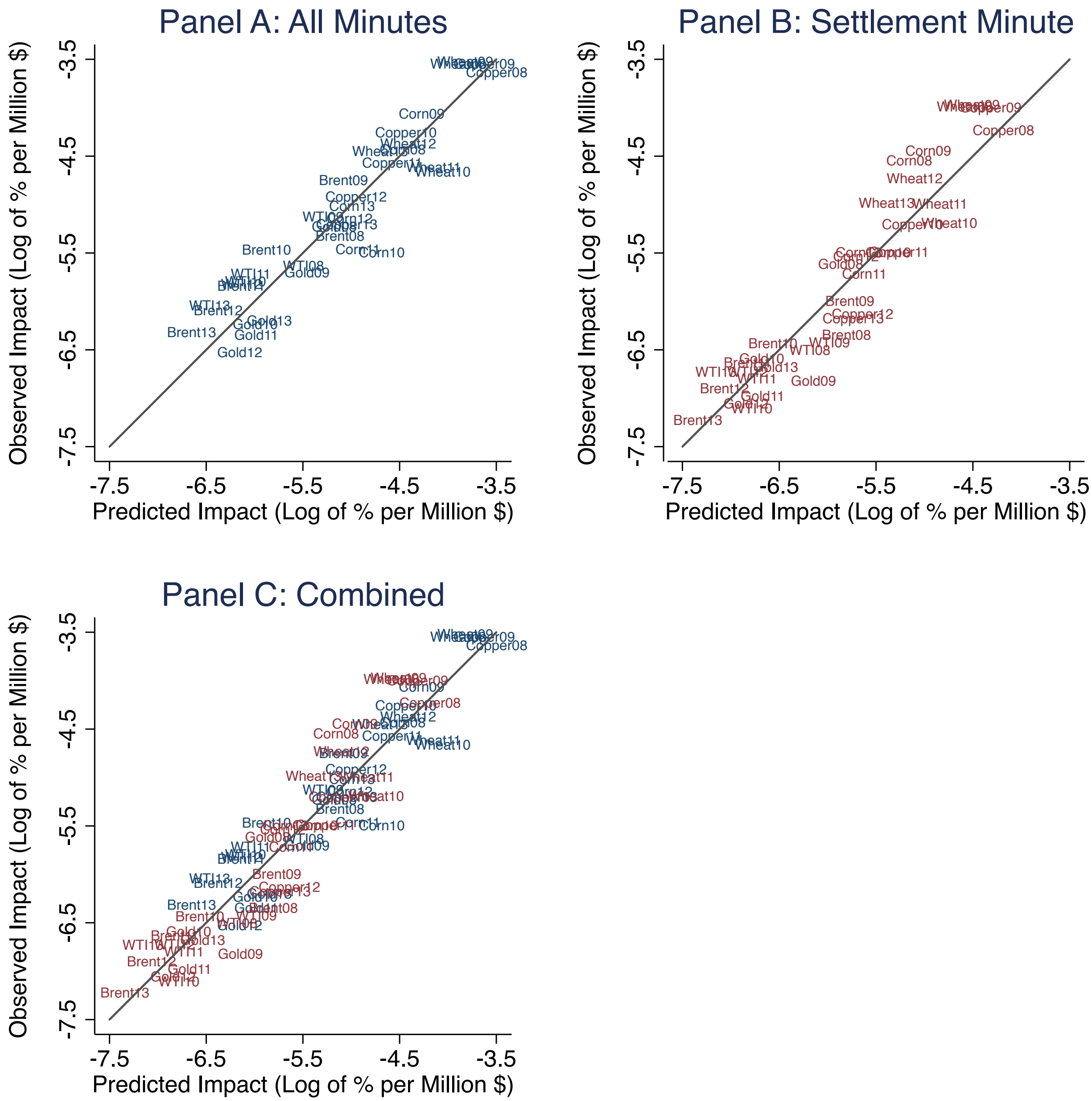

Figure 2. Regression fit for inferring order flow price impact from daily data
This figure plots the fit for regressions of the log of predicted price impacts for each commodity in a calendar year on the logs of average daily futures volume and daily futures volatility (See columns (1) - (3) of Panel A in Table 4).

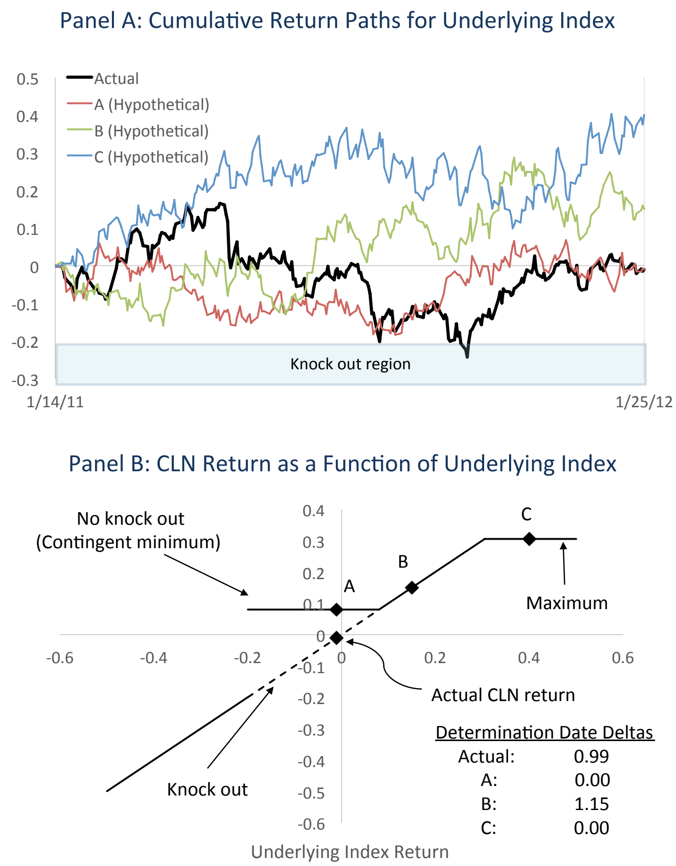

Figure 3. Return Paths and Determination Date Deltas for a Sample CLN
The figure illustrates the \$51,437,000 Capped Market Plus Notes linked to the S&P GSCI® Crude Oil Excess Return Index. These notes have a knock-out buffer, a contingent minimum return, and a maximum return. A knock-out occurs if the index value falls below 80% of the pricing date value on any day over the life of the notes, and if a knock-out occurs then the contingent minimum of 8% is removed. Panel A shows the actual return path for the index and three hypothetical return paths. Panel B shows the piecewise linear payoff structure across the ending cumulative returns of the underlying index along with the determination date delta for each path. The delta is calculated as (Ending Note Value × Slope of Payoff on Determination Date) / (Face Value of the Note). See section 4.1 for a detailed explanation of the four determination date delta values.

Figure 4. Sources of Order Flow from Financial Investors and Predicted Price Impacts The figure shows plots of sources of order flows and the predicted price impact from financial investors in commodity markets. Panel A and show weekly changes in position of commodity-index traders for corn and Panel B shows the predicted price impact from these trades using the estimates calculated using the regression specification in Table 4. Panel C and D repeats this analysis for wheat. Panel E shows the size of the delta hedging trades associated with CLN pricing and Panel F shows the predicted price impact of these trades.

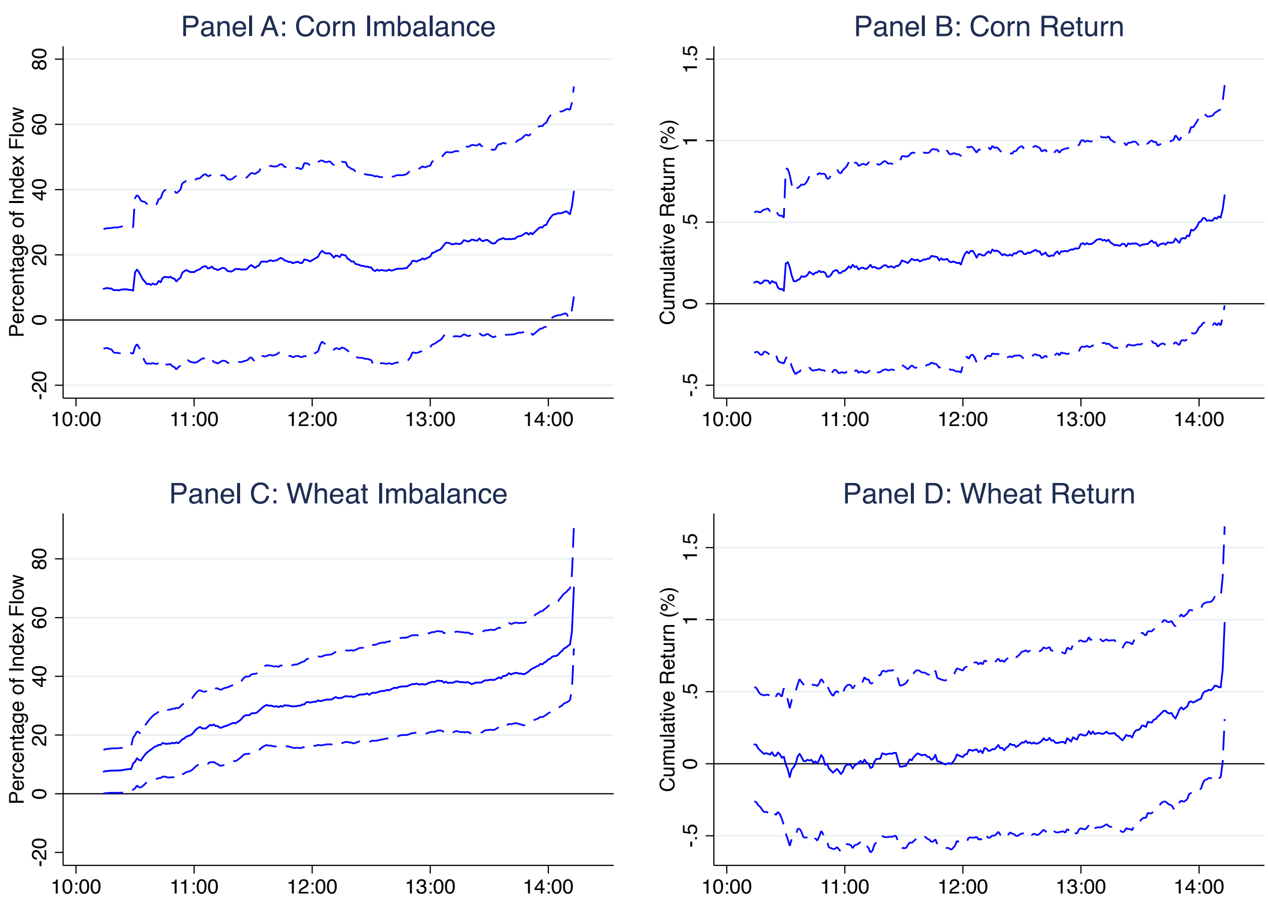

Figure 5. Intraday Impact of Changes in the Positions of Commodity-Index Traders: Full Day

The figure plots the slope coefficient and 95% confidence interval from regressions where the dependent variables are cumulative futures imbalances and 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.

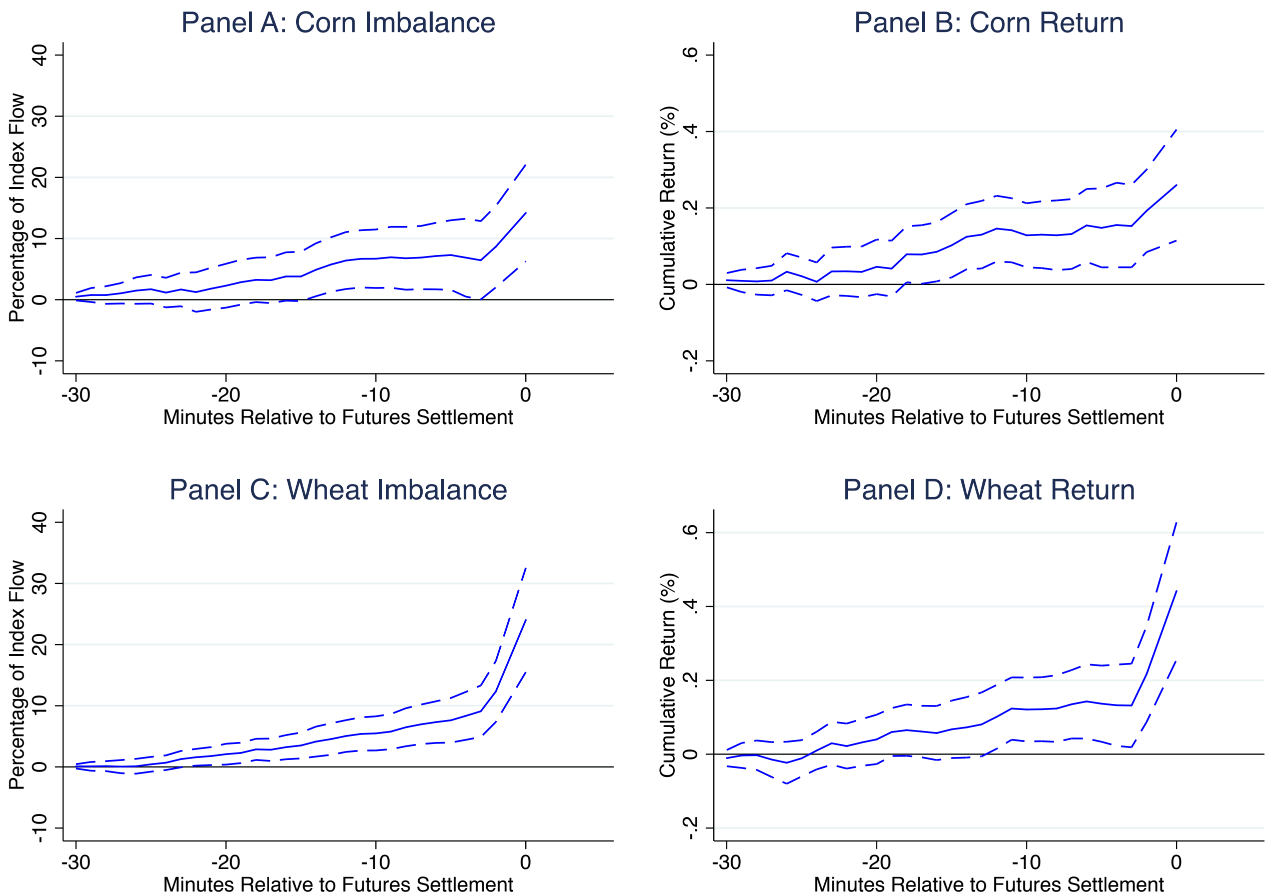

Figure 6. Intraday Impact of Changes in the Positions of Commodity-Index Traders: 30 Minutes Prior to Settlement

The figure plots the slope coefficient and 95% confidence interval from regressions where the dependent variables are cumulative futures imbalances and 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.

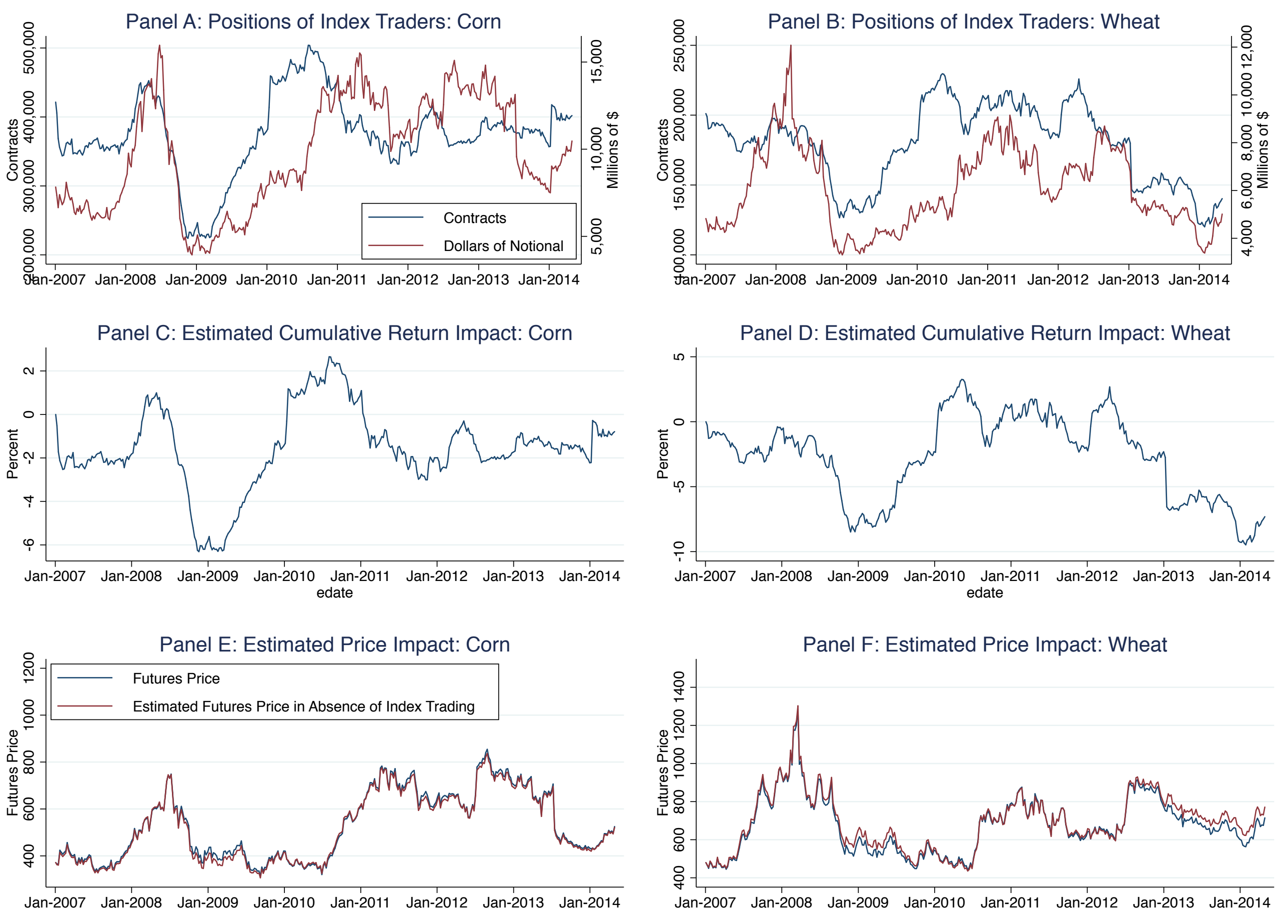

Figure 7. Estimated Cumulative Impact of Index Trader Flows
The figure shows the positions of index traders from the CFTC in corn and wheat along with the estimated price impacts of changes in these positions in using our estimates of price impact in the 30 minutes prior to futures settlement (Table 6 column (5)). Panels A and B show the positions of index traders in futures contracts and millions of dollars. Panels C and D show the cumulative sums of weekly impacts, which are calculated by multiplying each week's standardized change in index trader positions by the estimate of impact from Table 6. Panels E and F show the observed futures price and the futures price adjusting the cumulative return impact. This adjustment is done by multiplying the observed futures price by $(1 + CumulativeReturnImpact)$, where the $CumulativeReturnImpact$ is shown in panels C and D.

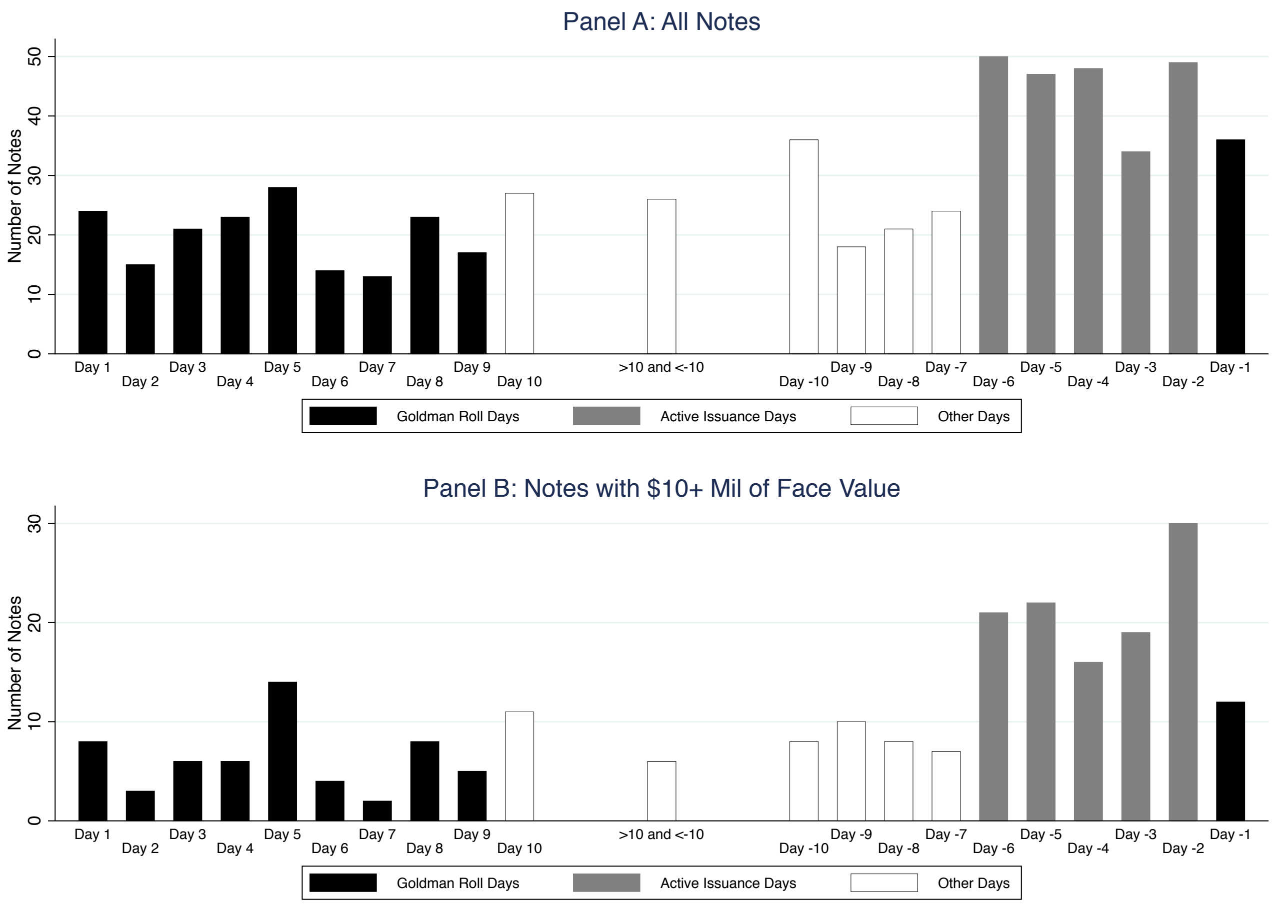

Figure 8. CLN Pricing Days Across the Trading Month
This figure shows the pricing frequency of CLNs across the trading month. The left hand bars represent the first 10 trading days of the the calendar month. The right hand bars represent the last 10 trading days of the calendar month. The central bar represents all notes issued more than 10 trading days from the start and end of the month (a period of 0-2 days depending on the month). The y-axis represents the number of notes issued on this trading day. The Goldman Roll period is defined as in HPW. We define the Active Issuance period as the 5-day period ending with the 2nd to last trading day of the month. As shown in Panel B, this is the period when the frequency of large CLN pricing is greatest.

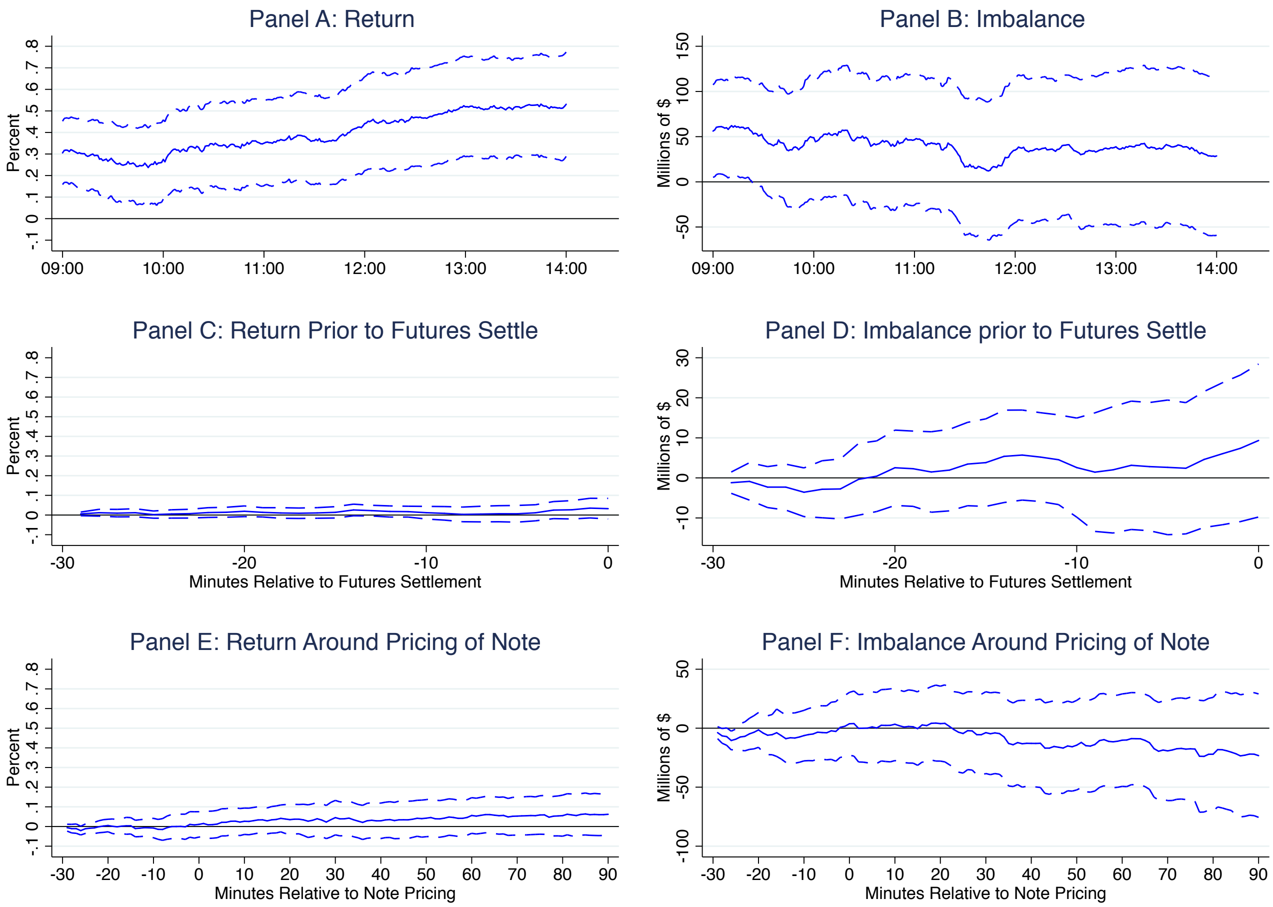

Figure 9. Intraday Returns and Imbalances on CLN pricing dates during Active Issuance Period

The figure shows the average returns and imbalances over expanding windows of the trading day for the underlying commodity on the pricing dates of CLNs with at least \$10 million of face value issued in the Active Issuance Period for which we have intraday data (See Table 8). 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 through 2pm in New York. Panels C and D show cumulative return and imbalance in the 30 mintues prior to the daily settlement. Panels E and F show returns and imbalance in the 30 minutes prior to and 90 minutes after the pricing of the note.

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	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	13.2	219.7	23
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	59.4	6.7	23.5	57.7	5.7	14.7	191	20.6
20130612	170	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	18	186.5	18.7
20130614	161.8	51.1	14.3	48.8	66.5	5.3	42.4	307.5	34
20130617	150.1	71.7	7	54	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	26.9	271.1	15.8
20130620	7.1	13.9	0.1	282.9	81.5	3.3	45.5	343.9	19
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	255.7	12.2
20130627	-	-	-	188.4	67.5	2.4	33.5	255.3	16
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, 2008 to April 1st 2014 for Brent Crude, and January 1st, 2007 to April 1st 2014, for all other commodities. The settlement minute is the minute prior to daily settlement. We exclude minutes before 7:30 AM or after 4:00 PM in New York.

CME WTI Crude Oil (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	38,351	-2.1	33.2	-0.2
St. Dev.	0.09	46,415	169.4	42.1	14.9
# of Min					921,522

CME WTI Crude Oil (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	-0.01	217,517	-50.9	187.8	-4.1
St. Dev.	0.11	91,007	412.4	90	35.8
# of Min					1,824

ICE Brent Crude Oil (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	13,443	-0.4	14.3	0
St. Dev.	0.09	21,784	101.9	23.2	10.4
# of Min					793,281

ICE Brent Crude Oil (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	-0.01	72,268	-2.1	79.3	-0.3
St. Dev.	0.11	60,912	223.4	67.8	23.4
# of Min					1,572

CME Gold (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	17,141	-1.3	21.6	-0.2
St. Dev.	0.05	26,047	92.6	36.1	12.1
# of Min					918,897

CME Gold (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	66,494	18	83.3	2
St. Dev.	0.06	42,180	189.5	63.4	23.9
# of Min					1,825

CME Copper (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	3,709	-0.1	2.8	0
St. Dev.	0.07	6,654	27.8	5.4	2.2
# of Min					894,550

CME Copper (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	32,386	10.2	23.2	0.7
St. Dev.	0.12	27,388	116.9	24.5	9.2
# of Min					1,867

CME Corn (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	33,550	-6.9	9.2	-0.2
St. Dev.	0.13	69,547	277.7	17.9	7.5
# of Min					510,149

CME Corn (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0.01	434,837	119.7	120.2	4.3
St. Dev.	0.25	298,308	1030.5	96.6	29.9
# of Min					1,810

CME Wheat (All Minutes)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(Mil $)	
Mean	0	12,891	-2.6	4.5	-0.1
St. Dev.	0.15	30,431	106.8	9.5	3.7
# of Min					486,757

CME Wheat (Settlement Minute)

	Ret.	Vol.	Imb.	Vol.	Imb.
	(%)	(# Contracts)		(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. Price Impact Regressions

The table shows the results from univariate regressions where the dependent variable is one-minute returns and the independent variable is one-minute imbalance. Return is measured in percentage and imbalance is measured in millions of dollars, (ie. a coefficient of 0.01 represents a return response of 0.01% per million dollars of imbalance). 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 minute prior to futures settlement. 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 and minutes prior to 7:30 AM or after 4:00 PM in New York.

	WTI Crude		Brent Crude		Gold	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imbalance	0.0034***	0.0012***	0.0029***	0.0010***	0.0022***	0.0012***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
	[275.1]	[19.0]	[155.5]	[12.8]	[99.8]	[11.1]
Constant	0.0006***	0	0.0001	-0.0052*	0.0003***	-0.0003
	(0.0001)	(0.0023)	(0.0001)	(0.0027)	(0.0000)	(0.0013)
	[7.8]	[0.0]	[0.6]	[-1.9]	[8.5]	[-0.2]
Observations	929,018	1,824	800,867	1,572	926,415	1,825
R-squared	0.328	0.172	0.124	0.046	0.305	0.224

	Copper		Corn		Wheat	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imbalance	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]
Constant	0.0003***	-0.0024	0.0011***	-0.0065	0.0010***	-0.0194**
	(0.0001)	(0.0026)	(0.0001)	(0.0050)	(0.0002)	(0.0077)
	[5.2]	[-0.9]	[8.1]	[-1.3]	[5.4]	[-2.5]
Observations	902,105	1,867	516,997	1,810	493,374	1,808
R-squared	0.147	0.113	0.188	0.297	0.148	0.254

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

Table 4. Inferring the Price Impact of Order Flow from Daily Data

Panel A shows the results of regressions to estimate the price impact of order flow from daily data. The dependent variables are the log of the price impacts estimated for a single commodity in a calendar year. The independent variables are the log of daily futures return volatility and the log of the average daily volume (in millions of $ of futures notional) across all maturities of futures for a given commodity. Price impacts are defined as the slope of a regression of minute-by-minute returns (in %) on minute-by-minute imbalance (in millions of $) as in Table 3. All variables are obtained for Brent, WTI, Gold, Copper, Wheat, and Corn for each calendar year from 2008 to 2013. In column (1), the impacts are computed using all minutes. In column (2), the impacts are computed using only the minute prior to daily futures settlement. In column (3), the two sets of impacts are pooled in a single regression with a settlement minute dummy variable. Panel B uses the regression estimates of specification (3) in Panel A and estimates impacts for a broad set of commodity contracts. The contracts are sorted from lowest impact to highest. Estimates are calculated for the period 2003 to 2014 where data are available and averages for all years are reported (See Table IA.3 in internet appendix for all commodity-year impact estimates.)

Panel A: Regressions of Price Impacts on Daily Volatility and Volume

	Log(Order Flow Impact)		
	All Minutes (1)	Settlement Minutes (2)	Combined (3)
Log(Daily Volatility)	0.853***	0.747***	0.800***
	[5.506]	[4.408]	[6.864]
Log(Average Volume)	-0.532***	-0.671***	-0.601***
	[-11.471]	[-13.226]	[-17.240]
Settlement Dummy			-0.689***
			[-8.633]
Constant	3.257***	3.443***	3.694***
	[5.117]	[4.950]	[7.693]
Observations	36	36	72
R-squared	0.871	0.886	0.888

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

Panel B: Average Predicted Impacts by Commodity

Contract	Daily Volatility (%)	Average Volume ($Mil/Day)	Estimated Impact All Min (%/$Mil)	Estimated Impact Settle Min (%/$Mil)
LME Copper	1.16	15,631	0.004	0.002
CME Crude Oil	2.12	37,551	0.004	0.002
LME Aluminum	0.99	7,694	0.005	0.003
ICE Brent Crude Oil	1.91	31,049	0.006	0.003
CME Gold	1.20	14,456	0.006	0.003
CME Soy	1.65	7,656	0.009	0.004
LME Zinc	1.30	3,087	0.012	0.006
CME Corn	1.86	5,002	0.012	0.006
CME Natural Gas	3.13	9,207	0.013	0.006
LME Nickel	1.51	2,849	0.015	0.007
CME Silver	2.12	4,159	0.019	0.010
CME Wheat	2.06	2,257	0.021	0.011
CME Copper	1.84	2,571	0.023	0.012
LME Lead	1.49	1,360	0.024	0.012
LME Tin	1.31	533	0.034	0.017
ICE Cotton	1.86	720	0.035	0.017
CME Platinum	1.37	383	0.065	0.033
CME RBOB Gasoline	2.28	9,663	0.088	0.044
CME Palladium	2.03	169	0.169	0.085

Table 5. Size and Predicted Price Impacts for Sources of Financial Investment

The table shows summary statistics for two sources of financial investment in commodity markets. Panel A shows the weekly changes in position of commodity-index traders from the CFTC. Panel B shows the total face value and the calculated trade size necessary to delta hedge the notes on the pricing dates for each commodity. Panel C summarizes days with CLN determination for all commodities. All three panels also report the predicted price impact of order flow associated with each source. This is calculated as the size of the potential flow (The Change in Position for Panel A and Delta Hedge Size for Panels B and C) multiplied times the estimate of price impact per million dollars of imbalance for the applicable commodity-year combination (see Table 4).

Panel A: Changes in Positions of Index Traders

		Change in Position ($Mil)				Predicted Impact (%)			
	N	mean	stdev	min	max	mean	stdev	min	max
Corn	382	-8.3	225.8	-972.7	1278.9	-0.03	1.02	-3.90	4.73
Wheat	382	-7.8	140.4	-1254.0	414.0	-0.05	1.12	-6.00	3.52
					Correlation of Changes in Corn and Wheat:		0.23		

Panel B: Pricing Dates of Commodity-Linked Notes

		Notional ($Mil)			Δ Hedge Size ($Mil)			Predicted Impact(%)		
	N	mean	min	max	mean	min	max	mean	min	max
Gold	199	17.2	2.0	157.9	12.1	0.1	108.2	0.020	0.000	0.198
Brent Crude	114	12.5	2.0	103.4	7.5	0.4	56.0	0.010	0.000	0.310
WTI Crude	80	13.8	2.0	75.9	8.8	0.5	63.0	0.012	0.001	0.083
Palladium	41	13.3	2.3	80.2	7.7	0.7	43.5	0.194	0.010	1.034
LME Copper	34	16.0	2.1	155.5	13.8	0.4	172.4	0.025	0.001	0.312
Silver	25	23.2	2.0	84.9	15.9	0.4	54.9	0.071	0.001	0.267
Corn	18	18.7	2.0	59.9	15.3	1.2	51.1	0.088	0.004	0.404
Natural Gas	8	15.1	3.1	55.4	7.6	1.4	27.1	0.039	0.010	0.110
RBOB Gasoline	4	16.9	2.5	42.3	12.5	0.4	33.8	0.038	0.001	0.102
Cotton	2	7.5	5.0	10.0	4.3	3.2	5.5	0.045	0.033	0.057
Platinum	2	35.4	7.3	63.6	43.1	4.7	81.6	0.684	0.062	1.307
Lead	1	5.0	5.0	5.0	4.7	4.7	4.7	0.076	0.076	0.076
Zinc	1	11.0	11.0	11.0	10.3	10.3	10.3	0.072	0.072	0.072
Nickel	1	23.0	23.0	23.0	21.6	21.6	21.6	0.186	0.186	0.186
Aluminum	1	17.0	17.0	17.0	15.9	15.9	15.9	0.039	0.039	0.039
Tin	1	4.0	4.0	4.0	3.7	3.7	3.7	0.090	0.090	0.090
Total	532	15.6	2	157.9	10.7	0.1	172.4	0.039	0.000	1.307

Panel C: Determination Dates of Commodity-Linked Notes

		Notional Value ($Mil)			Δ Hedge Size ($Mil)			Predicted Impact (%)		
	N	mean	min	max	mean	min	max	mean	min	max
Prior to 2019/01	524	15.8	2.0	184.0	7.7	-23.3	228.0	-0.03	-2.76	0.02
...and $\Delta > 0$	214	18.0	2.0	156.0	18.7	0.0	228.0	-0.07	-2.76	0.00
...and $10+ Mil	92	35.2	10.0	156.0	36.8	0.9	228.0	-0.13	-2.76	0.00
Prior to 2014/02	414	16.3	2.0	184.0	8.4	-14.8	228.0	-0.03	-2.76	0.01
...and $\Delta > 0$	160	19.4	2.0	156.0	21.9	0.0	228.0	-0.08	-2.76	0.00
...and $10+ Mil	71	37.5	10.0	156.0	42.4	0.9	228.0	-0.15	-2.76	0.00

Table 6. Regressions of Return and Imbalance on Changes in the Positions of Commodity-Index Traders

The table shows the results from regressions of weekly futures imbalance and futures returns on changes in the positions of index traders as reported by the CFTC. 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)), futures 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

Dependent Var:	Futures Imbalance				Futures Return		
	Full Day (1)	30 Minutes Prior to Settle (2)	Settle Minute (3)		Full Day (4)	30 Minutes Prior to Settle (5)	Settle Minute (6)
Δ Corn Index Positions	0.371**	0.137***	0.0433***	Standardized Δ Corn Index Positions	0.619*	0.281***	0.0811***
	[2.354]	[3.743]	[4.616]		[1.951]	[4.794]	[3.818]
Constant	-108.3***	-8.619***	0.25	Constant	0.315	0.068	0.0774***
	[-10.43]	[-3.014]	[0.380]		[1.318]	[1.135]	[3.806]
Obs	382	382	382	Obs	382	382	382
R-sq	0.024	0.043	0.078	R-sq	0.017	0.055	0.04

Panel B: Changes in Wheat Index Positions

Dependent Var:	Futures Imbalance				Futures Return		
	Full Day (1)	30 Minutes Prior to Settle (2)	Settle Minute (3)		Full Day (4)	30 Minutes Prior to Settle (5)	Settle Minute (6)
Δ Wheat Index Positions	0.514***	0.244***	0.113***	Standardized Δ Wheat Index Positions	0.492	0.481***	0.243***
	[4.466]	[5.596]	[3.776]		[1.531]	[5.047]	[3.864]
Constant	-37.73***	-5.966***	-2.693***	Constant	-0.0571	-0.273***	-0.169***
	[-9.907]	[-4.525]	[-4.010]		[-0.229]	[-3.582]	[-4.117]
Obs	382	382	382	Obs	382	382	382
R-sq	0.07	0.124	0.104	R-sq	0.01	0.095	0.085

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

Table 7. Average Returns and Predicted Impacts of Delta Hedges on CLN Pricing Dates

Panels A-D show average futures returns and the average value of the predicted price impacts of delta hedging trades on days with CLN pricing. Panel A includes all dates with CLN pricing in the sample. Panel B includes only dates with more than $10 million of face value. Panels C and D are the same as A and B, but only consider the commodities (Brent crude oil, WTI crude oil, copper, gold, and corn) and periods where we have intraday data. In each panel, column (1) includes all dates, column (2) considers dates outside of the monthly Goldman Roll Period, column (3) considers dates during the Goldman Roll Period, column (4) considers dates in the Active Issuance Period, and column (5) considers days outside of the Active Issuance Period. (See Figure 8 for definition of the Goldman Roll and Active Issuance periods). Panel E regresses the pricing date returns on dummies indicating if the date is in the Active Issuance Period or outside of the Goldman Roll Period. The four columns correspond to the samples in column (1) of Panels A - D.

Panel A: All Dates

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.13*	0.28***	-0.12	0.44***	-0.05
tstat	[1.74]	[3.29]	[-0.85]	[4.32]	[-0.54]
Predicted Impact of Delta Hedges					
Avg.	0.04	0.04	0.03	0.06	0.03
Obs	532	338	194	201	331

Panel B: Dates w/ $10+ Million of Face Value

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.29***	0.42***	0.01	0.66***	-0.03
tstat	[2.84]	[3.55]	[0.07]	[5.03]	[-0.22]
Predicted Impact of Delta Hedges					
Avg.	0.08	0.08	0.07	0.09	0.06
Obs	220	153	67	104	116

Panel C: All Dates w/ Available Intraday Data

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.02	0.17**	-0.23	0.36***	-0.21**
tstat	[0.24]	[1.99]	[-1.55]	[3.53]	[-1.99]
Predicted Impact of Delta Hedges					
Avg.	0.02	0.02	0.01	0.02	0.01
Obs	426	264	162	171	255

Panel D: Dates w/ $10+ Mil. and Intraday Data

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.18*	0.33***	-0.15	0.57***	-0.20
tstat	[1.76]	[2.86]	[-0.73]	[4.68]	[-1.30]
Predicted Impact of Delta Hedges					
Avg.	0.03	0.03	0.03	0.03	0.03
Obs	171	118	53	84	87

Panel E: Regressions with Dummy Variables

	Pricing Day Return			
Sample:	Panel A	Panel B	Panel C	Panel D
Active Issuance Period Dummy	0.40**	0.76***	0.55***	0.84***
	[2.28]	[2.92]	[2.71]	[3.24]
Non-Goldman Roll Dummy	0.16	-0.11	0.04	-0.12
	[0.80]	[-0.37]	[0.20]	[-0.44]
Constant	-0.12	0.01	-0.23*	-0.15
	[-0.85]	[0.07]	[-1.84]	[-0.84]
Obs	532	220	426	171
R-sq	0.02	0.05	0.04	0.08

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

Table 8. Intraday Futures Returns and Imbalance on CLN pricing dates in Active Issuance Period

Table shows the average returns (in %) and imbalance (in millions of $) over various intraday periods during the pricing dates of CLNs in the Active Issuance Period. The sample is restricted to the commodities (Brent crude oil, WTI crude oil, copper, gold, and corn) and periods where we have intraday data. Panel A shows returns and Panel B shows imbalance in the associated futures market. Panels C and D repeat the analysis but restricts the sample to days with at least $10 million of face value.

Panel A: Return on Pricing Dates in Active Issuance Period

	Full Day (1)	Prior to 9:00 AM (2)	30 Min Prior to Settle (3)	Settle Minute (4)	30 Min Prior to CLN Pricing (5)	One Hour Centered on CLN Pricing (6)	Pricing Minute (7)
Average	0.36***	0.14*	0.06**	-0.00	0.02	0.03	0.00
	[3.53]	[1.80]	[2.15]	[-0.41]	[0.66]	[0.78]	[0.84]
Observations	171	171	171	171	171	171	171

Panel B: Imbalance on Pricing Dates in Active Issuance Period

	Full Day (1)	Prior to 9:00 AM (2)	30 Min Prior to Settle (3)	Settle Minute (4)	30 Min Prior to CLN Pricing (5)	One Hour Centered on CLN Pricing (6)	Pricing Minute (7)
Average	5.43	11.63	12.18*	2.98*	-0.63	-9.59	0.49
	[0.18]	[0.68]	[1.88]	[1.69]	[-0.07]	[-0.81]	[0.32]
Observations	171	171	171	171	171	171	171

Panel C: Return on Pricing Dates in Active Issuance Period w/ $10+ Mil of Face Value

	Full Day (1)	Prior to 9:00 AM (2)	30 Min Prior to Settle (3)	Settle Minute (4)	30 Min Prior to CLN Pricing (5)	One Hour Centered on CLN Pricing (6)	Pricing Minute (7)
Average	0.57***	0.31***	0.03	-0.00	0.01	0.03	0.01
	[4.68]	[4.13]	[1.23]	[-0.43]	[0.33]	[0.80]	[1.06]
Observations	84	84	84	84	84	84	84

Panel D: Imbalance on Pricing Dates in Active Issuance Period w/ $10+ Mil of Face Value

	Full Day (1)	Prior to 9:00 AM (2)	30 Min Prior to Settle (3)	Settle Minute (4)	30 Min Prior to CLN Pricing (5)	One Hour Centered on CLN Pricing (6)	Pricing Minute (7)
Average	55.11	56.15**	9.34	1.95	3.38	-3.79	2.17
	[1.27]	[2.18]	[0.97]	[0.86]	[0.25]	[-0.22]	[1.28]
Observations	84	84	84	84	84	84	84

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

Table 9. Futures Returns on CLN Determination Dates

The table repeats the analysis in Table 7, but uses the average return on days with CLN determination rather than CLN pricing, and with predicted return calculated as the inverse of the determination date delta times the face value. Panels A uses all days with a note that has a delta greater than zero on the a determination date prior to 1/1/2019. Panel B restricts this to days with at least $10 million of Face Value. Panels C and D further restricts the sample to notes with determination dates before 2/1/2014 to replicate the determination date event study of HPW.

Panel A: All Dates

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg	0.03	0.12	-0.14	0.32**	-0.14
tstat	[0.32]	[0.95]	[-0.67]	[2.01]	[-1.00]
Predicted Impact of Unwinding Delta Hedges					
Avg	-0.07	-0.08	-0.04	-0.04	-0.08
Obs	214	147	67	81	133

Panel B: Dates w/ $10+ Mil Face Value

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg	-0.11	-0.04	-0.26	0.25	-0.46*
tstat	[-0.67]	[-0.27]	[-0.67]	[1.44]	[-1.76]
Predicted Impact of Unwinding Delta Hedges					
Avg	-0.13	-0.14	-0.08	-0.06	-0.19
Obs	92	64	28	45	47

Panel C: Dates prior to 2014/02

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg	0.09	0.08	0.36*	-0.05	-0.08
tstat	[0.65]	[0.35]	[1.94]	[-0.33]	(0.02)
Predicted Impact of Unwinding Delta Hedges					
Avg	-0.08	-0.09	-0.05	-0.05	-0.09
Obs	160	110	50	53	107

Panel D: Prior 2014/02 w/ $10+ Mil Face Value

	All (1)	Outside Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Outside Active Issuance Period (5)
Realized Daily Returns					
Avg	-0.00	-0.09	0.21	0.32	-0.25
tstat	[-0.00]	[-0.43]	[0.54]	[1.31]	[-0.97]
Predicted Impact of Unwinding Delta Hedges					
Avg	-0.15	-0.17	-0.09	-0.07	-0.21
Obs	71	50	21	31	40

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

Internet Appendix for Order Flows and Financial Investor Impacts in Commodity Futures Markets

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IA.1 Vector Autoregressions as in Hasbrouck 1991

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 log 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:

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

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:

$$\begin{aligned} r_t = v_{1,t} &+ a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \ldots \\ x_t &= c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \ldots + v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \ldots \end{aligned}$$

The VAR 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. This VMA representation allows for the calculation of impulse response functions. Hasbrouck 1991 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:

$$R_w^2 = \frac{(\sum_{t=0}^{\infty} b_t^*)^2 \sigma_2^2}{(\sum_{t=0}^{\infty} b_t^*)^2 \sigma_2^2 + (1 + \sum_{t=1}^{\infty} a_t^*)^2 \sigma_1^2} \tag{1}$$

When examining equity data, Hasbrouck 1991 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: b_0 and b_0^* , which are the initial impact of order flow and the initial price impact of the unpredictable portion of order flow. Higher values for these coefficients may suggest a higher fraction of trades come from the informed, or that the information held by informed traders is more valuable, or that the market is illiquid for other reasons. $\sum b_t^*$, the permanent price impact of an innovation in order flow. We illustrate this with impulse response functions to test if the impact of an innovation in order flow is reversed in subsequent minutes. R_w^2, the fraction of the efficient price variance explained by order flow innovations (as with b_0^*, a higher value implies more information coming from trades, but this measure is relative to the amount of information that arrives through public announcements).

Table IA.1 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, where 100 contracts translates into approximately \$2.5 million of notional over the sample).

The parameter b_0 from equation the VAR is shown in the first row of each of the return columns in Table IA.1. This is the estimated response of the futures price to the order imbalance in the current minute. When the regressions from Table IA.1 are converted to the VMA representation (results not shown), we find that the values of b_0 from the VAR are very close to the values of b_0^*. This is not surprising, because as shown in the remaining rows of Table IA.1, 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 0.033 for WTI futures shows that a minute with 100 contracts (about $10 million notional) of buy (sell) imbalance will create a same-minute price increase (decrease) of 3.3 basis points. A roughly $10 million dollar flow yields an impact of approximately 3 basis points for gold, similar to the WTI, but a trade of $10 million notional value trade moves copper and corn prices approximately 10 basis points (the coefficient for corn must be multiplied by four to adjust for the lower notional value per contract). 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^2_w 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 IA.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 seven-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.

IA.2 Nonlinearities in Settlement Minute Returns

Figure IA.2 shows scatter plots of imbalance and returns in the 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.

IA.3 Price Impacts of Order Flow In Different Subperiods of the Trading Month

In this table we repeat the analysis of Table 3 in the main text, but add dummy variables for both the Goldman Roll Period and the Active Issuance Period (see Figure 7 in the main text). Table IA.2 shows the results. The coefficients on the interaction with the dummy variables tend to be very small relative to the baseline estimates of impact, and the coefficients on the interaction terms are not consistent in sign. We conclude that there is little different in price impacts for trades in the Goldman Roll or the Active Issuance Period.

IA.4 Predicted Price Impacts for Commodities and Calendar Years

Table IA.3 shows the daily average volume, daily volatility, and predicted impacts for a large set of commodities from 2003 to 2014 where we have data. The average of these estimates and the regression specification are reported in Table 4 in the main text.

IA.5 Retail Trading in the United States Oil Fund

In this section we examine 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).

Panel A of Table IA.4 shows summary statistics for trading volume in the USO. 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-minute 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) as reported in the main text. This suggests that futures trades driven by uninformed volume from USO retail traders should have a relatively small effect on futures markets.

In Panel B of Table IA.4 we test for impacts of this volume. We first test for price impact of this volume at a daily frequency, and in doing so we obtain a puzzling result. Days with buying (selling) by retail investors in the USO tend to be days with negative (positive) return (column (6))). However, when we examine the relation of retail imbalance and returns at the one-minute frequency, 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 (column (7)), the finding reverses, and we find a small positive association between retail order flow and price changes, but this effect is very minor relative to the overall volatility of this market.

IA.6 Predicted Impacts and Actual Returns for CLN Pricing Dates

Figure IA.3 shows scatter plots (with regression lines and equations) of actual pricing date returns on predicted pricing date returns calculated as the size of the associated delta hedging trades times the commodity-year price impact estimates from Table IA.3. Panel D includes a dummy variable for whether or not the note was issued in the Active Issuance Period.

As we see from the figures, for most specifications there is a significant slope with a point estimate near one. This is broadly consistent with the idea that larger notes do in fact create some larger impact on prices. Even so, the predicted impacts of the notes are not large enough to explain the results. This is evident by the strongly significant intercept terms for the notes outside of the Goldman Roll or in the Active Issuance Period. Panel D shows all notes with a dummy variable for the active issuance period, and this dummy variable has a positive and highly significant coefficient of approximately 45 basis points. This suggests that it is whether or not the note is issued in this period, rather than the note's size, that associates it with a large positive pricing date return.

References

Hasbrouck, J. 1991. The summary informativeness of stock trades: An econometric analysis. *The Review of Financial Studies* 4:571–595.

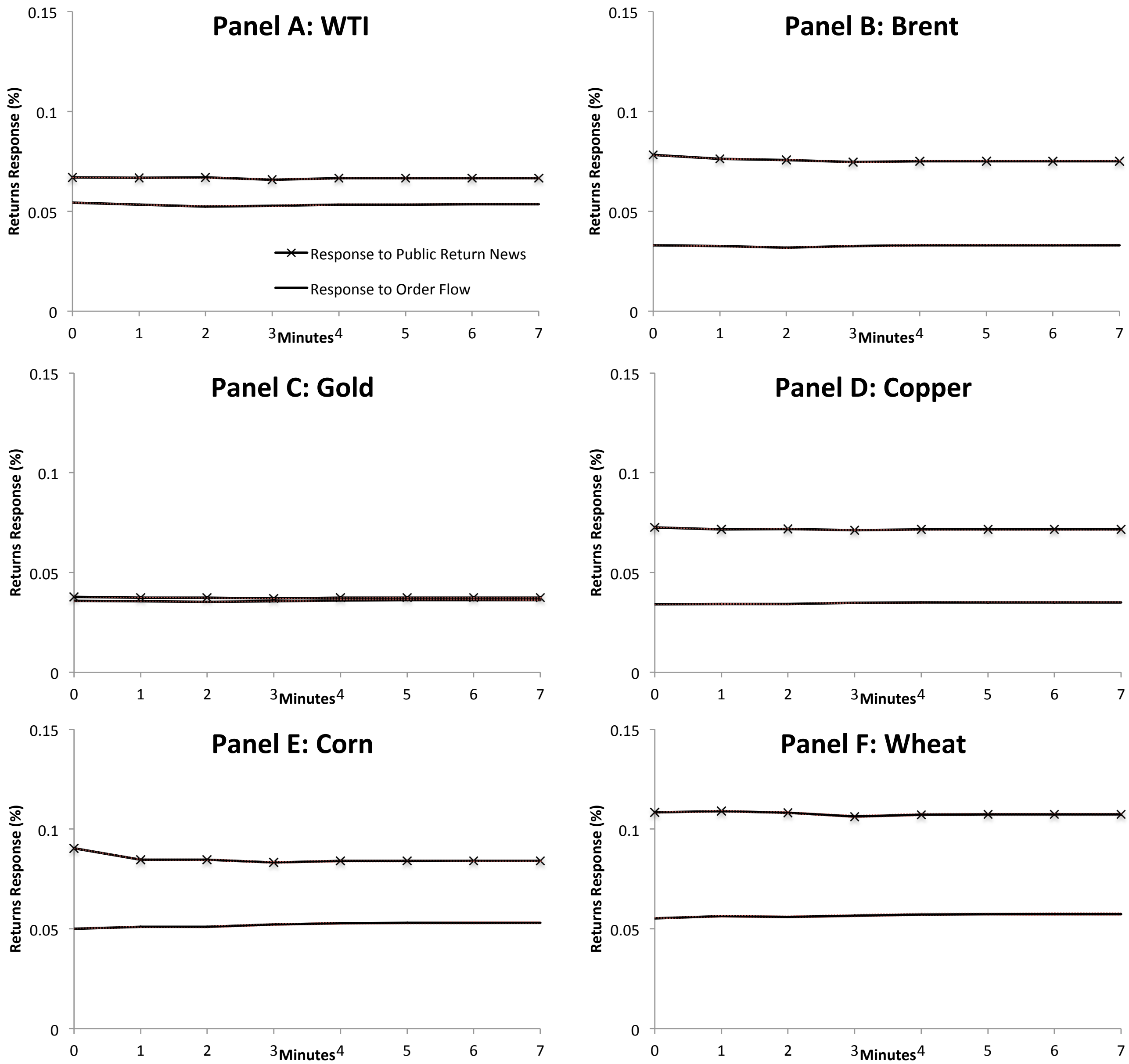

Figure IA.1. Return Impulse Response Functions for VARs
The figure shows the impulse response of returns to innovations in order flow and public news from the vector autoregression specification estimated in Table 3. Plots show return responses to one standard deviation innovations in public return news and unanticipated order flow.

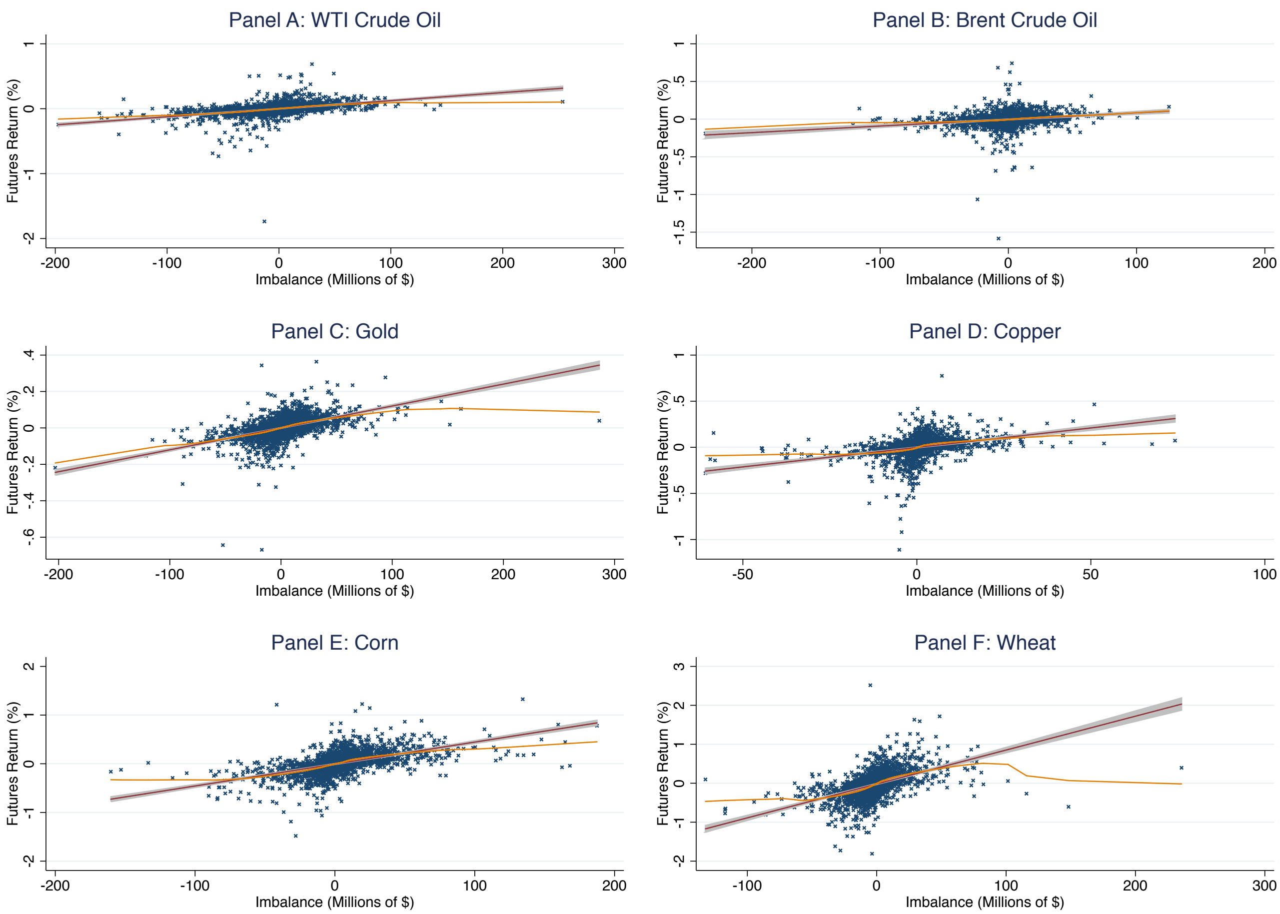

Figure IA.2. Nonlinearities in Imbalance and Return in Minute Prior to Futures Settlement

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 $\alpha = 0.8$. Data are 1/1/2007 to 4/1/2014. We exclude data prior to 1/1/2008 for Brent.

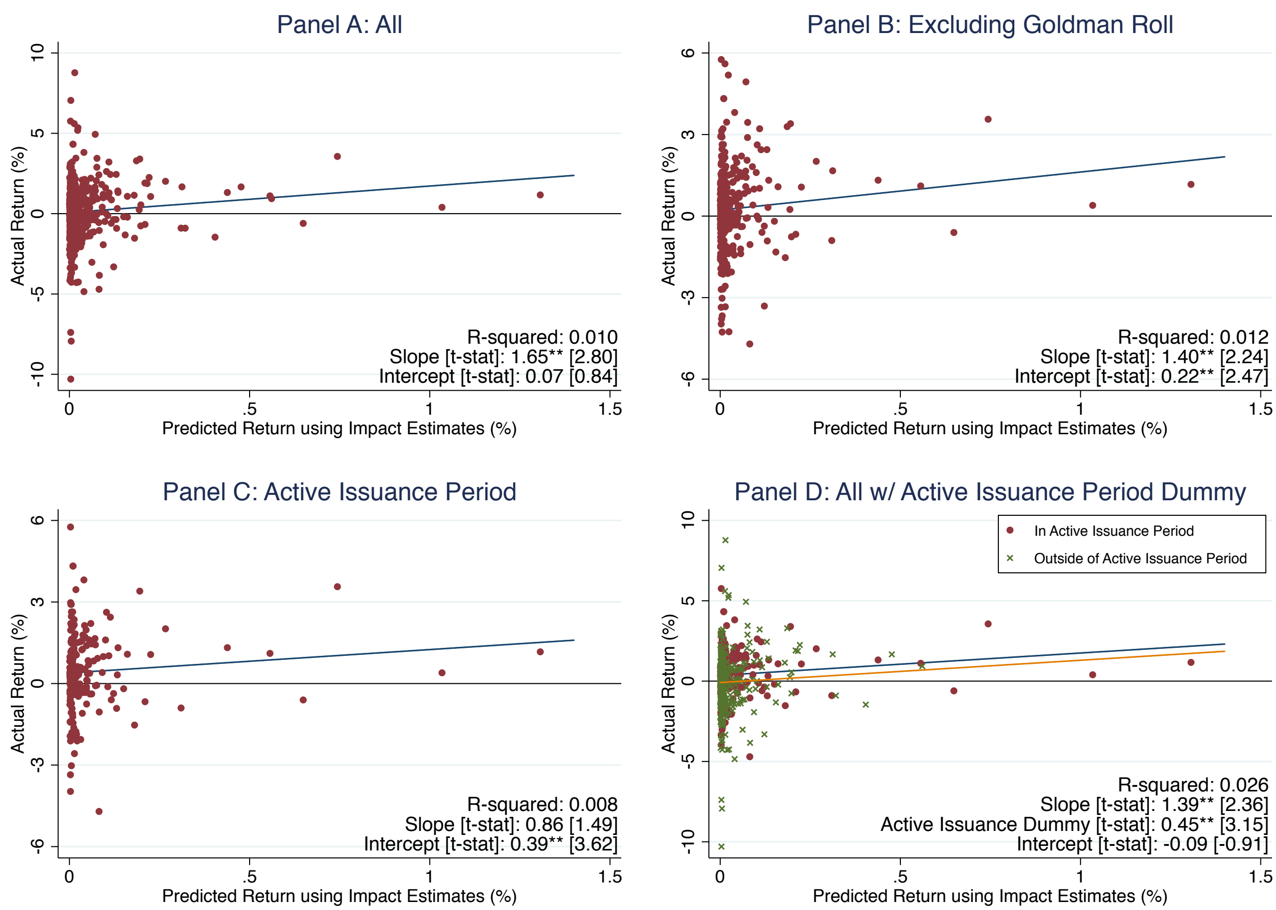

Figure IA.3. Actual Returns vs. Predicted Returns on CLN pricing dates
Figure shows scatter plots with regression lines of actual pricing date returns on predicted pricing date returns calculated as the size of the associated delta hedging trades times the commodity-year price impact estimates from Table IA.3. Panel D includes a dummy variable for whether or not the note was issued in the Active Issuance Period.

Table IA.1. Full Sample Price Impact VARs

The table shows the results from vector autoregressions of the form described in section IA.1. R^2_w 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. The sample is 1/1/2007 to 4/1/2014. We exclude data prior to 2008 for Brent and minutes prior to 7:30 AM or after 4:00 PM in New York.

	WTI Crude		Brent Crude		Gold		Copper		Corn		Wheat	
	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance	Return	Imbalance
Imb. (t)	0.033***		0.033***		0.031***		0.097***		0.020***		0.053***	
	[778.258]		[377.948]		[730.820]		[434.507]		[407.343]		[312.961]	
Imb (t-1)	-0.003***	0.089***	-0.004***	0.127***	-0.002***	0.062***	-0.006***	0.078***	-0.000***	0.103***	-0.001***	0.085***
	[-62.650]	[66.277]	[-41.088]	[104.247]	[-36.209]	[47.071]	[-22.881]	[65.939]	[-3.181]	[63.330]	[-6.285]	[53.497]
Imb (t-2)	-0.001***	0.029***	-0.002***	0.047***	-0.001***	0.030***	-0.005***	0.039***	-0.001***	0.051***	-0.002***	0.038***
	[-25.083]	[21.670]	[-19.935]	[38.760]	[-16.365]	[22.641]	[-18.549]	[32.783]	[-15.182]	[31.108]	[-9.215]	[23.055]
Imb (t-3)	-0.001***	0.029***	-0.002***	0.042***	-0.001***	0.028***	-0.003***	0.033***	-0.001***	0.035***	-0.002***	0.027***
	[-21.857]	[21.871]	[-16.525]	[34.798]	[-18.914]	[22.021]	[-13.401]	[28.185]	[-16.457]	[22.729]	[-8.448]	[16.793]
Ret (t-1)	-0.058***	1.650***	-0.037***	0.443***	-0.061***	1.900***	-0.034***	0.175***	-0.102***	1.589***	-0.063***	0.299***
	[-55.155]	[64.120]	[-33.273]	[30.564]	[-58.543]	[75.018]	[-31.644]	[34.466]	[-74.581]	[39.908]	[-43.874]	[24.441]
Ret (t-2)	-0.014***	0.440***	-0.012***	0.144***	-0.026***	0.681***	-0.001	0.082***	-0.026***	0.486***	-0.020***	0.109***
	[-13.515]	[17.065]	[-11.029]	[9.900]	[-24.994]	[26.798]	[-0.673]	[16.211]	[-18.938]	[12.230]	[-13.035]	[8.343]
Ret (t-3)	-0.007***	0.125***	-0.009***	0.060***	-0.012***	0.288***	-0.001	0.029***	-0.011***	0.127***	-0.010***	0.027**
	[-7.101]	[4.893]	[-8.099]	[4.145]	[-11.746]	[11.419]	[-0.786]	[5.709]	[-9.606]	[3.653]	[-6.954]	[2.194]
Cons	0.001***	-0.017***	0	-0.003***	0.000***	-0.012***	0.000***	-0.001***	0.001***	-0.060***	0.001***	-0.022***
	[8.280]	[-9.939]	[0.603]	[-2.817]	[9.294]	[-12.070]	[5.297]	[-3.266]	[9.829]	[-15.818]	[5.199]	[-15.132]
Obs	919,910	919,910	792,989	792,989	915,852	915,852	874,572	874,572	493,111	493,111	475,674	475,674
R^2	0.397	0.03	0.153	0.029	0.368	0.027	0.178	0.016	0.255	0.03	0.172	0.016
R^2_w	0.382		0.145		0.354		0.171		0.248		0.165	

t-stats in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table IA.2. Price Impact of Order Flow in Goldman Roll and Active Issuance Periods

This table shows regressions as in Table 3 in the main text, with a dummy variable indicating if the trading day of the month falls in the Goldman Roll Period (Panel A) or the Active Issuance Period (Panel B) interacted with imbalance. See Figure 7 in the main text for a description of the Goldman Roll and the Active Issuance Period. Both the regression constant and dummy variable terms are supressed and only the interaction term is shown.

Panel A: Price Impact of Imbalance in Goldman Roll Period

	WTI Crude		Brent Crude		Gold		Copper		Corn		Wheat	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imbalance	0.0034***	0.0012***	0.0029***	0.0010***	0.0021***	0.0010***	0.0106***	0.0038***	0.0068***	0.0041***	0.0165***	0.0098***
	(0.00005)	(0.00009)	(0.00006)	(0.00011)	(0.00006)	(0.00015)	(0.00031)	(0.00047)	(0.00029)	(0.00028)	(0.00088)	(0.00064)
	[63.0]	[12.9]	[47.7]	[8.9]	[36.1]	[6.8]	[34.1]	[8.2]	[23.6]	[14.5]	[18.8]	[15.4]
Period Dummy × Imbalance	-0.0001	0.0002	-0.0002*	0.0001	0.0002**	0.0004**	0.0016***	0.0008	-0.0006	0.0005	-0.0027*	-0.0013
	(0.00008)	(0.00013)	(0.00009)	(0.00015)	(0.00007)	(0.00020)	(0.00050)	(0.00066)	(0.00053)	(0.00048)	(0.00143)	(0.00137)
	[-0.8]	[1.3]	[-1.9]	[0.4]	[2.2]	[2.2]	[3.2]	[1.2]	[-1.1]	[0.9]	[-1.9]	[-0.9]
Obs	930,690	1,824	802,294	1,572	928,071	1,825	903,770	1,867	517,023	1,810	493,386	1,808
R sq	0.327	0.173	0.124	0.046	0.305	0.232	0.148	0.121	0.212	0.289	0.179	0.261

Panel B: Price Impact of Imbalance in Active Issuance Period

	WTI Crude		Brent Crude		Gold		Copper		Corn		Wheat	
	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute	All Minutes	Settle Minute
Imbalance	0.0033***	0.0012***	0.0029***	0.0010***	0.0022***	0.0013***	0.0115***	0.0041***	0.0065***	0.0045***	0.0145***	0.0090***
	(0.00004)	(0.00007)	(0.00005)	(0.00009)	(0.00004)	(0.00015)	(0.00029)	(0.00039)	(0.00033)	(0.00028)	(0.00088)	(0.00096)
	[77.7]	[16.8]	[57.3]	[11.2]	[55.1]	[8.8]	[39.9]	[10.6]	[19.9]	[16.0]	[16.4]	[9.4]
Period Dummy × Imbalance	0.0004***	0.0005***	-0.0002**	-0.0001	-0.0003***	-0.0002	-0.0007	0.0005	-0.0000	-0.0006	0.0027*	0.0002
	(0.00009)	(0.00017)	(0.00009)	(0.00017)	(0.00009)	(0.00020)	(0.00055)	(0.00078)	(0.00057)	(0.00052)	(0.00146)	(0.00131)
	[4.3]	[2.7]	[-2.6]	[-0.4]	[-2.8]	[-1.2]	[-1.3]	[0.7]	[-0.0]	[-1.1]	[1.8]	[0.2]
Obs	932,513	1,824	803,865	1,572	929,873	1,825	905,297	1,867	517,087	1,810	493,401	1,808
R sq	0.328	0.175	0.124	0.046	0.305	0.226	0.147	0.113	0.212	0.289	0.178	0.259

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

Table IA.3. Estimated Impact of Order Flow by Commodity and Year

This table shows the predicted price impact of order flow for different commodity contracts. For each commodity-year the table shows the average daily volume across all futures maturities and the standard deviation of the nearest-to-maturity future return. Impact for all minutes and the settlement minute are then calculated using the regression specification of Table ?? in the main text.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
LME Copper													
Millions $ Day					15,262	18,393	12,871	22,616	30,455	28,505	31,456	28,009	15,631
Stdev Daily Returns					0.020	0.028	0.024	0.017	0.018	0.012	0.011	0.008	0.012
Est. Impact All Min.					0.005	0.006	0.007	0.004	0.003	0.003	0.002	0.002	0.004
Est. Impact Settle Min.					0.003	0.003	0.003	0.002	0.002	0.001	0.001	0.001	0.002
NYMEX Crude Oil													
Millions $ Day	5,591	8,745	13,412	18,492	34,988	53,928	33,670	53,040	65,585	52,734	57,454	52,970	37,551
Stdev Daily Returns	0.023	0.022	0.020	0.017	0.019	0.037	0.034	0.017	0.022	0.016	0.012	0.015	0.021
Est. Impact All Min.	0.011	0.008	0.006	0.004	0.003	0.005	0.005	0.002	0.002	0.002	0.002	0.002	0.004
Est. Impact Settle Min.	0.005	0.004	0.003	0.002	0.001	0.002	0.003	0.001	0.001	0.001	0.001	0.001	0.002
LME Aluminum													
Millions $ Day					10,618	12,422	7,835	10,113	14,267	11,933	12,287	12,849	7,694
Stdev Daily Returns					0.013	0.019	0.021	0.017	0.013	0.012	0.011	0.011	0.010
Est. Impact All Min.					0.005	0.006	0.008	0.006	0.004	0.004	0.004	0.004	0.005
Est. Impact Settle Min.					0.002	0.003	0.004	0.003	0.002	0.002	0.002	0.002	0.003
ICE Brent													
Millions $ Day	2,702	3,816	6,697	11,426	16,817	26,136	18,150	31,930	58,080	65,145	68,566	63,124	31,049
Stdev Daily Returns	0.021	0.023	0.019	0.016	0.017	0.035	0.027	0.016	0.018	0.014	0.010	0.013	0.019
Est. Impact All Min.	0.015	0.013	0.008	0.005	0.004	0.007	0.006	0.003	0.002	0.002	0.001	0.002	0.006
Est. Impact Settle Min.	0.008	0.007	0.004	0.003	0.002	0.003	0.003	0.001	0.001	0.001	0.001	0.001	0.003

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Table IA.3. – continued from previous page

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
COMEX Gold													
Millions $ Day	1,766	2,464	2,804	3,841	7,034	13,276	13,799	21,745	30,858	29,056	26,522	20,304	14,456
Stdev Daily Returns	0.010	0.010	0.008	0.015	0.010	0.019	0.014	0.010	0.013	0.010	0.014	0.009	0.012
Est. Impact All Min.	0.013	0.011	0.009	0.010	0.006	0.005	0.004	0.003	0.003	0.002	0.003	0.003	0.006
Est. Impact Settle Min.	0.007	0.005	0.004	0.005	0.003	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.003
COMEX Soy													
Millions $ Day	2,252	2,785	2,431	2,684	5,534	9,107	7,324	7,825	11,773	15,177	13,010	11,975	7,656
Stdev Daily Returns	0.014	0.022	0.017	0.012	0.014	0.029	0.022	0.014	0.014	0.015	0.013	0.014	0.017
Est. Impact All Min.	0.013	0.016	0.014	0.011	0.008	0.010	0.009	0.006	0.005	0.004	0.004	0.005	0.009
Est. Impact Settle Min.	0.006	0.008	0.007	0.005	0.004	0.005	0.004	0.003	0.002	0.002	0.002	0.002	0.004
LME Zinc													
Millions $ Day					4,081	3,015	2,638	3,900	4,816	5,753	5,949	6,891	3,087
Stdev Daily Returns					0.025	0.029	0.026	0.022	0.017	0.014	0.011	0.012	0.013
Est. Impact All Min.					0.014	0.020	0.019	0.013	0.009	0.007	0.006	0.006	0.012
Est. Impact Settle Min.					0.007	0.010	0.009	0.007	0.005	0.004	0.003	0.003	0.006
COMEX Corn													
Millions $ Day	887	1,150	1,148	2,504	4,070	6,497	3,785	6,056	10,714	9,967	7,465	5,781	5,002
Stdev Daily Returns	0.013	0.015	0.015	0.018	0.020	0.027	0.023	0.020	0.022	0.019	0.016	0.014	0.019
Est. Impact All Min.	0.022	0.020	0.020	0.014	0.012	0.012	0.014	0.009	0.007	0.006	0.007	0.007	0.012
Est. Impact Settle Min.	0.011	0.010	0.010	0.007	0.006	0.006	0.007	0.004	0.004	0.003	0.003	0.004	0.006
NYMEX Natural Gas													
Millions $ Day	4,138	4,219	6,691	6,286	8,327	13,682	7,882	11,147	12,294	10,555	12,538	12,728	9,207
Stdev Daily Returns	0.043	0.034	0.031	0.039	0.030	0.030	0.042	0.027	0.021	0.031	0.019	0.030	0.031
Est. Impact All Min.	0.028	0.019	0.013	0.019	0.011	0.008	0.019	0.008	0.006	0.010	0.006	0.009	0.013
Est. Impact Settle Min.	0.014	0.010	0.007	0.009	0.005	0.004	0.009	0.004	0.003	0.005	0.003	0.004	0.006

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Table IA.3. – continued from previous page

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
LME Nickel													
Millions $ Day					3,384	2,626	2,370	3,834	4,414	4,696	5,031	7,838	2,849
Stdev Daily Returns					0.027	0.036	0.032	0.022	0.019	0.015	0.012	0.017	0.015
Est. Impact All Min.					0.017	0.028	0.026	0.013	0.011	0.009	0.007	0.007	0.015
Est. Impact Settle Min.					0.009	0.014	0.013	0.007	0.005	0.004	0.004	0.003	0.007
COMEX Silver													
Millions $ Day	404	674	808	1,252	1,811	2,729	2,397	5,405	14,150	8,278	6,807	5,193	4,159
Stdev Daily Returns	0.013	0.023	0.014	0.028	0.016	0.032	0.024	0.020	0.030	0.019	0.021	0.015	0.021
Est. Impact All Min.	0.035	0.038	0.024	0.032	0.016	0.024	0.018	0.010	0.008	0.007	0.009	0.008	0.019
Est. Impact Settle Min.	0.018	0.019	0.012	0.016	0.008	0.012	0.009	0.005	0.004	0.004	0.004	0.004	0.010
COMEX Wheat													
Millions $ Day	469	541	639	1,314	2,497	3,148	1,869	2,675	3,460	4,038	3,390	3,041	2,257
Stdev Daily Returns	0.018	0.018	0.016	0.019	0.021	0.032	0.024	0.023	0.025	0.020	0.012	0.017	0.021
Est. Impact All Min.	0.040	0.037	0.029	0.021	0.016	0.022	0.022	0.017	0.016	0.012	0.010	0.012	0.021
Est. Impact Settle Min.	0.020	0.018	0.015	0.011	0.008	0.011	0.011	0.009	0.008	0.006	0.005	0.006	0.011
COMEX Copper													
Millions $ Day	247	411	657	1,001	1,206	1,456	1,550	3,474	4,910	5,778	5,650	4,511	2,571
Stdev Daily Returns	0.013	0.020	0.015	0.024	0.021	0.030	0.027	0.018	0.019	0.014	0.012	0.010	0.018
Est. Impact All Min.	0.047	0.045	0.028	0.032	0.025	0.032	0.027	0.012	0.010	0.007	0.007	0.007	0.023
Est. Impact Settle Min.	0.024	0.023	0.014	0.016	0.012	0.016	0.013	0.006	0.005	0.004	0.003	0.004	0.012
LME Lead													
Millions $ Day					1,219	1,290	1,033	1,663	2,619	2,937	2,817	2,745	1,360
Stdev Daily Returns					0.028	0.037	0.031	0.024	0.021	0.016	0.012	0.010	0.015
Est. Impact All Min.					0.032	0.046	0.041	0.023	0.015	0.012	0.010	0.010	0.024
Est. Impact Settle Min.					0.016	0.023	0.021	0.012	0.008	0.006	0.005	0.005	0.012

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Table IA.3. – continued from previous page

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
LME Tin													
Millions $ Day					376	522	1,242	636	984	779	926	928	533
Stdev Daily Returns					0.020	0.031	0.025	0.019	0.023	0.018	0.013	0.010	0.013
Est. Impact All Min.					0.048	0.061	0.029	0.034	0.030	0.029	0.021	0.019	0.034
Est. Impact Settle Min.					0.024	0.030	0.014	0.017	0.015	0.014	0.011	0.009	0.017
COMEX Cotton													
Millions $ Day	372	360	385	468	723	792	375	1,005	1,437	918	965	844	720
Stdev Daily Returns	0.018	0.023	0.017	0.014	0.013	0.026	0.020	0.021	0.026	0.019	0.013	0.014	0.019
Est. Impact All Min.	0.045	0.056	0.043	0.033	0.025	0.039	0.049	0.027	0.027	0.027	0.021	0.023	0.035
Est. Impact Settle Min.	0.023	0.028	0.022	0.017	0.012	0.019	0.025	0.014	0.014	0.014	0.010	0.012	0.017
COMEX Platinum													
Millions $ Day	38	51	68	85	133	217	200	479	672	812	961	885	383
Stdev Daily Returns	0.012	0.014	0.008	0.015	0.010	0.027	0.017	0.013	0.013	0.013	0.013	0.009	0.014
Est. Impact All Min.	0.140	0.129	0.085	0.097	0.061	0.089	0.063	0.032	0.026	0.023	0.021	0.019	0.065
Est. Impact Settle Min.	0.070	0.065	0.043	0.049	0.031	0.045	0.032	0.016	0.013	0.011	0.010	0.009	0.033
COMEX RBOB Gasoline													
Millions $ Day			7	1,134	6,872	8,723	5,979	9,866	14,666	17,897	16,385	15,103	9,663
Stdev Daily Returns			0.030	0.023	0.021	0.036	0.029	0.017	0.020	0.015	0.014	0.014	0.023
Est. Impact All Min.			0.790	0.028	0.009	0.014	0.013	0.006	0.005	0.004	0.004	0.004	0.088
Est. Impact Settle Min.			0.397	0.014	0.004	0.007	0.007	0.003	0.003	0.002	0.002	0.002	0.044
COMEX Palladium													
Millions $ Day	8	25	26	49	57	74	44	193	331	287	429	503	169
Stdev Daily Returns	0.024	0.023	0.017	0.025	0.011	0.030	0.022	0.024	0.022	0.017	0.016	0.012	0.020
Est. Impact All Min.	0.594	0.276	0.210	0.201	0.108	0.192	0.191	0.085	0.058	0.051	0.038	0.030	0.169
Est. Impact Settle Min.	0.298	0.139	0.106	0.101	0.054	0.096	0.096	0.043	0.029	0.025	0.019	0.015	0.085

Table IA.4. Regressions of Return and Imbalance on USO Retail Imbalance

Panel A reports summary statistics for imbalance in the USO. Panel B shows regressions of return and imbalance in WTI futures on retail imbalance in the United States Oil Fund (USO). In columns (1)-(3) and (5)-(7) the independent variable is the sum USO retail imbalance for each trading day. In columns (1) and (5), the dependent variables are the sum of WTI imbalance and WTI returns for all minutes in each trading day. In columns (2) and (6) the dependent variables are the sum across the 30 minutes prior to futures settlement in each trading day. In columns (3) and (7) the dependent variables are the imbalance and return in the single minute prior to settlement. In columns (4) and (8) all variables are measured at the 1-minute frequency. Data are from 1/1/2007 to 4/1/2014.

Panel A: Summary Stats for USO Order Flow Imbalance

		Imbalance ($Mil)				Predicted Impact (%)			
	N	mean	stdev	min	max	mean	stdev	min	max
By Minute:									
All Trades	692,738	0.0	1.5	-348.5	299.1	0.00	0.00	-0.35	0.49
Retail Trades	692,738	0.0	0.2	-98.3	36.5	0.00	0.00	-0.23	0.06
By Day:									
All Trades	1,824	-2.0	35.7	-351.6	366.1	0.00	0.06	-0.41	0.87
Retail Trades	1,824	0.2	5.9	-92.4	74.0	0.00	0.01	-0.22	0.11

Panel B: Regressions of WTI Return and Imbalance on USO Retail Imbalance

	WTI Futures Imbalance				WTI Futures Return			
	Daily	30 Min Prior to Settle	Settle Minute	All Minutes	Daily	30 Min Prior to Settle	Settle Minute	All Minutes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
USO Retail Imb. (Day)	-0.694	-1.850***	-0.089		-0.086***	-0.016***	0.000	
	[-0.362]	[-2.726]	[-0.546]		[-10.197]	[-6.151]	[0.212]	
USO Retail Imb. (Minute)				1.405***				0.003**
				[2.80]				[2.331]
Constant	-85.446***	11.386***	-4.110***	-0.167***	0.024	0.046***	-0.005**	0.000
	[-7.370]	[2.987]	[-4.866]	[8.90]	[0.471]	[2.936]	[-2.045]	[1.081]
Obs	1,824	1,824	1,824	692,738	1,824	1,824	1,824	692,738
R-sq	0.000	0.005	0.000	0.000	0.054	0.020	0.000	0.000

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