Is the Supply Curve for Commodity Futures Contracts Upward Sloping?

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Abstract: *Annual rebalancing of the S&P GSCI index provides a novel and strong identification to estimate the shape of supply curves for commodity futures contracts. Using the 24 commodities included in the S&P GSCI for 2004–2017, we show that cumulative abnormal returns (CARs) reach a peak of 59 basis points in the middle of the week following the rebalancing period, but the impact is temporary as it declines to near zero within the next week. The findings provide clear evidence that the supply curve for commodity futures contracts is upward sloping in the short-run but almost flat in the longer-run.*

Keywords: commodity futures, index, limits to arbitrage, order flow, rebalancing

JEL categories: G13, G14, G23

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1 Introduction

Arbitrage is central to modern financial economics. Standard asset pricing theory assumes frictionless arbitrage so one can buy or sell any amount of an asset without significantly affecting its price, so long as the transaction contains no new information. Financial economists have long been interested in estimating the impact of uninformed order flows on asset prices in the context of demand shocks, such as large buying or selling activities due to additions or deletions on constituent stocks for major equity indexes (e.g., Harris and Gurel, 1986; Shleifer, 1986). The abnormal returns around these index composition changes are often explained by limits to arbitrage (e.g., Shleifer and Vishny, 1997). While the price impact of uninformed order flow has been extensively studied in financial markets, the question has received much less attention in commodity markets.

Commodities as an alternative asset class have become increasingly popular over time and attracted a substantial amount of retail investment starting in the early 2000s. Financial institutions and retail investors have gained access to commodities through a variety of tools, such as exchange-traded funds (ETFs), exchange-traded notes (ETNs), and over-the-counter swaps whose returns are tied to prices of individual commodities or commodity indexes. According to data collected by Barclays (Figure 1), global commodity-linked investment rose from a negligible amount in the early 2000s to a peak of nearly $450 billion in early 2012. Investment declined sharply in the years following the peak, but bounced back to about $300 billion in recent years, still a very large amount by historic standards.

The increasing participation of financial investors in commodity futures markets, coupled with the 2007–08 boom and bust in commodity prices, raised concerns among traders, market analysts, and regulators whether the trading activities of financial investors adversely impacted commodity futures prices. Theoretical models suggest that financial investment may affect commodity futures prices through various channels, including liquidity (Hamilton and Wu, 2014), stock and commodity market integration (Basak and Pavlova, 2016), funding constraints of financial intermediaries (Acharya, Lochstoer, and Ramadorai, 2013; Etula, 2013), and informational frictions (Sockin and Xiong, 2015). All of the theoretical models are suggestive of limits to arbitrage in commodity futures markets.

Empirical studies of the price impact of financial investment in commodity futures markets mainly use time-series models to examine the association between positions of commodity index traders and futures prices (e.g., Stoll and Whaley, 2010; Buyuksahin and Harris, 2011; Irwin and Sanders, 2012; Singleton, 2014; Cheng, Kirilenko, and Xiong, 2015; Hamilton and Wu, 2015; Brunetti, Buyuksahin, and Harris, 2016; Chari and Christiano, 2017).[2] All of these studies suffer from identification problems to some degree. First, the time series models implicitly assume that trader position-taking is exogenous to price movements. This assumption may not hold because financial investors (or the firms offering the commodity products) can initiate trades based on price expectations, introducing reverse causality from price to trading activity. Second, the total position held by financial investors in commodity futures is simply the opposite of the total position held by other players in the market given that futures trading is a zero-sum game. Market clearing implies that the observed position changes of financial traders may comprise multiple and opposite motives for trading, resulting in an uncertain sign between trading activities of financial investors and futures returns (Cheng, Kirilenko, and Xiong, 2015).[3]

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[2] See Irwin and Sanders (2011), Cheng and Xiong (2014), and Haase, Zimmermann, and Zimmermann (2016) for thorough reviews.

[3] The same identification problems also exist in studies that examine the role of hedging pressure in determining futures price through a risk premium (e.g., Dusak, 1973; Fama and French, 1987; Bessembinder and Chan, 1992; de Roon, Nijman, and Veld. 2000; Kang, Rouwenhorst, and Tang, 2017). Hedging pressure, constructed from hedgers' positions, tends to be endogenous and reflects mixed trading motives of hedgers and speculators in a zero–sum market. Kang, Rouwenhorst, and Tang (2017) tackle this issue by using a smoothed (moving-averaged) hedging pressure to filter out short-term trading needs.

In this article, we provide a novel identification strategy to estimate the price impact of uninformed order flows from financial investors in commodity futures markets. The identification is achieved through the annual rebalancing of the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), one of the leading benchmarks for commodity investment. The S&P GSCI determines market index weights based on historical production and rebalances them once a year. The changes in weights cause exogenous and uninformed order flows in commodity futures markets during the index rebalancing period. If commodity futures markets are frictionless and the supply of contracts (long or short) is perfectly elastic, the uninformed demand represented by index rebalancing should be absorbed instantaneously and futures prices will not be affected. In the presence of limits to arbitrage, the supply of commodity futures contracts is upward sloping and the uninformed order flow from index rebalancing will create pressure on prices. Under limits to arbitrage, the price pressure from uninformed order flows can be temporary or permanent, depending on the "resiliency" of the market (Bessembinder et. al, 2016)

There are several reasons why S&P GSCI rebalancing provides strong identification to estimate the shape of supply curves for commodity futures contracts. First, the rebalancing is a public and predetermined event, with a gap between the announcement in early November and implementation from the 5th through the 9th business day of the following January. If S&P GSCI rebalancing contains new fundamental information, it should affect prices following the announcement date and not during the implementation period. Second, the rebalancing is a purely exogenous event. Weight changes due to rebalancing are fully determined by historical information about world production of the physical commodity and futures market liquidity, which often have a one-and-a-half to two-year lag due to data availability. The stale production and liquidity information conveyed by weight changes should be irrelevant to prices during the announcement or implementation periods associated with S&P GSCI rebalancing. This allows us to examine the impact of uninformed order flows on commodity futures prices without concerns about reverse causality. Third, the changes in positions due to the rebalancing reflect a single motive, unlike aggregate position data that may reflect multiple and heterogeneous trading motives (Cheng, Kirilenko, and Xiong, 2015). Fourth, the rebalancing requires investors that track the S&P GSCI index to initiate trades by buying or selling additional commodity futures contracts rather than passively reacting to orders of other traders in the market. This enables us to attribute potential price impacts during the rebalancing period to the activities of index traders, which is important in a zero-sum market. Fifth, the magnitude of the uninformed order flow from index rebalancing in commodity futures markets is large, which is clearly important when identifying and estimating price impacts.

Using the 24 commodities included in the S&P GSCI for 2004–2017, we show that the cumulative abnormal returns (CARs) for the rebalancing period tend to have the same signs as changes in index weights. A long-short strategy that assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) index weight changes yields significantly positive returns. The price impact reaches a peak of 59 basis points in the middle of the week following the rebalancing period, but the impact is temporary as it declines to near zero within the next week. A similar pattern of price impact prevails across contracts along the futures curve, although it is slightly weaker for deferred-month contracts. Cross-sectional regression estimates show that the percentage changes in index weights, as a proxy for the size of the rebalancing flows, explain a significant portion of the variation in the CARs for the rebalancing period and the following week. This is consistent with limits to arbitrage, which implies that price pressure increases in the magnitude of uninformed order flow. We obtain similar results when simultaneously considering the rebalancing of the S&P GSCI and the Bloomberg Commodity Index, another leading benchmark for commodity investment. The findings provide clear evidence that the supply curve for commodity futures contracts is upward sloping in the short-run but almost flat in the longer-run. Hence, the impact of trading activities of financial investors in commodity futures markets is likely modest and temporary.

Our work contributes to several strands of literature. First, we contribute directly to the literature that focuses on identification of the price impact of financial investment in commodity futures markets. Tang and Xiong (2012) use a difference-in-difference approach and find that prices of non-energy commodities have become increasingly correlated with crude oil since 2004, especially for those included in popular commodity indexes. This difference-in-difference approach has been criticized for omitting relevant variables that could explain the rising correlations (e.g., Buyuksahin and Robe, 2014; Bhardwaj, Gorton, and Rouwenhorst, 2015). When analysing the relationship between returns in commodity futures markets and daily financial index trader positions, Cheng, Kirilenko, and Xiong (2015) use changes in the VIX volatility index as an instrument for index position changes and Brunetti, Buyuksahin, and Harris (2016) use changes in the total number of accounts for all large traders as an instrument. Results are mixed across the two studies, which is not surprising because both confront weak instrument problems. Henderson, Pearson, and Wang (2015) use commodity-linked note (CLN) issuances as events and estimate abnormal returns around pricing and determination dates. They report evidence of sizable impacts of financial investment on commodity futures prices. However, Ready and Ready (2018) examine intraday prices on the pricing days of the CLNs and find that the size of note issuances is not large enough to generate the observed price impacts. In addition, they show that CLN issuance does not cause but reacts to changes in prices, which invalidates Henderson, Pearson, and Wang's identification strategy. In contrast to these studies, our identification strategy is straightforward and built on an important exogenous event—the annual rebalancing of the S&P GSCI. This provides the strongest identification in the literature to date with respect to estimating the price impact of the order flows of financial investors in commodity markets.

Second, our work contributes to the large body of literature that examines the effects of changes in index compositions for a variety of assets (e.g., Harris and Gurel, 1986; Shleifer, 1986; Kaul, Mehrotra, and Morck, 2000; Chen, Noronha, and Singal, 2004; Greenwood, 2005; Hau, Massa, and Peress, 2010; Chan, Kot, and Tang, 2013; Claessens and Yafeh, 2013; Schnitzler, 2018). A limitation of these studies is that some of the changes in index compositions may not be pre-announced, especially in the early part of sample periods, and so, the announcements may act as shocks to the market.[4] In addition, the inclusion of a stock in an index may also convey positive information about the firm. Denis et al. (2003) find that newly added firms to the S&P 500 index experience significant increases in both earnings forecasts and realized earnings, suggesting that additions are not information free. This information effect makes the identification strategies based on index composition changes less effective. Our identification strategy is built on the rebalancing of the S&P GSCI, and therefore, is not subject to these limitations because there is always about a two-month gap between announcement and implementation of the rebalancing. There is no reason to believe that an event conveys any new fundamental information two months *after* it is announced to the public. Moreover, the information effect should not be applicable to S&P

[4] For example, the S&P has not had the same policy regarding announcements through time. Before October 1989, the announcement day and the effective day of additions and deletions were the same. After that, the S&P pre-announced changes to index membership about a month in advance of the effective inclusion date.

GSCI rebalancing because it is based on stale public information that does not contain insights about the future performance of commodity prices.

Third, our work contributes to the literature on limits to arbitrage in commodity markets. Previous research has shown that limits to arbitrage play a role in determining the market impacts of trading activities in commodity futures markets, especially during times of market distress (Acharya et al., 2013; Etula, 2013; Cheng, Kirilenko, and Xiong, 2015). A recent study by Boons and Prado (2019) finds that basis-momentum, the difference in momentum between first– and second–nearby futures contracts, has power in predicting commodity spot and term premiums. These authors argue that the basis-momentum factor captures imbalances in the supply and demand of futures contracts when speculators and intermediaries are subject to financial constraints. Consistent with their findings, we show that the identified price impact during index rebalancing periods is increasing in the proxy for the size of the rebalancing flows and larger during the Great Recession.

Fourth, we contribute to the literature on sunshine trading versus predatory trading. With sunshine trading, predictable and uninformed order flows, such as those related to the rebalancing of major commodity indexes, have modest and temporary market effects because the flows attract natural counterparties and additional liquidity suppliers (Admati and Pfleiderer, 1991). Predatory trading occurs when a trader learns that another trader will transact a large quantity and then profits by trading in the same direction before the trader can initiate a position (Brunnermeier and Pederson, 2005), which may substantially harm market quality. Bessembinder et al. (2016) provide empirical evidence in this regard by studying the predictable "roll" trades undertaken by a large ETF in the crude oil futures market. They find narrower bid-ask spreads, greater order book depth, and improved resiliency on roll dates and conclude that other traders provide liquidity rather than exploit the predictable ETF roll trades in a predatory manner. Since trades associated with S&P GSCI rebalancing are predictable in terms of timing (but less so in terms of magnitude), our results contribute directly to this literature.[5] Specifically, we find that the peak cumulative abnormal return for a long–short strategy is 59 basis points in the middle of the week following rebalancing and it largely disappears within the next seven business days. This moderate but temporary price impact in the face of large rebalancing order flows suggests that commodity futures markets are highly liquid, resilient, and strategically competitive, similar to the conclusions reached by Bessembinder et. al (2016).

The article proceeds as follows. Section 2 describes the construction and rebalancing scheme of the S&P GSCI. A formal derivation is presented to link order flows due to the rebalancing to changes in weights of the index. Section 3 presents the event study framework used to examine price behavior around the announcement and rebalancing dates. Section 4 discusses the main results and presents robustness checks. Section 5 provides conclusions. We provide extra tables for data description in the Data Appendix.

2 The S&P GSCI Index Construction and Rebalancing

In this section, we first describe the S&P GSCI and its rebalancing scheme. We then develop a relationship between order flows due to the rebalancing and changes in weights of the index. Last, we evaluate the economic significance of order flows due to the S&P GSCI rebalancing.

2.1 The S&P GSCI

The S&P GSCI, launched by Goldman Sachs in 1991, is the first major investable commodity index and serves as a benchmark for investment in commodity markets. The index

[5] The magnitude of the roll trades studied by Bessembinder et al. (2016) is not known with certainty either.

comprises 24 commodities from all sectors (energy, metals, grains, softs, and livestock) and the composition has remained the same since 2002.[6] The wide range of constituent commodities provides diversification across sectors and within each sector. The S&P GSCI holds long positions in front-month futures contract, which usually is the most liquid contract. The index rolls positions from expiring contracts to later-month contracts to avoid physical delivery. The roll takes place within a five-day window from the 5^{th} through the 9^{th} business day each month, and on each day, an equal amount (one-fifth) of the positions are rolled.[7]

The S&P GSCI is a production-weighted index. The percentage dollar weight of commodity c on day d is,

$$w_d^c = \frac{CPW^c * DCRP_d^c}{\sum_c (CPW^c * DCRP_d^c)}, \tag{1}$$

where $DCRP$ is the Daily Contract Reference Price, which is the settlement price of the futures contract held by the index and expressed in U.S. dollars per physical unit, and CPW is the Contract Production Weight, which measures the relative significance of the commodity and is expressed in physical units. Just as market capitalization is used to assign weights to components of equity indexes, the S&P GSCI assigns weight to each commodity in proportion to the amount of that commodity flowing through the economy. Note that CPW does not contain a time subscript because it remains the same during each calendar year except the rebalancing period. Although CPW is fixed most of the time, the percentage dollar weight varies from day-to-day as price changes.

[6] The S&P GSCI transitioned from including Unleaded Gasoline to including RBOB Gasoline in 2007.

[7] The detailed roll scheme is provided in the Data Appendix.

The CPW is constructed based on historical world production and futures trading volume (S&P GSCI Methodology, April 2017, p. 12). For commodity c,

$$CPW^c = Percentage\ TQT^c \frac{WPA^c}{10^6}, \tag{2}$$

where *Percentage TQT* is the Percentage Total Quantity Traded and *WPA* is the World Production Average. TQT is measured by total trading volume of futures contracts during the relevant annual calculation period, which refers to the 12-month period ending on August 31$^{\text{st}}$ of the calendar year immediately preceding the year for which the composition of the S&P GSCI is being determined. *WPA* is the average quantity of world production of each commodity over the most recent five years for which complete world production data is available for all S&P GSCI commodities. The production data often has a lag of two years due to reporting delays. The same *WPA* is used for commodities that belong to any of the following groups: (i) Chicago wheat and Kansas wheat, (ii) feeder cattle and live cattle, and (iii) WTI crude oil, Brent crude oil, heating oil, RBOB gasoline, and gasoil. The CPWs are obtained by allocating *WPA* in proportion to *Percentage TQT*, which equals the TQT of one commodity divided by the total TQT of commodities within a given group. In this case, CPWs are jointly determined by world production and trading volume. For the rest of the commodities, *Percentage TQT* equals one and CPWs are fully determined by world production. Equations (1) and (2) state that the constituent weights of the S&P GSCI depend on CPWs, which in turn rely on historical world production and futures market trading volume.

2.2 The S&P GSCI Rebalancing

The S&P GSCI adjusts the CPWs once a year to reflect changes to production and trading volume. Specifically, the index provider announces new CPWs in late October or early November each year, which will take effect in the following January from the 5$^{\text{th}}$ through 9$^{\text{th}}$

business day. We refer to this five-day window as the S&P GSCI rebalancing period. Implementation of new *CPW*s causes changes in weights, which in turn requires investors to adjust their positions tied to the S&P GSCI to minimize tracking error. This position adjustment is mechanical in the sense that investors must complete it regardless of changes in price. The index transitions from old *CPW*s to new ones at an even pace, requiring investors to buy or sell an equal number of futures contracts on each of the rebalancing dates to achieve minimal tracking error. In practice, investors do not necessarily trade the same number of contracts each day; instead, they may complete the adjustment of positions over a shorter or longer period of time. If a portion of the position adjustment falls out of the rebalancing period, we expect that the order flows to have a smaller impact on futures price. That is, our analysis of futures returns over the rebalancing period leads to an underestimate of the true impact of the rebalancing flows. Note also that the rebalancing period overlaps the January roll period, which implies that investors need to not only roll their positions but also buy or sell additional number of contracts in response to weight changes due to the rebalancing. The key difference is that the roll simply closes positions in the front-month contract and re-establishes them in the next month contract without generating net flows, whereas rebalancing causes net flows into or out of the market through trading additional contracts in the next monthly expiration. We will discuss distinct effects of the rebalancing and the rolls on prices in the "Results" section.

The weights of commodity c prior to and after the rebalancing are defined as

$$w^c_{old} = \frac{CPW^c_{old} * DCRP^c_0}{\sum_c (CPW^c_{old} * DCRP^c_0)} \tag{3}$$

and

$$w^c_{new} = \frac{CPW^c_{new} * DCRP^c_0}{\sum_c (CPW^c_{new} * DCRP^c_0)}, \tag{4}$$

respectively, based on old and new CPWs. $DCRP_0$ denotes the settlement price of the contract held by the index on day 0, the last business day prior to the rebalancing period.[8] Since the same prices are used in Equations (3) and (4), the changes in weight due to the rebalancing are driven only by CPW changes. An increase in CPW for a commodity raises its own weight but simultaneously reduces weights for all the other commodities. The sum of weight changes over commodities is equal to zero.

We show in the Appendix that order flows due to the S&P GSCI rebalancing are proportional to changes in weights:

$$Order\ Flow^c = k * (w^c_{new} - w^c_{old}), \tag{5}$$

where k is a constant and can be interpreted as the notional value of total assets tied to the S&P GSCI. Equation (5) allows us to measure order flows due to the rebalancing by changes in weights, which are purely driven by CPW changes and reflect no new fundamental information about futures price.

The timing of rebalancing trades within the day could impact estimated price impacts (Ready and Ready, 2018). In particular, financial investors tracking the S&P GSCI could in theory decide when to trade within the day based on price trends. However, financial investors in commodity futures markets are most likely to trade during times of higher trading volume and lower trading costs. For example, Bessembinder et al. (2016) show that the United States Oil Fund, the largest of the ETFs that track crude oil prices, routinely trades at the settlement price to complete its roll trades. Ready and Ready (2018) document that index traders in agricultural futures trade at or near the daily settlement. As rebalancing trades occur at the same time as roll trades, it is reasonable to assume that

[8] The use of day 0 price is resulted from the definition of normalizing constant of the index (see Equation (A.10) in the Appendix).

rebalancing trades occur at or very near the daily settlement price. This supports our use of daily settlement prices to measure the market impact of uninformed order flows in commodity futures markets due to the annual rebalancing of the S&P GSCI.

2.3 Economic Significance of the S&P GSCI Rebalancing

We evaluate the economic significance of the S&P GSCI rebalancing by estimating the actual value of order flows in commodity futures markets. The pre- and post-rebalancing weights are constructed based on Equations (3) and (4) using old and new CPWs and prices of the futures contract held by the index on the last business day prior to the rebalancing period (day 0). We assume that the notional value of total assets tied to the S&P GSCI is two-thirds of the total index investment in major U.S. futures markets, as measured by the Commodity Futures Trading Committee (CFTC) *Index Investment Data* (IID) report for 2008–2015.[9,10] Hence, order flows are obtained by multiplying the notional value of total investment in the S&P GSCI by weight changes. The number of futures contracts equals order flow divided by value of the contract.

Figure 2 shows the order flows due to the S&P GSCI rebalancing for WTI crude oil for 2008–2015. The number of contracts is expressed as a percentage of open interest, which is the average of daily open interest of the contract that the index rolls into over a 2-week window prior to the rebalancing period. The period from 2010 through 2013 saw substantial flows out of WTI crude oil market over the S&P GSCI rebalancing period, with a peak of \$5,731 million or 33% of daily open interest in 2013. These flows are still very large even if the trades occurred evenly on the five rebalancing dates. The large outflows during this

[9] The IID report, initially compiled under a special call issued by the CFTC to swap dealers and index traders in June 2008, provides the most accurate measure of total index investment in major U.S. commodity futures markets. The CFTC discontinued release of the IID report in November 2015.

[10] Masters (2008) estimates the value of total assets invested in the S&P GSCI and the Bloomberg Commodity Index, and argues that the former is nearly twice as large as the latter, which is consistent with our assumption.

period are due to the fact that the S&P GSCI continually reduced the weight of WTI crude oil and increased the weights of Brent crude oil and other energy products.

We calculate the order flows due to the S&P GSCI rebalancing for all 24 commodities and report them in Table 1. Because either positive or negative flows could affect price, we focus on the magnitude of weight changes and order flows by taking the average of their absolute values across years for each commodity. Order flows are measured in dollars and numbers of contracts. The number of contracts is also expressed as percentages of volume and open interest, where volume (open interest) is the average of daily trading volume (open interest) of the contract that the index rolls into over a 2-week window prior to the S&P GSCI rebalancing period.[11] Table 1 shows a large variation in order flows across commodities. The absolute change in weights due to the rebalancing is 1.87% for WTI crude oil, creating a flow of $1,795.8 million in absolute terms. This means that investors need to buy or sell 20,400 additional March WTI crude oil contracts during the rebalancing period, accounting for 25.59% and 10.74% of daily volume and open interest, respectively. The flows are also large for wheat, cattle, and other energy products. The average flow across commodities is $206.4 million in total or $41.3 million per day. For comparison, Henderson, Pearson, and Wang (2015) document an average proceed of $14.8 million related to CLN issues and report that the induced hedge flows have a significant and permanent impact on futures price. Consequently, the order flows due to the S&P GSCI rebalancing are economically large enough to allow for a potential price impact.

The economic significance of the S&P GSCI rebalancing is further examined by calculating changes in positions held by index traders around the rebalancing period based on the

[11] The reported volume and open interest for LME contracts cannot be directly compared with those for U.S. contracts because of different contract specifications and trading times. We follow the Bloomberg Commodity Index Methodology and use one-third of the reported volume and open interest for LME contracts for a fair comparison.

CFTC *Supplemental Commitment of Traders* (SCOT) report. The SCOT report provides a breakdown of each Tuesday's open interest for 12 agricultural futures markets since January 3, 2006. We examine the gross long positions held by index traders for 11 of the 12 SCOT agricultural futures (soybean oil is excluded) included in the S&P GSCI for four different periods: i) the 2-weeks containing the rebalancing period; ii) the 2-weeks prior to the rebalancing period; iii) the 2-weeks after the rebalancing period; and iv) other non-rebalancing weeks. Table 2 presents the average absolute percentage changes in positions held by index traders for those four periods. For 9 of the 11 commodities (except cocoa and feeder cattle), the absolute changes in index positions for the 2-weeks containing the rebalancing period are 2 to 4 times larger than changes that precede or follow the rebalancing period.[12] The relatively large changes in positions for the 2-weeks containing the rebalancing period are likely driven by changes in weights, lending further support to the economic significance of order flows due to S&P GSCI rebalancing.

3 Methods

We follow standard event study methodology and use abnormal returns to measure the price impact of order flows due to the S&P GSCI rebalancing. The abnormal return is the difference between the actual return and the expected return,

$$AR_{i,t} = R_{i,t} - E[R_{i,t}|X_t], \tag{6}$$

where $AR_{i,t}$, $R_{i,t}$, and $E[R_{i,t}|X_t]$ are the abnormal, actual, and expected returns, respectively, and X_t is the conditioning information. The actual return is the difference in log daily settlement prices of the futures contract held by the index. The expected return refers

[12] The percentage changes in positions held by index traders are large for cocoa and feeder cattle during non-rebalancing weeks, which may be driven by idiosyncratic behaviors given that the total position held by index traders in these two markets is small.

to the return that would be expected if the rebalancing does not take place and is defined as the predicted value of $R_{i,t}$ conditional on X_t.

We consider three estimates for the expected return. First, the expected return is assumed to be zero, consistent with the longstanding view that historical returns to most individual commodity futures do not differ from zero (e.g., Erb and Harvey, 2006). In this case, the abnormal return is identical to the actual return. The second estimate of the expected return is based on a constant-mean model,

$$R_{i,t} = \mu_i + \epsilon_{i,t}, \tag{7}$$

where μ_i is the mean return for commodity i. In this case, the expected return is equal to a constant that is estimated from historical returns. Last, we estimate the expected return based on a multi-factor model, which assumes a linear relationship between futures return and a group of economic factors (Z_t). Specifically,

$$R_{i,t} = \mu_i + \beta_i' Z_t + \epsilon_{i,t}, \tag{8}$$

where β_i is a vector of coefficients that measures dependence of $R_{i,t}$ on Z_t. We follow Henderson, Pearson, and Wang (2015) and include the following factors in Z_t:

(1) The return on the S&P 500 Index, which measures the impact of changes in expectations about U.S. economic growth.

(2) The return on the MSCI Emerging Markets Asia Index, which measures the impact of changes in expectations about emerging markets economic growth. Its next day return is also included to account for trade non-synchronicity between Asian and U.S. markets.

(3) The return on the JP Morgan Treasury Bond Index, which captures the linkage between commodity futures and interest rate markets.

(4) The return on the Trade Weighted U.S. Dollar Index, which reflects the fact that the U.S. Dollar is the most common settlement currency for commodity transactions.

(5) The percentage change in the VIX Index, which measures the relationship between commodity prices and innovations to VIX found by Cheng, Kirilenko, and Xiong (2015).

(6) The percentage change in the Baltic Dry Index, which is a widely-used indicator of global economic conditions and measures changes to the cost of transporting raw materials by sea.

(7) The change in the 10-year breakeven inflation rate, representing changes in expected inflation. The one-day lagged dependent variable is included to control for potential autocorrelation in returns.

We obtain futures prices for the 24 commodities included in the S&P GSCI for 2004–2017 from the Commodity Research Bureau. The Baltic Dry Index is collected from Bloomberg and the rest of the factors are from Federal Reserve Bank of St. Louis.

The constant-mean and multi-factor models are estimated over the 60-business-day window preceding the S&P GSCI rebalancing period. The estimation window ends one week before the rebalancing period to ensure that abnormal returns reflect rebalancing effects and the expected return does not. For each day following the estimation window, the expected return is the product of the estimated parameters and the values of the factors on that day and the abnormal return is the actual return minus the expected return. For the multi-factor model, the R-squared has an average of 13.5% and is larger for energy and metals, which is not surprising given that energy and metal markets are integrated more closely with the global economy and financial markets. Detailed estimation results for the expected return are omitted to save space.

We define the cumulative abnormal return (CAR) as the sum of abnormal returns starting from day 0, the day immediately prior to the S&P GSCI rebalancing period. The CAR is calculated for each of the rebalancing dates (days 1–5) and the following 10 business days. To reflect the rebalancing effects, we calculate the average CARs depending on direction of weight changes. If order flows due to the rebalancing impact futures price, we expect the CARs to diverge over the rebalancing period—positive CARs for weight increases and negative CARs for weight decreases. However, the CARs can be biased due to cross-market dependence, which may arise from common shocks that occur on the rebalancing days and affect all markets (e.g., quantitative easing by the Federal Reserve) or markets within a sector (e.g., an oil production cut by the Organization of the Petroleum Exporting Countries).[13,14] This is similar to issues encountered in cross-sectional equity returns in which stocks from the same industry tend to be correlated with each other. To mitigate the problem, we calculate the average CARs for a long-short strategy, which assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The long-short strategy provides a more robust measure of the price impact of order flows due to rebalancing since the effects of cross-market dependence on the long-side should largely offset the effects on the short side. In the presence of a price impact, the average CARs for the long-short strategy should be positive for the rebalancing period and reverse afterwards if the impact is not permanent.

4 Results

In this section, we measure the impact of the S&P GSCI rebalancing on commodity futures prices. We first examine cumulative abnormal returns (CARs) following the announcement

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[13] Another factor that contributes to cross-market dependence is the long-run upward trend in prices during the 2000s commodities boom.

[14] Estimating abnormal returns based on the constant-mean or multi-factor model does not tackle the cross-market dependence issue because the estimation window is one-week ahead of the S&P GSCI rebalancing period.

date of the rebalancing. Next, we estimate CARs for the rebalancing period. Then, we check whether the rebalancing effects are consistent across contracts along the futures curve. After that, a regression model is used to explain the CARs for the rebalancing period. Last, we examine the rebalancing effects of the Bloomberg Commodity Index.

4.1 Announcement date event study

The assertion that order flows due to the S&P GSCI rebalancing convey no new fundamental information about price is essential to our identification strategy. Recall that the changes in weights due to the rebalancing are driven by CPW changes that rely on historical production and trading volume information. Hence, the rebalancing flows reflect no new information. More importantly, new CPWs are announced in early November each year, which is about two months prior to the rebalancing period.[15] If weight changes due to the rebalancing incorporate new information on fundamentals, we would expect to observe price reactions immediately following the announcement date not during the actual rebalancing period. Even if the announcement of new CPWs acts as a shock to the market, the corresponding changes in weight should not be treated as relevant information for a rebalancing period that occurs two months later.

To examine whether commodity futures prices react to the announcement of CPWs, we calculate CARs for a long-short strategy following the S&P GSCI announcement date in late October or early November of each year. The long-short strategy assigns an equal weight to each commodity and takes a long position in commodities with positive weight changes and a short position in commodities with negative weight changes. Figure 3 shows the average CARs across years and their 95% confidence intervals. Abnormal returns are

[15] The announcement dates of the S&P GSCI rebalancing were: 10/29/2003, 11/3/2004, 10/24/2005, 11/6/2006, 11/1/2007, 11/3/2008, 11/3/2009, 11/4/2010, 11/3/2011, 11/5/2012, 11/7/2013, 11/11/2014, 11/5/2015, and 11/10/2016.

based on the zero-mean model. Results based on abnormal returns from the constant-mean and multi-factor models are similar and omitted to save space. The CAR is normalized to be zero on day 0, the day immediately prior to the announcement date. The average CARs for the long-short strategy are 15 and 31 basis points on the announcement date (day 1) and the following day (day 2), respectively, and decline to nearly zero thereafter. The 95% confidence interval indicates that the average CARs are statistically significant only on day two and do not differ from zero on the rest of the days. These results suggests that the announcement of new weights has a significant but very short-lived impact on futures prices. The impact emerges on day two instead of day one because the CPW announcements are released after futures markets close. It is not clear why the commodity futures markets react to announcements because the weights are highly unlikely to contain new information as argued earlier. One possibility is that the order flow impacts during implementation of rebalancing trades two-months later are large enough that they are anticipated by the market. Another possibility is an informational friction along the lines of Sockin and Xiong (2015), where some traders misperceive the announcement as representing changes in commodity demands. Finally, it is important to keep in mind that while a significant price impact following CPW announcements is observed it only lasts for a single day.

4.2 Rebalancing date event study

4.2.1 Rebalancing price effects

Given that there is a two-month lag between CPW announcement and implementation dates, annual CPW changes do not contain new information relevant to the market during the rebalancing period. As a result, rebalancing trades unambiguously contain no new information and the uninformed order flows should identify the shape of supply curves for commodity futures contracts (long or short). We use the same event study procedure to examine futures returns for the S&P GSCI during the rebalancing period as we did for announcement dates.

Figure 4 shows the average CARs for the long-short strategy for each of the rebalancing dates and the following 10 business days and associated 95% confidence intervals. As before, the CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 represent the S&P GSCI rebalancing dates. Abnormal returns are based on the zero-mean return model. The average CARs for the long-short strategy are positive throughout and statistically significant at the 5% level on days two, four, and seven. The point estimates of average CARs reach a peak of 59 basis points on day seven and decrease continually to 10 basis points on day 15. This suggests that order flows due to rebalancing increase futures return by up to 0.59%, but the impact is nearly completely reversed within the following seven days. We can infer that the supply curve for commodity futures contracts is upward sloping in the short-run and flat in the longer-run.

Previous studies find an abnormal return of about 200–300 basis points on the day following additions, deletions, or redefinitions of major equity indexes (e.g., Harris and Gurel, 1986; Shleifer, 1986), much larger than our estimate of a peak price impact of 59 basis points. Henderson, Pearson, and Wang (2015) report an abnormal return of 22–36 basis points on the pricing date of CLN issues and assert that the impact is permanent. However, Ready and Ready (2018) argue that Henderson, Pearson, and Wang's estimate of price impact is too large relative to the size of CLN order flows. We use the slope estimates from Ready and Ready's regressions of one-minute order flow imbalance on one-minute returns for gold, copper, WTI crude oil, Brent crude oil, and corn to conduct a robustness check on our CAR estimates. We take the estimates of average absolute order flow over 2008–2015 reported in Table 1 (millions of dollars) for these five markets and then multiply the averages by the slope coefficients in Ready and Ready's Table 4 (predicted return per million dollars of uninformed order flow) to obtain the total predicted price impact. The average total price impact estimated in this manner across the five markets is 78 basis points. Hence, our estimated peak price impact of 59 basis points due to S&P GSCI rebalancing is reasonably consistent with the estimates found in Ready and Ready's (2018) study.

We also examine the CARs for positive and negative changes in weights, respectively. The CARs are expected to be positive when weights increase and negative when weights decrease. Figure 5 shows the average CARs for positive ($\Delta w \geq 0$) and negative ($\Delta w < 0$) weight changes, respectively, and their 95% confidence intervals. The average CARs for $\Delta w \geq 0$ are positive but do not differ from zero on all days except day three. The average CARs for $\Delta w < 0$ are significantly negative and larger in magnitude for all days. Note that there is a significant price drop in many commodity markets on day three and this makes CARs for both $\Delta w \geq 0$ and $\Delta w < 0$ smaller or more negative on day three and thereafter. Consequently, average CARs do not necessarily have the same signs as weight changes. Nonetheless, there is a significant divergence in average CARs between positive and negative weight changes from days one to seven, suggesting that order flows due to the rebalancing tend to have a larger impact for negative weight changes. The divergence in CARs for positive and negative weight changes declines after day seven, consistent with the previous finding that the price impact is short-lived. While the same overall conclusion is reached here, the long-short strategy is not as sensitive to large price movements on any particular day, and hence, is more appropriate for measuring rebalancing effects. Therefore, we focus on the returns to the long-short strategy in the remaining analysis of CARs.

To check the sensitivity of the results to different expected return models, we calculate the average CARs based on zero-mean, constant-mean, and multi-factor models, respectively, and present them in Table 3. The t-statistic is for the null hypothesis that the average

CAR equals zero. The top panel of Table 3 presents results when the expected return is from the zero-mean model, in which the abnormal return is identical to the raw return. This provides the same information as Figures 4 and 5 and has already been discussed. The middle panel of Table 3 shows similar results when the expected return is from a constant-mean model. This is not surprising given that the estimated intercept in the constant-mean model does not differ significantly from zero most of the time. The bottom panel of Table 3 presents results when the expected return is from the multi-factor model. The average CARs remain positive for $\Delta w \geq 0$ and negative for $\Delta w < 0$, though insignificant on most of the days. The long-short strategy yields positive average CARs ranging between 7 and 45 basis points and are statistically significant at the 5% level on days two and four. Regardless of the expected return model, the average CARs are smaller or even negative on day 15, two weeks after the rebalancing period. Once again, these results suggest that uninformed order flows due to S&P GSCI rebalancing significantly impact commodity futures prices but the impact is almost entirely reversed in a few days. Since the results are similar across expected return models (Table 3), we focus on the raw futures return obtained from the zero-mean return model in the following sections.

4.2.2 Rebalancing and index rolls

The S&P GSCI rebalancing period overlaps exactly with the January roll period, where index positions are "rolled" from the expiring contract to the next-month contract. Investors tracking this index need to complete both the rebalancing and roll trades during the same period. A natural question to ask is whether the identified rebalancing effects are due to roll trades that occur at the same time. To separate rebalancing effects from possible roll effects, we examine the returns for a group of commodities that do not experience rolls during the January rebalancing period. Ten commodities satisfy this criterion, including cocoa, coffee, corn, cotton, feeder cattle, silver, soybeans, sugar, Chicago wheat, and Kansas wheat. Figure 6 shows the average CARs for the long-short strategy defined earlier using the 10 non-roll commodities. The average CARs based on all commodities are included for comparison. While the average CARs based on non-roll commodities are somewhat less statistically significant because of a smaller number of observations, no major differences are found in the average level of CARs compared to those based on all commodities. This result provides clear evidence that the identified price impact is due to rebalancing rather than monthly January rolls.

It is actually not surprising that rebalancing price impacts are largely unaffected by roll trades. First, rolling involves selling the expiring contract and buying the next-month contract, while rebalancing involves buying and selling the next-month contract only. Therefore, the only overlap between roll and rebalancing trades is when the next-month contract is bought. There is no overlap when rebalancing trades sell the next-month contract. Second, several studies test whether the spread between front-month contracts and the next month contracts increases during index roll periods, and the results are decidedly mixed. Four studies find that spreads in commodity futures markets are either unaffected or slightly narrow following index rolls (Stoll and Whaley, 2010; Aulerich, Irwin, and Garcia, 2013; Hamilton and Wu, 2015; Sanders and Irwin, 2016) and three studies (Mou, 2010; Brunetti and Reiffen, 2014; Bessembinder et. al, 2016) report evidence of expanded spreads after index rolls.

4.2.3 Rebalancing and the Great Recession

The Great Recession of 2008–09 witnessed large price drops in many commodity markets simultaneously. Institutional investors were also subject to serious funding constraints during the recession period. We explore whether part of the rebalancing effects can be attributed to the Great Recession by excluding the January 2009 rebalancing, which falls within the recession interval specified by the National Bureau of Economic Research. Figure

7 shows the average CARs for the long-short strategy defined earlier for 2004–2017 with the exception of 2009. The abnormal returns are again calculated for all commodities included in the S&P GSCI using a zero-mean model. The average CARs for all years are included for comparison. The average CARs are consistently larger when the 2009 rebalancing is excluded, suggesting a bigger impact of order flows due to rebalancing outside of the Great Recession. Theoretical models (e.g., Acharya, Lochstoer, and Ramadorai, 2013; Etula, 2013) suggest rebalancing effects should be weaker during non-recessionary periods when investors are less likely to face financial constraints. We obtain the opposite result, probably because weight changes in 2009 are smaller than in other years. A full analysis of the question of whether uninformed order flow has a larger impact on commodity futures price during the Great Recession will require controlling for the size of flows. We conduct such a test in a cross-sectional regression model in a following section.

4.2.4 Rebalancing and large commodity markets

Another interesting question is whether the identified price effects emerge only in the biggest commodity markets. Recall that the S&P GSCI is concentrated in energy with a combined weight above 45% for WTI and Brent crude oil. These two oil markets also have the largest changes in weights (Table 1). To explore whether the rebalancing effects are concentrated in crude oil futures markets, we drop WTI and Brent crude oil and examine the returns for the rest of the 22 commodities. Figure 8 shows the average CARs for the long-short strategy with and without WTI and Brent crude oil and associated 95% confidence intervals. The average CARs for non-oil commodities are slightly larger but show a very similar pattern as those for all commodities. This suggests that uninformed order flows due to the rebalancing have a slightly stronger impact on futures price when crude oil markets are excluded. Although crude oil has the largest order flows, the price impact is not necessarily the biggest thanks to their high levels of market depth. In contrast, the price impact may be more significant for small markets where market depth is lower. This likely explains the result in Figure 8 that the rebalancing effects are slightly larger without crude oil. Thus, the identified price impacts of order flows due to the rebalancing are not specific to a few seemingly important markets such as crude oil.

4.2.5 Rebalancing and front-running

It is possible that traders attempt to front-run the rebalancing period to exploit the price impact of uniformed order flows due to the rebalancing. Specifically, one may enter long positions in commodities with weight increases and short positions in commodities with weight decreases ahead of the rebalancing period. To allow for front-running, we report in Figure 9 the average CARs for the long-short strategy defined earlier for the period that starts one week preceding the S&P GSCI rebalancing period. Abnormal returns are normalized to be 0 on day –5, the day one week prior to the rebalancing period (days 1–5). While the average CAR for the long-short strategy increases for the pre-rebalancing week, none of the CARs are statistically significant. The overall pattern of the CARs is similar to that shown in Figure 4, but the additional variability from the five days previous to the rebalancing period adds considerable noise to the estimates, and hence the lack of statistical significance. These results indicate that front-running before the rebalancing period does not contribute to the identified rebalancing effects.

4.2.6 Rebalancing effects along the futures curve

We have shown that the uninformed order flows due to the S&P GSCI rebalancing temporarily impact futures prices of the front-month contracts. An interesting question is how the uninformed order flows impact the entire futures curve. Henderson, Pearson, and Wang (2015) report that hedge flows of CLNs issues have an equal impact across the futures term structure. This is consistent with the prediction of the rational theory of storage that futures prices for storable commodities are tightly integrated. To examine whether the identified rebalancing effects emerge across the futures term structure, we calculate CARs for the long-short strategy defined earlier for contracts that have at least two, four, and six months to maturity, respectively, and present the results in Figure 10. We do not consider contracts with maturity longer than six months because these contracts are much less frequently traded in many markets. The average CARs for the nearby contract (that the index rolls into) are included for comparison. The average CARs for the 2- and 4-month contracts almost coincide with those for the nearby contract, while the average CARs for the 6-month contract are slightly smaller throughout. The 95% confidence intervals indicate that there is no significance difference among the four series of average CARs. This result suggests that uninformed order flows due to rebalancing not only affect prices of the front-month contracts but also shift the entire futures curve, though to a lesser degree for the back-month contracts. Once again, the average CARs all achieve a peak on day seven and reverse back to almost zero within the following week, implying that the entire futures curve will shift back after the rebalancing period.

4.3 Cross-sectional regressions

Acharya, Lochstoer, and Ramadorai (2013) and Etula (2013) emphasize the role of financial intermediaries as arbitrageurs in determining prices in the commodity futures market. The implication is that the price impacts should increase in the size of the rebalancing order flows because of limits to arbitrageurs' capacity to take the other side of the trades. Similarly, the price impact should be larger during the Great Recession when arbitrageurs confronted financial constraints.

We employ cross-sectional regressions to link the CARs to proxies for the magnitude of the rebalancing flows. In particular, we estimate the following regression model:

$$CAR[1,d]_{it} = \alpha_t + \beta_1(\Delta w/w)_{it}^{S\&P\ GSCI} + \beta_2 D^{09}(\Delta w/w)_{it}^{S\&P\ GSCI} + \epsilon_{it}, \tag{9}$$

where $CAR[1,d]_{it}$ is the cumulative abnormal return for commodity i from days 1 to d in year t in percentage terms, α_t is a time effect that captures the common component in returns across commodities in year t, D^{09} is the dummy variable that takes one for year 2009 and zero otherwise, and $(\Delta w/w)^{S\&P\ GSCI}$ is the percentage change in weights. Since the same weight change is unlikely to impact prices for corn to the same degree as it for WTI crude oil, we use the percentage changes in weight to control for the effects of market size (Hau, Massa, and Peress, 2010). In the presence of limits of arbitrage, we expect that CARs increase in percentage weight changes, i.e., $\beta_1 > 0$. Also, the same amount of flows should have a larger price impact during times of the Great Recession, i.e., $\beta_2 > 0$. The regressions are estimated using a fixed-effects model.[16]

We estimate separate regressions for CARs from days 1 to d, where d takes values of 1, 2, 3, 4, 5, 10, and 15, and report the estimation results in Table 4. The t-statistics are provided in parentheses. The fixed effects coefficients for each year are omitted to save space. The top panel of Table 4 presents results when the abnormal return is from a zero-mean model. The estimated coefficients on $\Delta w/w^{S\&P\ GSCI}$ are positive and statistically significant at the 5% level on days 3, 4, 5, and 10. An estimated coefficient of 0.11 means that a 1% increase in weight increases the CAR by 11 basis points, or equivalently, a one-standard-deviation increase in $\Delta w/w^{S\&P\ GSCI}$ (4.33%) leads to a 48 basis point increase in the CAR for the rebalancing period (days [1, 5]). The price impact is larger when the CAR is calculated for days 1–10, which mirrors the finding in Figure 4 where the average CAR for the long-short strategy reaches a peak in the middle of the week following the rebalancing period (day 7). In contrast, the estimated coefficient on $\Delta w/w^{S\&P\ GSCI}$ is smaller and insignificant when the CAR is calculated for days 1–15, suggesting that the price impact disappears over a

[16] The specification of model (9) is equivalent to a model that includes year dummy variables.

longer period. The R-squared ranges between 22% and 31%, suggesting that the percentage changes in weight explain a reasonably large portion of the variation in the CARs.

The estimated coefficient on $D^{09}\Delta w/w^{S\&P\ GSCI}$ in Table 4 are positive for days 3, 4, 5, 10, and 15, though not statistically significant. The magnitude of the coefficients on $D^{09}\Delta w/w^{S\&P\ GSCI}$ is noteworthy. In particular, the coefficients on $D^{09}\Delta w/w^{S\&P\ GSCI}$ for days 3, 4, and 5 are 1.2 to 2.3 times larger than the coefficients on $\Delta w/w^{S\&P\ GSCI}$. This is consistent with expectation that the price impact of uninformed order flows is higher during the Great Recession of 2008–09 due to financial constraints facing financial intermediaries. It is not surprising that coefficients on $D^{09}\Delta w/w^{S\&P\ GSCI}$ are estimated imprecisely as there is only one major recession in the sample period.

The middle panel of Table 4 reports similar results when the abnormal return is from the constant-mean model. The estimated coefficients on $\Delta w/w^{S\&P\ GSCI}$ are positive but smaller for all regressions. The t-statistics also decrease, making the coefficient estimates less significant. Recall that the expected return is estimated from a constant-mean model over a 60-business-day window that ends one week preceding the rebalancing period. We often obtain positive intercept estimates especially in the first half of the sample period because of the upward trend in prices during the commodities boom. A non-zero intercept helps explain a small portion of the variation in the CARs, which reduces the estimated price impacts and the R-squared values. Once again, the coefficients on $D^{09}\Delta w/w^{S\&P\ GSCI}$ for days 3, 4, 5, 10, and 15 are substantially larger than the coefficients on $\Delta w/w^{S\&P\ GSCI}$.

When the abnormal return is estimated from a multi-factor model including a constant and several economic variables (bottom panel of Table 4), the estimated coefficients on $\Delta w/w^{S\&P\ GSCI}$ are almost identical to those when the raw return is used and the corresponding t-statistics are slightly smaller. Most importantly, no matter which model is used for estimating expected returns, the pattern of the results is similar. The change in weight, as a proxy for the order flows, explains a non-trivial portion of the variation in the CARs for the rebalancing period and the following week. In addition, the coefficients for price impact during the Great Recession tend to be much larger than for non-recessionary periods.

As a robustness check, we use the change in weight divided by open interest ($\Delta w/OI$) as the independent variable for the cross-sectional regressions. The open interest is the average of daily open interest of the nearby contract over a 10-day window prior to the rebalancing period and expressed in million contracts. By using the open interest to proxy for market size, we find again that the CARs can be well explained by the scaled weight changes.[17]

The cross-sectional regressions provide direct evidence that the proxies for the magnitude of the rebalancing order flows of the S&P GSCI have significant power in explaining abnormal returns. This finding is consistent with limits to arbitrage where price pressure is increasing in uninformative order imbalance, particularly during recessions.

4.4 Rebalancing of the Bloomberg Commodity Index

The S&P GSCI is not the only important commodity index that changes its weights. The Bloomberg Commodity Index (BCOM), another benchmark for investment in commodity futures markets, assigns weight to each commodity from the 6$^{\text{th}}$ through 10$^{\text{th}}$ business day in January, one day lagged relative to the S&P GSCI rebalancing period.[18] We repeat the event analysis by considering both the S&P GSCI and BCOM rebalancing. The BCOM includes 22 commodities with 20 of them included in the S&P GSCI (soybean oil and soybean meal are excluded). The BCOM is constructed in a similar way as the S&P GSCI but differs by imposing caps on the weights of sectors and individual markets. Since the weights

[17] The regression results are provided in the online appendix.

[18] The Bloomberg Commodity Index was launched in 1998 as the Dow Jones–AIG Commodity Index, renamed to Dow Jones–UBS Commodity Index in 2009, and current name in 2014.

of the BCOM also depend on historical production and trading volume information, order flows due the BCOM rebalancing are exogenous for the same reasons we present for the S&P GSCI in the introduction. We evaluate the joint rebalancing effect of the two commodity indexes by considering weight changes that are common to both indexes. Each year, we keep commodities if their weight changes are driven by the S&P GSCI rebalancing alone or if the weight change implied by the S&P GSCI rebalancing points in the same direction as that implied by the BCOM rebalancing. Otherwise, the price impact may be weakened if the rebalancing of the two indexes imply opposite weight changes.[19] By doing so, we have 230 observations left.

We evaluate the joint rebalancing effect of the two commodity indexes in a regression framework. Specifically, we include the percentage changes in weight of the S&P GSCI and the BCOM as separate independent variables and re-estimate model (9). Table 5 presents the estimated coefficients and t-statistics in parentheses. The dependent variable is the CAR for days [1, d] in percentage terms, where d takes values of 2, 3, 4, 5, 10, and 15. When d equals 1, only the S&P GSCI rebalancing exists and the results are the same as those in Table 4. The top panel of Table 5 reports results based on abnormal returns from the zero-mean model. The estimated coefficients on $\Delta w/w^{S\&P\ GSCI}$ are positive and statistically significant at a level of 0.05 on days 3, 4, 5, and 10. More importantly, the magnitudes of the estimated coefficients are almost identical to those reported in Table 4. The estimated coefficients on $\Delta w/w^{BCOM}$ are overall smaller and less significant. The coefficient on $\Delta w/w^{BCOM}$ has the same size as the coefficient on $\Delta w/w^{S\&P\ GSCI}$ on day 2 but declines to or below zero for the other days, suggesting that order flows due to the

[19] Since we do not know the relative size of assets tied to the S&P GSCI and the BCOM, the net rebalancing effect cannot be measured accurately. By assuming that the value of total assets tied to the S&P GSCI is two times as large as that tied to the BCOM, we calculate a weighted average of the weight changes implied by the two indexes and find similar results.

BCOM rebalancing is small and has little impact on futures price. Not surprisingly, the R-squared does not improve compared to values in Table 4 given the limited impact of BCOM rebalancing. The middle and bottom panels of Table 5 report similar results based on abnormal returns from the constant-mean and multi-factor models. In each panel, the estimated coefficients on $\Delta w/w^{BCOM}$ are smaller in magnitude than the coefficients on $\Delta w/w^{S\&P\ GSCI}$, strengthening the result that the BCOM rebalancing is less important and its associated order flows have limited effect on commodity futures prices.

5 Conclusions

The rebalancing of the S&P Goldman Sachs Commodity Index (S&P GSCI) provides a novel and strong identification to estimate the shape of supply curves for commodity futures contracts (long or short). Each year, the S&P GSCI reassigns weights to each commodity in the index during the January rebalancing period and the weight changes generate large and uninformed order flows in commodity futures markets. Using the 24 commodities included in the S&P GSCI for 2004–2017, we show that the cumulative abnormal returns (CARs) for the rebalancing period tend to have the same sign as changes in index weights. A long-short strategy that assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) index weight changes yields significantly positive returns. The price impact reaches a peak of 59 basis points in the middle of the week following the rebalancing period, but the impact is temporary as it declines to near zero within the next week. A similar pattern of price impact prevails across contracts along the futures curve, although it is slightly weaker for deferred-month contracts. Cross-sectional regression estimates show that the percentage changes in index weights, as a proxy for the size of the rebalancing flows, explains a significant portion of the variation in the CARs for the rebalancing period and the following week. This is consistent with limits to arbitrage, which implies that price pressure increases in the magnitude of uninformed order flow, especially during recessionary periods. The findings provide clear evidence that the supply curve for commodity futures contracts is upward sloping in the short-run but almost flat in the longer-run. Hence, the impact of trading activities of financial investors in commodity futures markets is likely modest and temporary.

Our results are consistent with those of Bessembinder et al. (2016), who argue that predictable and uninformed order flows such as those related to the rebalancing of major commodity indexes have modest and temporary market effects because they attract natural counterparties and additional liquidity suppliers. This explains our finding that large and predictable order flows due to the S&P GSCI rebalancing have a moderate and temporary impact on commodity futures price. Given the magnitude of rebalancing order flows, our results provide important evidence that commodity futures markets are highly liquid, resilient, and strategically competitive.

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7 Appendix: Derivation of Equation (5)

This appendix provides a derivation of Equation (5), which shows that order flows due to the S&P GSCI rebalancing are proportional to weight changes.

The S&P GSCI Excess Return Index is constructed in a cumulative manner with a base value of 100 on January 2, 1970 (S&P GSCI Methodology, April 2017, p. 23).[20] That is,

$$S_d = S_{d-1}(1 + CDR_d), \tag{A. 1}$$

where S_d is the value of the index on day d and CDR_d is the Contract Daily Return computed as a percentage change in the Total Dollar Weight (TDW), i.e., $CDR_d = \frac{TDW_d}{TDW_{d-1}} - 1$. The TDW_d on any business day that occurs during the rebalancing period is defined as (S&P GSCI Methodology, April 2017, p. 21)

$$TDW_d = \sum_c \left[\frac{NC_{new}}{NC_{old}} CPW_{old}^c * CRW1_d * DCRP1_d^c + CPW_{new}^c * CRW2_d * DCRP2_d^c \right], \tag{A. 2}$$

where CPW_{old}^c and CPW_{new}^c are the Contract Production Weights of commodity c prior to and after the rebalancing, $CRW1_d$ and $CRW2_d$ are the Contract Roll Weights of the first and second nearby futures contracts that take 0.8/0.2, 0.6/0.4, 0.4/0.6, 0.2/0.8, and 0/1 on the 5$^{\text{th}}$ through 9$^{\text{th}}$ business days, $DCRP1_d^c$ and $DCRP2_d^c$ are the Daily Contract Reference Prices of the first and second nearby futures contracts of commodity c, and NC_{old} and NC_{new} are the normalizing constants prior to and after the rebalancing, respectively.

For investors who track the S&P GSCI Excess Return Index, replication requires that the notional value of the index on day d must be equal to the sum of notional values of the positions held in each commodity market. That is,

$$S_d = \sum_c [X1_d^c * CS^c * DCRP1_d^c + X2_d^c * CS^c * DCRP2_d^c], \tag{A. 3}$$

[20] A derivation based on the S&P GSCI Total Return Index leads to the same result.

where CS^c is the Contract Size of commodity futures, and $X1_d^c$ and $X2_d^c$ are the positions of the first and second nearby futures contracts, respectively. Substituting Equations (A.2) and (A.3) into Equation (A.1) gives

$$\sum_c \frac{S_{d-1}}{TDW_{d-1}}\left[\frac{NC_{new}}{NC_{old}} CPW_{old}^c * CRW1_d * DCRP1_d^c + CPW_{new}^c * CRW2_d * DCRP2_d^c\right] = \sum_c [X1_d^c * CS^c * DCRP1_d^c + X2_d^c * CS^c * DCRP2_d^c]. \tag{A.4}$$

Note that Equation (A.4) holds for any values of $DCRP1_d^c$ and $DCRP2_d^c$, implying

$$X1_d^c = \frac{S_{d-1}}{TDW_{d-1}} \frac{NC_{new}}{NC_{old}} \frac{CPW_{old}^c * CRW1_d}{CS^c}, \tag{A.5}$$

$$X2_d^c = \frac{S_{d-1}}{TDW_{d-1}} \frac{CPW_{new}^c * CRW2_d}{CS^c}. \tag{A.6}$$

The total futures position in commodity c is given by

$$X1_d^c + X2_d^c = \frac{S_{d-1}}{TDW_{d-1}} \frac{1}{CS^c}\left[\frac{NC_{new}}{NC_{old}} CPW_{old}^c * CRW1_d + CPW_{new}^c * CRW2_d\right]. \tag{A.7}$$

Recall that the S&P GSCI rebalancing occurs within a 5-day window from the 5th to the 9th business day in January. Let $d = \{1, 2, 3, 4, 5\}$ be the rebalancing days and X_d^c be the total futures position. We have $CRW1_0 = 1$ and $CRW2_0 = 0$ for the day immediately prior to the start date of the rebalancing period ($d = 0$), and $CRW1_5 = 0$ and $CRW2_5 = 1$ for the last rebalancing day ($d = 5$). The total futures positions on those two days are:

$$X_0^c = \frac{S_0}{TDW_0} \frac{1}{CS^c} \frac{NC_{new}}{NC_{old}} CPW_{old}^c \text{ and } X_5^c = \frac{S_5}{TDW_5} \frac{1}{CS^c} CPW_{new}^c. \tag{A.8}$$

Since Equation (A.1) implies $\frac{S_0}{TDW_0} = \frac{S_5}{TDW_5}$, the position change is:

$$X_5^c - X_0^c = \frac{S_0}{TDW_0} \frac{1}{CS^c} (CPW_{new}^c - \frac{NC_{new}}{NC_{old}} CPW_{old}^c). \tag{A.9}$$

The ratio of normalizing constant is defined as (S&P GSCI Methodology, April 2017, p. 17),

$$\frac{NC_{new}}{NC_{old}} = \frac{\sum_c (CPW^c_{new} * DCRP^c_0)}{\sum_c (CPW^c_{old} * DCRP^c_0)}, \tag{A. 10}$$

where $DCRP^c_0$ is the price of the first nearby futures contract of commodity c on the last business day immediately prior to the start date of the rebalancing period. Substituting Equation (A.10) into Equation (A.9) and rearranging the terms gives

$$(X^c_5 - X^c_0) * DCRP^c_0 * CS^c = k * (w^c_{new} - w^c_{old}), \tag{A. 11}$$

where $k = S_0 \frac{NC_{new}}{NC_{old}}$, $w^c_{new} = \frac{CPW^c_{new} * DCRP^c_0}{\sum_c (CPW^c_{new} * DCRP^c_0)}$, and $w^c_{old} = \frac{CPW^c_{old} * DCRP^c_0}{\sum_c (CPW^c_{old} * DCRP^c_0)}$.

The left-hand side of Equation (A.11) represents the notional value of investment flow into or out of the market. k is a constant and can be interpreted as the total investment tied to the index. The weight change, $w^c_{new} - w^c_{old}$, is driven only by CPW change given that the same prices are used for calculating weights prior to and after the rebalancing period. Therefore, order flows due to the S&P GSCI rebalancing are proportional to weight changes.

8 Figures and Tables

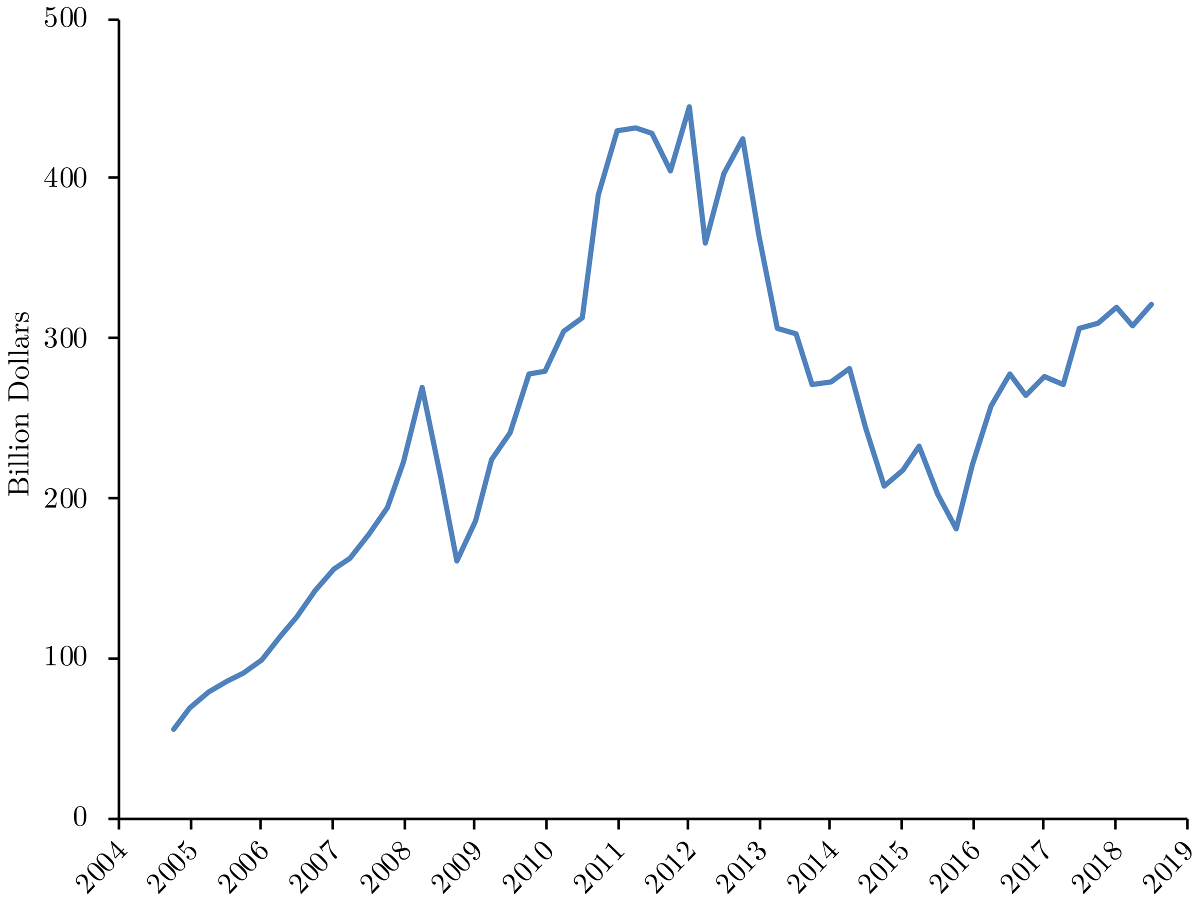

Figure 1. Total global commodity-linked investment

The figure shows total global commodity-linked investment as estimated quarterly by Barclays. Three categories of commodity-linked investment are included in the total: broad index swaps, exchange traded products and medium term notes. The sample period is the fourth quarter of 2004 through the third quarter of 2018.

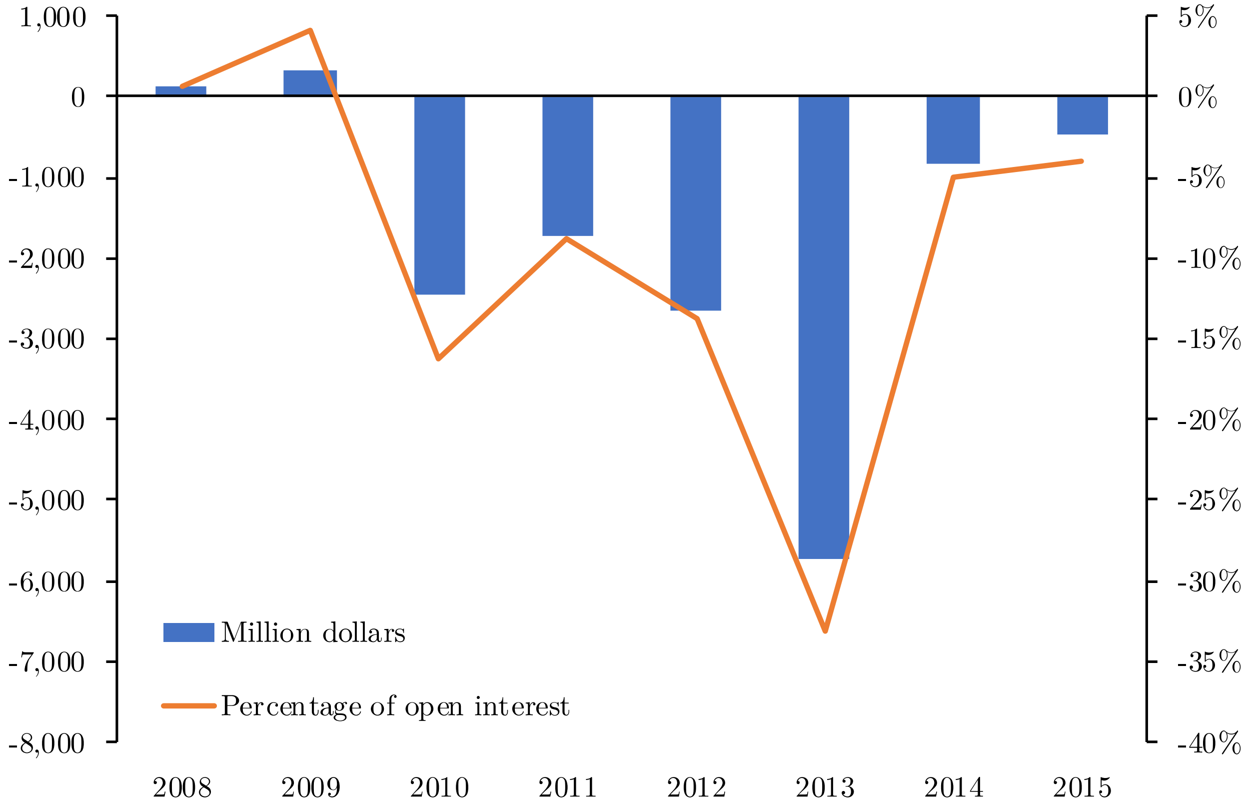

Figure 2. Order flows due to the S&P GSCI rebalancing for WTI crude oil

The figure shows order flows into or out of WTI crude oil market due to the S&P GSCI rebalancing for 2008–2015. Order flows are measured in dollars and percentages of open interest, where open interest is the average of daily open interests of the contract held by the index over a 2-week window prior to the rebalancing period. The notional value of total assets tied to the S&P GSCI is assumed to be two-thirds of the total index investment in major U.S. futures markets based on the CFTC IID report.

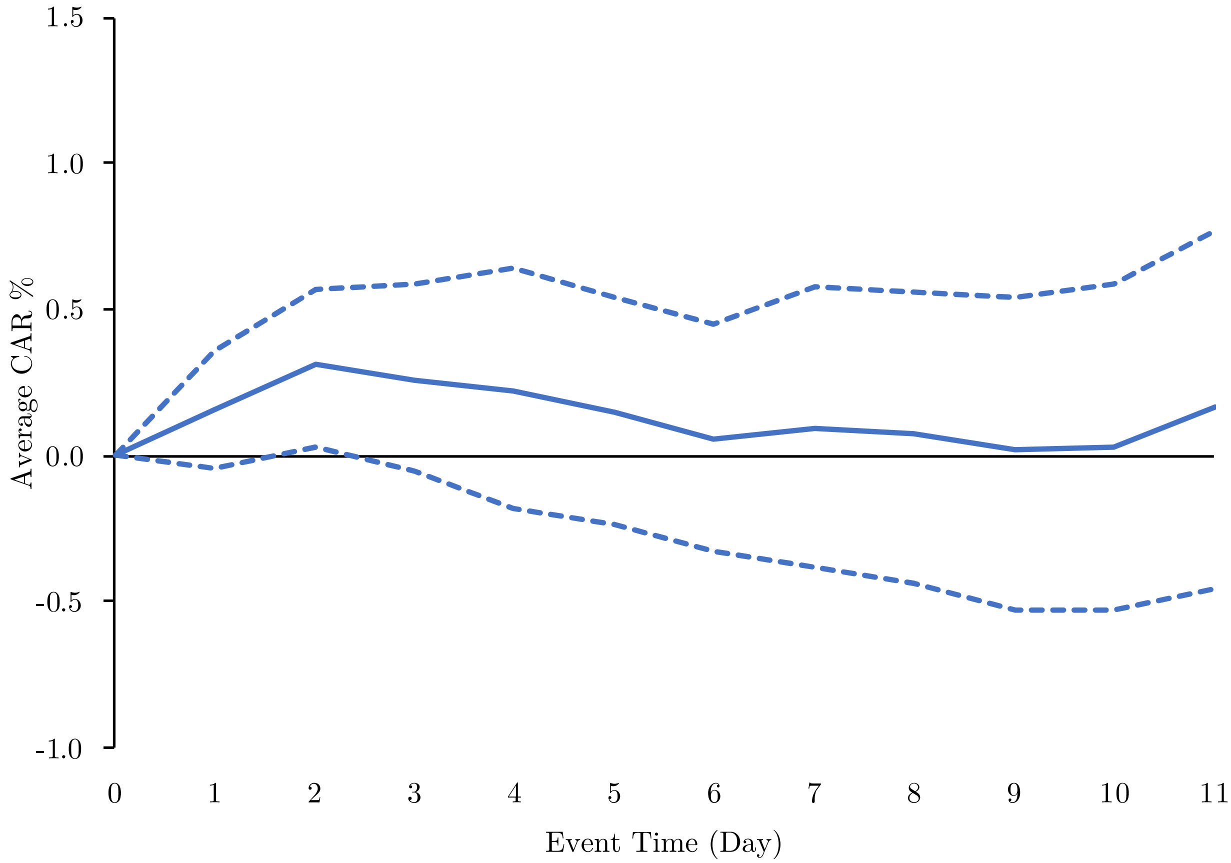

Figure 3. Average cumulative abnormal returns for a long-short strategy following the S&P GSCI rebalancing announcement date

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy following the S&P GSCI rebalancing announcement date. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing announcement date, and expressed in percentage terms. Day 1 is the rebalancing announcement date. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

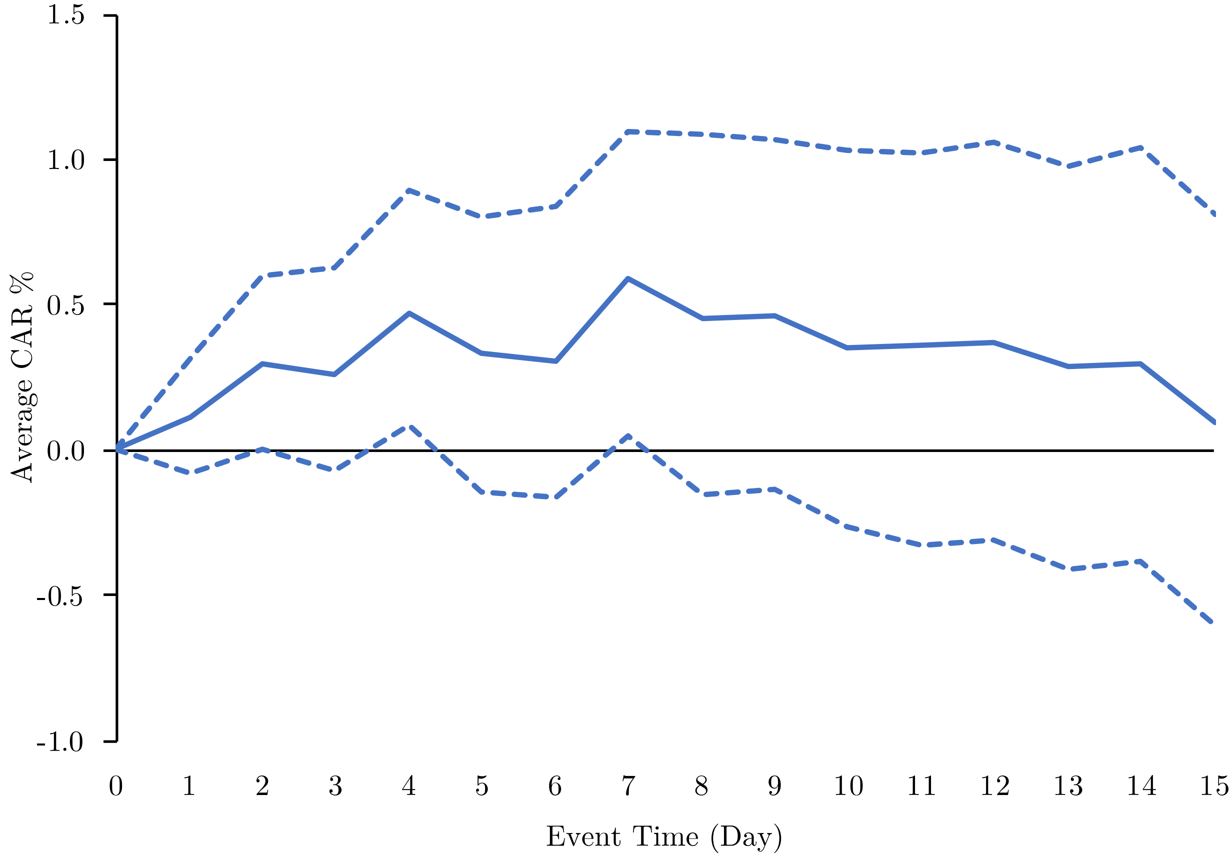

Figure 4. Average cumulative abnormal returns for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

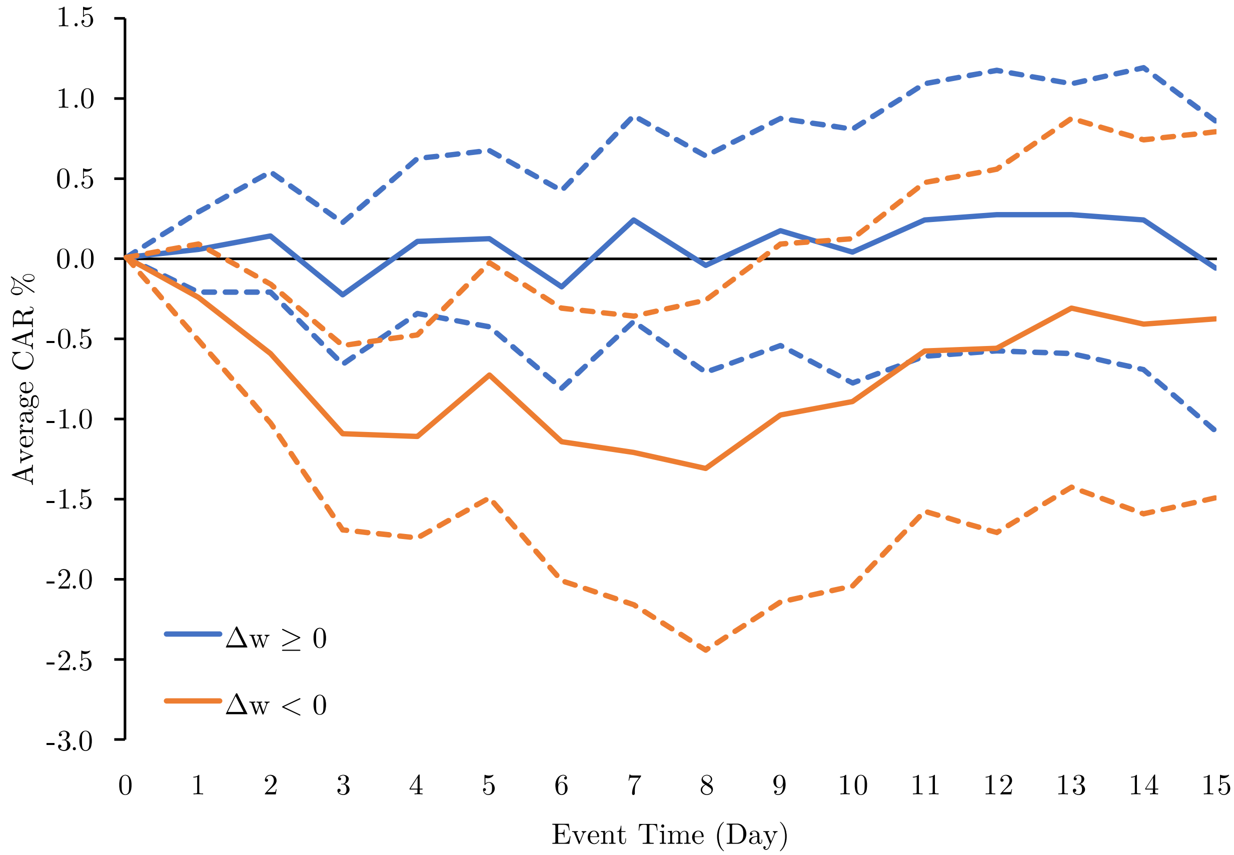

Figure 5. Average cumulative abnormal returns for positive and negative weight changes over the S&P GSCI rebalancing period and the following 10 days

The figure shows the average cumulative abnormal returns (CARs) for positive and negative weight changes over the S&P GSCI rebalancing period and the following 10 days. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

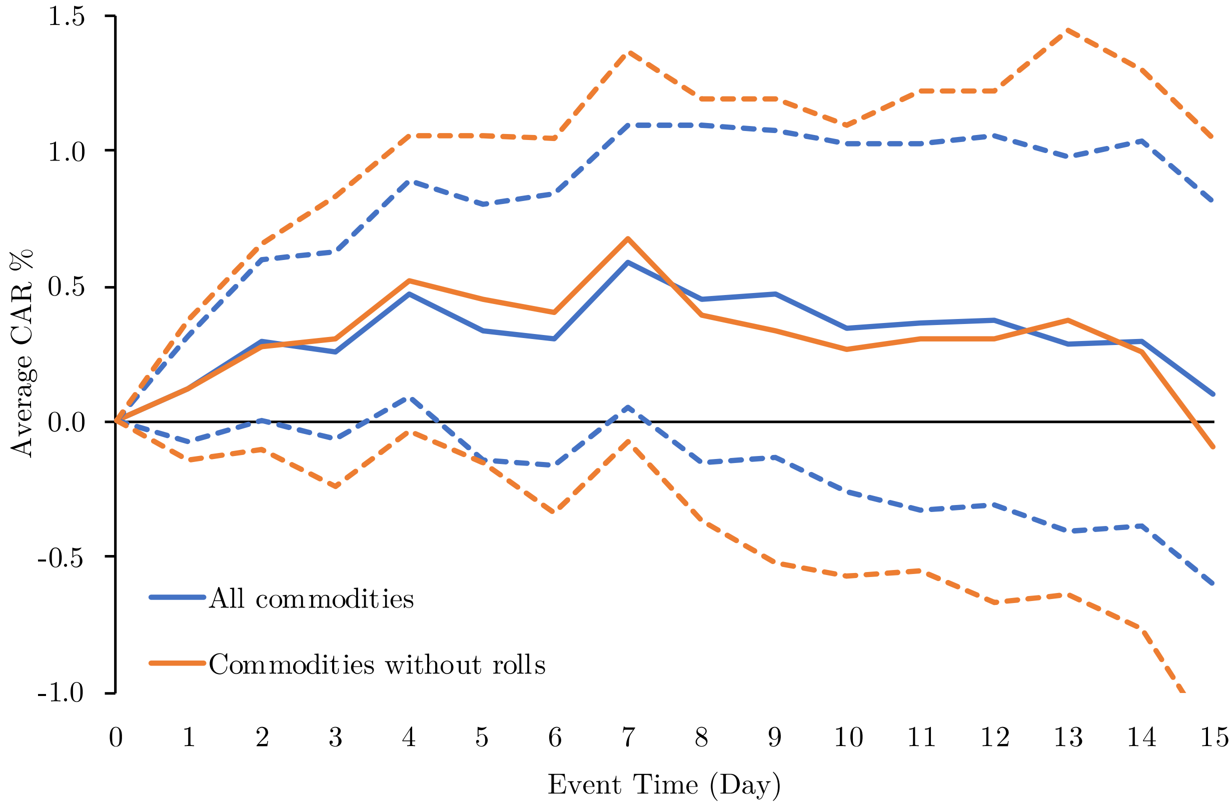

Figure 6. Average cumulative abnormal returns for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days for commodities that have no rolls

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days for commodities that have no rolls. The commodities that experience rebalancing alone are: corn, cocoa, coffee, cotton, feeder cattle, silver, soybeans, sugar, Chicago wheat, and Kansas wheat. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

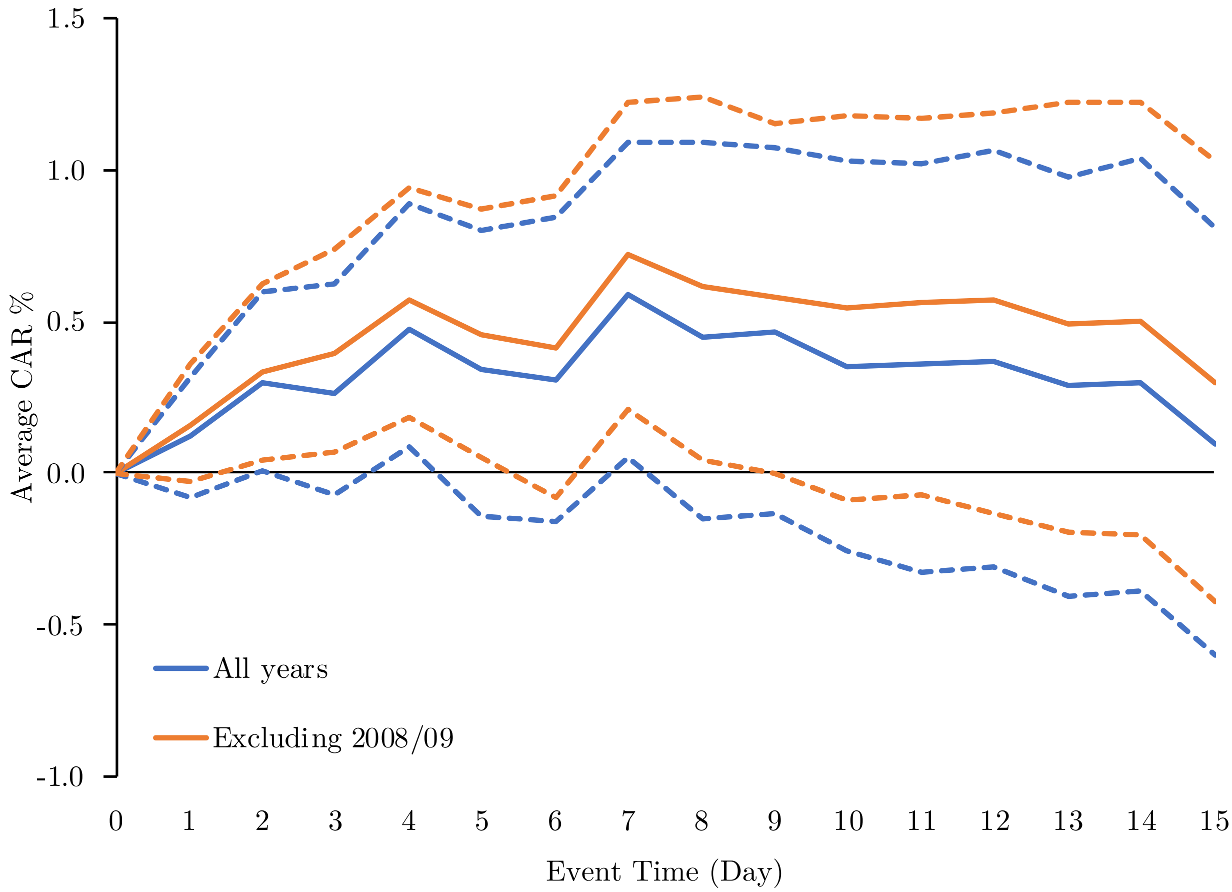

Figure 7. Average cumulative abnormal returns for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days excluding the Great Recession

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days when the Great Recession (2008/09 rebalancing) is excluded. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the S&P GSCI rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

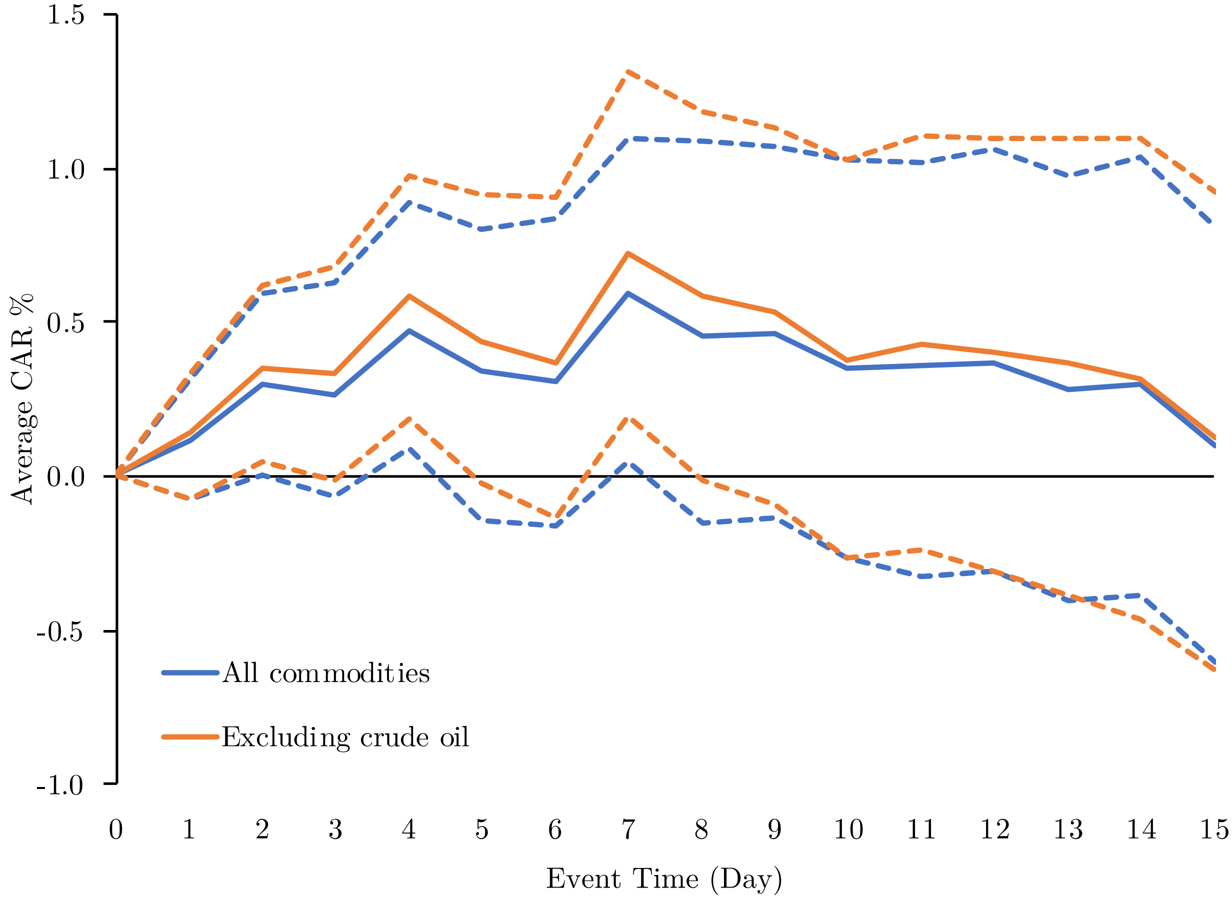

Figure 8. Average cumulative abnormal returns for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days with and without crude oil

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days with and without WTI and Brent crude oil. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the S&P GSCI rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

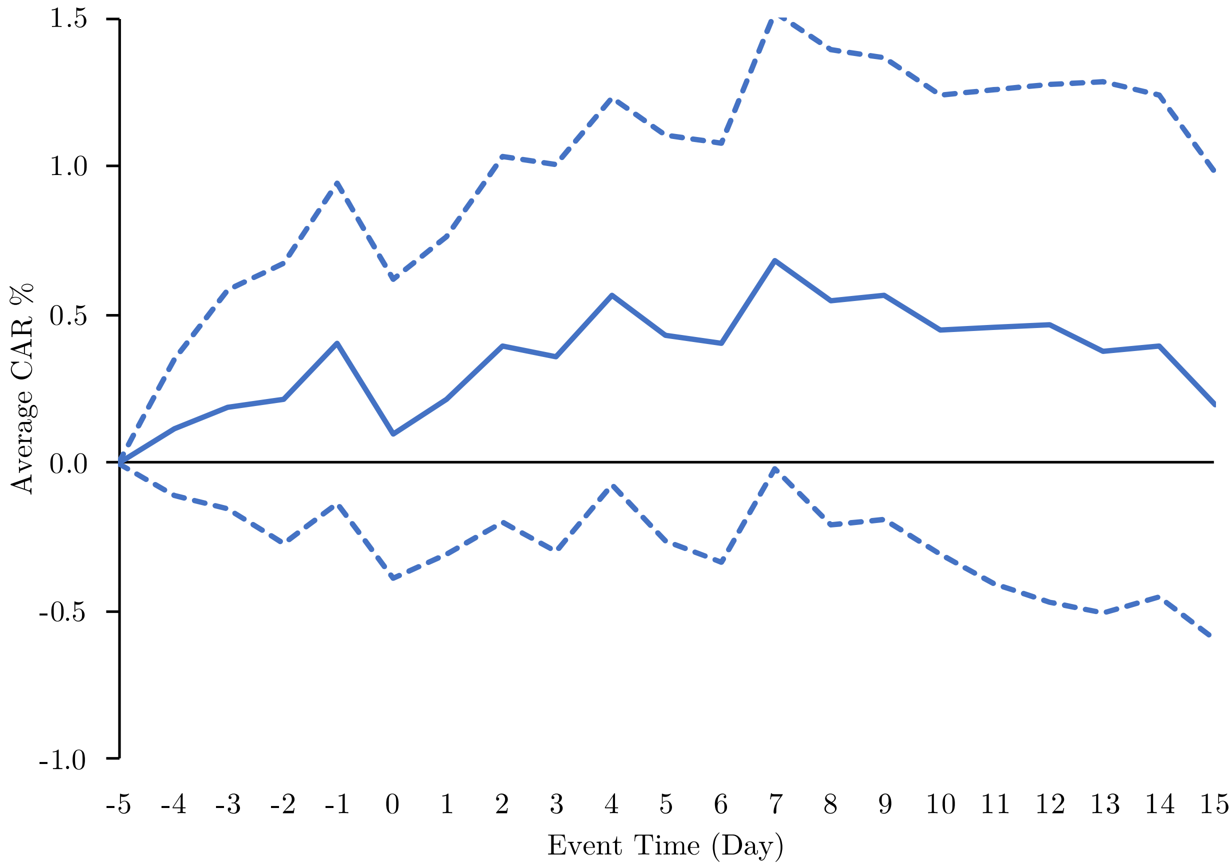

Figure 9. Average cumulative abnormal returns for a long-short strategy over the period that begins one week prior to the S&P GSCI rebalancing period

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the period that begins one week prior to the S&P GSCI rebalancing period. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day –5, the day a week preceding the rebalancing period, and expressed in percentage terms. Days 1–5 denote the S&P GSCI rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

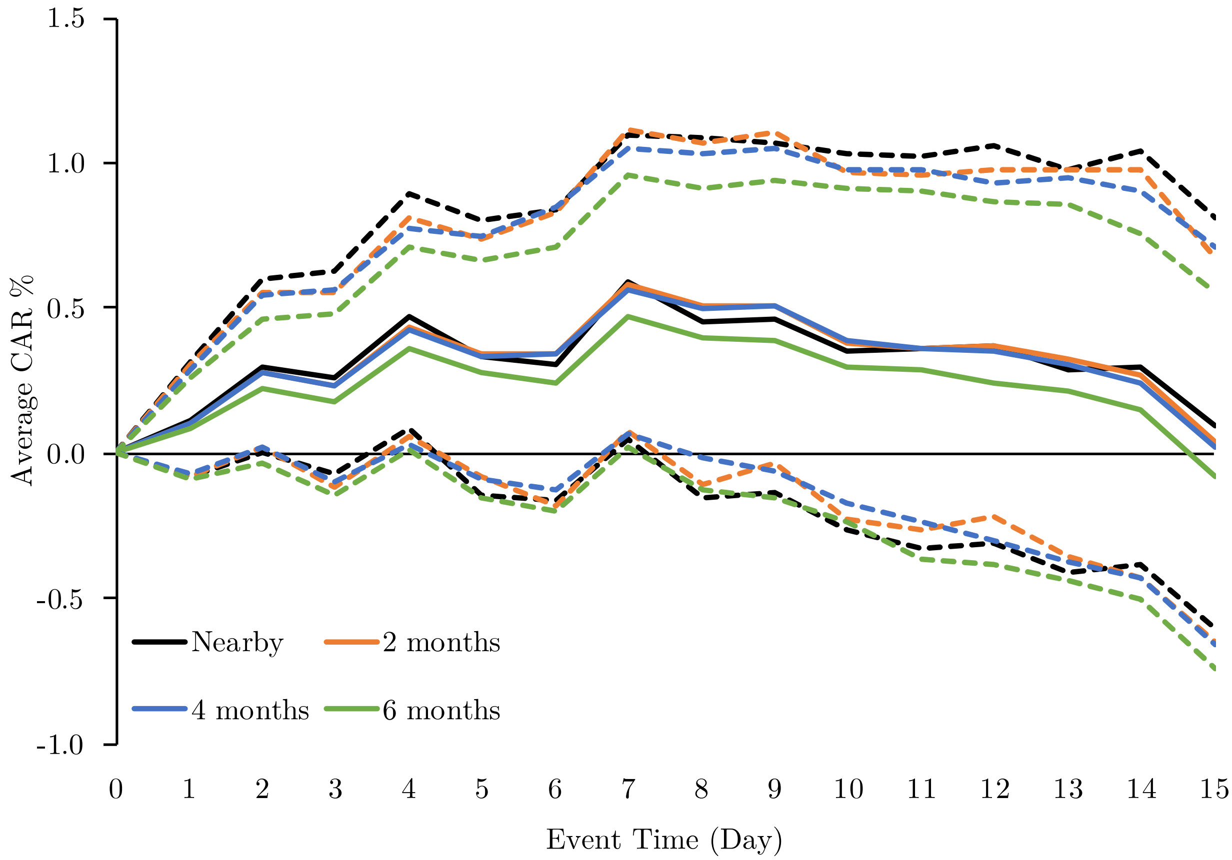

Figure 10. Average cumulative abnormal returns for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days for contracts with various maturities

The figure shows the average cumulative abnormal returns (CARs) for a long-short strategy over the S&P GSCI rebalancing period and the following 10 days. The CARs are based on prices from contracts that have at least k-month to maturity, where k = 2, 4, and 6. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. The CARs are normalized to be zero on day 0, the day immediately prior to the rebalancing period, and expressed in percentage terms. Days 1–5 denote the rebalancing dates. Abnormal returns are based on a zero-mean model. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017. Dashed lines indicate 95% confidence intervals.

Table 1. Order flows due to S&P GSCI rebalancing

	Absolute weight change (%)	Order flow due to the rebalancing in absolute terms			
		Dollar (million)	Number of Contracts	Percent of volume	Percent of open interest
Chicago Wheat	0.11	80.04	2,160	5.43	1.04
Kansas Wheat	0.14	106.68	2,832	31.42	4.20
Corn	0.09	76.77	3,097	2.60	0.55
Soybeans	0.07	53.43	942	1.15	0.42
Coffee	0.01	11.01	184	1.59	0.24
Sugar	0.02	15.17	689	1.58	0.23
Cocoa	0.01	6.22	222	2.68	0.29
Cotton	0.03	26.87	605	5.16	0.56
Lean Hogs	0.05	41.68	1,271	14.38	2.18
Live Cattle	0.06	55.08	1,311	11.85	1.73
Feeder Cattle	0.04	30.57	437	16.41	2.98
WTI Crude Oil	1.87	1795.78	20,400	25.59	10.74
Heating Oil	0.41	303.29	2,874	14.79	6.06
RBOB Gasoline	0.60	376.08	3,909	24.77	8.14
Brent Crude Oil	1.39	1208.66	12,878	31.67	16.96
Gasoil	0.56	513.13	7,034	23.61	12.28
Natural Gas	0.09	70.83	1,404	4.37	0.95
Aluminum	0.06	51.70	233	0.39	0.07
Copper	0.04	31.32	88	0.21	0.06
Nickel	0.01	6.59	15	0.13	0.03
Lead	0.01	10.22	195	1.38	0.41
Zinc	0.01	10.19	798	2.37	0.63
Gold	0.08	69.71	2,313	25.25	4.48
Silver	0.00	2.74	55	0.15	0.06
Average	0.24	206.41	2,748	10.37	3.14

The table reports the average weight changes and order flows due to rebalancing in absolute values for each of the 24 commodities included in the S&P GSCI for 2008–2015. Weight change is the difference of percentage dollar weights before and after the rebalancing. Order flows are measured in dollars, number of contracts, percent of volume, and percent of open interest, where volume (open interest) is the average of daily volumes (open interests) of the contract held by the index over a 2-week window prior to the rebalancing period. The notional value of total assets tied to the S&P GSCI is assumed to be two-thirds of the total index investment in major U.S. futures markets, which is available from the CFTC IID report for 2008–2015.

Table 2. Changes in agricultural index trader positions around the S&P GSCI rebalancing period

	2-week containing the rebalancing period	2-week prior to the rebalancing period	2-week after the rebalancing period	Other non-rebalancing weeks
Chicago Wheat	3.91	0.89	1.98	1.66
Kansas Wheat	4.92	1.69	2.43	2.42
Corn	4.35	1.05	1.34	1.57
Soybeans	3.21	1.70	1.81	1.74
Coffee	5.71	1.37	2.27	1.69
Sugar	4.55	1.07	2.46	1.56
Cocoa	2.50	2.22	5.05	3.26
Cotton	3.69	1.07	2.44	1.83
Lean Hogs	4.81	1.12	2.22	1.65
Live Cattle	4.00	0.96	1.75	1.31
Feeder Cattle	3.32	1.97	3.80	3.11
Average	4.09	1.37	2.50	1.98

The table presents the average absolute percentage changes in gross long positions held by index traders for four different periods—2-week containing the rebalancing period, 2-week prior to the rebalancing period, 2-week after the rebalancing period, and other non-rebalancing weeks. Index positions are from the weekly CFTC SCOT report for 1/3/2006–12/27/2016. The SCOT report provides a breakdown of each Tuesday's open interest for 12 agricultural commodity markets and our calculations are for 11 of the 12 commodities included in the S&P GSCI (soybean oil is excluded).

Table 3. Average cumulative abnormal returns over the S&P GSCI rebalancing period

	All		Δw > 0		Δw < 0		Long-Short	
	N = 336		N = 213		N = 123		N = 336	
Days	CAR	*t*-stat	CAR	*t*-stat	CAR	*t*-stat	CAR	*t*-stat
				Zero-mean model				
[1, 1]	-0.06	-0.58	0.05	0.39	-0.24	-1.54	0.12	1.24
[1, 2]	-0.13	-0.87	0.14	0.70	-0.59	-2.67***	0.30	2.08**
[1, 3]	-0.54	-3.03***	-0.22	-1.01	-1.10	-3.78***	0.26	1.40
[1, 4]	-0.34	-1.72*	0.10	0.40	-1.11	-3.41***	0.47	2.35***
[1, 5]	-0.19	-0.80	0.12	0.42	-0.72	-1.96**	0.34	1.42
[1, 10]	-0.30	-0.94	0.04	0.09	-0.89	-1.62	0.35	1.10
[1, 15]	-0.18	-0.49	-0.07	-0.14	-0.38	-0.66	0.10	0.26
				Constant-mean model				
[1, 1]	-0.02	-0.23	0.06	0.43	-0.16	-1.04	0.09	1.01
[1, 2]	-0.06	-0.43	0.15	0.76	-0.44	-2.01**	0.26	1.72*
[1, 3]	-0.45	-2.65***	-0.20	-0.87	-0.88	-3.40***	0.20	1.17
[1, 4]	-0.22	-1.11	0.13	0.54	-0.83	-2.73***	0.39	2.01**
[1, 5]	-0.04	-0.19	0.16	0.57	-0.39	-1.14	0.24	1.13
[1, 10]	-0.02	-0.07	0.12	0.30	-0.26	-0.51	0.17	0.54
[1, 15]	0.24	0.58	0.05	0.10	0.57	0.91	-0.18	-0.42
				Multi-factor model				
[1, 1]	-0.02	-0.20	0.04	0.25	-0.12	-0.74	0.07	0.62
[1, 2]	0.11	0.74	0.34	1.55	-0.27	-1.19	0.32	2.04**
[1, 3]	-0.16	-0.87	0.12	0.48	-0.65	-2.36***	0.32	1.65
[1, 4]	0.14	0.64	0.46	1.70	-0.42	-1.24	0.45	2.06**
[1, 5]	0.42	1.63	0.62	1.88*	0.07	0.16	0.37	1.43
[1, 10]	0.77	2.14**	0.79	1.75*	0.73	1.03	0.23	0.62
[1, 15]	0.98	1.97**	0.62	1.06	1.61	1.77	-0.20	-0.39

The table presents the average cumulative abnormal returns (CARs) over the S&P GSCI rebalancing period in percentage terms. Average CARs are calculated for all weight changes (All), positive weight changes ($\Delta w \geq 0$), negative weight changes ($\Delta w < 0$), and a long-short strategy. The long-short strategy assigns an equal weight to each commodity and holds a long (short) position in commodities that experience positive (negative) weight changes. Abnormal returns are calculated based on the zero-mean, constant-mean, and multi-factor models using futures prices of the contract held by the index. Days 1–5 denote the rebalancing dates. The *t*-statistic is for the null hypothesis that the average CAR equals zero and *, **, and *** indicate significance at levels of 10%, 5%, and 1%, respectively. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017.

Table 4. Cross-sectional regressions of cumulative abnormal return on weight change due to the S&P GSCI rebalancing

CAR	[1, 1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]	[1, 10]	[1, 15]
			Zero-mean model				
$\Delta w/w^{S\&P\ GSCI}$	0.04*	0.06*	0.09***	0.14***	0.11**	0.15**	0.08
	(1.76)	(1.82)	(2.43)	(3.12)	(2.17)	(2.03)	(1.01)
$D^{09}\Delta w/w^{S\&P\ GSCI}$	-0.03	-0.03	0.11	0.19	0.25	0.14	0.11
	(-0.30)	(-0.25)	(0.67)	(1.07)	(1.19)	(0.45)	(0.32)
R^2	0.19	0.20	0.31	0.26	0.27	0.22	0.27
			Constant-mean model				
$\Delta w/w^{S\&P\ GSCI}$	0.03	0.05	0.08*	0.12***	0.08	0.10	0.01
	(1.43)	(1.41)	(1.93)	(2.52)	(1.54)	(1.33)	(0.09)
$D^{09}\Delta w/w^{S\&P\ GSCI}$	-0.01	0.00	0.15	0.25	0.32	0.28	0.32
	(-0.13)	(-0.02)	(0.94)	(1.35)	(1.48)	(0.90)	(0.86)
R^2	0.16	0.19	0.21	0.16	0.14	0.16	0.30
			Multi-factor model				
$\Delta w/w^{S\&P\ GSCI}$	0.04	0.05	0.09**	0.13***	0.12*	0.17*	0.08
	(1.60)	(1.39)	(2.11)	(2.67)	(1.90)	(1.95)	(0.73)
$D^{09}\Delta w/w^{S\&P\ GSCI}$	-0.00	-0.01	0.13	0.25	0.29	0.22	0.15
	(-0.02)	(-0.05)	(0.72)	(1.22)	(1.16)	(0.60)	(0.32)
R^2	0.25	0.15	0.18	0.16	0.16	0.15	0.22

The table presents the estimation results of regressions of cumulative abnormal return (CAR) on weight change due to the S&P GSCI rebalancing. The dependent variable is the CAR for days 1 to d, where d = 1, 2, 3, 4, 5, 10, and 15. Days 1–5 are the S&P GSCI rebalancing dates. Abnormal returns are calculated based on the zero-mean, constant-mean, and multi-factor models using futures prices of the contract held by the index. The independent variable is the percentage change in weight ($\Delta w/w^{S\&P\ GSCI}$) due to the S&P GSCI rebalancing. Regressions are estimated using a fixed-effects model with time effect. The *t*-statistics are in parentheses and *, **, and *** indicate significance at levels of 10%, 5%, and 1%, respectively. The sample consists of 24 commodities included in the S&P GSCI for 2004–2017.

Table 5. Cross-sectional regressions of cumulative abnormal return on weight change due to the S&P GSCI and BCOM rebalancing

CAR	[1, 2]	[1, 3]	[1, 4]	[1, 5]	[1, 10]	[1, 15]
			Zero-mean model			
$\Delta w/w^{S\&P\ GSCI}$	0.06*	0.10***	0.15***	0.12***	0.15**	0.09
	(1.84)	(2.67)	(3.44)	(2.48)	(2.16)	(1.07)
$\Delta w/w^{BCOM}$	0.06***	0.05**	0.02	0.01	-0.04	0.01
	(2.68)	(2.16)	(0.63)	(0.42)	(-0.76)	(0.17)
R^2	0.22	0.31	0.26	0.27	0.22	0.27
			Constant-mean model			
$\Delta w/w^{S\&P\ GSCI}$	0.05	0.08**	0.13***	0.10*	0.11	0.02
	(1.47)	(2.23)	(2.89)	(1.91)	(1.55)	(0.28)
$\Delta w/w^{BCOM}$	0.06***	0.06***	0.02	0.02	-0.02	0.03
	(2.77)	(2.32)	(0.81)	(0.63)	(-0.42)	(0.55)
R^2	0.21	0.22	0.16	0.15	0.16	0.31
			Multi-factor model			
$\Delta w/w^{S\&P\ GSCI}$	0.05	0.10***	0.15***	0.13**	0.18**	0.09
	(1.42)	(2.35)	(3.03)	(2.21)	(2.12)	(0.81)
$\Delta w/w^{BCOM}$	0.06***	0.06**	0.04	0.03	0.04	0.08
	(2.50)	(2.21)	(1.38)	(0.80)	(0.69)	(1.07)
R^2	0.17	0.19	0.17	0.16	0.15	0.22

The table presents the estimation results of regressions of cumulative abnormal return (CAR) on weight change due to the S&P GSCI and BCOM rebalancing. The dependent variable is the CAR for periods of days 1 to d, where d = 2, 3, 4, 5, 10, and 15. Days 2–5 are the rebalancing dates common to the S&P GSCI and the BCOM. Abnormal returns are calculated based on the zero-mean, constant-mean, and multi-factor models using futures prices of the contract held by the S&P GSCI. The independent variables are the percentage changes in weights due to the S&P GSCI and the BCOM rebalancing. Regressions are estimated using a fixed-effects model with time effect. The t-statistics are in parentheses and *, **, and *** indicate significance at levels of 10%, 5%, and 1%, respectively. The sample consists of 20 commodities included in both the S&P GSCI and BCOM for 2004–2017.

9 Data Appendix

Table A1. Commodity futures included in the S&P GSCI

Commodity	Trading facility	Contract expiration at month begin											
		1	2	3	4	5	6	7	8	9	10	11	12
Chicago Wheat	CBT	H	H	K	K	N	N	U	U	Z	Z	Z	H
Kansas Wheat	KBT	H	H	K	K	N	N	U	U	Z	Z	Z	H
Corn	CBT	H	H	K	K	N	N	U	U	Z	Z	Z	H
Soybeans	CBT	H	H	K	K	N	N	X	X	X	X	F	F
Coffee	ICE	H	H	K	K	N	N	U	U	Z	Z	Z	H
Sugar	ICE	H	H	K	K	N	N	V	V	V	H	H	H
Cocoa	ICE	H	H	K	K	N	N	U	U	Z	Z	Z	H
Cotton	ICE	H	H	K	K	N	N	Z	Z	Z	Z	Z	H
Lean Hogs	CME	G	J	J	M	M	N	Q	V	V	Z	Z	G
Live Cattle	CME	G	J	J	M	M	Q	Q	V	V	Z	Z	G
Feeder Cattle	CME	H	H	J	K	Q	Q	Q	U	V	X	F	F
WTI Crude Oil	NYM	G	H	J	K	M	N	Q	U	V	X	Z	F
Heating Oil	NYM	G	H	J	K	M	N	Q	U	V	X	Z	F
RBOB Gasoline	NYM	G	H	J	K	M	N	Q	U	V	X	Z	F
Brent Crude Oil	ICE	H	J	K	M	N	Q	U	V	X	Z	F	G
Gasoil	ICE	G	H	J	K	M	N	Q	U	V	X	Z	F
Natural Gas	NYM	G	H	J	K	M	N	Q	U	V	X	Z	F
Aluminum	LME	G	H	J	K	M	N	Q	U	V	X	Z	F
Copper	LME	G	H	J	K	M	N	Q	U	V	X	Z	F
Nickel	LME	G	H	J	K	M	N	Q	U	V	X	Z	F
Lead	LME	G	H	J	K	M	N	Q	U	V	X	Z	F
Zinc	LME	G	H	J	K	M	N	Q	U	V	X	Z	F
Gold	CMX	G	J	J	M	M	Q	Q	Z	Z	Z	Z	G
Silver	CMX	H	H	K	K	N	N	U	U	Z	Z	Z	H

The table lists futures contracts of the 24 commodities included in the S&P GSCI. CBT represents the Chicago Board of Trade. KBT represents the Kansas City Board of Trade. ICE represents the Intercontinental Exchange. CME represents the Chicago Mercantile Exchange. NYM represents the New York Mercantile Exchange. LME represents the London Metal Exchange. The table also lists maturities of the futures contracts held by the index at the beginning of each calendar month. Futures month codes are: January (F), February (G), March (H), April (J), May (K), June (M), July (N), August (Q), September (U), October (V), November (X), and December (Z).

Table A2. Reference percentage dollar weights of the components in the S&P GSCI

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Chicago Wheat	3.97	3.81	2.36	2.18	3.39	3.85	3.99	2.97	3.16	3.19	3.42	2.93	3.53	3.87	3.33
Kansas Wheat	1.75	1.40	0.88	0.92	0.80	0.80	0.83	0.69	0.98	0.67	0.78	0.75	0.87	1.07	0.94
Corn	4.23	4.07	2.33	2.09	3.28	3.31	4.03	3.34	4.61	4.71	4.99	3.39	4.19	5.48	3.86
Soybeans	2.45	3.09	1.71	1.43	1.84	2.21	2.92	2.37	2.55	2.62	2.91	2.77	2.95	3.81	2.54
Coffee	0.68	0.67	0.77	0.65	0.69	0.55	0.78	0.76	1.02	0.81	0.57	0.67	0.93	1.03	0.76
Sugar	1.60	1.24	1.25	1.77	1.24	0.91	1.92	2.27	2.33	1.86	1.46	1.39	1.58	2.47	1.66
Cocoa	0.44	0.30	0.22	0.18	0.22	0.22	0.38	0.39	0.30	0.23	0.23	0.30	0.45	0.59	0.32
Cotton	1.64	1.72	0.96	0.86	0.89	0.78	0.97	1.25	1.88	1.07	1.01	1.07	1.19	1.54	1.20
Lean Hogs	2.06	2.38	1.96	1.49	1.51	1.00	1.55	1.57	1.48	1.59	1.69	2.11	2.33	2.67	1.81
Live Cattle	4.13	3.88	2.85	2.62	2.72	2.03	3.06	2.60	2.39	2.59	2.72	3.16	4.87	5.19	3.20
Feeder Cattle	0.81	0.93	0.77	0.66	0.54	0.39	0.51	0.44	0.41	0.51	0.50	0.72	1.57	1.53	0.74
WTI Crude Oil	25.34	25.75	31.05	37.11	35.60	39.86	35.05	34.86	30.28	24.66	23.64	24.40	23.03	22.91	29.54
Heating Oil	7.41	7.10	8.40	5.99	4.65	4.85	4.58	4.63	4.73	6.16	6.02	5.88	5.29	4.03	5.69
RBOB Gasoline	7.99	8.02	7.65	1.46	4.64	4.72	4.33	4.66	4.80	5.99	6.03	5.74	5.36	4.64	5.43
Brent Crude Oil	11.85	11.82	14.20	14.94	13.02	13.71	14.00	15.17	17.38	22.43	23.22	24.69	20.20	16.40	16.65
Gasoil	3.76	3.89	4.58	5.25	4.56	5.25	5.79	6.29	7.48	8.58	8.29	7.36	5.82	4.87	5.84
Natural Gas	11.36	10.09	9.59	9.87	7.17	6.32	5.18	4.10	2.83	1.96	2.55	3.18	3.28	3.20	5.76
Aluminum	3.12	3.31	2.78	3.08	3.52	2.45	2.51	2.73	2.55	2.14	2.02	2.00	2.88	3.27	2.74
Copper	1.76	2.39	2.24	3.39	4.03	3.02	2.85	3.68	3.74	3.27	3.21	3.11	3.84	4.08	3.19
Nickel	0.64	0.93	0.79	0.80	1.63	0.79	0.66	0.83	0.79	0.58	0.53	0.55	0.70	0.66	0.78
Lead	0.22	0.31	0.28	0.28	0.52	0.46	0.41	0.51	0.47	0.40	0.45	0.47	0.60	0.74	0.44
Zinc	0.51	0.57	0.53	0.93	1.30	0.57	0.57	0.72	0.61	0.51	0.53	0.59	0.88	1.01	0.70
Gold	2.10	2.11	1.67	1.82	1.95	1.70	2.82	2.81	2.67	2.99	2.80	2.41	3.25	4.40	2.53
Silver	0.19	0.23	0.19	0.23	0.29	0.24	0.31	0.36	0.54	0.49	0.44	0.34	0.41	0.55	0.34

The table presents the reference percentage dollar weights for the 24 commodities included in the S&P GSCI for 2004–2017. Reference percentage dollar weights are calculated based on Equation (1), where reference price is the average of the prices of the contract held by the index on the last day of each calendar month over the annual calculation period.