Order Flows and Financial Investor Impacts in Commodity Futures Markets*

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Abstract

We investigate the impacts of financial investors in commodity markets using intraday trade-and-quote data for commodity futures. 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 order flows and price impacts are consistent with the magnitudes of the index flows, and are concentrated in the minutes just prior to daily futures settlement, when the price impact of order flow 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 that these notes are an order of magnitude too small for the price impacts of hedging trades to explain these returns. We provide evidence that the positive returns are more consistent with CLN issuance responding to commodity prices rather than vice-versa.

JEL Codes: G12, G13

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1 Introduction

Increasing financial investment in commodity futures over the last decade has generated substantial interest in the impact of this investment on commodity markets. Theoretical work (e.g. Hamilton and Wu (2014), Sockin and Xiong (2015), and Goldstein and Yang (2017)) predicts that the trading of financial investors can impact prices even if the investors are uninformed about fundamentals. However, the empirical evidence is mixed. For instance, Irwin and Sanders (2011) and Stoll and Whaley (2010) find no evidence of returns associated with changes in the positions of commodity-index investors reported by the CFTC. In contrast Henderson, Pearson, and Wang (2015) (henceforth HPW) find commodity price increases on the days with the issuance of Commodity-Linked Notes (CLNs), a financial vehicle typically marketed to retail investors, and argue that these price increases are evidence that the uninformed trades necessary to hedge these notes can move prices. In this paper, we re-examine the empirical relation between financial investors and commodity markets using intraday trade-and-quote data for commodity futures.

Using data from the Globex electronic trading platform, we construct 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. We regress returns on imbalance to estimate the price impact associated with a given dollar value of buying or selling.[1] Our intraday data also let us examine the relation between financial investor positions and futures markets at specific times during the trading day, thus increasing 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 financial investors may concentrate their trading in this period.[2]

The increase in the holdings of index funds and other retail investment vehicles 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

[1] These data include all trades on the Globex (both informed and uninformed) but do not include "open outcry" trades which were a significant portion of volume over this period. We argue that both of these features of the data lead us to estimate impacts that are likely above the true price impacts of trading by uninformed financial investors. See section 3.1 for a detailed discussion.

[2] This concentration of uninformed investors at the close is consistent with the theoretical predictions of Admati and Pfleiderer (1988). If financial investors are attempting to match the performance of an index linked to settlement prices, they will have additional incentive to concentrate their trades near the close.

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 CLNs following HPW.[3]

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 confirm this result, but we are able to extend our analysis using our intraday data. Even at the daily frequency, we find significant evidence of order flow 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 buying (selling) volume and positive (negative) returns, broadly consistent with the size of the index flows and our estimates of price impact.[4]

This finding is, to our knowledge, the first directly demonstrating price impacts from changes in index investor positions. The intraday nature of the finding also helps to address the endogeneity that faces empirical research on financialization. While theory predicts contemporaneous impacts of these investors on prices, there is also the possibility that changes in price lead to changes in the positions of investors (see Cheng, Kirilenko, and Xiong (2014) for a discussion). However, to explain our results, it would have to be that index investors are responding only to returns that occur in the minutes just prior to futures settlement. While this is theoretically possible, we think it is more likely that those trading on the behalf of index investors trade near the close, thereby impacting commodity futures markets.

The order flows from index traders in wheat and corn are quite large relative to the overall

[3]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.6.

[4]The economic impacts of our estimates are modest in some respects but potentially large in others. While index flows have strong explanatory power for returns near the close, they do not explain much of the variance in prices at daily or weekly frequencies. However, we also find similar effects in long-term futures, suggesting that the market interprets the price impacts as permanent. If this is the case, they could potentially accumulate over time to create significant impacts on the level of prices. See Section 4.3.

size of corn and wheat futures markets, so it may not be surprising that we find significant price impacts. In contrast, in our second set of tests we consider CLNs, and find that they are much smaller in relation to the size of the associated futures markets, making the positive returns on CLN issuance something of a puzzle.

To construct our sample of CLNs, we follow HPW and collect notes linked to a single commodity issued prior to February 2014 with at least $2 million of face value. When they consider the subset of these notes with pricing days outside of the Goldman Roll Period of Mou (2010), 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 at least $10 million of face value. 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.

Consistent with HPW, we find a significantly positive average return on the pricing dates outside of the Goldman Roll, with very similar magnitudes. However, while HPW limit their results primarily to simple averages of pricing date returns, we use Monte Carlo valuation to explicitly calculate the size of the necessary hedging trades for each note, and 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 75% of the notes, and for the subset of these notes with $10+ million of face value we observe an average return of approximately 30 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 hedging trades naively executed near the settlement would be only three basis points.[5] Additionally, looking within the trading day, we find that in contrast to the returns associated with index flows, most of the positive return occurs well before the pricing of the notes, which typically occurs at the close of the futures market or in a settlement period with equally high liquidity. Interestingly, we do find some evidence of hedging trades and returns associated with CLN issuance in the minutes just before the pricing of the notes, but consistent with the small size of the notes, these effects are far to small to explain the overall pricing day return.

[5] We also find similar results when we use daily data to extrapolate our estimates of price impacts to CLNs linked to commodities that are outside of our intraday sample.

In order to further 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, as roll trades primarily impact calendar spreads as opposed to the level of the front-month future. Moreover, as noted by Neuhierl and Thompson (2016), the predictable returns around the roll had disappeared by 2007, and more than 95% of the notes were issued in 2007 or later. Lastly, using our intraday data, we find no differences in the price impact of imbalance during the roll period.

Given these results, 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 only present for notes priced in the five days prior to the last day of the trading month.[6] 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".

This Active Issuance Period is consistent with the monthly marketing cycle for structured notes described in Egan (2018). The characteristics of the note, including the underlying contract and payout functions, are set at the beginning of the month, and then demand is solicited over the month. Supply is then elastically issued near the end of the month to meet this demand. While we typically see only one 424b filing associated with each CLN issuance, for a handful of notes we were able to find preliminary filings in the weeks prior indicating that a note would be issued. These filings specify an expected maturity date and structure for the note, but do not specify the face value, and more interestingly, do not specify the pricing or issue dates. This suggests that CLN issuers have flexibility to determine the specific date that the notes are priced and issued, so the association between issuance and returns prior to the pricing of the note could simply be evidence that CLN issuers or brokers prefer to market and issue notes on days with rising prices, or that demand for these notes is high on days in which prices are rising. The lack of positive returns for notes issued outside of the monthly cycle may reflect that these notes are marketed differently.

Taken together, our results suggest that CLN issuance may be reacting to changes in prices,

[6] The discrepancies between the observed returns and the predicted returns are even more stark when considering this period. Depending on the subset of notes, we find that the average pricing returns are between 8 and 20 times larger than the predicted returns given the size of the necessary hedging trades.

as opposed to causing them. 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) on the determination date. 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 54 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 -10 basis points (t-stat of 0.49).[7] 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 return.

1.1 Related Literature

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 flows from uninformed traders impact commodity futures prices.

Our goal in this paper is testing this theoretical prediction. While we believe this is one of the

[7] After viewing our notes HPW concluded that, in their original 42 day sample, 10 days were mistakenly included, and 24 days were mistakenly excluded, and that in a new sample of 56 days they find a one day return of -15 basis points (t-stat of 0.76) and a two day return of -51 basis points (t-stat of 1.78). Our sample yields a smaller two day effect of -42 basis points (t-stat of 1.44). We also believe that is unlikely that CLN issuers would wait until the day after determination to unwind any hedging trades. We discuss the comparison of our sample with the refined sample provided by HPW in Section 4.5 and also in Section IA.8 of the internet appendix.

first attempts to look for price impacts of financial traders using intraday data, there are several papers that test the predictions of these models using daily, weekly, or monthly data. Some of these papers find evidence supporting the impacts of financialization, either in the form of price impacts or predictable returns, including Buyuksahin and Robe (2011), Tang and Xiong (2012), Singleton (2013), Cheng et al. (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).[8] More recently, Yan, Irwin, and Sanders (2019) examine index fund rebalancing and find temporary price 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 financial investment in commodity 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

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

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 non-trivial, but is smaller than Globex volume. NYMEX suspended floor trading in WTI futures and many other futures products in July of 2015, but for all of our sample floor trading remained an active part of these markets.

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 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 when we do analysis by minute, we limit our WTI sample to the time periods from 7:30 a.m. to 4:00 p.m.

New York time. This time window captures 88% of the total WTI volume in the front and next month contracts. We use this same time window for minute-by-minute analysis of Brent, gold and copper. For corn and wheat we use 9:30 a.m. through the close, which was 2:15 p.m. New York for most of our sample, but was delayed until 3:00 p.m. in late 2012 and early 2013.

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 we call 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.[9] 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

[9] See section IA.1.

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, where imbalance is calculated using the side that triggered each trade. O'Hara (2015) argues that equity markets have become a highly fragmented mix of different trading protocols and this in combination with the different speeds of various traders makes it impossible to construct a consistent picture of the state of the market, thereby making traditional imbalance calculations unreliable, especially when trying to infer the presence of informed traders. These difficulties led Easley, de Prado, and O'Hara (2016) to use futures markets as a laboratory to test alternative methods for calculating imbalances, because futures markets are centralized with a single limit book protocol. We recognize, however, that even in futures markets there can be issues with calculating imbalances, but given our objective to assess the impact of uninformed trading we believe that our approach is likely to overstate this impact. We provide an intuitive discussion of these ideas below, and in the internet appendix we present a simple model of trading and returns that formalizes the intuition.

We note that trades can come from a mix of informed and uninformed traders, and the informed trades are likely to have a larger impact. We are unable to distinguish between the two types, so our estimates produce an average of the two impacts. We also note that our data only include Globex trading in the primary futures contract. To the extent that hedgers spread orders across Globex and floor trades, or use other markets, the total imbalance will be greater than the imbalance that we measure, and we are assigning the entire price impact to a subset of the imbalance. Finally, we find that a statistically significant, though economically modest, portion of imbalance is predictable at one-minute horizons, with high returns and past imbalance predicting positive future imbalance. However, we find that this again biases our estimates up, as our aggregation procedure would consider the earlier return as a result of the subsequent uninformed trading.

It is true that simple noise in the imbalance classification can result in an errors-in-variables problem that would bias our regression estimates downward.[10] One particular concern is the quote based classification method will not capture uninformed liquidity traders who place non-marketable limit orders. Easley et al. (2016) suggest that the tick test may be helpful in identifying these traders. The idea is that in order to ensure execution these traders will need to quote aggressively, so they will tend to continuously push the execution prices in the direction of their trading. For example, a large buyer will need to keep raising the bid price in order to attract sellers. Thus a series of trades the bid at increasing prices may suggest the presence of an aggressive buyer, and these trades will be classified as buys by the tick test. Of course, a series of trades at the bid at increasing prices may also indicate a sequence of positive public signals, so using the tick test will likely produce an upwardly biased estimate of impact. The internet appendix discusses the use of the tick test as an alternative way to construct the imbalance and formally demonstrates this upward bias.

Given these issues, signing trades via the tick test provides a useful robustness check. Intuitively, considering any trade associated with a positive (negative) price move as a (buy) or sell is going to maximize the estimated impact of trading. In the next sections we report our measures of imbalance using both methods, and find that the two measures are very highly correlated. As expected the tick-test yields slightly larger impact measures, but they are very similar to those using the quote-based identification strategies.[11] We therefore conduct our subsequent analysis using price impact estimates and imbalance from the quote-based strategy as we view them to be more accurate, but using tick-test imbalance does not materially change any of the implications of our tests.

3.2 Summary of Near Month Imbalance and Returns

Table 2 shows summary statistics for our six futures contracts. The left hand panels show summaries for all minutes in the sample, while the right-hand panels show summaries for only the minute prior to futures settlement. We measure returns in percent, and express both volumes and imbalances as millions of dollars of futures notional. We calculate imbalance using both a quote-based rule as in Lee and Ready (1991) and the tick test. As the table shows, we find in all cases that the

[10]We show in the internet appendix that this will be mitigated by the fact that, measured imbalance is likely to be less volatile than true imbalance, because when there are more buys(sells) than sells(buys) in an interval, more buys(sells) are likely to be misclassified and treated as sells (buys).

[11]This is potentially due to the fact that quotes are generally only one or two ticks in our markets, making it difficult for a trader to take a position inside the best bid or offer (see Li, Wang, and Ye (2018)).

correlations between the two types of imbalances are quite high.

Trade volumes are large and, trade volumes, imbalances, and returns are quite volatile over the period. Average one-minute volume ranges from approximately $30 million of notional for WTI to approximately $2.6 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 $2.5 and $9 million per minute for copper, corn and wheat. Both volume and the volatility of imbalance are much higher in the settlement minutes. For instance, in the WTI, volume goes up by a factor of six and the volatility of imbalance is more than double in the settlement minute.

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). Panel A shows results using the quote-based classification, and Panel B shows results using the tick test. The left column for each commodity in Table 3 shows the results of these regressions using all minutes in the sample. For each commodity, we find that imbalance in futures markets has significant explanatory power for futures prices, suggesting that trading in these markets play an important role in price discovery.[12] The R^2 values range from 33% for WTI to 13% for Brent. The slope estimates provide our measure of impact, and range from 0.0022 for gold to 0.0153 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 1.53 basis points.

The right hand column for each commodity shows the same regression but restricts the sample to only the minute prior to futures settlement. Here we see large reductions in the impact associated with a given amount of trading, with impacts typically between two-thirds and one-half of what see in the full sample. We are likely observe the impact of financial investors during this period because they will be drawn by the lower transaction costs and because they often have an incentive to trade at or near the daily settlement price. Indeed, the lower transaction cost may in part result from their tendency to concentrate their trading in the interval.

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

Panel B repeats Panel A but uses the tick test to classify trades as buys or sells. Consistent with the intuition given above, the impact measures tend be slightly larger than those using the quote-based imbalance. What is striking however, is that in economic terms, the magnitudes are essentially indistinguishable. This gives us comfort that our quote based measures of impacts are not an underestimate of the true impact. We therefore use the quote-based method for all of the remaining analysis, but our conclusions are unchanged if we use the tick test.

To help visualize 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 price 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 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 price 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.[13] 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. 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.[14]

3.4 Inferring Price Impacts from Daily Data for Other Commodities

Roughly 25% 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 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

[13] We also see similar spikes at other times where various price indices are calculated. For instance, the 10:00 AM volume spike and drop in impact in the gold market corresponds to the London PM Fix.

[14] The regressions shown in Table 3 and Figure 1 assume a linear impact of imbalance on returns. The Figure IA.3 in the internet appendix examines the settlement minute imbalance and returns and finds that the relation is mostly linear, but that very large imbalance can lead to lower price impacts than predicted by our linear estimates.

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.[15] 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.

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.[16] We find 597 notes, of which approximately 75% 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.[17]

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.

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

[16] 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.

[17] 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.

4.1 Calculating CLN Deltas

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.[18]

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 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.[19] 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

[18] 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.

[19] 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.

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.[20] 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 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, 594 notes (out of the 597 issued through January 2014) had matured by the end of 2018. Of these, 342 of had a delta of zero on the determination date.

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

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 weekly changes in the positions of index traders for corn and wheat. Both of these flows are quite substantial in magnitude. The standard deviations of weekly 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 multiply this estimate by 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 \$11 million. This yields an average predicted price impact of approximately four basis points if the note was traded near the futures settlement. This is the first indication that these notes are too small for their associated hedging trades to explain the positive returns documented by HPW.

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 order flow 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. Looking at the patterns in impacts in Figure 1, we see that the price impacts begin to decline roughly 30 minutes prior to the daily settle. Accordingly, we also estimate our regressions using the last 30 minutes of the trading day (aggregated across days in the week) as our dependent variable. Table 6 shows the results.

One of the predictions of theoretical models of financialization is that uninformed traders can create largely permanent changes in prices. For instance, the model of Hamilton and Wu (2014) predicts that index purchases of the near month future will translate into price impacts across the futures curve due to the risk aversion of sophisticated arbitrageurs, while the models of Sockin and Xiong (2015) and Goldstein and Yang (2017) deliver a similar prediction due to incomplete information. In order to test this prediction, we also perform our regressions using imbalance and returns to the futures contract that matures one month beyond the Lead month contract.[21]

Columns (1) of both panels in Table 6 show the results for imbalance summed across the week. The coefficients in column (1) of 0.37 for corn and 0.51 for wheat are strongly significant, and indicate that for a given weekly change in index positions we see corresponding weekly imbalances in the active month futures in the same direction that average 37% and 51% of the changes in index positions. While it may seem puzzling that our estimates are lower than 100% this not surprising. During our sample, open outcry trading in the pit was still a substantial part of these markets (e.g. Shah and Brorsen (2011)). Floor trading would likely be particularly attractive to a large uninformed trader, so we would expect these traders to utilize floor orders to execute these trades. Furthermore, Column (3) repeats the analysis using the next month contract. Here we see positive but insignificant point estimates, suggesting that some of the trading is occurring in the next month contract. One caveat is that the lumpy nature of trading in the next month contract lead to large standard errors and makes these point estimates hard to interpret. Trading in the next month also tends to be buyer initiated, so the constants are much larger for these regressions.

Column (5) 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 (0.58 and 0.59) with a magnitude of approximately one half of the predicted impact given the size of the positions (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 (2011), 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 in the active months equal to approximately 14% and 24% of the total change in index positions for corn and wheat respectively. Column (6) shows that these imbalances close to settlement are translating into a return impact. A one standard deviation increase in index traders' positions is

[21]See section IA.7 in the internet appendix for summary data on these futures.

translating into a 25 basis point price increase across the week over these minutes for corn, and a 48 basis point increase for wheat. Column (4) shows that there is again positive imbalance in the next month contract, and this statistically significant in wheat. Column (8) shows that there is a price impact of nearly exactly the same size in the next month future. This is consistent with models of financialization, and suggests that the market does not view these price impacts as purely temporary. All of the return results near the settlement have strong statistical significance (t-stats range from 3.0 to 6.1). 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 4 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.[22]

Figure 5 focuses on the 30 minutes prior to the daily settlement. Again the plots show regression coefficients for expanding windows. For example, looking at 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 near 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 in both near month and next month futures, it is difficult to tell from our data whether and to what degree these impacts reverse. 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 4 show that overnight

[22]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.

returns are essentially unrelated to the weekly index flows, but the wide confidence intervals make it difficult to draw conclusions.[23]

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 4% and 9% of the price variation in the 30 minutes prior to close for corn and wheat respectively. Although the coefficients are similar in column (4), the R-squared falls to 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 6 plots cumulative changes in the positions of index traders and estimated impacts. For this analysis, we use the active month 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 6 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

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

where we would expect to see the hedging trades and their associated price impact.[24]

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 had disappeared by 2007. Moreover, we find no difference in the price impacts of order flow in the Goldman Roll period.[25] 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 7 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.[26] We refer to this five day period as the "Active Issuance Period".

This period of increased issuance is consistent with the monthly marketing cycle documented by Egan (2018). For these notes, it is likely that the commodity and structure of the note is set early in the month, and the demand for the note is solicited up until the issuance at the end of the month. For the few notes we find with preliminary 424b filings, we see that the trade date and amount are typically left unspecified, suggesting a flexibility on the part of the issuer to change this date to attempt to increase demand.[27] This period is entirely outside of the Goldman Roll,

[24] 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 are the most significant on the actual pricing date, we focus on these specifications for parsimony.

[25] See Table IA.2 in the internet appendix.

[26] 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.

[27] See for instance a preliminary filing (https://www.sec.gov/Archives/edgar/data/886982/000119312510145119/d424b2.htm) with the trade date left blank and final filing (https://www.sec.gov/Archives/edgar/data/886982/000119312510148422/d424b2.htm) associated with a note linked to gold.

so these notes are 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. While we cannot verify this directly, the lack of returns associated with other notes suggests that these notes are issued differently, and may be the result of more immediate needs of customers or issuers.

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 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 537 total) have a positive average return of 44 basis points, while the remaining 336 days have an average return of negative 5 basis points. For this subset of returns, the observed pricing day return is approximately eight times as large as 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 seven basis points. The average return is thus nearly ten 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 75% of the notes for which we have intraday data.[28] Here we find nearly identical patterns in average returns. We note that these commodities have large futures markets, so the observed pricing date returns approximately 20 times larger than the predicted impacts when restricting to the Active Issuance Period.

Panel E shows similar analysis, but uses the full set of dates in each subset from column (1)

[28] We exclude copper here since all of our copper CLNs are linked to the LME future contract.

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.

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. This relative measure of face value to open interest is intended as a measure of potential trade impact, which we have calculated explicitly. We therefore perform a similar test to see if notes with higher predicted impacts have higher pricing day returns.

Figure 8 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 4. 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 very close to 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 in 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 51 basis points. This again shows that it is whether or not the note is issued in Active Issuance Period, rather than the note's size, that associates it with a large positive pricing date return.

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

1. 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.
2. The pricing date returns for this subset of notes are generally an order of magnitude too large to be explained by the size of the delta hedging trades.
3. While larger notes are associated with slightly larger returns, this effect not enough to explain

the unconditionally large returns associated with CLNs issued at the end of the month.

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. This date is specified when the note is issued, so these results are not subject to the endogeneity concerns related to the pricing date analysis.

4.5 Determination Date Returns for Commodity-Linked Notes

Table 8 shows our analysis of futures returns on days with CLN determination. Following HPW, we restrict our analysis to notes which still have positive exposure to 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 initially had 50, and after consultation with HPW included four notes we had missed, giving us 54 as opposed to their sample of 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 -10 basis points (t-stat of 0.49). Looking at the table, we do not find a negative average return that is significant for additional samples of the determination dates, either including the Goldman Roll or extending the sample of determination dates through 2018.

After seeing our initial results HPW re-examined their set of 42 notes, and found that they had mistakenly included 10 notes and mistakenly excluded 24 notes.[29] They provided a refined sample of 56 notes in which they find a determination day return of -15 basis points and a t-stat of (0.76). However, despite finding no negative return on the day after the determination date in the published paper, their new set has a return of -51 basis points (t-stat 1.78) in the two-day window starting at the determination date. HPW also propose a change of methodology, namely

[29]See Henderson, Pearson, and Wang (2019).

the exclusion of determination dates coinciding with the pricing of other notes, that again changes the average returns on the determination date to -33 basis points (t-stat of 1.92), and a two-day return of -53 basis points (t-stat of 2.46). They did not provide the list of notes pricing on the indicated days, and we were unable to replicate this result, so we do not include a formal evaluation of this analysis.

We would make a few points about this refined sample even in the absence of the change in methodology. The first is that the source of the finding is very different than the original published result, as it primarily comes from the day after the determination day as opposed the determination day itself. The second, is that given our findings, it seems unlikely that the issuers would wait until the day after the determination day to unwind the hedges. The notes are small enough that they can be easily unwound in the minutes just prior to the pricing of the note.[30] Even if this is not the case, it seems that issuers would start early in the day to unwind the hedge, as waiting a day exposes the issuer to overnight price changes as they wait for liquidity to return to the market in the morning. Moreover, we disagree with some of the choices in their new set, and present a comparison with our set in the internet appendix, where we also show an insignificant two-day return of -42 basis points (t-stat of 1.44) for this subset of our notes.

While we have made choices that we believe make the most sense, it is clear that there may be more than one "correct" way to conduct this test. At the very least, these discrepancies between our results, the original HPW result, the refined sample HPW result, and the refined sample result after HPW's change in methodology, as well as the insignificant results for other periods and subsets of notes, highlight the tenuousness of the negative determination date return in comparison to the much more robust finding of positive returns on CLN pricing days.

As a final test, we examine intraday patterns on CLN pricing and determination dates, to see if we can observe any evidence of hedging trades executing near the close of the market.

4.6 Intraday Patterns on CLN Pricing and Determination Dates

Our final 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-

[30]In the next section we present some evidence that the notes are in fact being unwound in the minutes just prior to pricing.

index traders.

Table 9 shows the results. Panel A considers pricing days in the Active Issuance Period for which we have intraday data. Column (1) shows the full day return from Table 7, and column (2) shows how much of this return accumulates before the period beginning 30 minutes prior to the note. For Brent, WTI, and Corn, the notes all price at the close of the associated futures market. However for gold, most of the notes price at the London 3:00 PM fix, which is 10:00 or 11:00 AM in New York depending on the time of year. Unlike the patterns we see with index traders, we find that most of the return has accumulated before the note pricing. When we look at the windows 30-, 15-, and 5-minutes prior to the pricing in columns (3) - (5), we do see moderate positive returns concentrated just prior to the pricing, and the magnitude of these returns is roughly consistent with our impact estimates.[31]

In columns (6) - (8) we test for imbalance near the pricing date. To control for any unconditional directional imbalance we use a regression specification. We proceed by constructing a sample using all days for each commodity and minute in which we had a note price. Therefore we include the closing minutes for Brent, WTI, and corn, as well as the London PM Fix, futures settlement minute, and NYSE closing time in gold markets (we have some gold notes linked to the SPDR Gold ETF (ticker:GLD)). We then estimate a regression with commodity-period fixed effects, and include a dummy variable that takes a value of one if there is a CLN pricing on that day, in that market, in that minute. The estimate is then the slope of this dummy variable. This estimate is designed to capture the imbalance associated with a CLN in excess of any mean imbalance typically seen in that market at that time of day. As column (8) shows, we find evidence of positive imbalance in the five minutes prior to the close, and this is again broadly consistent in magnitude with the predicted size of the hedging trades.

Panel B repeats this analysis for all notes in the sample, not just those in the Active Issuance Period. Here, though there is no full day effect, we still find positive returns and imbalance near the pricing. Again the magnitudes are consistent with size of the notes, suggesting that there are hedging trades for all notes near the pricing, not just those in the active issuance period. Panel C repeats this analysis again but using the full set of determination days. Here, while we don't

[31] Columns (2) and (3) do not sum up to column (1) due to the early pricing of gold notes, and the number of observations is larger in columns (3) - (5) due to dates with multiple pricings at different times.

find a significant return effect, we do find a modestly significant negative excess imbalance of $17.8 million in the 15 minutes prior to pricing.

Interestingly, in unreported results we do not find stronger imbalance effects in the minutes near pricing for larger notes, suggesting that larger notes may be more likely to be traded on the floor or earlier in the day. However, we view these intraday findings as consistent with the notes being hedged and creating a modest impact. However, consistent with all of our earlier findings, these hedging trades are too small, and therefore the most likely explanation of the link between CLN pricing and positive returns is due to increased CLN issuance on days with rising commodity prices.

5 Conclusion

In this paper we construct order flow imbalances for six major commodity futures markets. We find that order flows in these futures markets have a large explanatory power for prices. We also document substantial intraday variation in price impacts, with high volumes and low price impact around futures settlements. We use our findings on price impacts to examine the potential impacts of financial investors in this market.

We first examine the impact from changes in the positions of commodity-index investors for corn and wheat futures using data from CFTC. Consistent with theoretical models of financialization, we find strong evidence for order flow imbalances and price impacts associated with these positions, concentrated in the minute prior to the daily futures settlement.

In our second set of tests we examine commodity-linked notes following Henderson et al. (2015). We find that the positive returns associated with the issuance of these notes documented by Henderson et al. (2015) are surprisingly large given the notes' size, occur primarily prior to the pricing of the notes, and are only present in notes issued near the end of the month when issuance frequency is substantially higher. In contrast to Henderson et al. (2015), we 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.

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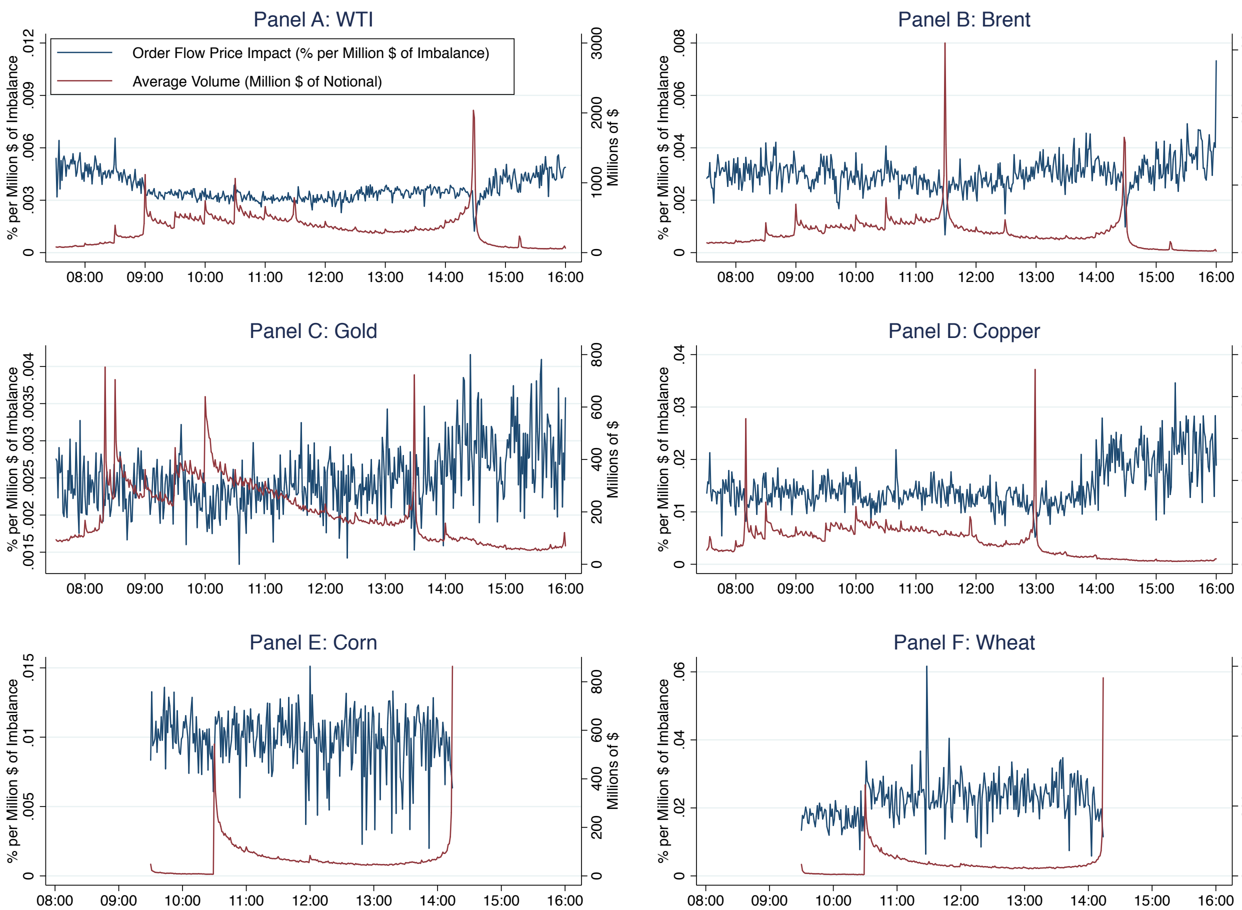

Figure 1. Volume and Price Impact of Order Flow Across the Trading Day
The figure shows the average intraday volume (in red) by minute for each commodity as well as the minute-by-minute price impact (in blue). The price impact is measured as the slope in a univariate regression of return (%) on order flow 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).

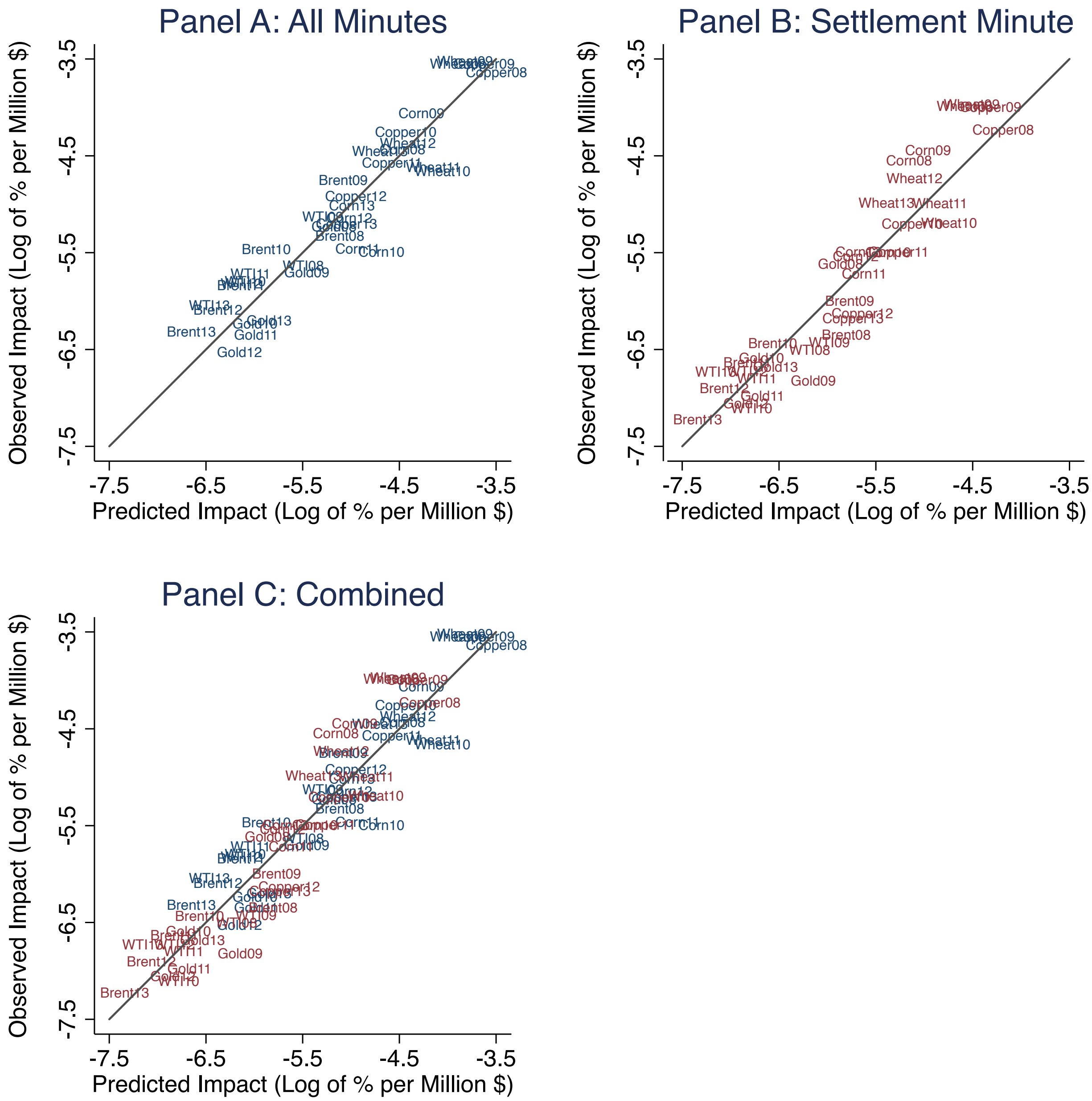

Figure 2. Regression fit for inferring order flow price impact from daily data
This figure plots the fit for regressions of the log of predicted price impacts for each commodity in a calendar year on the logs of average daily futures volume and daily futures volatility (See columns (1) - (3) of Panel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

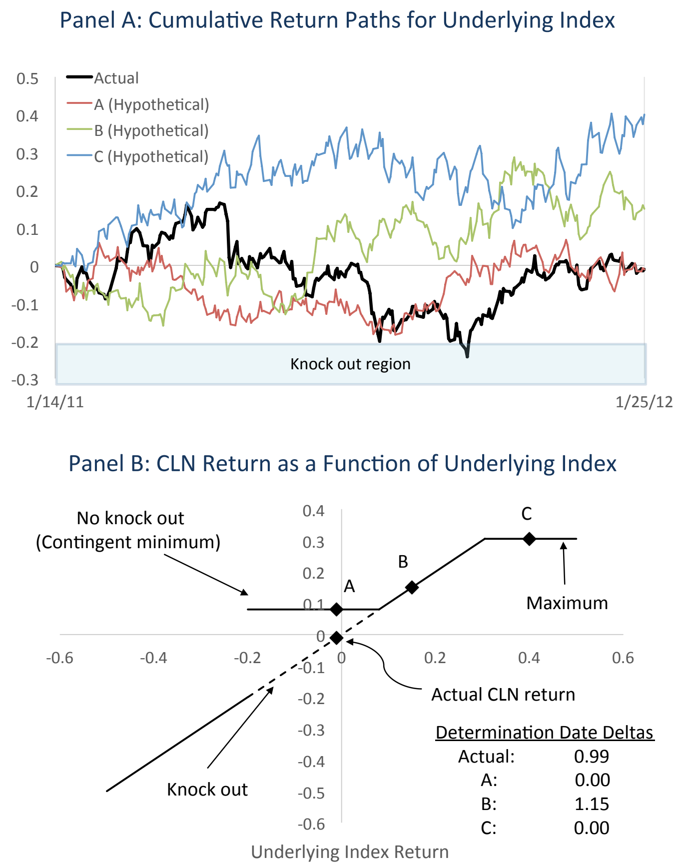

Figure 3. Return Paths and Determination Date Deltas for a Sample CLN
The figure illustrates the $51,437,000 Capped Market Plus Notes linked to the S&P GSCI® Crude Oil Excess Return Index. These notes have a knock-out buffer, a contingent minimum return, and a maximum return. A knock-out occurs if the 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.

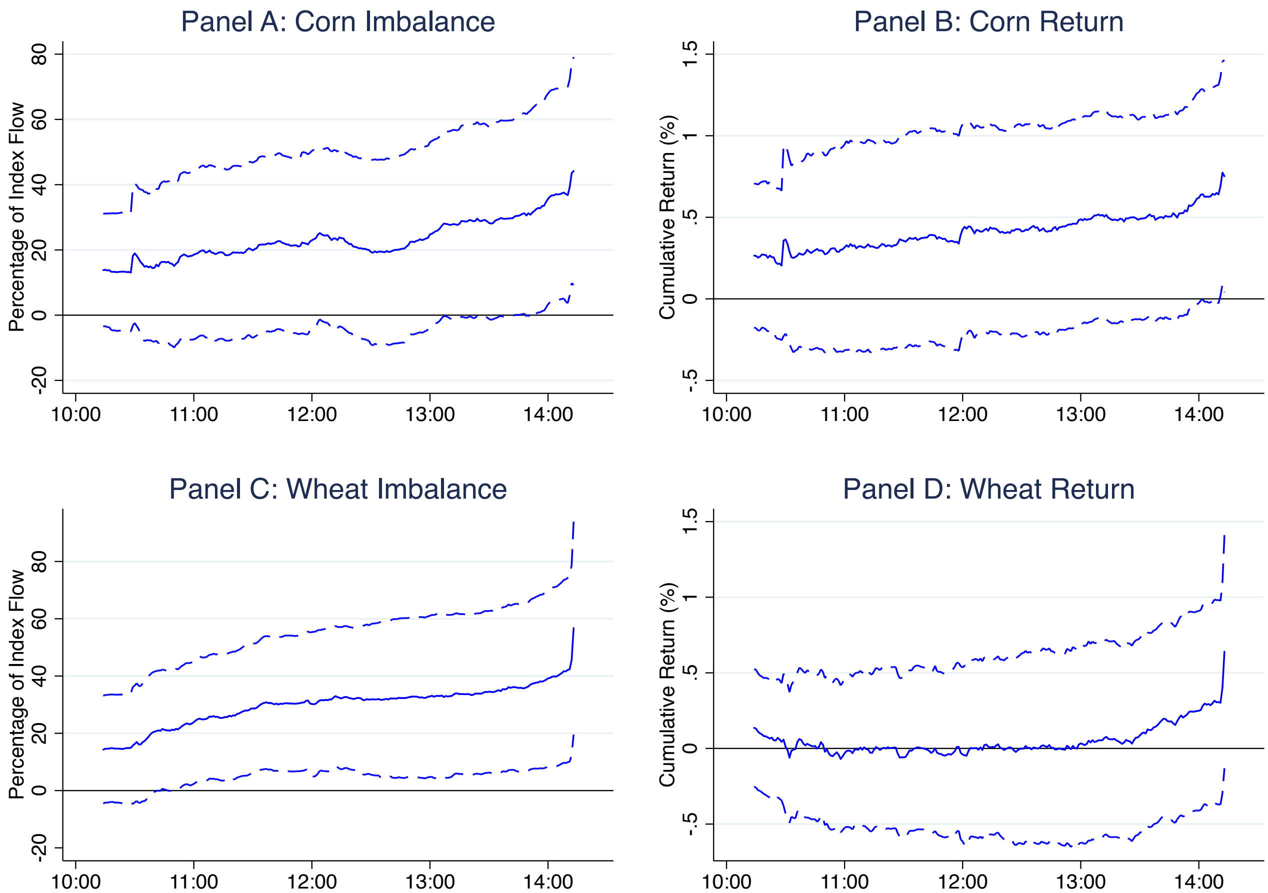

Figure 4. Intraday Impact of Changes in the Positions of Commodity-Index Traders: Full Day

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 days settlement summed across the trading days in the week. Data are 1/1/2007 to 4/1/2014 excluding the period from 5/21/2012 to 4/5/2013 when the settlement was delayed until 3pm New York time.

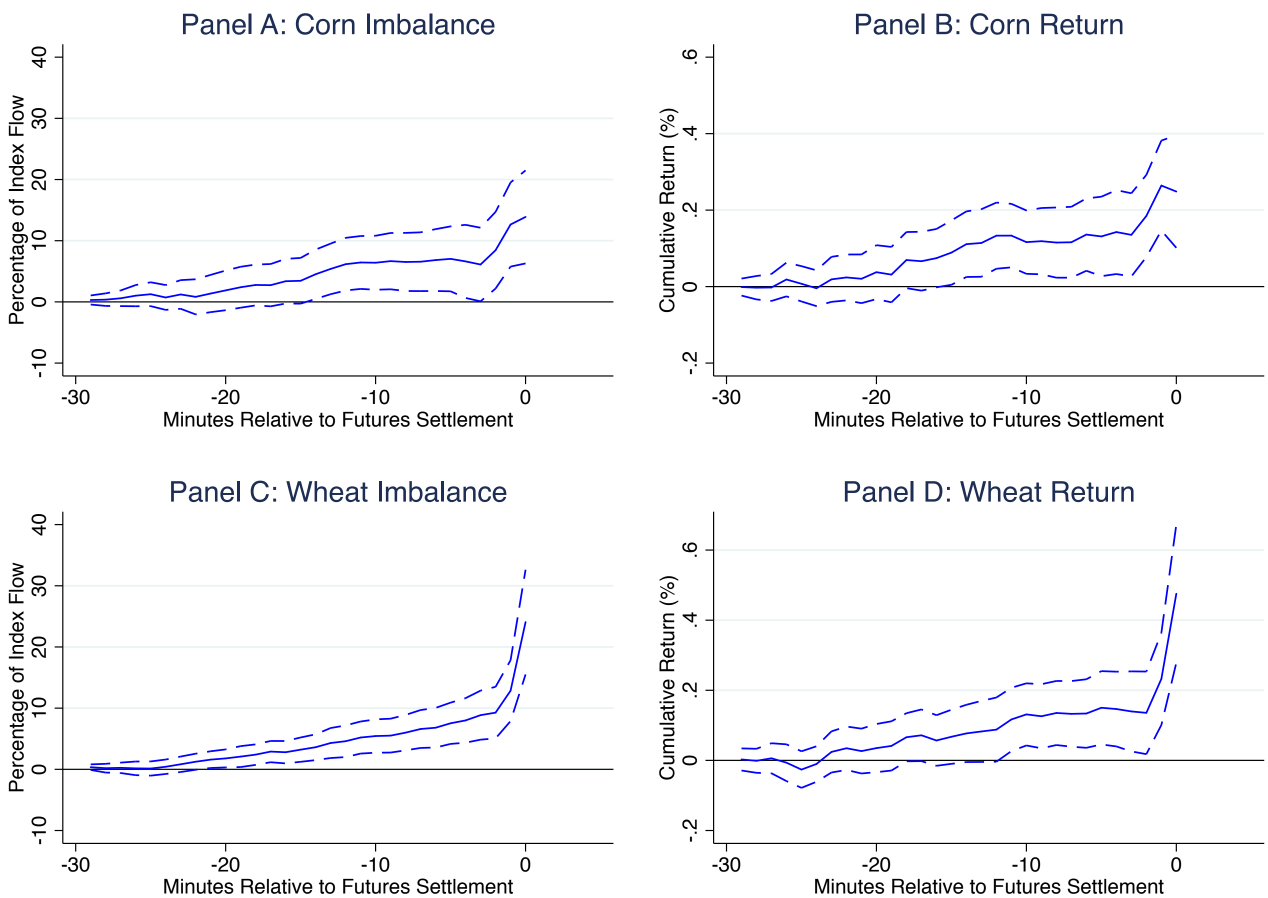

Figure 5. Intraday Impact of Changes in the Positions of Commodity-Index Traders: 30 Minutes Prior to Settlement
The figure plots the slope coefficient and 95% confidence interval from regressions where the dependent variables are cumulative futures imbalances and returns for expanding windows across 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.

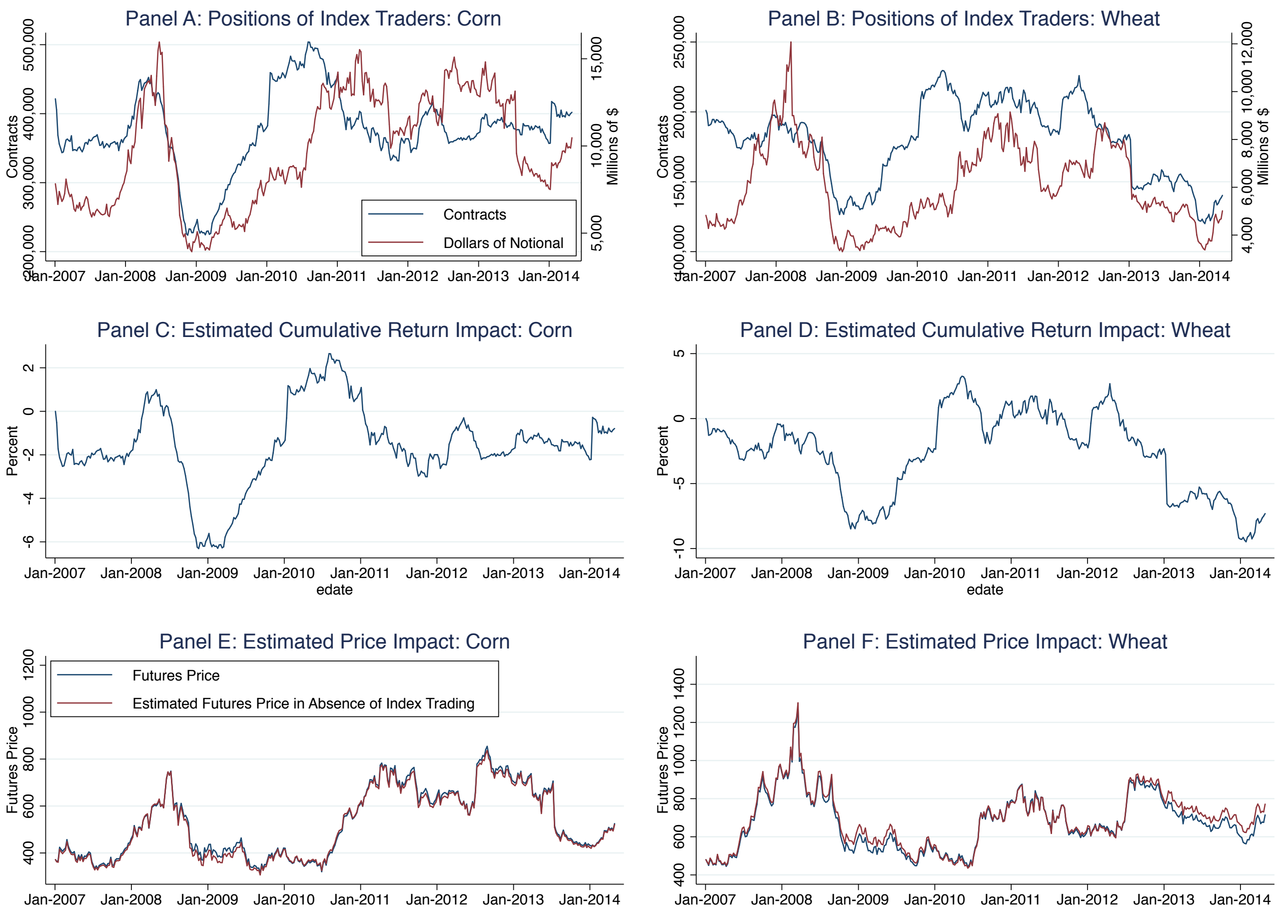

Figure 6. Estimated Cumulative Impact of Index Trader Flows

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 weeks 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.

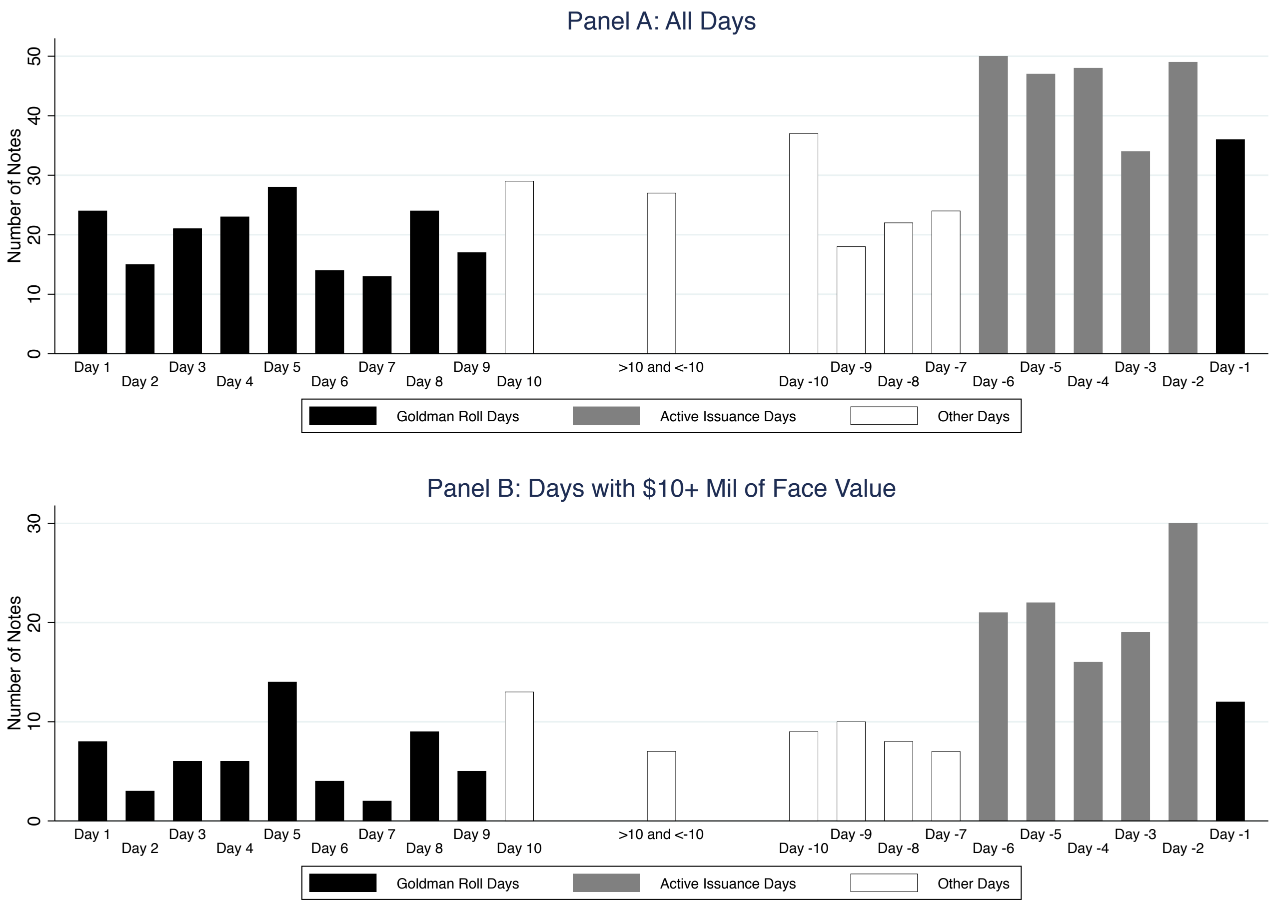

Figure 7. CLN Pricing Days Across the Trading Month
This figure shows the pricing frequency of CLNs across the trading month. The left hand bars represent the first 10 trading days of the the calendar month. The right hand bars represent the last 10 trading days of the calendar month. The central bar 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.

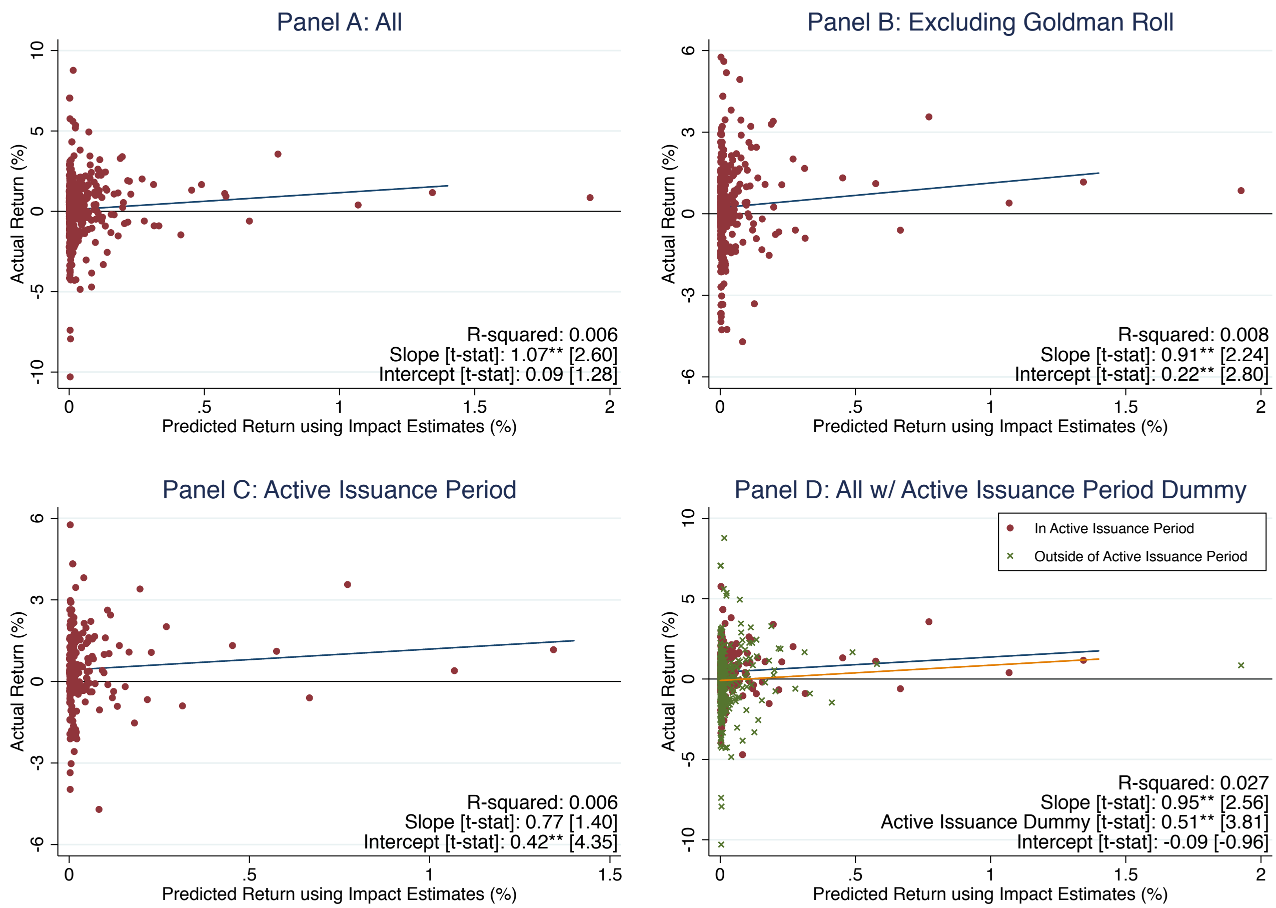

Figure 8. Actual Returns vs. Predicted Returns on CLN pricing dates
Figure shows scatter plots with regression lines of actual pricing date returns on predicted pricing date returns calculated as the size of the associated delta hedging trades times the commodity-year price impact calculated using daily data and the regressions described in Table 4. Panel A shows all notes, Panel B shows all notes excluding the Goldman Roll, Panel C shows all notes issued in the active issuance period, and Panel D shows all notes but includes a dummy variable for whether or not the note was issued in the Active Issuance Period.

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). Imbalance is calculated using both a quote-based method similar to Lee and Ready (1991), and using the tick test. Statistics for volume and imbalance are reported in 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. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	30.07	-0.15	-0.07
St. Dev.	0.10	41.87	14.04	14.77
# of Min:	1,055,204	Corr of Q-B and T-T:		0.94

CME WTI Crude Oil (Settlement Minute)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	-0.01	193.31	-4.18	-2.28
St. Dev.	0.11	88.51	36.06	36.27
# of Min	1,816	Corr of Q-B and T-T:		0.86

ICE Brent Crude Oil (All Minutes)

	Ret. (%)	Vol.	Q-B Imb. (Mil $)	T-T imb.
Mean	0.00	13.11	-0.01	-0.08
St. Dev.	0.23	23.03	9.42	9.98
# of Min:	1,045,483	Corr of Q-B and T-T:		0.87

ICE Brent Crude Oil (Settlement Minute)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	81.81	0.00	-1.07
St. Dev.	0.10	68.19	22.68	21.72
# of Min	1,812	Corr of Q-B and T-T:		0.79

CME Gold (All Minutes)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	19.23	-0.13	-0.15
St. Dev.	0.05	34.50	11.37	11.92
# of Min:	1,050,246	Corr of Q-B and T-T:		0.83

CME Gold (Settlement Minute)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	83.23	2.04	1.58
St. Dev.	0.06	63.35	23.87	23.43
# of Min	1,825	Corr of Q-B and T-T:		0.89

CME Copper (All Minutes)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	2.62	-0.01	0.00
St. Dev.	0.09	7.27	2.20	2.47
# of Min:	1,010,765	Corr of Q-B and T-T:		0.83

CME Copper (Settlement Minute)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	23.23	0.66	0.82
St. Dev.	0.12	24.49	9.17	8.93
# of Min	1,867	Corr of Q-B and T-T:		0.86

CME Corn (All Minutes)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	8.91	-0.18	0.02
St. Dev.	0.15	18.08	7.50	8.48
# of Min:	587,859	Corr of Q-B and T-T:		0.78

CME Corn (Settlement Minute)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.01	120.40	4.26	4.84
St. Dev.	0.24	96.25	29.91	30.09
# of Min	1,811	Corr of Q-B and T-T:		0.93

CME Wheat (All Minutes)

	Ret. (%)	Vol. (Mil $)	Q-B Imb. (Mil $)	T-T imb. (Mil $)
Mean	0.00	4.39	-0.09	-0.03
St. Dev.	0.16	9.71	3.62	4.03
# of Min:	537,251	Corr of Q-B and T-T:		0.77

CME Wheat (Settlement Minute)

	Ret. (%)	Vol.	Q-B Imb. (Mil $)	T-T imb.
Mean	-0.04	73.08	-1.91	-1.92
St. Dev.	0.36	62.39	20.38	19.66
# of Min	1,810	Corr of Q-B and T-T:		0.90

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.

Panel A: Classification of trades using Quote-Based Rule

	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***	0.0013***	0.0029***	0.0010***	0.0022***	0.0013***	0.0113***	0.0042***	0.0065***	0.0044***	0.0150***	0.0091***
t-stat	(0.00001)	(0.00007)	(0.00002)	(0.00008)	(0.00002)	(0.00011)	(0.00010)	(0.00034)	(0.00019)	(0.00024)	(0.00048)	(0.00078)
SE	[274.6]	[18.9]	[150.5]	[12.9]	[99.9]	[11.1]	[112.8]	[12.3]	[35.3]	[18.1]	[31.3]	[11.6]
Obs	929,215	1,816	800,222	1,563	928,083	1,825	903,777	1,867	517,023	1,810	493,386	1,808
R sq	0.338	0.174	0.130	0.052	0.304	0.224	0.147	0.113	0.212	0.288	0.177	0.259

Panel B: Classification of trades using Tick-Test

	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***	0.0015***	0.0033***	0.0016***	0.0023***	0.0015***	0.0112***	0.0054***	0.0062***	0.0047***	0.0153***	0.0105***
t-stat	(0.00001)	(0.00007)	(0.00002)	(0.00008)	(0.00002)	(0.00014)	(0.00009)	(0.00036)	(0.00021)	(0.00023)	(0.00049)	(0.00074)
SE	[295.6]	[22.5]	[176.2]	[20.5]	[107.9]	[10.7]	[128.5]	[15.0]	[29.3]	[20.3]	[31.3]	[14.2]
Obs	929,215	1,816	927,067	1,812	928,083	1,825	903,777	1,867	485,926	1,773	473,208	1,770
R sq	0.382	0.256	0.185	0.125	0.359	0.295	0.184	0.174	0.256	0.337	0.244	0.322

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	Settlement Minutes	Combined
	(1)	(2)	(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 trade in the settlement minute 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

Panel B: Pricing Days of Commodity Linked Notes

		Face Value ($Mil)			Δ Hedge Size ($Mil)			Predicted Impact(%)		
	N	mean	min	max	mean	min	max	mean	min	max
Gold	200	17.1	2.0	157.9	12.1	0.1	108.2	0.01	0.00	0.31
Brent Crude	114	12.5	2.0	103.4	7.5	0.4	56.0	0.05	0.03	0.06
WTI Crude	80	13.8	2.0	75.9	8.8	0.5	63.0	0.01	0.00	0.08
Palladium	41	13.3	2.3	80.2	7.7	0.7	43.5	0.02	0.00	0.20
LME Copper	34	16.0	2.1	155.5	13.8	0.4	172.4	0.02	0.00	0.31
Silver	25	23.2	2.0	84.9	15.9	0.4	54.9	0.04	0.01	0.11
Corn	21	27.9	2.0	205.0	23.8	1.2	182.7	0.20	0.01	1.07
Natural Gas	8	15.1	3.1	55.4	7.6	1.4	27.1	0.70	0.06	1.34
RBOB Gasoline	4	16.9	2.5	42.3	12.5	0.4	33.8	0.04	0.00	0.10
Cotton	2	7.5	5.0	10.0	4.3	3.2	5.5	0.08	0.08	0.08
Platinum	2	35.4	7.3	63.6	43.1	4.7	81.6	0.07	0.07	0.07
Lead	1	5.0	5.0	5.0	4.7	4.7	4.7	0.19	0.19	0.19
Zinc	1	11.0	11.0	11.0	10.3	10.3	10.3	0.04	0.04	0.04
Nickel	1	23.0	23.0	23.0	21.6	21.6	21.6	0.09	0.09	0.09
Aluminum	1	17.0	17.0	17.0	15.9	15.9	15.9	0.07	0.00	0.27
Tin	1	4.0	4.0	4.0	3.7	3.7	3.7	0.19	0.00	1.93
Soybeans	1	19.6	19.6	19.6	19.2	19.2	19.2	0.10	0.10	0.10
Total	537	15.9	2	205.0	11.1	0.1	182.7	0.04	0.00	0.35

Panel C: Determination Dates of Commodity Linked Notes

		Face Value ($Mil)			Δ Hedge Size ($Mil)			Predicted Impact (%)		
	N	mean	min	max	mean	min	max	mean	min	max
All Days	534	16.0	2.0	205.0	7.4	-23.3	228.0	-0.03	-2.84	0.02
. . . and positive Δ	219	18.5	2.0	205.0	18.6	0.2	228.0	-0.07	-2.84	-0.00
. . . and $10+ Mil	104	33.2	10.0	158.0	33.2	0.9	228.0	-0.12	-2.84	-0.00
Prior to 2014/02	425	16.3	2.0	158.0	7.9	-18.6	228.0	-0.03	-2.84	0.01
. . . and positive Δ	160	19.3	2.0	205.0	21.3	0.2	228.0	-0.09	-2.84	-0.00
. . . and $10+ Mil	79	33.6	10.0	156.0	37.0	0.9	228.0	-0.15	-2.84	-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. In each panel, the regressions in the two leftmost columns use the active near month contract to calculate the dependent variable. For the two rightmost columns, the next-longest maturity contract is used. For the imbalance regressions (columns (1) - (4)), futures imbalance and changes in index trader positions are measured in number of contracts. For the return regressions (columns (5) - (8)), futures returns are measured in percent and changes in index positions are standardized to have a standard deviation of one. In the odd number columns, the dependent variable is the imbalance or return for the entire trading day summed across the trading days in the week. For the even numbered columns, 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. Data are 1/1/2007 to 4/1/2014.

Panel A: Corn Futures Imbalance

Dependent Var:	Active Month Imbalance		Next Month Imbalance	
	Full Day (1)	Last 30 Min (2)	Full Day (3)	Last 30 Min (4)
Δ Corn Index Positions	0.371**	0.137***	0.32	0.07
	[2.354]	[3.743]	[0.63]	[0.99]
Constant	-108.3***	-8.619***	574.29***	83.49***
	[-10.43]	[-3.014]	[14.28]	[14.17]
Obs	382	382	382	382
R-sq	0.02	0.04	0.01	0.00

Panel B: Corn Futures Returns

	Active Month Return		Next Month Return	
	Full Day (5)	Last 30 Min (6)	Full Day (7)	Last 30 Min (8)
Standardized Δ Corn Index Positions	0.58*	0.25***	0.55*	0.25***
	[1.74]	[3.32]	[1.69]	[3.44]
Constant	0.03	0.11	0.05	0.12*
	[0.13]	[1.62]	[0.24]	[1.88]
Obs	382	382	382	382
R-sq	0.02	0.04	0.02	0.04

Panel C: Wheat Futures Imbalance

Dependent Var:	Active Month Imbalance		Next Month Imbalance	
	Full Day (1)	Last 30 Min (2)	Full Day (3)	Last 30 Min (4)
Δ Wheat Index Positions	0.514***	0.244***	0.36	0.09**
	[4.466]	[5.596]	[1.40]	[2.19]
Constant	-37.73***	-5.966***	165.98***	25.66***
	[-9.907]	[-4.525]	[14.43]	[14.37]
Obs	382	382	382	382
R-sq	0.07	0.13	0.00	0.01

Panel D: Wheat Futures Returns

	Active Month Return		Next Month Return	
	Full Day (5)	Last 30 Min (6)	Full Day (7)	Last 30 Min (8)
Standardized Δ Wheat Index Positions	0.59*	0.48***	0.56*	0.47***
	[1.80]	[4.74]	[1.78]	[5.04]
Constant	-0.0571	-0.273***	-0.15	-0.24***
	[-0.229]	[-3.582]	[-0.63]	[-3.12]
Obs	382	382	382	382
R-sq	0.01	0.09	0.01	0.09

Robust 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, 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 7 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. Predicted impacts are calculated as in Table 5.

Panel A: All Days

	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.13*	0.28***	-0.13	0.44***	-0.06
t-stat	[1.71]	[3.33]	[-0.94]	[4.32]	[-0.57]
Predicted Impact of Delta Hedges					
Avg.	0.04	0.05	0.03	0.06	0.04
Obs	537	342	195	201	336

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

	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.29***	0.42***	0.01	0.66***	-0.03
t-stat	[2.84]	[3.55]	[0.07]	[5.03]	[-0.22]
Predicted Impact of Delta Hedges					
Avg.	0.04	0.09	0.09	0.07	0.10
Obs	220	153	67	104	116

Panel C: All Days w/ Available Intraday Data

	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.00	0.15*	-0.23	0.37***	-0.20*
t-stat	[0.04]	[1.69]	[-1.47]	[3.17]	[-1.87]
Predicted Impact of Delta Hedges					
Avg.	0.01	0.02	0.01	0.02	0.01
Obs	393	244	149	141	252

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

	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)
Realized Daily Returns					
Avg.	0.13	0.30**	-0.21	0.55***	-0.20
t-stat	[1.28]	[2.54]	[-1.01]	[3.99]	[-1.40]
Predicted Impact of Delta Hedges					
Avg.	0.03	0.03	0.04	0.03	0.03
Obs	154	104	50	69	85

Panel E: Regressions with Dummy Variables

	Pricing Day Return			
Sample:	Panel A	Panel B	Panel C	Panel D
Active Issuance Period Dummy	0.39**	0.66***	0.52***	0.75***
	[2.28]	[2.64]	[3.02]	[3.12]
Non-Goldman Roll Dummy	0.18	0.05	0.08	0.01
	[0.91]	[0.17]	[0.39]	[0.04]
Constant	-0.13	-0.05	-0.23	-0.21
	[-0.94]	[-0.26]	[-1.47]	[-1.01]
Obs	537	220	393	154
R-Sq	0.02	0.05	0.03	0.08

t-stats in brackets
*** p < 0.01, ** p < .05, * p < 0.10

Table 8. Average Returns and Predicted Impacts of Delta Hedges 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 negative one times 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 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 repeats this analysis but restricts the sample to notes with determination dates before 2/1/2014 to replicate the determination date event study of HPW.

Panel A: All Days

	All Days	Excluding Goldman Roll	During Goldman Roll	During Active Issuance Period	Excluding Active Issuance Period
	(1)	(2)	(3)	(4)	(5)
Realized Daily Returns					
Average	0.03	0.14	-0.21	0.41**	-0.18
tstat	[0.31]	[1.15]	[-0.94]	[2.61]	[-1.29]
Predicted Impact of Unwinding Delta Hedges					
Average	-0.10	-0.12	-0.05	-0.05	-0.13
Obs	202	141	61	74	128

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

	All Days	Excluding Goldman Roll	During Goldman Roll	During Active Issuance Period	Excluding Active Issuance Period
	(6)	(7)	(8)	(9)	(10)
Realized Daily Returns					
Average	-0.10	-0.03	-0.26	0.27	-0.42
tstat	[-0.57]	[-0.20]	[-0.61]	[1.43]	[-1.61]
Predicted Impact of Unwinding Delta Hedges					
Average	-0.18	-0.22	-0.09	-0.07	-0.28
Obs	91	66	25	43	48

Panel C: Days prior to 2014/02

	All Days	Excluding Goldman Roll	During Goldman Roll	During Active Issuance Period	Excluding Active Issuance Period
	(1)	(2)	(3)	(4)	(5)
Realized Daily Returns					
Average	0.05	0.05	0.05	0.33*	-0.08
tstat	[0.44]	[0.38]	[0.21]	[1.72]	[-0.53]
Predicted Impact of Unwinding Delta Hedges					
Average	-0.12	-0.15	-0.05	-0.06	-0.15
Obs	157	108	49	50	107

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

	All Days	Excluding Goldman Roll	During Goldman Roll	During Active Issuance Period	Excluding Active Issuance Period
	(6)	(7)	(8)	(9)	(10)
Realized Daily Returns					
Average	-0.01	-0.10	0.21	0.27	-0.21
tstat	[-0.06]	[-0.49]	[0.54]	[1.08]	[-0.87]
Predicted Impact of Unwinding Delta Hedges					
Average	-0.21	-0.25	-0.10	-0.08	-0.30
Obs	75	54	21	31	44

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

Table 9. Intraday Futures Returns and Imbalance around CLN Pricings and Determinations

Table shows the average returns (in %) and imbalance (in millions of $) over various intraday periods during the pricing and determination dates of CLNs. Panel A examines pricing days in the Active Issuance Period, Panel B examines all pricing days, and Panel C examines all determination days. The sample is restricted to the commodities (Brent crude oil, WTI crude oil, gold, and corn) and periods where we have intraday data. Column (1) shows the average full day return ending at the close of the futures market. Column (2) shows the average return ending 30 minutes prior to the pricing or determination time of the first note on the day. (Some days have multiple gold notes, and most, but not all, of the gold notes price at 3 PM London time. For the other commodities all of our notes price at the close of the futures market). Columns (3) - (5) show average returns in the periods 30, 15, and five minutes before the pricing or determination of the note. Columns (6) - (8) show the average excess imbalance in the windows just prior to the pricing or determination of the note. We calculate average excess imbalance with a regression approach. The regression sample is constructed by including the imbalance observations for all minutes and commodities that have any note pricing during the sample. For instance, in column (6) part of our sample is the imbalance in the 30 minutes prior to the close of the WTI on all days, since WTI notes price at this time. We control for commodity-period fixed effects, and our estimate for excess imbalance is the coefficient on a dummy that takes a value of one if there is the pricing or determination of a note at that minute, in that market, on a given day.

Panel A: All Pricing Days within Active Issuance Period

	Mean Returns (%)					Excess Imbalance ($ Mil)		
	Full Day (1)	Before 30 min prior to pricing (2)	30 min prior to pricing (3)	15 min prior to pricing (4)	5 min prior to pricing (5)	30 min prior to pricing (6)	15 min prior to pricing (7)	5min prior to pricing (8)
Estimate	0.40***	0.29**	0.02	0.04*	0.03	0.88	11.98*	11.13**
	[3.36]	[2.56]	[0.74]	[1.68]	[1.65]	[0.09]	[1.75]	[2.55]
Obs	141	141	143	143	143	13,272	13,272	13,272

Panel B: All Pricing Days

	Mean Returns (%)					Excess Imbalance ($ Mil)		
	Full Day (1)	Before 30 min prior to pricing (2)	30 min prior to pricing (3)	15 min prior to pricing (4)	5 min prior to pricing (5)	30 min prior to pricing (6)	15 min prior to pricing (7)	5min prior to pricing (8)
Estimate	0.01	-0.05	0.01	0.03	0.03***	2.71	9.50*	9.17***
	[0.16]	[-0.64]	[0.41]	[1.61]	[3.09]	[0.37]	[1.86]	[3.03]
Obs	393	393	396	396	396	13,272	13,272	13,272

Panel C: All Determination Days

	Mean Returns (%)					Excess Imbalance ($ Mil)		
	Full Day (1)	Before 30 min prior to determ. (2)	30 min prior to determ. (3)	15 min prior to determ. (4)	5 min prior to determ. (5)	30 min prior to determ. (6)	15 min prior to determ. (7)	5min prior to determ. (8)
Estimate	0.17	0.16	0.00	-0.02	-0.00	-17.13	-17.82*	-4.63
	[1.48]	[1.61]	[0.08]	[-0.95]	[-0.08]	[-1.23]	[-1.91]	[-0.89]
Obs	119	119	119	119	119	13,272	13,272	13,272

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_w^2 from the VMA representation, both results suggesting that order flow imbalance in these markets is playing a major role in price discovery.

To ascertain whether or not these price impacts from order flow reverse in subsequent minutes. We use the VMA representation to calculate impulse response functions. The graphs of these functions are shown in Figure 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.3 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 Scenarios for Order Flow Impact in a Simple Model

In this section we present a simple model of order flows and returns and examine how our impact estimates relate to the true impact of uninformed order flow under various scenarios. Throughout this discussion we ignore small sample issues and focus on the limiting case when the sample size is sufficiently large.

We start with a benchmark case and then consider scenarios relating to

1. Uninformed and informed order flow
2. Endogenous uninformed order flow
3. Off-exchange order flow
4. Order flow classification errors
5. Signing trades with the tick-rule
6. Using the tick-rule with microstructure effects and time-aggregation

We show that in scenarios 1-3, inclusion of these effects will bias our estimate of price impact upward, and thus lead our estimates of price impact to overstate the true price impact of uninformed trading. In contrast, in scenario 4, errors in classifying trades as buy or sell driven can lead to an underestimation of price impact, but this underestimation is bounded by the R^2 in the impact regressions. Finally, in scenario 5 we argue that using the tick-test can solve this potential issue, as signing trades in this way creates classification errors that maximize the impact estimate, and thus deliver an estimate that is the upper bound for the true impact. In scenario 6 we extend this to a more realistic setting with short-term reversals coming from microstructure dynamics of the spread, and find that for realistic distributions of imbalance, the tick-test again provides an upper bound for the true permanent impact of a trade.

In the next section we show that we obtain very similar impact estimates classifying trades via the tick-rule in our data, and thus we conclude that our price estimates are likely to overstate the actual impact of an uninformed trader.

IA.4.1 Benchmark

Consider the following simple process for returns.

$$r_t = \nu_t + \beta x_t$$

Here x_t represents order flow imbalance and ν_t represents returns coming from a public signal. For the benchmark case, we are thinking of a simple stylized model with a standard limit order book where price impacts are permanent, liquidity suppliers are competitive, buying and selling are symmetric, and there are no frictions like fixed costs of market making. In that simple case, each trade price is the new "efficient price" conditioned on the last trade sign and magnitude, so immediately after a trade the quote midpoint equals the last trade price and also equals the efficient price. Also, in this simple setup, the regression equation applies both at the trade level and aggregated across multiple trades. Later we will consider the possibility that some of the uninformed traders use limit orders at the inside of the spread, and the possibility that some of the price effects are temporary.

We assume that all right hand-side variables are drawn from symmetric distributions with mean zero. We assume that the ν_t realizations are i.i.d., and in this benchmark case that the x_t realizations are i.i.d.

Suppose that we are also able to sign trades with perfect accuracy, so that our observed order flow is $\hat{x}_t = x_t$. In this simple case, if we regress r_t on $\hat{x}_t$ as we do in our impact regressions, we will infer an estimated beta $\hat{\beta} = \beta$, and our empirical estimate of impact will be consistent.

IA.4.2 Scenario 1: Uninformed and informed order flow

Now consider a process where there are both informed and uninformed traders, and that market participants can differentiate between them, but the econometrician cannot.

$$r_t = \nu_t + \beta_{inf} x_{inf,t} + \beta_{uninf} x_{uninf,t}$$

Here assume that both types of order flow are uncorrelated with each other and the public signal, and that $\beta_{inf} > \beta_{uninf}$. Suppose again that we can sign trades again with perfect accuracy, so our estimate of order flow is $\hat{x}_t = x_{inf,t} + x_{uninf,t}$. In this case our impact estimate will be

$$\hat{\beta} = \frac{\sigma^2_{x,inf}\beta_{inf} + \sigma^2_{x,uninf}\beta_{uninf}}{\sigma^2_{x,inf} + \sigma^2_{x,uninf}}$$

Since this estimate reflects both uninformed and informed trading, it will be an upwardly biased estimate of the impact of uninformed traders.

IA.4.3 Scenario 2: Endogenous uninformed order flow

In our estimates in section IA.1, we find that a statistically significant, though economically modest, portion of order flows is predictable at one-minute horizons, with high returns and past imbalance predicting high future imbalance. This suggests that within a minute, uninformed order flows may be correlated with the realization of returns coming from either informed order flow or the public signal. We focus on the public signal. We start by again specifying a return process

$$r_t = \nu_t + \beta_{inf} x_{inf,t} + \beta_{uninf} x_{uninf,t}$$

But we now allow for positive correlations by specifying that $x_{uninf,t} = z_t + \gamma_\nu \nu_t + \gamma_{inf} x_{inf,t}$ with $\gamma_\nu > 0$ and $\gamma_{inf} > 0$. In this case, observed imbalance is the same as in the previous scenario. The estimate of impact is

$$\hat{\beta} = \frac{\sigma^2_{x,inf}(1+\gamma_{inf})(\beta_{inf} + \gamma_\nu \beta_{uninf}) + \sigma^2_z \beta_{uninf} + \sigma^2_\nu \gamma^2_\nu (1+\beta_{uninf})}{(1+\gamma_{inf})^2 \sigma^2_{x,inf} + \sigma^2_z + \sigma^2_\nu \gamma^2_\nu}$$

Consider now the case where there is no informed order flow to focus on the effect of γ_ν. Then

$$\hat{\beta} = \beta_{uninf} + \frac{\sigma_\nu^2 \gamma_\nu^2}{\sigma_z^2 + \sigma_\nu^2 \gamma_\nu^2}$$

The endogeneity here induces extra covariance between the uninformed order flow and returns, and again biases the impact upwards.

Now consider the case where there is no public information to focus on the effect of γ_{inf}. Here we have

$$\hat{\beta} = \frac{\sigma_{x,inf}^2 (1+\gamma_{inf})(\beta_{inf} + \gamma_\nu \beta_{uninf}) + \sigma_z^2 \beta_{uninf}}{(1+\gamma_{inf})^2 \sigma_{x,inf}^2 + \sigma_z^2} = \beta_{uninf} + \frac{\sigma_{x,inf}^2 (1+\gamma_{inf})(\beta_{inf} - \beta_{uninf})}{(1+\gamma_{inf})^2 \sigma_{x,inf}^2 + \sigma_z^2}$$

The correlation here leads to larger amounts of uninformed volume to mask informed flows, so the upward bias of the previous scenario is lessened, but the estimate will still be higher than the true uninformed impact.

IA.4.4 Scenario 3: Off-exchange volume

While the Globex is a large portion of total CME futures volume, in all of our commodities there is substantial floor trading over most of the sample period. In addition, there may be close substitutes in other futures markets. For example, we capture the COMEX copper contract, but for most of the period the LME contract has slightly higher volume. It is reasonable to assume that a trader, such as a commodity index fund, might spread orders across both the Globex and the floor to minimize impact. To see how this effects our estimates consider

$$r_t = \nu_t + \beta x_{on,t} + \beta x_{off,t}$$

We assume that the correlation of order flow ($\rho_{on,off} > 0$) is positive to represent orders being routed to both trading venues. Suppose again that we can sign trades with perfect accuracy, so our estimate of order flow is simply the imbalance on the observed exchange $\hat{x}_t = x_{on,t}$. In this case our impact estimate will be

$$\hat{\beta} = \beta \left(1 + \frac{\rho_{on,off} \sigma_{x,off}}{\sigma_{x,on}} \right)$$

Since this estimate is based on only a subset of true order flows, it will again be an upwardly biased estimate of the impact of uninformed traders.

IA.4.5 Scenario 4: Mis-classified trades

Our quote based method of classification should allow us to essentially recover the "true" buyer or seller as identified by the "aggressor" party that crossed the spread to trade. However, there is still a worry that a buy trade is executed by posting a limit-buy order which is then hit by a market-maker or HFT. We note that this is likely to be a small set of trades, as such strategies would require small tick sizes relative to the spread to execute. In our commodity futures markets spreads are usually only one, and seldom more than two, ticks wide in the liquid periods around the close for all of commodities. Nevertheless it is important to understand how this may affect our estimates, as this is a scenario which can potentially lead to erroneously small estimates of impact.

Therefore consider again the original benchmark model

$$r_t = \nu_t + \beta x_t$$

but assume that imbalance is observed with classification error $\hat{x}_t = x_t + \epsilon_t$. One of the key features of our setup is that there is likely negative correlation between the error term and x_t. This is mechanical, as any mis-classified buy will considered a sell, so a period with many buys would likely have a negative error term. In this case, we have

$$\begin{aligned}
\hat{\beta} &= \beta \frac{\sigma_x^2 + \rho_{\epsilon,x}\sigma_x\sigma_\epsilon}{\sigma_x^2 + \sigma_\epsilon^2 + 2\rho_{\epsilon,x}\sigma_x\sigma_\epsilon} \\
&= \beta\left(1 + \frac{-\rho_{\epsilon,x}\sigma_x\sigma_\epsilon + \sigma_\epsilon^2}{\sigma_x^2 + \sigma_\epsilon^2 + 2\rho_{\epsilon,x}\sigma_x\sigma_\epsilon}\right)
\end{aligned}$$

Therefore, while measurement errors will bias our estimates downward, the likely negative correlation between our mis-classification and true imbalance will have the opposite effect.

It can also be shown via simple algebra that the empirical R^2 in this model is

$$R^2 = \frac{\hat{\beta}}{\beta}\left(\frac{\beta^2\sigma_x^2 + \beta^2\rho_{\epsilon,x}\sigma_\epsilon\sigma_x}{\beta^2\sigma_x^2 + \sigma_\nu^2}\right)$$

Consider in the extreme case that $\rho_{\epsilon,x} = 0$ and $\sigma_\nu = 0$, then we have $R^2 = \frac{\hat{\beta}}{\beta}$, and the R^2 is a bound on the understatement of impact. Given that our R^2 are typically between 15% and 35%, this implies that this sort of mis-classification can only induce an estimated impact of 15% or 35% the true value, and this only if there is no variation from public information and there is no negative correlation between the errors and the actual imbalance.

While it seems plausible that much of the variation is coming from information not revealed from trades (either public information or trades on other venues) it is nevertheless hard to estimate precisely the degree of this bias. We therefore consider an alternate, tick-based classification, and consider its implications next.

IA.4.6 Scenario 5: Tick Classification

Consider again the benchmark model.

$$r_t = \nu_t + \beta x_t$$

In this case however, suppose that t indexes individual trades, and consider the implications of performing the tick-test classification. The econometrician observes the magnitude $|x_t|$, and the sign is then assigned as positive if $r_t > 0$ and negative if $r_t < 0$. This then gives observed imbalance

$\hat{x}_t = -x_t$	if: $\nu_t > \beta x_t$ and $x_t < 0$	**MC as buy**
$\hat{x}_t = -x_t$	if: $\nu_t < \beta x_t$ and $x_t > 0$	**MC as sell**
$\hat{x}_t = x_t$	else	**Correct**

Given this measure of imbalance, our OLS strategy yields an impact estimate of

$$\hat{\beta} = \beta + 2p_{\mathbf{MC}} \frac{E_{\mathbf{MC}}\left[|x_t r_t|\right]}{Var(x_t)}$$

where $p_{\mathbf{MC}}$ is the probability of a mis-classification, and $E_{\mathbf{MC}}$ is the expected value conditional on mis-classification. The positive values of the expectation lead to an overstated measure of price impact.

In essence, assuming that any trade that corresponded with an up (down) move in price is a buy (sell), is the most conservative approach to avoid understating impacts, and therefore yields an upper bound for the level of impact from a given level of investment. Intuitively, assuming that a given trade caused whatever movement coincided with the trade, even if that movement is the result of public information, leads to an overstatement of any impact.

However, this simple model assumes that all trade impact is immediate and permanent. In reality, when we sign trades with the tick method, we would often sign as a buy a trade near the ask, and if quotes do not react to each trade then the subsequent trade is more likely to be classified as a sell due to short-term reversal. Therefore we next consider a model to examine the implications of these effects.

IA.4.7 Scenario 6: Tick classification w/ microstructure effects and aggregation

Suppose that liquidity supply includes some combination of carrying costs and monopoly power, so that the initial trade price impact is larger than the permanent price impact. Specifically, let trade-price returns at a trade-time horizon evolve according to

$$r_t = \nu_t + \beta x_t - \Gamma \beta x_{t-1}$$

Where $\Gamma \in (0, 1)$ captures short term reversals due to liquidity and the dynamics of the spread. The permanent impact of imbalance is therefore $\beta(1 - \Gamma)$. We assume quote midpoints continue to capture only the permanent price impacts.

If we could observe x_t and estimated impact via OLS at the trade horizon, our estimate would $\hat{\beta} = \beta$, which would be an overstatement of the true impact.

However, our approach aggregates up all trades in a minute. To see the effect of this aggregation, assume that each minute m consists of N trades.

The trade-price return for a minute is

$$R_m = \sum_{s=1}^{N} r_s = \sum_{s=1}^{N} [\nu_s + \beta x_s (1 - \Gamma)] - \Gamma(\beta x_0 - \beta x_N)$$

Here the last term comes from the serial correlation generated by observations at the start and end of the aggregation period.

Since x_0 is uncorrelated with $\sum_{s=1}^{N} x_s = X_m$, but x_N is positively correlated, the last term will lead to an overstatement of impact (we miss the reversal of the last trade) in a regression using trade prices, but we use quote midpoints for the aggregate returns over the minute, so we have

$$R_m = \nu_m + \beta(1 - \Gamma)X_m$$

It is clear here that if we can correctly sign trades to recover X_m, our impact estimate will be equal to the permanent impact $\beta(1 - \Gamma)$. We now see how applying the tick-test impacts this estimate, and we will show once again that it biases our estimates upward above the true impact.

We use the tick test to sign trades as in the previous scenario, however a complication arises because the short-term reversal from the Γx_{t-1} term now impacts the signing of the trades.

$$\begin{aligned}
\hat{x}_t &= -x_t & &\text{if: } \nu_t - \beta\Gamma x_{t-1} > \beta x_t \text{ and } x_t < 0 & &\textbf{MC as buy} \\
\hat{x}_t &= -x_t & &\text{if: } \nu_t - \beta\Gamma x_{t-1} < \beta x_t \text{ and } x_t > 0 & &\textbf{MC as sell} \\
\hat{x}_t &= x_t & &\text{else} & &\textbf{Correct}
\end{aligned}$$

After signing trades, we then sum up to calculate per-minute imbalance, and we likewise calculate per-minute return over the period.

Observed imbalance with the tick rule is

$$\hat{X}_m = \sum_{s=1}^{N} (x_s + 2(\mathbb{1}_{MCBuy} x_s - \mathbb{1}_{MCSell} x_s))$$

Define

$$\pi_t = \hat{x}_t - x_t$$
$$\Pi_m = \sum_{s=1}^{N} \pi_t = \hat{X}_m - X_m$$

Here π_t is the classification error for each trade. (e.g. difference between the observed imbalance from the tick-test and the true imbalance). Note that, conditional on a misclassification, $|\pi_t| = 2|x_t|$. Π_t is the sum of these errors for each minute.

The OLS regression coefficient of our strategy is then

$$
\begin{aligned}
\hat{\beta} &= \frac{Cov(R_m, \hat{X}_m)}{Var(\hat{X}_m)} \\
&= \frac{\beta(1-\Gamma)Var(X_m) + \beta(1-\Gamma)Cov(\Pi_m, X_m) + Cov(\nu_m, \Pi_m)}{Var(X_m) + Var(\Pi_m) + 2Cov(X_m, \Pi_m)} \\
&= \beta(1-\Gamma)\left(1 + \frac{\frac{Cov(\nu_m,\Pi_m)}{\beta(1-\Gamma)} - Cov(\Pi_m, X_m) - Var(\Pi_m)}{Var(X_m) + Var(\Pi_m) + 2Cov(X_m, \Pi_m)}\right)
\end{aligned}
$$

Where the second equation follows from $R_m = \nu_m + \beta(1-\Gamma)X_m$ and $\hat{X}_m = X_m + \Pi_m$, and the final equation is obtained via some simple algebra. Since the denominator is the variance of observed imbalance, and is therefore positive, we have

$$
\hat{\beta} \geq \beta(1-\Gamma) \iff \frac{Cov(\nu_m, \Pi_m)}{\beta(1-\Gamma)} - Cov(\Pi_m, X_m) - Var(\Pi_m) \geq 0
$$

The first term captures again the fact that our impact measure using the tick-test will be an overstatement of true permanent impact if our signing errors covary positively with the arrival of public information, (which is the case by the same argument as the previous scenario). The second term comes from the fact that microstructure reversals induce a negative correlation between misclassifications and aggregate returns. For instance, a period with many buy trades will see many negative reversals, and therefore a larger number of subsequent buys mis-classified as sells. This negative covariance will again bias our estimate up. The last term is a measurement-error term, and will bias our estimates down.

Focusing on the last two terms, and noting that all variables are mean zero, and that covariances are zero beyond one lag, we have

$$
\begin{aligned}
Var(\Pi_m) &= Np_{MC}E_{\mathbf{MC}}(4x_t^2) + NCov(\pi_t, \pi_{t-1}) \\
&= Np_{MC}E_{\mathbf{MC}}(4x_t^2) + Np_{MCMC}E_{\mathbf{MCMC}}(4x_t x_{t-1})
\end{aligned}
$$

Where $MCMC$ identifies observations where both the current trade and the previous trade are mis-classified. We also have

$$
\begin{aligned}
Cov(\Pi_m, X_m) &= Np_{MC}E_{\mathbf{MC}}\left(-2x_t^2 - 2x_t x_{t-1}\right) \\
Cov(\Pi_m, X_m) &= Np_{MC}E_{\mathbf{MC}}\left(-4x_t^2 - 2x_t(x_{t-1} - x_t)\right)
\end{aligned}
$$

So that

$$
-Cov(\Pi_m, X_m) - Var(\Pi_m) = N\left[p_{MC}E_{\mathbf{MC}}\left(2x_t(x_{t-1} - x_t)\right) - p_{MCMC}E_{\mathbf{MCMC}}(4x_t x_{t-1})\right]
$$

Note that, if $\sigma_\nu = 0$, the only way there can be a mis-classification is if there are two consecutive trades in the same direction with the second trade being of smaller magnitude than the first. For instance, a large buy generates a negative return subsequent return which leads to the mis-signing of a following buy (this is necessary but not sufficient). Therefore the first expectation on the right-hand size is positive. To generate two consecutive mis-classifications requires three trades in the same direction of descending magnitudes (an occurrence that happens one out of 24 sequences of three trades), and the second term on the right will typically be a second-order effect (In fact $\frac{1}{6}p_{MC} > p_{MCMC}$).

It is possible to choose probability distributions for x_t that will generate a slight understatement of permanent impact for values of Γ very close to one (i.e. highly discrete bimodal distributions so that the measurement-error term dominates). However, we find in simulations with reasonable distributions that the tick-test method will overstate impacts due to the induced negative covariance between returns and identified imbalance. Figure IA.2 demonstrates this. We simulate 10,000 minutes with 10,000 trades in each minute for imbalance drawn from the normal, logistic, and Laplace distributions (the latter two distributions are platykurtic consistent with the data). Each plot shows the ratio of our estimated imbalance method using the tick-test relative to the true permanent impact ($\frac{\hat{\beta}}{\beta(1-\Gamma)}$) as a function of Γ, and the amount of public information. For the plots, we vary σ_ν to achieve a target R^2 coming from public information. This R^2 is varied from zero ($\sigma_\nu = 0$) to 0.8. As the plot shows, the estimated impact is equal to the true permanent impact in the case where there $\Gamma = 0$ and $\sigma_\nu = 0$, but otherwise $\hat{\beta}$ is an overestimate of the true impact, even in the cases where $\sigma_\nu = 0$.

IA.5 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.6 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.5 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.5 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.7 Summary Data for Next Month Corn and Wheat Futures

Table IA.4 shows summary data for both active month and next month futures in corn and wheat contracts. Panel A repeats the summary data for corn and wheat shown in Table 2 in the main text. Panel B repeats the same analysis but this time for the next month future (typically the third calendar month). The main take away is that volumes are lower, but average imbalances are higher. What trading there is in the next month tends to be concentrated in buyer initiated trades.

IA.8 Comparison of Determination Date Sample with Henderson, Pearson, and Wang (2015)

As mentioned in the main text, we do not find a significant average negative determination date return for any subset of our notes. This is contrast to the published result of Henderson, Pearson, and Wang 2015, who find a return of -42 basis points (t-stat of 2.50) on the determination dates of 42 notes with greater than $10 million outside of the Goldman Roll. They find a two-day return, that includes both the determination day and the following day, of -39 basis points (t-stat of 1.80).

We contacted HPW noting our inability to replicate this finding, and they re-examined their set of determination days. After comparing their results with our data, HPW concluded that of their original 42 days, 10 were mistakenly included, and 24 were mistakenly excluded, and therefore they produced a refined set of 56 days. They find determination day returns of -15 basis points (t-stat of 0.76) on these dates. However, when they look at the two-day window including the day after the determination date, this effect rises to -51 basis points (t-stat of 1.78).

After reviewing the refined sample of HPW, we disagree with the some of the choices made about notes in the sample. After considering the refined set of HPW, we arrived at our set of 54 notes (we had 50 in our original set, due to four where we missed the 424b filings), which excludes 3 notes in HPW's set, and includes one extra note. This is the set that is shown in column (2) of Panel D in Table 8 in the main text. Table IA.6 shows the results of Table 8 but recalculated using the two-day window, and shows that we still find no significant result. Our two-day return is -42 basis points (t-stat of 1.44) for the relevant subsample.

Table IA.7 shows the discrepancies between the two subsamples. There are two gold notes that seem to us to be clearly in the Goldman Roll period, and therefore should be excluded. These do not have much an effect on the result. Two other notes drive most the discrepancy in our return result.

The first is a Natural Gas note linked to the price of the U.S. Natural Gas ETF (ticker:UNG). We include such notes (for instance there are several linked to the SPDR Gold ETF (ticker:GLD)). Commodity linked notes typically link to various proprietary commodity indices rather than an explicit futures contract. We do not believe that being linked to a separately traded price that tracks a single commodity should disqualify a note, particularly since authorized participants can deliver futures to create shares of the underlying ETF.

The second note is a "daily liquidity note" issued by J.P. Morgan linked to corn.[1] These notes are issued for a given face value, but are not fully sold initially. Furthermore, the issuer offers to buy the note back at a market value (calculated using the underlying commodity price) at any point during the life of the note. In this sense, they behave more like an ETN than a standard note, so we do not include them in our analysis. For this particular note, the filing specifies that $2.5 million was sold, so it may have been issued, but it was certainly not a large note, and there was no guarantee that it was not sold back to the issuer prior to the determination date.

The determination date of the natural gas note coincided with a large positive return on both the determination date and the following day, and the corn note coincided with a large negative return on the day after the determination date. Therefore our inclusion of the natural gas note and

[1]See filing: https://www.sec.gov/Archives/edgar/data/19617/000089109210002989/e39481_424b2.htm.

exclusion of the corn note leads to a less negative estimate of average return.

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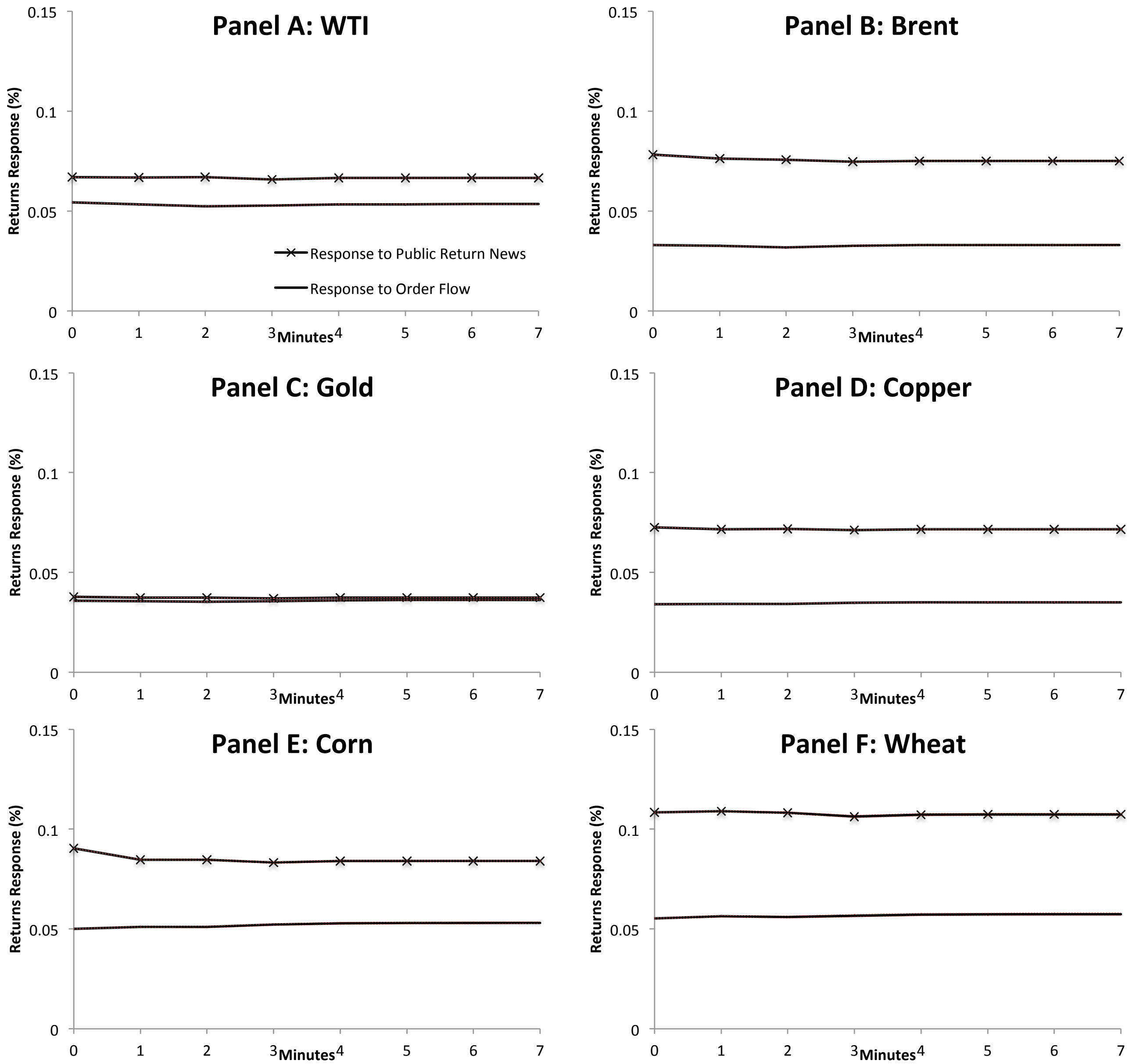

Figure IA.1. Return Impulse Response Functions for VARs
The figure shows the impulse response of returns to innovations in order flow and public news from the vector autoregression specification estimated in Table 3. Plots show return responses to one standard deviation innovations in public return news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

Figure IA.2. Simulated tick-test impacts with microstructure effects and time-aggregation

The figure shows the ratio of estimated impacts to the true permanent impact ($\frac{\hat{\beta}}{\beta(1-\Gamma)}$) coming from simulations of the model described in section IA.4.7. The model is simulated for 10,000 minutes each with 10,000 trades, each trade is signed with tick-test and then imbalance and returns are aggregated up to the one minute level. The estimated impact of trading ($\hat{\beta}$) is then calculated via an OLS regression of minute-by-minute returns on minute-by-minute imbalance. Each plot shows the ratio of estimated impact to true permanent impact for various values of short-term reversal (Γ) and for different amounts of return variance coming from public information. Different panels show results of simulations drawing imbalance from different probability distributions.

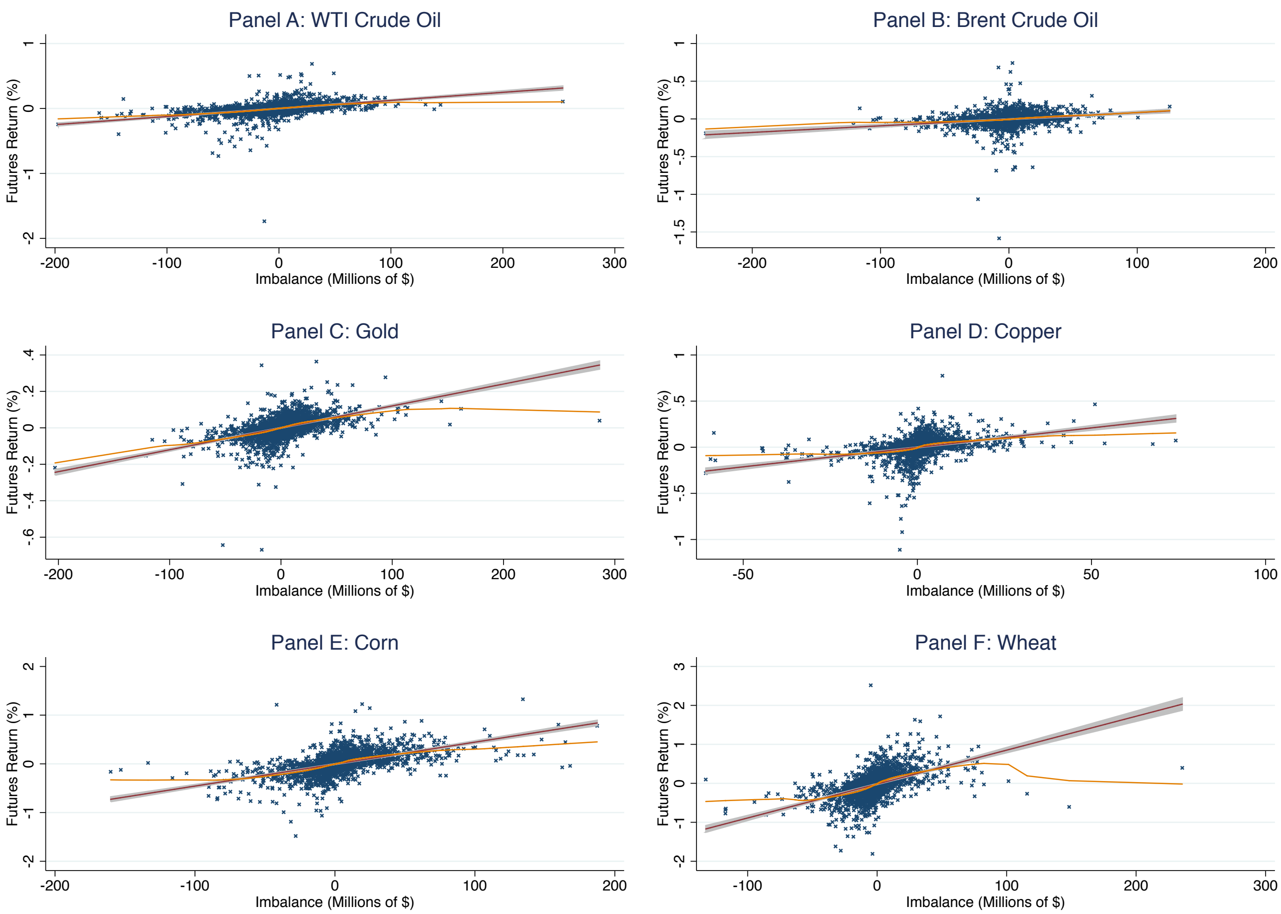

Figure IA.3. Nonlinearities in imbalance and raturns in minute prior to futures settlement

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.

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_w^2 shown in the final row is the percentage of variation in returns explained by unexpected innovations in order flow, calculated from a vector moving average representation of the VAR. Return is measured in percent, while imbalance is measured in 100s of contracts. 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_w^2	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 4 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. Summary of Next Month Futures for Corn and Wheat

This table shows summary statistics for return, volume, and imbalance for corn and wheat futures. Panel A repeats the values for the active month contracts in corn and wheat shown in Table 2 in the main text. Panel B shows this same analysis using the next month future.

Panel A: Active Month Futures

	CME Wheat (All Minutes)				CME Wheat (Settlement Minute)		
	Ret. (%)	Vol. (Mil $)	Imb.		Ret. (%)	Vol. (Mil $)	Imb.
Mean	0	8.9	0.02	Mean	0.01	120.4	4.3
St. Dev.	0.15	18.1	8.48	St. Dev.	0.24	96.3	29.9
# of Min			587,859	# of Min			1,811

	CME Wheat (All Minutes)				CME Wheat (Settlement Minute)		
	Ret. (%)	Vol. (Mil $)	Imb.		Ret. (%)	Vol. (Mil $)	Imb.
Mean	0	4.39	-0.1	Mean	-0.04	73.1	-1.9
St. Dev.	0.16	9.71	3.62	St. Dev.	0.36	62.4	19.7
# of Min			537,251	# of Min			1,810

Panel B: Next Month Futures

	CME Wheat (All Minutes)				CME Wheat (Settlement Minute)		
	Ret. (%)	Vol. (Mil $)	Imb.		Ret. (%)	Vol. (Mil $)	Imb.
Mean	0	1.12	0.88	Mean	0.01	15.7	11.55
St. Dev.	0.14	4.38	4.06	St. Dev.	0.24	28.1	19.28
# of Min			587,859	# of Min			1,811

	CME Wheat (All Minutes)				CME Wheat (Settlement Minute)		
	Ret. (%)	Vol. (Mil $)	Imb.		Ret. (%)	Vol. (Mil $)	Imb.
Mean	0	0.79	0.37	Mean	-0.03	14.37	6.7
St. Dev.	0.17	1.12	2.33	St. Dev.	0.35	25.69	13.7
# of Min			537,251	# of Min			1,810

Table IA.5. 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

Table IA.6. Two-Day Futures Returns on CLN Determination Dates

The table repeats the analysis in Table 8 in the main text, but uses the average cumulative return on both the date of CLN determination and the following day. 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 Days						**Panel B: Notes w/ $10+ Mil Face Value**				
	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)	All Days (6)	Excluding Goldman Roll (7)	During Goldman Roll (8)	During Active Issuance Period (9)	Excluding Active Issuance Period (10)
Realized Daily Returns										
Average	-0.06	-0.05	-0.10	0.33	-0.29	-0.19	-0.31	0.15	0.02	-0.37
	[-0.45]	[-0.28]	[-0.43]	[1.53]	[-1.52]	[-0.91]	[-1.29]	[0.41]	[0.06]	[-1.15]
Predicted Impact of Unwinding Delta Hedges										
Average	-0.10	-0.12	-0.05	-0.05	-0.13	-0.18	-0.22	-0.09	-0.07	-0.28
Obs	202	141	61	74	128	91	66	25	43	48

Panel C: Days prior to 2014/02						**Panel D: Prior 2014/02 w/ $10+ Mil Face Value**				
	All Days (1)	Excluding Goldman Roll (2)	During Goldman Roll (3)	During Active Issuance Period (4)	Excluding Active Issuance Period (5)	All Days (6)	Excluding Goldman Roll (7)	During Goldman Roll (8)	During Active Issuance Period (9)	Excluding Active Issuance Period (10)
Realized Daily Returns										
Average	-0.17	-0.25	-0.01	0.19	-0.34	-0.27	-0.42	0.14	-0.05	-0.42
	[-1.01]	[-1.12]	[-0.03]	[0.76]	[-1.56]	[-1.09]	[-1.44]	[0.33]	[-0.14]	[-1.22]
Predicted Impact of Unwinding Delta Hedges										
Average	-0.12	-0.15	-0.05	-0.06	-0.15	-0.21	-0.25	-0.10	-0.08	-0.30
Obs	157	108	49	50	107	75	54	21	31	44

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

Table IA.7. Discrepancies with refined determination date sample of HPW

This table lists the discrepancies between our subset of 54 days with determination dates outside of the Goldman Roll Period, prior to February 2014, with at least $10 million of face value, and the refined set of 56 days provided to us by HPW.

Notes Included by HPW

Determination Date	. Commodity	Face Value	Day 0 Return	Day 1 Return	Explanation
10/4/13	Gold	143,249,000	-0.58	1.15	We exclude because this is the 4th trading day of the month and therefore in the Goldman Roll Period
10/7/13	Gold	35,000,000	1.15	-0.05	We exclude because this is the 5th trading day of the month and therefore in the Goldman Roll Period
7/22/13	Corn	20,000,000	-0.60	-3.37	We exclude because this is a "daily liquidity note". Only $2.5 million was sold at issue, remainder held by brokerage arm of the issuer. The issuer also offers to buy the note back at market value during the life of the note.

Notes Excluded by HPW

Determination Date	. Commodity	Face Value	Day 0 Return	Day 1 Return	Explanation
7/27/10	Natural Gas	18,319,000	1.37	2.12	Note is linked to the UNG natural gas ETF. We include notes linked to ETFs which hold only commodity futures or spot positions in a single commodity.