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ABSTRACT

Using intraday data, we find that unidirectional causality runs from commodity index linked commodity futures to non-index linked commodity futures for up to one hour but disappears when using daily data. Also, the economic significance of index to non-index commodity transmission declines to zero within about an hour. Finally, we find that the magnitude of index-to-non index returns relationships are positively related to the amount of speculation, both long and short, in the GSCI commodity index futures contract. We conclude that speculative pressures exerted by commodity index investors can impact non-index commodities. These results are likely not due to speculative pressure itself, but rather the subsequent price destabilizing trades of uninformed, positive feedback traders.

Keywords: Commodity Futures, Commodity Index Futures, Speculation

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ABSTRACT

Using intraday data, we find that unidirectional causality runs from commodity index linked commodity futures to non-index linked commodity futures for up to one hour but disappears when using daily data. Also, the economic significance of index to non-index commodity transmission declines to zero within about an hour. Finally, we find that the magnitude of index-to-non index returns relationships are positively related to the amount of speculation, both long and short, in the GSCI commodity index futures contract. We conclude that speculative pressures exerted by commodity index investors can impact non-index commodities. These results are likely not due to speculative pressure itself, but rather the subsequent price destabilizing trades of uninformed, positive feedback traders.

1. Introduction

Does speculation distort commodity futures prices and increase price volatility? Debate over the issue has been increasing. First, a report by the United States Commodity Futures Trading Commission (CFTC) finds a coincident increase in commodity futures index activity and commodity prices. The CFTC believes that this is evidence of commodity index speculation causing price distortions in individual commodities. However, two recent articles refute this explanation.

Blanch et al. (2008) of Merrill Lynch find that commodity index futures open interest and volume mitigate futures price volatility. Thus, it seems that commodity index futures activity has a price stabilizing influence. Also, Blanch et al. find that both index and non-index linked commodity prices increased during the recent commodity price boom. However, the prices of non-index commodities as well as commodities dropped from the S&P GSCI have increased more so than the index linked prices. They argue that if speculation was to blame, index-linked commodities would have had higher price increases than non-index linked commodities during the recent commodity price bubble. Blanch et al. conclude that the run up in commodity prices was due to loose monetary policy and not speculative pressures from commodity index futures.

Stoll and Whaley (2010) study the impact of commodity index futures speculation and the price dynamics of individual commodity futures. They conclude that index speculators did not bring about increases in individual commodity prices. They make this claim based on three findings. First, they examine the comovement among different commodity futures. They find that correlations are "low" except for highly fungible commodities. They also find a high correlation between index and non-index linked commodity futures. That is, the returns of commodity futures in commodity index funds (e.g. S&P GSCI and DJ-AIG) have a high correlation with commodities that are not in commodity index funds.

Stoll and Whaley's second analysis centers on causality between index fund flows and individual commodity returns. They do this by regressing weekly fund flows and own-returns onto future (individual) commodity returns. Finding little statistical evidence of causal relationships, they conclude that speculation does not impact commodity prices. Third, Stoll and Whaley note that while fund flows into commodity index futures doubled during the commodity price bubble, a large percentage of these flows originated from traders motivated by portfolio rebalancing or index maintenance needs. Discounting the possibility that portfolio rebalancing done on purely fundamental grounds could lead to both upward commodity price pressure as well as a vicious cycle of price destabilizing speculation, Stoll and Whaley conclude that activity in commodity index funds is "by definition" not speculatory nor price destabilizing.

Yet, the above reports, as well as the literature refuting the price impact of speculation on commodity prices, suffer from the use of low frequency data. This is a critically important issue given that futures markets are generally active, liquid, and highly efficient. Thus, the prior literature may not have used sufficiently granular data to capture fast futures market dynamics. We reexamine the issue of index speculation on commodity futures prices. We do this by using both contemporaneous correlation and Granger causality analyses between index linked commodities and non-index linked commodities at daily and intraday frequencies. We hypothesize that unidirectional causal relationships exist between index linked commodities to non-index linked commodities suggesting that speculation in commodity index futures leads to price pressures in individual non-index linked commodity futures, either directly or indirectly.

The rationale for our tests is straightforward: if commodity index futures do not have pricing impacts on individual commodity futures, then there should be no unique relationship (causal or correlative) between index and non-index linked commodity futures. If, however, there is a causal relationship between index activity and commodity prices, then index linked prices will undirectionally impact non-index prices. Unlike the bulk of recent literature on speculation, we use both daily and intraday data. The reason for this is that commodity futures markets enjoy a high level of cross and own market efficiency due to their high level of liquidity, ease of position taking, and use of leverage. Thus, our analysis captures the impact of speculative pressures at frequencies that other studies do not.

We find that while daily cross commodity correlations are high, cross commodity returns transmission does not occur for commodity contracts within our sample. Thus, daily transmission does not occur between commodity pairs that are both included in a commodity index (e.g. gold and silver) or between those pairs that include an index based commodity and a non-index based commodity (e.g. gold and palladium). For example, corn and wheat which are included in commodity index futures do not have Granger causing relationships at daily frequencies. Similarly, corn and wheat causal relationships with oats, a commodity not included in commodity index funds, are also nonexistent. When combined with the high cross commodity correlations, the causality results indirectly suggest that cross commodity dynamics do occur. However, these causal relationships occur at speeds too fast for low frequency data to detect.

Using intraday data, we find that index/non-index correlations are initially low but increase in magnitude at increasingly longer horizons. Further, we find that index to index linked commodity futures (e.g. gold and silver) causality rarely occurs even at 5 minute frequencies. However, there exists unidirectional causality from index to non-index linked commodity futures that lasts up to one hour but disappears at daily frequencies (e.g. gold and palladium). Also, the economic significance of the index/non-index causality declines as the time horizon increases. According to the argument presented above, our results suggest that commodity index futures activity impacts index linked commodity futures. The index futures pressure is then transmitted indirectly through the index linked to non-index linked commodity futures channel.

We directly test if the price impact from index-linked to non-index linked commodity futures is a function of speculative interest (i.e. the ratio of non-commercial to commercial positions as reported by the CFTC Commitment of Traders report). We find that the magnitude of index/non-index price pressures is positively and significantly related to the amount of speculation occurring within a given weekly interval. This positive relationship exists for both long speculation as well as short speculation with no statistical difference between the two speculation types. Finally, in addition to results reported during the entire sample, we find that the speculation/price pressure relationship exhibits a threshold effect wherein "excessive" speculation (speculation ratios above their respective means) produces greater index/non-index price pressures.

While our results suggest that index speculation is directly linked to price pressures in individual commodity contracts, we suggest that uninformed "positive feedback" traders are to blame. Specifically, De Long et al. (1990a) note that rational speculation can bring about uninformed positive feedback trading which, in turn, increases price volatility. Further, rational speculators and uninformed feedback traders may create vicious, mutually reinforcing cycles of increased speculation and increased feedback activity leading to even higher volatility (Andreassen and Kraus, 1990). Finally, despite the fact that some speculation can be price stabilizing either due to the provision of trading opportunities or by incorporating information into price (e.g. speculators using fundamental analysis; Reitz and Slopek, 2009), the unpredictability of noise traders' beliefs can prevent rational arbitragers from "leaning against the wind" leading prices to substantially deviate from fundamental value for extended periods of time (De Long et al., 1990b). Thus, even if the majority of commodity index futures activity is non-speculative in nature, as Stoll and Whaley (2010) report, the above example and the prior literature illustrate how even small levels of speculation can lead to substantial price path trends and destabilization.

Our study continues in Section 2 with a literature review on speculation and positive feedback trading. Section 3 continues with a description of our methodological approach. Section 4 provides our empirical results while Section 5 summarizes our findings and provides concluding remarks.

2. Literature Review

Prior literature is mixed as to whether speculation (either directly or indirectly) destabilizes asset prices. Examples of those indicating that speculation has pricing effects include Kocagil (1997) who finds that futures speculation fails to lower spot price volatility in the precious and industrial metals markets. Therefore, despite the liquidity they provide, speculators fail to stabilize commodity spot prices. Du et al. (2011) find that speculation and scalping activity increases oil price volatility. Endo and Yamaguchi (2010) also find that speculative hedge funds positively impact light sweet crude oil prices while Liao (2010) finds that speculators in the US Treasury futures market destabilize prices. Further, speculators' price destabilizing trades are only partially offset by the hedgers' price stabilizing activity.

Silvennoinen and Thorp (2010) find that commodity futures price volatility is a positive function of lower interest rates, cross asset volatility spillovers, and non-commercial commodity futures traders' (e.g. hedge fund) open interest. The impact of interest rates on commodity prices must be tempered by the fact that Anzuini et al. (2010) find that while monetary policy shocks do have a positive impact on commodity prices, these effects are economically small in magnitude.

With regard to the recent commodity price boom and bust, Einloth (2009) finds that while speculation did not have an impact on the price of crude oil during its run-up to $100, speculation did have an impact on oil prices in their ascent from $100 to $140. Cifarelli and Paladino (2010) contend that speculation was responsible for both the recent large positive and negative price swings in oil prices. Further, Cifarelli and Paladino state that fundamental factors did not have an economically large impact on oil prices. Kaufmann and Ullman (2009), however, argue that fundamental factors initiated the extended bull market in oil prices. However, speculators aggravated the price increase. Also, the interaction between fundamental and speculative factors caused a vicious cycle to emerge of increased fundamental expectations and increased speculative expectations.

Caballero et al. (2008) and Phillips and Yu (2010) suggest that the recent boom and subsequent bust in commodity prices were initially due to a low supply of profitable assets. This led to speculators chasing alternative and potentially more profitable asset classes. This, in turn, led to the emergence of assets bubbles in rotating asset classes. Thus, speculative activity rotated among assets classes including to, most recently, commodity futures. Finally, Röthig and Chiarella (2007) find that speculators' impact on commodity price volatility is asymmetric where speculators' impacts are greatest felt during price expansions.

Weiner (2002) contends that speculation, in itself, does not destabilize commodity prices. Rather, speculation only destabilizes commodity prices when the speculative activity is, on balance, sufficiently uninformed. In this case, speculators may herd and chase trends which, in turn, amplify market volatility through similar trading behavior. Reitz and Slopek (2009) provide some evidence towards Weiner's contribution in that there exists interplay between different speculator types. Specifically, trend extrapolating chartists destabilize commodity prices whereas speculators trading based on fundamental analysis fundamental analysts stabilize commodity prices. Thus, when speculators are less informed and use similar trading strategies (e.g. charting and trend following), commodity prices can destabilize and exhibit short-lived bull phases.

De Long et al. (1990a) examine the impact of "positive feedback traders" and, among other things, price volatility. From their model, they find that increased rational speculation increases uninformed positive feedback trading which, in turn, increases price volatility. For example, rational speculation based on expectations of continued price increases leads to an increase in positive feedback trading by uninformed investors (similar to momentum trading) leading to increased price volatility. Further, rational speculators and uninformed feedback traders may create a vicious, mutually reinforcing cycle of increased speculation and increased feedback activity leading to even higher volatility (Andreassen and Kraus, 1990).

What's more, when prices deviate substantially from fundamental market values, contrarian speculators' risk aversion prevents them from "leaning against the wind" of speculative and uninformed trading due to the uncertainty of noise trader sentiment. Therefore, price deviations from fundamental value may remain high despite (informed) arbitrage opportunities (De Long et al., 1990a, 1990b). Finally, uninformed, positive feedback traders interact with other market participants leading to increased volatility. For example, Grossman (1988) and Gennotte and Leland (1990) find that dynamic hedging activity leads to increased positive feedback trades. Also, Wang (2003) finds that hedgers themselves engage in positive feedback trading leading to destabilized futures prices (i.e. high market volatility).

With an eye towards the commodity and commodity futures markets, speculators tend to be overconfident (especially in up-trending markets; Yung and Liu, 2009) follow trends (Dale and Zyren, 1996; Büyüşahin and Harris, 2009), herd, and engage in positive feedback trading (Irwin and Yoshimaru, 1999; Röthig and Chiarella, 2007; Cifarelli and Paladino, 2010). Specifically, price changes caused by hedging activity can entice speculative managed money traders (e.g. hedge funds) to alter their positions. Further, the impacts of these positive feedback noise traders can be long lived (Sanders et al., 1996) implying that sustained positive feedback price effects can be persistent and not easily reversed. Finally, Holt and Irwin (2000) find that positive feedback can explain up to 8.8% of hedge fund trading variation.

Thus, vicious cycles can arise between commodity speculators, hedgers, and noise traders such that an increase in activity in one can increase the trading activity of the other. The vicious cycle of trading activity implies a vicious cycle of price destabilization as the behavior of one trader type feeds the behavior of other trader types. Thus, regardless of the extent, speculation in commodity index futures may lead to persistent price destabilizations in both index and non-index linked commodities.

Yet, the idea that index speculators and/or positive feedback noise traders are to blame for commodity price volatility initially seems at odds with prior literature. For instance, Bessembinder and Seguin (1992, 1993) note that uninformed traders prefer the futures markets over the spot markets given that futures markets offer traders a lower effective level of transactions costs. Further, Subrahmanyam (1991) notes that uninformed traders prefer index futures positions over individual spot positions for two reasons. The first reason is that the futures positions offer lower effective transactions costs. The second reason is that the diversifying nature of the indexes erodes the informational advantage informed traders possess in one or a limited number of individual contracts. Thus, prior literature notes that futures indexes attract uninformed traders.

Note that Bessembinder and Seguin empirically find that increased uninformed futures trading can lead to lower spot price volatility. Their approach is based on Kyle (1985) and Admati and Pfleiderer (1988) who theorize that increased uninformed trading leads to increased market depth which, in turn, leads to decreased price volatility. Thus, selections of the prior literature may lead one to conclude that index futures activity actually leads to lower commodity price volatility; a result that would be at odds with our hypothesis that commodity index futures increased individual commodity price volatility.

However, Kyle, Admati and Pfleiderer, and Bessembinder and Seguin do not take into account that, like informed traders, uninformed traders may be heterogeneously informed or motivated. For example, Sentana and Wadhwani (1992) and Shiller (1984) allow for feedback investors where a feedback investor buys (sells) when the market is rising (declining). As a result, it is possible that the noise traders enticed into the market by index speculators still provide liquidity to the commodity futures market. However, noise traders' net impact, after taking into account the effects of positive feedback trading (and the vicious speculation-noise trading cycle it can create), is still price destabilizing.

In the early to mid 1990's, commodity futures index funds emerged allowing investors the ability to enter into diversified commodity positions. These funds attracted significant trading activity given that they offered the elimination of commodity-specific risk while, at the same time, providing for the returns potential of commodity futures. Examples include the S&P GSCI Index (formerly Goldman Sachs Commodity Index) which is heavily weighted in energy futures, the Dow Jones-AIG Index which is more broadly diversified, as well as commodity-specific baskets offered under the Dow Jones-AIG banner. We propose that the boom in commodity futures index activity, including rational index-based activity and speculation, led to an increase in price-destabilizing positive feedback traders, and therefore pricing distortions in individual commodity futures prices.

3. Methodology

Our analysis focuses on whether index linked commodity futures Granger cause non-index linked commodity futures at intraday frequencies. We use two sets of three contracts in our analysis. The first set, precious metals, uses gold, silver, and palladium. Gold and silver futures comprise approximately 3.01% (7.86%) and 0.32% (2.89%) of the S&P GSCI (DJ-AIG) commodity index futures, respectively. Palladium, however, is not represented in either index. The gold and silver contracts trade on the Commodity Exchange Incorporated (COMEX), the palladium contract trades the New York Mercantile Exchange (NYMEX), and all three contracts have roughly the same opening and closing open outcry sessions.

The second set of commodity futures, grains, is comprised of wheat (Chicago), corn, and oats all of which trade on the Chicago Board of Trade (CBOT). Wheat and corn comprise approximately 3.90% (4.80%) and 3.55% (5.72%) of the S&P GSCI (DJ-AIG) commodity index futures, respectively. Like palladium, oat futures are not represented in either index. Unlike the precious metals group, all contracts in the grains group have exactly the same overlapping open outcry session times. All daily and intraday data spans January 2006 to December 2010.

[Insert Table 1 about here]

In addition to focusing on index to non-index linked commodity causality, we propose that the fast market dynamics of commodity futures cannot be captured using low frequency data. As such, we use both daily and intraday data. Our daily data originates from Commodity

Systems Incorporated (CSI) Unfair Advantage platform. We use rolling continuous contracts where the price of the nearest-to-expiration, most liquid contract is selected to compute log returns.

Our intraday data originates from TickData.com's TickWrite data platform. All prices are constructed using a rolling, continuous contract based on the nearest-to-expiration, most liquid contract. Despite the rise of electronic trading in the futures markets, a nontrivial percentage of trading in our contracts occurs in the open outcry pits. Thus, we use both open outcry and electronic trades and assume that any pricing differentials between the electronic and open outcry platforms are trivial due to arbitrage.

[Insert Fig. 1 about here]

While our tick data originates from both electronic and open outcry trading, we perform all estimations on data during the mutually overlapping open outcry sessions of each commodity pair. As shown in Fig. 1, all of our selected contracts trade almost 24 hours a day. Yet, the peak average number of trades throughout the day occurs during the open outcry hours. Performing estimations using the relatively sparse, electronic-only trading times may lead to erroneous results driven more by illiquid market conditions and not fundamental or speculative factors. All of the intraday data originally is reported in a trade-by-trade format. We aggregate this tick data into 5, 10, 15, 30, and 60 minute intervals and use open-to-close interval prices to calculate log returns.

Our analyses center on running contemporaneous correlations and causality tests over increasing intraday time intervals as well as daily intervals. For our causality analyses, we use the following generalized time series model estimated using the Newey-West (1987) heteroskedasticity and serial correlation correction:

$$r_{j,t} = \alpha_{j,0} + \sum_{m=1}^{M} \underbrace{\beta_{j,m} r_{j,t-m}}_{Own\ Effects} + \sum_{m=1}^{M} \underbrace{\lambda_{j,m} r_{i,t-m}}_{Cross\ Effects} + \varepsilon_{j,t} \tag{1}$$

where r_j is the return of commodity j, r_i is the return of commodity i, and M is the number of lag lengths. We choose 12, 2, and 1 for M for 5, 30, and 60 minute aggregated intraday data, respectively. For estimations using daily data we use 5 lags. Choosing the lag lengths as we did allows us to capture up to one hour (one week) of impacts when using the intraday (daily) data. Also, including own-lags ensures that our results are purely due to cross market effects and not the impacts of unaddressed own impacts.

To test for cross commodity causal effects, we using the following two joint coefficient restriction tests:

$$H_{0,1}: \lambda_{j,1} = ... = \lambda_{j,M} = 0$$

$$H_{0,2}: \lambda_{j,1} + ... + \lambda_{j,M} = 0$$

The first test assumes that the cross commodity coefficients are jointly equal to zero. Rejection of this hypothesis implies that market i's returns impact market j's returns. The second test assumes that the sum of cross commodity coefficients is equal to zero. Rejection of this hypothesis again suggests a Granger causing relationship from commodity i to commodity j. More importantly, we can interpret the (jointly) significant coefficient sums as a measure of the economic significance of cross commodity effects. Given the relatively large sample sizes, we use the 1% and 5% significance levels for (all) intraday and daily interval estimations, respectively.

In our analysis, we propose that the relationships among different commodity futures and among different traders due to speculative interest in commodity index futures occur at high frequencies due to commodity future markets' relatively high levels of liquidity and efficiency.

Thus, prior studies may not be capturing the impact of speculation mainly due to their use of low frequency data (e.g. daily intervals and above). As a result, we expect to uncover four findings from our results if the above intuition holds.

First, we expect to find little to no index to non-index causality over daily frequencies. Second, we expect to find significant index to non-index causality over some or all of the intraday intervals. However, (third) we expect that the economic significance of these impacts declines over increasingly aggregated periods indicating that the impacts of index activity is quickly incorporated in commodity prices with declining severity. Fourth, and finally, we expect to see little to no non-index to index linked commodity causality as well as little index to index linked commodity causality over any aggregation window. In the case of the former, this is due to index speculation activity being more influential than speculation activity in non-index commodities. In the case of the latter, we expect that the fast dynamics of the commodity futures marketplace should incorporate index speculation into index-linked commodities quickly.

As is seen in Fig. 1, index based commodity futures contracts have a higher average number of trades throughout the mutually overlapping open outcry session relative to the non-index contracts (i.e. palladium and oats). As such, the possibility arises that our results are not due to some economic phenomena but rather non-synchronous trading bias. To examine this issue, we perform a robustness analysis on all index/non-index pairs using the MINSPAN procedure as suggested by Harris et al. (1995) and successfully applied to thinly traded market pairs by Booth et al. (2002). Elaboration on the non-synchronous trading bias, the MINSPAN procedure, and the results of our robustness estimations are presented in the Appendix.

Finally, to directly link commodity index speculation to the price impact on non index commodity futures, we estimate the following model:

$$\hat{\Lambda}_{j,t} = \alpha_0 + \zeta_1 Spec_{Long,t} + \zeta_2 Spec_{Short,t} + \sum_{k=1}^{K} \theta_k I_{k,t} + \varepsilon_{j,t} \tag{2}$$

where $\Lambda_{j,t}$ is the sum of estimated cross-commodity parameters from Eq.1 for commodity j over a one week period. $\Lambda_{j,t}$ proxies for the strength of the index-to-non index price pressures and hence an indirect measure of the impact of commodity index speculation. We model this magnitude as a function of both long ($Spec_{Long}$) and short ($Spec_{Short}$) speculative conditions in the Goldman Sachs / S&P GSCI Commodity Index futures contract during a given one week period (i.e. the ratio of non-commercial to commercial open positions found in the CFTC Commitment of Traders report) as well as different sets of indicator variables used to control for different index-to-non index relationships. Thus, ζ_1 (ζ_2) measures the impact of long (short) speculative positions on index-to-non index commodity futures price pressures.

4. Results

4.1 Daily Estimations

We begin our analysis with correlation and causality tests using daily data.

[Insert Table 2 about here]

From Table 2 we find that all daily cross commodity correlations are statistically significant at the 1% level and economically significant. There is no clear pattern in index vs. index and index vs. non-index linked commodity correlations. For example, the gold/silver correlation is 0.811 while the gold/palladium and silver/palladium correlations are 0.547 and 0.628, respectively. However, while the corn/wheat correlation is 0.626, the corn/oat and wheat/oat correlations are 0.514 and 0.621, respectively. Thus, correlations are fairly even across index/index and index/non-index pairs at daily frequencies indicating no major contemporaneous difference between relation types. Using low frequency data may lead one to believe that commodities directly responsive to index speculation do not behave differently from commodities with no direct link to index speculation (as in Stoll and Whaley, 2010).

We now shift our focus to daily returns transmission.

[Insert Table 3.1 about here]

[Insert Table 4.1 about here]

For the both the precious metals and grains estimations, we find no causality running from index-to-non index commodity futures or from non index-to-index commodity futures. These results hold regardless of whether we are performing a zero coefficient or sum of coefficient restriction test. Thus, in isolation, our returns transmission results indicate a lack of interaction between index and non-index commodity futures which might lead one to conclude that speculative pressures on index linked commodities do not impact non-index linked commodity prices. Yet, when the transmission results are combined with the contemporaneous correlation results, a different story emerges. Specifically, high contemporaneous correlations and a lack of causal relationships may indicate that transmission relationships do, in fact, exist; they just occur at frequencies higher than what the daily data can capture.

As an example, consider the relationship between the Standard and Poor's 500 Index (S&P) versus the S&P 500 Index futures contract (SP) traded on the Chicago Mercantile Exchange. As noted in Chan et al. (1991), there is an intraday bidirectional relationship between price moves in the SP and S&P where the SP futures contract dominates the causal relationship. As such we expect that the S&P index will adjust to SP price moves. This is due to speculators, portfolio rebalancers, and arbitragers adjusting their positions based on the pricing information of the futures contract. Also, these relationships occur at very high frequencies given that the SP contract trades in an active and efficient market. Using daily data, we would find that S&P/SP

correlations are high and significant whereas daily S&P/SP returns causality would be trivial or nonexistent. However, using high frequency data, we would find that intraday correlations are less economically significant and that the causality tests are more frequently significant. Thus, the choice of data frequency can greatly impact one's assessment of cross market dynamics.

The example above illustrates how returns transmission may appear to be insignificant when using inappropriately aggregated (i.e. daily) data. In the context of our study, it is possible that high correlations and low causality at daily frequencies, in fact, implies that index to non-index linked causality still occurs. It is just that low frequency data is insufficiently granular to capture this relationship.

4.2 Intraday Estimations

We now turn our focus to intraday estimations performed on increasingly aggregated intervals. Examining the intraday contemporaneous correlations reported in Table 2, we find that index/index correlations are high in magnitude and not radically different from daily frequencies, regardless of the aggregation window. For example, the gold/silver pair has correlations of 0.732 and 0.811 for 5 minute intervals and daily intervals, respectively. Similarly, the wheat/corn correlations are 0.549 and 0.626 for the 5 minute intervals and daily intervals, respectively. Also note that the increase in correlations for the two index/index pairs is fairly gradual. This phenomenon is better captured in Fig. 2 of intraday aggregated cross commodity correlations.

[Insert Fig. 2 about here]

The similarity in intraday vs. daily correlations in the index/index pairs is not, however, repeated for the index/non-index pairs (i.e. a commodity pair where one commodity contract is represented in a commodity index and the other commodity contract is not). In each case, a large difference exists between the daily and intraday correlations. For example, the gold/palladium correlations at the 5 minute and daily intervals are 0.187 and 0.547, respectively. The silver/palladium correlations for the 5 minute and daily intervals are 0.184 and 0.628, respectively. This pattern repeats itself for the grain index/non-index correlations.

Fig. 2 displays the disparities between index/index versus index/non-index correlations. Where, again, index/index intraday correlations are never far from the daily correlations, regardless of frequency. However, the intraday index/non-index correlations show increasing disparity relative to the daily correlations as interval granularity increases. Also, by 60 minutes, the intraday correlations are more inline with their daily counterparts. Based on the S&P/ES discussion above, the increasing correlations over increasingly aggregated intraday intervals may indicate that intraday lead-lag relationships are occurring at relatively high frequencies for the index/non-index pairs and that these causal relationships can not be directly captured with low frequency data.

To test whether index/non-index cross commodity causality exists, and therefore whether index futures activity is impacting individual commodity futures prices, we perform causality tests using intraday data.

[Insert Tables 3.2, 3.3, 3.4 about here]

First we examine the precious metals estimations across different intraday windows in Table 3. We find that we fail to reject either of the two coefficient restriction tests between index versus index linked commodity futures returns (e.g. gold and silver). Thus, regardless of whether we are using the 5, 30, or 60 minute aggregation windows, bidirectional index to index linked commodity causality does not exist. When the intraday index/index causality results are combined with the intraday correlation results, our inability to find transmission may indicate that index/index transmission occurs at frequencies faster than 5 minutes. This would not be surprising given that both the gold and silver futures contracts are highly liquid and actively traded. Thus, while we do not rule out index/index causality at very high frequencies, we cannot find evidence of it at frequencies greater than or equal to 5 minutes.

Unlike the index/index causality results, the intraday index to non-index linked commodity causality results in Table 3 are quite different. Specifically, we reject both restriction tests at the 1% significance level for unidirectional transmission from index linked to non-index linked commodity futures (e.g. gold to palladium; silver to palladium) for all three aggregation windows. Thus, pricing pressures flow from index to non-index precious metals, and not in reverse. These causal relationships maintain statistical significance even into the 60 minute aggregation window but are much less economically significant than in the 5 minute results. More on this point, both the gold-to-palladium and silver-to-palladium relationships decline in economic significance over longer time frames indicating that the impact of index linked commodities decays over increasing time windows. We take these results as evidence that pressures resulting from index activity leads to very fast changes in commodity prices, even those commodities that should not be fundamentally linked with index activity (i.e. the non-index linked commodities).

[Insert Tables 4.2, 4.3, 4.4 about here]

We find similar behavior in the grains group as is described for the precious metals group. Specifically, we find that no index to index causal relationships exist at the 1% level in either direction with the exception of the 5 minute corn-to-wheat relationship. It should be noted that only the zero coefficient, and not the summed coefficient restriction test is violated indicating that the 5 minute corn-to-wheat relationship is statistically, but not economically, significant. Despite the one violation, we again find strong evidence of unidirectional causality from the two index linked commodities (wheat and corn) to the non-index linked commodity (oats). Also, while the results remain statistically significant even at the 60 minute window, the economic significance of the index/non-index relationships decline over increasing horizons.

[Insert Fig. 3 about here]

As stated in Section 3 (Methodology), beyond a disappearance of statistical causal relationships over higher data frequencies, a decline in summed coefficients indicates that the economic significance of the cross market interactions decays over longer horizons. Fig. 3 graphs the sum of cross-commodity coefficients over increasing time horizons. For the index/index relationships (e.g. gold-to-silver), we find that most relationships are of low economic magnitude and do not change much over increasing time aggregations. The only major exception to this is the gold-to-silver pair which shows some economic significance but, given the lack of statistical significance, renders the summed coefficients effectively zero. Also, for the non index-to-index relationships, the summed coefficients are of low magnitude and (reasonably) time invariant. Thus, cross commodity price pressures for the index-to-index and non index-to-index relationships are non-existent.

For the index-to-non index relationships, however, an entirely different story emerges. Specifically, 5 minute impacts from commodity index linked futures have a large economic (and statistical) impact on non commodity index linked futures and that this relationship declines to economic insignificance within about 60 minutes. For example, 5 minute shocks range from 0.127% to 0.263% (average of 0.176%) whereas 60 minute shocks range from 0.047% to 0.084% (average of 0.065%). Thus, price pressures are transmitted from index linked commodity futures to non index linked commodity futures and the magnitude of such pressures declines quickly. These results provide evidence that using highly aggregated data (e.g. daily and weekly data) can erroneously lead one to believe that cross-commodity price pressures are nonexistent.

Yet, given the differences in average trading frequencies between the liquid index linked and the illiquid non-index linked commodity futures, a concern is that the results above may be due to non-synchronous trading bias and not speculative impacts from commodity index futures. As such, we repeat our correlation and causality analyses using trade pairs matched by the Harris et al.'s (1995) MINSPAN procedure. While we provide detailed results in the Appendix, a summary of the results indicate that, again, both statistically and economically significant causality runs from index linked to non-index linked commodity futures. Also, correlations between index and non-index linked pairs is between 0.089-0.106; far below the daily contemporaneous correlations of 0.514-0.621. Thus, we conclude that our results are robust to both non-synchronous trading bias and differences in cross-commodity liquidity.

From the results above, we can conclude four things. First, we conclude that index linked commodity futures returns have unidirectional impacts on non-index linked commodity futures returns. This finding indicates that index price pressures can transmit, undirectionally, from commodities within a commodity futures index to commodity futures that are not within that index. If cross-commodity impacts are governed purely by fundamental factors, we should not see that index to non-index linked commodity causality exists while index/index causality does not exist. Thus, common fundamental factors are not driving our cross-commodity findings.

Our second conclusion is that, given the time frames involved, these cross-commodity impacts are nontrivial for traders exploiting the high leverage and low transactions costs of the futures markets. For example, for a one percent increase in gold futures prices could reward an unlevered palladium trader up to 0.263% in the span of an hour. Third, these causal relationships do not continue far into the future; all relationship decay into economic insignificance (less than 0.1% reaction) within 60 minutes. Fourth, and most importantly, the index/non-index causality that exists during intraday frequencies fails to persist at daily and higher frequencies. Thus, index activity impacts individual, non-index linked commodity futures prices. However, these pressures are not directly or easily detectable using low frequency data as in prior studies.

4.3 Commodity Index Speculation and Price Pressures

While the results above indicate that price pressures from commodity index linked futures have fast, unidirectional, and economically significant impacts on commodity futures not represented in commodity index futures, they do not directly link the state of commodity index speculation and the extent of index-to-non index price pressures. If speculation was responsible (either directly or indirectly) for price movements in non-index futures, we should see that an increase in index speculation should lead to an increase in the magnitude of index/non-index price pressures.

We now directly test the impact of speculative conditions on index/non-index price pressures. We do so by estimating Eq.1 for all index/non-index relationships for each week that the CFTC Commitment of Traders (COT) data is available using 5 minute aggregated intervals. From there, we capture the sum of cross-commodity coefficients for each week and regress these sums onto long GSCI speculation ratios, short GSCI ratios, and a host of indicator variables to control for relationship type. We do this for both the full sample and for "excessive" speculative conditions (i.e. when either the ratio of long or short non-commercial to commercial positions in the GSCI commodity index futures contract is above its full-sample mean).

[Insert Table 5 about here]

From Table 5.1 (full sample), we find that increases in the long GSCI non-commercial/commercial positions ratio (i.e. long speculation) is associated with an increase in the magnitude of index/non-index price pressures that occurred during a given reporting week. This result is significant at the 5% level and of consistent sign despite controlling for different cross relationships (i.e. metals vs. grains or gold-to-palladium vs. silver-to-palladium, etc.). The impact of short speculation is smaller both economically and statistically: the p-value ranges from 0.066 to 0.068 which, given our sample size (912), makes the impact of short speculation only marginally significant.

From Table 5.2, we find that both long and short speculation has a positive impact on index/non-index price pressures during periods of "high" speculation. Specifically, both long and short speculation coefficients are significant at the 5% level, regardless of control indicator variables, and of positive sign. These results indicate that increases in speculative pressures in the GSCI commodity index futures contract increase the price impact from index-linked to non-index linked commodities. Note that, unlike the full sample results, the excess long (short) speculation coefficients are 1.72 (1.89) times the magnitude of the full sample coefficients indicating that there exists a threshold effect in the speculative/price pressure relationship. That is, while greater speculation leads to greater index-to-non index price pressures in all market conditions, speculation has a greater price impact once it exceeds a certain level. Also note that while different, the impact of long versus short speculation is never statistically different regardless of control indicators or excess speculative conditions. This result indicates that speculative interest has equal cross-commodity pricing effects, regardless of the (general) directionality of trades.

Thus, in addition to showing in Section 4.2 that index-linked commodity futures create positive, unidirectional price pressures on non-index linked commodity futures, we show that the force of such pressures is directly related to the level of both long and short speculative positions in a popular commodity index futures contract. These results provide further evidence that commodity index speculation is a driver of commodity prices.

5. Conclusion

We test whether index speculation impacts individual commodity prices for two different commodity futures groups: precious metals and grains. We do this using both daily and intraday data. Our daily results indicate that index and non-index commodity futures have high correlations but do not exhibit cross commodity transmission. These results could indicate that cross commodity transmission does not exist. Alternatively, our initial daily findings may indicate that cross commodity transmission does exist but at speeds not detectable at low frequencies.

Using intraday data, we find four main results that are almost identical across the two commodity groups. The first result is that cross commodity correlations are high for index vs. index based commodity futures (i.e. those futures that are included in broadly diversified commodity index) regardless of the time horizon. Yet, correlations between index and non-index based commodities are initially low at very high frequencies (e.g. 5 minute windows) and converge to the daily correlation levels as the time horizon increases (e.g. 60 minute windows). This first result indicates that index/non-index (e.g. gold vs. palladium) correlations are quite different from index/index (e.g. gold vs. silver) correlations at high frequencies and that these differences cannot be consistently detected at lower frequencies as in Stoll and Whaley (2010).

Our second finding is that index to index linked commodity futures transmission is not detectable at frequencies greater than or equal to five minutes. On the other hand, we find consistent evidence of intraday index to non-index returns causality. This transmission is unidirectional and lasts less than one trading day. Third, we find that the economic significance of index to non-index transmission is quite high at high frequencies. However, the economic significance of these relationships drops rapidly as the time horizon increases. The economic significance of these cross commodity causal relationships is approximately zero at horizons of one hour.

Collectively, these three findings indicate that commodity index activity impacts non index-linked commodities through index-linked commodities. In other words, index activity has pricing effects on individual commodity prices and these effects are not likely explained by fundamental forces (e.g. supply and demand) or the non-synchronous trading bias. Our fourth finding is that the extent of index to non-index price pressures is positively related to the amount of speculative activity, both long and short, in the GSCI commodity index futures contract. What's more, weeks of abnormally high speculation are associated with stronger index/non-index price pressures. Thus, not only do we show that commodity index activity can impact non-index futures prices, but also that these impacts are directly and positively related to index futures speculation.

Given the results above, we conclude that commodity index speculation plays a role in commodity price dynamics. Although, given that index speculators provide trading opportunities within the marketplace and may provide for more informative prices, speculation itself does not necessarily destabilize commodity prices. Rather, uninformed momentum and positive feedback traders trading on index speculation information destabilize prices in ways that even informed market participants cannot counter. Finally, given the contrast between our daily and intraday results, we additionally conclude that other's use of low frequency data lead them to erroneously reject the role of index speculation on commodity price dynamics. Thus, any future efforts studying speculation in the commodity futures markets must be done using high frequency, intraday data and preferably data which distinguish trader type over intraday horizons.

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Table 1. Commodity Contract Details

The following table reports contract specifications and trading times for the commodity futures contracts used in our analysis. Note that all times are reported in Chicago/Central Standard Time. Contract information comes from the Chicago Mercantile Exchange Group website while the index percentages come from Stoll and Whaley (2010).

Contract	Ticker	Exchange	Open Outcry Hours	% in GSCI	% in DJ-AIG
Gold	GC	COMEX	7:20 am - 12:30 pm	3.01%	7.86%
Silver	SI	COMEX	7:25 am - 12:25 pm	0.32%	2.89%
Palladium	PA	NYMEX	7:30 am - 12:00 pm	0.00%	0.00%
Wheat	W	CBOT	9:30 am - 1:15 pm	3.90%	4.80%
Corn	C	CBOT	9:30 am - 1:15 pm	3.55%	5.72%
Oats	O	CBOT	9:30 am - 1:15 pm	0.00%	0.00%

Table 2. Aggregated Contemporaneous Correlations

The following table reports contemporaneous cross-commodity correlations for the 5, 10, 15, and 60 minute intraday intervals as well as for daily intervals for the entire sample period (2006 to 2010). Note that all correlations are statistically significant at the 1% level.

Data Frequency	Intraday				Daily
	5 minutes	10 minutes	15 minutes	60 minutes	
Gold/Silver	0.732	0.753	0.764	0.783	0.811
Gold/Palladium	0.187	0.261	0.287	0.400	0.547
Silver/Palladium	0.184	0.260	0.289	0.409	0.628
Wheat/Corn	0.549	0.574	0.587	0.607	0.626
Wheat/Oats	0.202	0.256	0.285	0.358	0.514
Corn/Oats	0.262	0.322	0.352	0.428	0.621

Table 3. Precious Metals Granger Causality Estimations

The table panels below report restriction tests of cross-commodity estimations based on the following model:

$$r_{j,t} = \alpha_{j,0} + \sum_{m=1}^{M} \underbrace{\beta_{j,m} r_{j,t-m}}_{Own\,Effects} + \sum_{m=1}^{M} \underbrace{\lambda_{j,m} r_{i,t-m}}_{Cross\,Effects} + \varepsilon_{j,t}$$

where r_k is the log return for a given commodity futures contract in the precious metals group (multiplied by 100). p(Zero) reports the p-value of a zero coefficient restriction test, p(Sum) reports the p-value of a summed coefficient restriction test, while Sum reports the sum of cross commodity coefficients. Each estimation is performed over the entire sample of January 2006 to December 2010 and uses the Newey-West heteroskedasticity/serial correlation correction. Note that for the 60 minute estimations, p(Zero) is the p-value of a single coefficient while Sum is the reported coefficient. Also, cell (i,j) reports the impact of commodity i on commodity j.

Table 3.1. Daily Estimations

	Gold			Silver			Palladium		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Gold	--	--	--	0.151	0.254	0.308	0.922	0.884	-0.024
Silver	0.305	0.678	-0.041	--	--	--	0.441	0.465	0.077
Palladium	0.120	0.711	-0.023	0.202	0.412	0.096	--	--	--

Table 3.2. 5 Minute Estimations

	Gold			Silver			Palladium		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Gold	--	--	--	0.444	0.288	0.062	0.000	0.000	0.263
Silver	0.026	0.227	0.021	--	--	--	0.000	0.000	0.142
Palladium	0.416	0.492	0.005	0.744	0.477	0.010	--	--	--

Table 3.3. 30 Minute Estimations

	Gold			Silver			Palladium		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Gold	--	--	--	0.122	0.052	0.084	0.000	0.000	0.174
Silver	0.402	0.723	-0.005	--	--	--	0.000	0.000	0.090
Palladium	0.559	0.940	0.001	0.639	0.640	0.006	--	--	--

Table 3.4. 60 Minute Estimations

	Gold			Silver			Palladium		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Gold	--	--	--	--	0.345	0.037	--	0.003	0.075
Silver	--	0.847	0.002	--	--	--	--	0.000	0.055
Palladium	--	0.185	0.008	--	0.311	0.012	--	--	--

Table 4. Grain Granger Causality Estimations

The table panels below report restriction tests of cross-commodity estimations based on the following model:

$$r_{j,t} = \alpha_{j,0} + \sum_{m=1}^{M} \underbrace{\beta_{j,m} r_{j,t-m}}_{Own\,Effects} + \sum_{m=1}^{M} \underbrace{\lambda_{j,m} r_{i,t-m}}_{Cross\,Effects} + \varepsilon_{j,t}$$

where r_k is the log return for a given commodity futures contract in the grains group (multiplied by 100). p(Zero) reports the p-value of a zero coefficient restriction test, p(Sum) reports the p-value of a summed coefficient restriction test, while Sum reports the sum of cross commodity coefficients. Each estimation is performed over the entire sample of January 2006 to December 2010 and uses the Newey-West heteroskedasticity/serial correlation correction. Note that for the 60 minute estimations, p(Zero) is the p-value of a single coefficient while Sum is the reported coefficient. Also, cell (i,j) reports the impact of commodity i on commodity j.

Table 4.1. Daily Estimations

	Corn			Wheat			Oats		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Corn	--	--	--	0.187	0.191	0.121	0.920	0.422	0.065
Wheat	0.239	0.199	-0.103	--	--	--	0.598	0.750	0.023
Oats	0.093	0.663	-0.045	0.327	0.744	-0.033	--	--	--

Table 4.2. 5 Minute Estimations

	Corn			Wheat			Oats		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Corn	--	--	--	0.002	0.580	0.019	0.000	0.000	0.170
Wheat	0.099	0.225	0.021	--	--	--	0.000	0.000	0.127
Oats	0.105	0.971	0.000	0.246	0.408	-0.014	--	--	--

Table 4.3. 30 Minute Estimations

	Corn			Wheat			Oats		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Corn	--	--	--	0.203	0.400	0.018	0.000	0.000	0.109
Wheat	0.577	0.647	0.006	--	--	--	0.000	0.001	0.057
Oats	0.488	0.234	0.015	0.036	0.939	-0.001	--	--	--

Table 4.4. 60 Minute Estimations

	Corn			Wheat			Oats		
	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum	p(Zero)	p(Sum)	Sum
Corn	--	--	--	--	0.081	0.041	--	0.000	0.084
Wheat	--	0.283	-0.012	--	--	--	--	0.000	0.047
Oats	--	0.828	0.002	--	0.798	0.000	--	--	--

Table 5. Speculation Impact Estimations

The table panels below report the estimation results of the following model:

$$\hat{\Lambda}_{j,t} = \alpha_0 + \zeta_1 Spec_{Long,t} + \zeta_2 Spec_{Short,t} + \sum_{k=1}^{K} \theta_k I_{k,t} + \varepsilon_{j,t}$$

where $\Lambda_{j,t}$ is the sum of estimated cross-commodity parameters from the following causality model:

$$r_{j,t} = \alpha_{j,0} + \sum_{m=1}^{12} \underbrace{\beta_{j,m} r_{j,t-m}}_{Own\,Effects} + \sum_{m=1}^{12} \underbrace{\lambda_{j,m} r_{i,t-m}}_{Cross\,Effects} + \varepsilon_{j,t}$$

estimated for each one-week period that CTFC Commitment of Trader reports are available for the Goldman Sachs/S&P GSCI commodity index futures contract. Each sum of parameters for the Gold-to-Palladium, Silver-to-Palladium, Corn-to-Oats, and Wheat-to-Oats relationships is modeled as a function of speculative interest in the GSCI futures contract (i.e. outstanding non-commercial to commercial contracts) as well as a set of indicator variables. Estimations 1, 2, and 3 employ no indicator variables, a precious metals indicator variable, and three relationship indicators, respectively. Panel A reports estimations during all market conditions whereas Panel B reports estimations during times when either long or short speculative ratios are greater than their (respective) means. All estimations are performed using the Newey-West heteroskedasticity/serial correlation correction and the Wald restriction test at the bottom of each panel reports the value and statistical significance of ζ_1 - ζ_2 (i.e. the impact of long speculation minus the impact of short speculation).

5.1. All Conditions

	(1)		(2)		(3)	
	Coef.	p-Value	Coef.	p-Value	Coef.	p-Value
Intercept	-0.039	0.642	-0.008	0.930	-0.045	0.603
Spec(Long)	0.381	0.020	0.381	0.022	0.381	0.023
Spec(Short)	0.221	0.068	0.221	0.066	0.221	0.066
Adjusted R^2	0.004		0.005		0.003	
Wald Test	0.160	0.393	0.160	0.398	0.160	0.402

5.2. Excess Conditions

	(1)		(2)		(3)	
	Coef.	p-Value	Coef.	p-Value	Coef.	p-Value
Intercept	-0.241	0.141	-0.252	0.147	-0.278	0.086
Spec(Long)	0.658	0.008	0.658	0.007	0.658	0.008
Spec(Short)	0.419	0.013	0.419	0.013	0.419	0.013
Adjusted R^2	0.013		0.011		0.009	
Wald Test	0.240	0.224	0.240	0.222	0.240	0.229

Fig. 1. Average Intraday Trades

The following six figures report the average number of trades during the January 2006 to December 2010 trading sessions using ten minute aggregated tick data. Averages are reported using the combined data from both electronic and open outcry trading sessions. All figures are relative to Chicago/Central Standard Time.

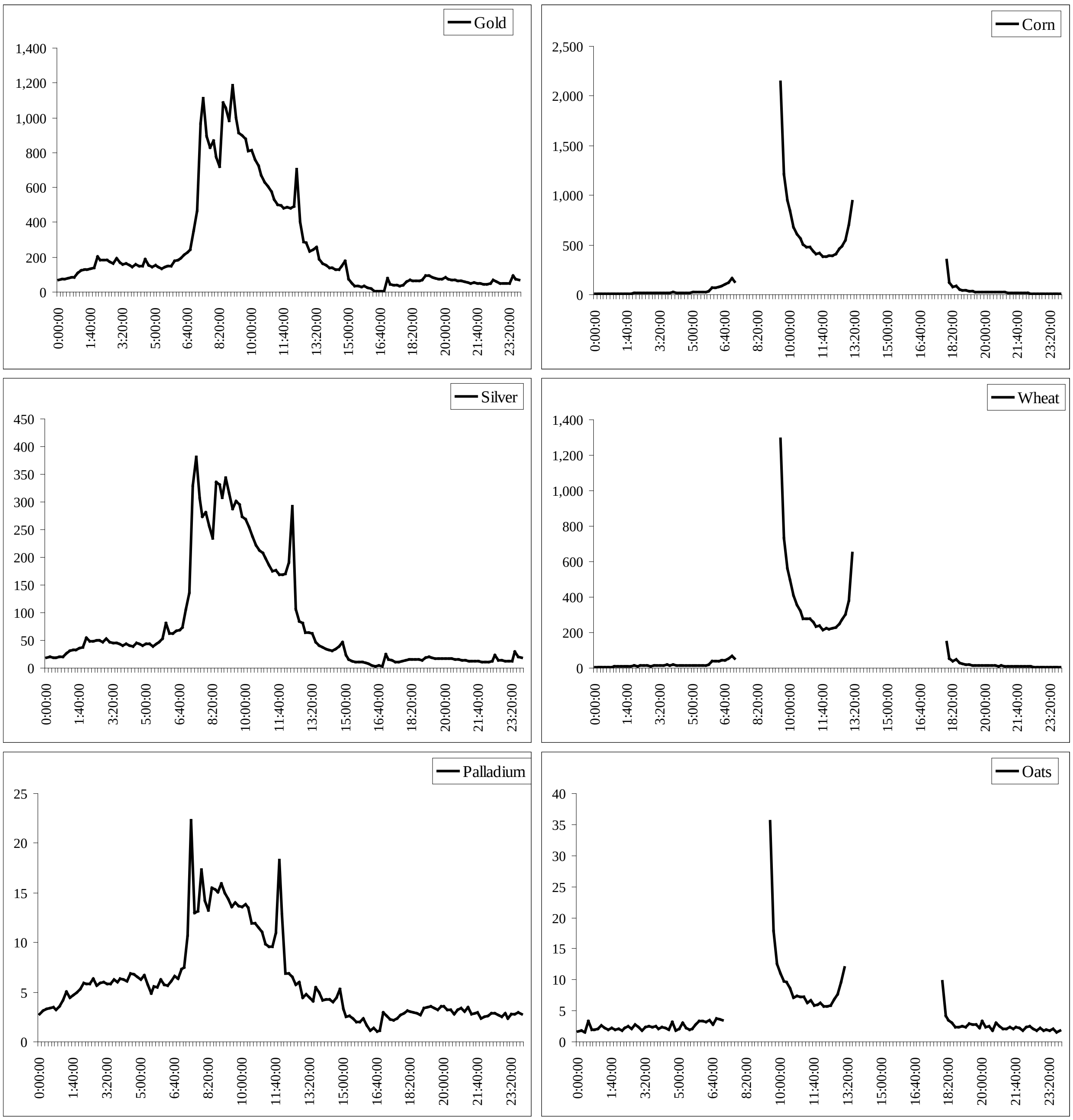
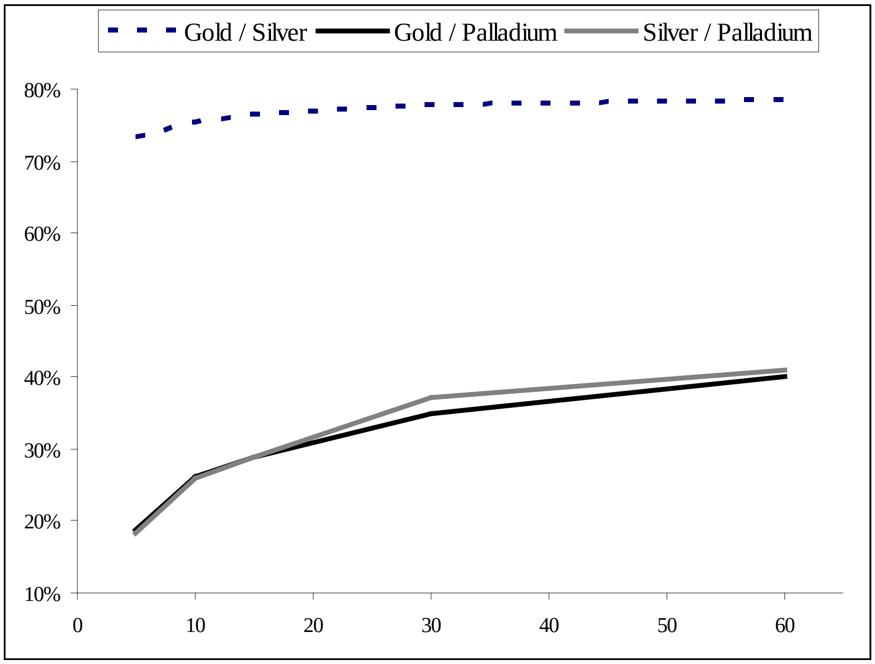


Fig. 2. Aggregated Correlations

The following figures report contemporaneous pair-wise correlations among intraday commodity futures returns over increasingly aggregated data for the entire sample (2006 to 2010). Each correlation is reported for the 5, 10, 15, 30, and 60 minute aggregated windows using tick data.



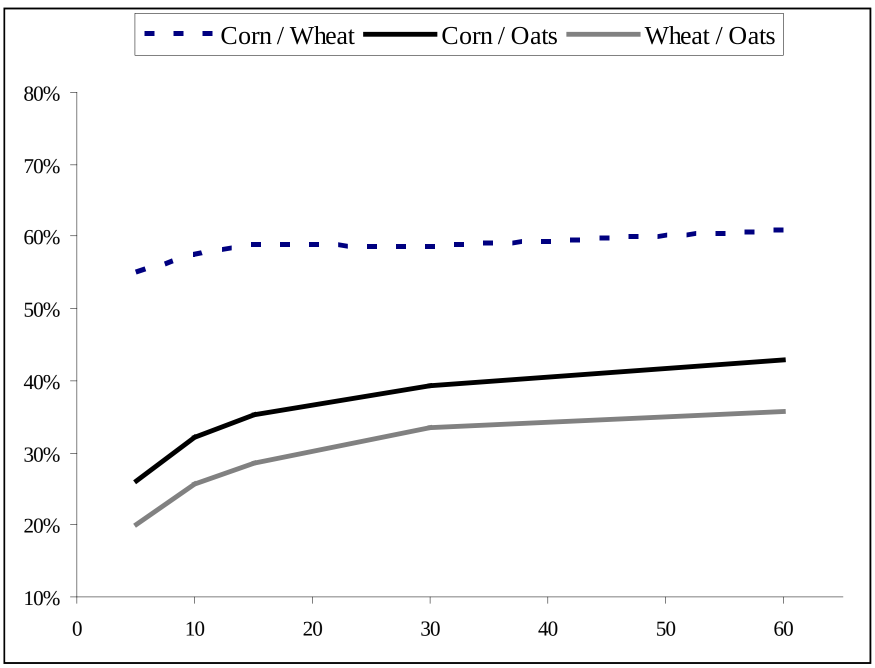
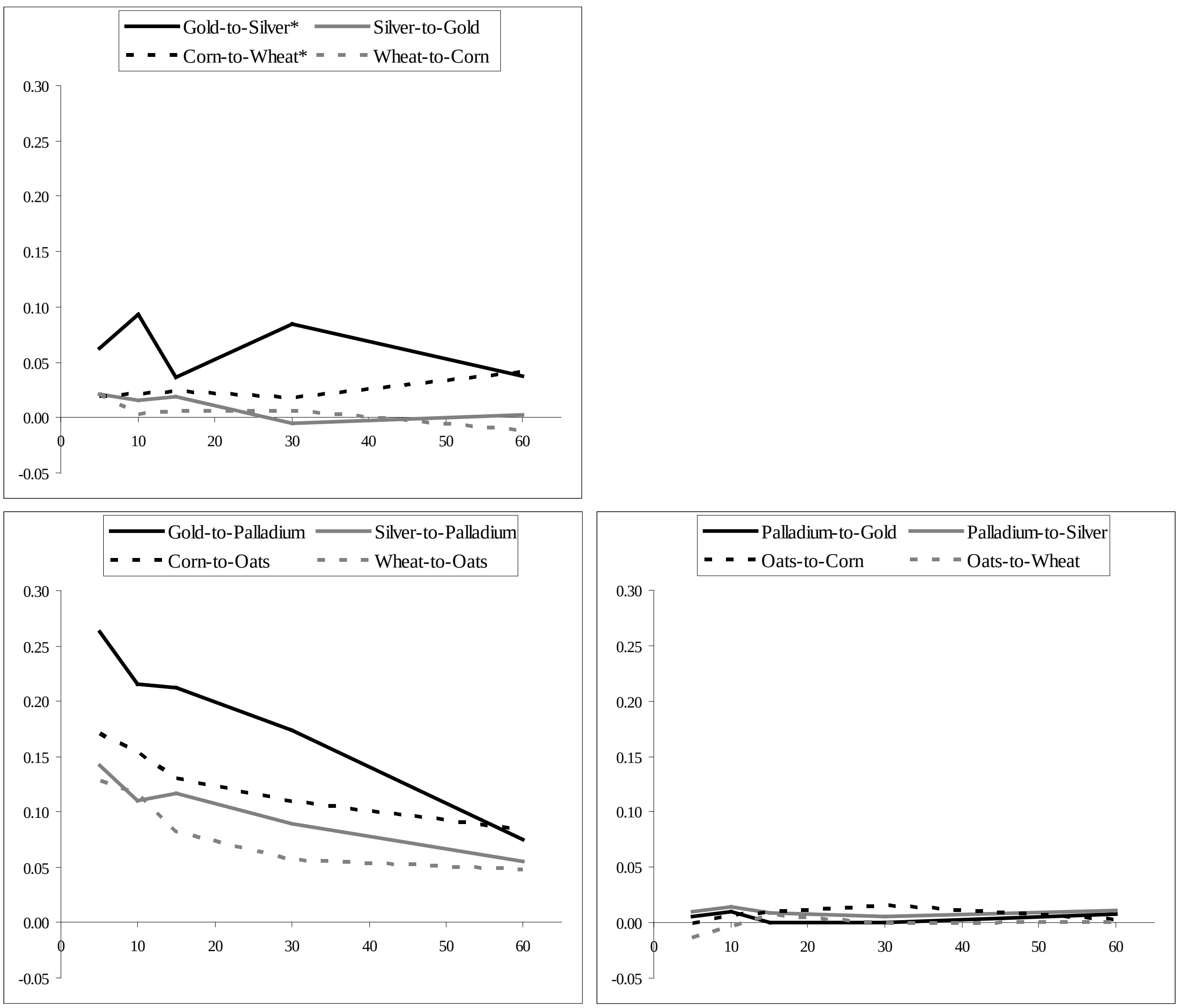


Fig. 3. Summed Coefficient Estimates

The following figures plot the sum of cross market coefficients estimated from the following model:

$$r_{j,t} = \alpha_{j,0} + \sum_{m=1}^{M} \underbrace{\beta_{j,m} r_{j,t-m}}_{Own\,Effects} + \sum_{m=1}^{M} \underbrace{\lambda_{j,m} r_{i,t-m}}_{Cross\,Effects} + \varepsilon_{j,t}$$

over increasingly aggregated time windows (5, 10, 15, 30, and 60 minutes). The upper left figure plots the sum of index-to-index coefficients, the lower left figure plots the sum of index-to-non index coefficients, while the lower right figure plots the sum of non index-to-index coefficients. Note that all figures are plotted using the same scale and that, despite the appearance of economic significance, the gold-to-silver and corn-to-wheat relationships plotted in the upper left figure are not statistically significant across any aggregation window.



Appendix A

As noted in Section 3 (Methodology), our analysis runs the risk of non-synchronous trading bias (NSTB). This NSTB could lead to the false rejection of our intraday Granger causality tests. To see why, consider the following hypothetical timeline of prices corresponding to trades in an illiquid and a liquid futures contract that occur within a given 5 minute interval:

Date	Time	Illiquid	Liquid
1/12/2007	9:30:00		506.60
1/12/2007	9:30:45	251.15	506.56
1/12/2007	9:30:46	251.12	
1/12/2007	9:31:10		506.29
1/12/2007	9:31:34		
1/12/2007	9:31:58	251.12	
1/12/2007	9:32:22		506.24
1/12/2007	9:32:46		
1/12/2007	9:33:10		506.80
1/12/2007	9:33:34		506.11
1/12/2007	9:33:58		507.00
1/12/2007	9:34:22	251.9	506.84
1/12/2007	9:34:46		
1/12/2007	9:34:59		507.13

In the case of trades occurring at 9:30:45 and 9:34:22, there is no NSTB given both the liquid and illiquid contracts trade contemporaneously. Yet, for trades in the illiquid contract occurring at 9:30:46 and 9:31:58 we have NSTB given the non-synchronized timing of the liquid and illiquid contracts. One solution could be to remove all imperfectly matched trades. Yet, to do so would censor potentially valuable data.

Another solution would be to ignore any NSTB and construct our aggregated windows regardless of trade synchronization. In the case above, we would use trades occurring at 9:30:00 and 9:34:59 (9:30:45 and 9:34:22) for the liquid (illiquid) contract. Assuming that the pattern represented in the table above occurs more often than not, our window construction may artificially imply that liquid trades occur before illiquid trades. Consequently, causality tests performed on the above data may erroneously indicate that the liquid contract's prices cause the illiquid contract's prices, regardless of reality.

Beyond data censoring and blind aggregation, a third data construction alternative could be the use of a price matching algorithm. Given the pitfalls of the other two schemes, we test our correlation and causation results using Harris et al.'s (1995) MINSPAN procedure. Specifically, we determine the last trade per second for both liquid and illiquid contract pairs (e.g. gold and palladium) using tick-by-tick data. These series are then merged based on common trading dates and times. If both contracts trade at the same time, then both contemporaneous prices are selected for the final dataset. If, however, no liquid contract price is available for a given illiquid contract price, we find the temporally nearest liquid contract price using a forward and backward looking procedure (i.e. the MINSPAN procedure).

The following table reports matching statistics for the strict (i.e. censoring) and MINSPAN trade matching procedures (where GC, SV, PA, CN, WC, and OA stand for the gold, silver, palladium, corn, wheat, and oat futures contracts, respectively):

		Precious Metals		Grains	
		GC vs. PA	SV vs. PA	CN vs. OA	WC vs. OA
Mean Time Between Trades		5.96	6.10	5.98	6.27
Total Possible Pairs:		290,137	290,137	184,192	184,192
Strict Matching:	Trade Pairs	198,377	105,035	89,797	67,121
	% Matched	68%	36%	49%	36%
MINSPAN Matching:	Trade Pairs	271,121	241,029	169,835	160,924
	% Matched	93%	83%	92%	87%

From the table above, we find that using strict trade-by-trade matching only constructs approximately 36%-68% of the total possible matched pairs. Yet, the MINSPAN procedure constructs about 83%-93% of the total possible matches. Thus, not only is the MINSPAN procedure capable of minimizing timing differences between each liquid and illiquid contract pair, it also prevents the wholesale data censoring that strict, trade-by trade matching would entail. Note that we find that the MINSPAN procedure pulls forwards (as opposed to backwards) approximately 50% of the time for each trading pair and that the estimation results are robust to variable ordering within the MINSPAN procedure (i.e. reversing the liquid and illiquid contract in the matching procedure).

For our robustness analysis, we calculate contemporaneous correlations as well as perform Granger causality tests using the MINSPAN data. Note that MINSPAN data does not require interval construction (i.e. data aggregation); rather correlations can be calculated and causality tests performed directly on the raw data. Thus, we simply estimate Eq.1 using 12 lags. We choose 12 lags given that the mean sequential time between trades is between 5.96 and 6.27 minutes throughout the 2006 to 2010 sample. Thus, our correlation and causality results should be (roughly) comparable to the five minute results presented in Tables II-IV. Note that we use a more stringent set of p-values in our MINSPAN results. The reason for this is that our MINSPAN datasets are approximately five times as large as the aggregated 5 minutes results in our primary analysis. Thus, we use the 0.10% significance level as our cutoff. The table below reports our results.

		Correlations		Granger Causality Tests		
		Corr.	p-value	p(Zero)	p(Sum)	Sum
Liquid	GC → PA	0.095	0.000	0.000	0.000	0.900
to	SV → PA	0.089	0.000	0.000	0.000	0.522
Illiquid	CN → OA	0.106	0.000	0.000	0.000	0.637
Relationships	WC → OA	0.094	0.000	0.000	0.000	0.397
Illiquid	PA → GC	--		0.027	0.001	0.015
to	PA → SV	--		0.073	0.000	0.032
Liquid	OA → CN	--		0.011	0.155	0.010
Relationships	OA → WC	--		0.431	0.250	0.012

From the table above, we find that the intraday contemporaneous correlations are all statistically significant but of low economic significance. These results contrast to the daily results which range in magnitude of 0.514 to 0.628 but coincide with the 5 minute results indicating low cross-commodity returns correlations. From the causality results, we find that both the zero equality (p(Zero)) and summed coefficient (p(Sum)) restriction tests are all statistically significant for the index-to-non index relationships. Further, the index-to-non index relationships are all economically significant (sum of cross commodity coefficients). For example, a one percent increase in gold (silver) prices can, within an approximate sixty minute window, increase palladium prices by 0.900% (0.522%). However, the non index-to-index causality tests are insignificant, statistically and economically, in all but one case; the one violation being the palladium-to-silver relationship which is not consistent across restriction tests and is not economically significant. Thus, the index/non-index causality results agree nicely with our aggregated intraday causality results.

In summary, despite relatively lower contract liquidity and trading volumes in the non-index commodity futures contracts, our intraday MINSPAN results are qualitatively similar to the intraday aggregated results. We conclude that our results presented in Section 4 are robust to non-synchronous trading bias.