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Abstract

Using proprietary data reported by swap dealers to the Commodity Futures Trading Commission, we present new evidence on the size and composition of 13 over-the-counter agricultural swaps markets, and show the existence of linkages with the equity markets. We use the spike in the Chicago Board Options Exchange Volatility Index in early 2020 to show that swaps trader positions were significantly impacted by the financial market volatility created by the COVID-19 pandemic. Following similar methods as Cheng et al. (2015), we find index swaps traders reduce their net long positions in response to tightening financial conditions, while commercial swaps traders absorb some of this risk by decreasing their net short positions. This internal swap market netting occurs in three of the four largest agricultural

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[2]Both authors are research economists in the CFTC Office of the Chief Economist. This research was produced in each author's official capacity. The analyses and conclusions expressed in this paper are those of the authors and do not necessarily reflect the views of other Commission staff, the Office of the Chief Economist, or the Commission. This paper has been cleared for public distribution by the CFTC Office of the Chief Economist.

markets, corn, soft red winter wheat, and sugar. Swap market netting translates into lower hedging demand for swap dealers in the futures market, especially when compared to other financial traders. Our results confirm that equity market shocks can affect traders in both commodity swaps and futures markets.

Keywords: commodity swaps, commodity futures, financialization, swap dealer, swap market netting

JEL codes: G12, G13, G23, Q13

1 Introduction

Agricultural commodity prices reached near record highs in late 2021, driven by shifting consumer demand, supply chain disruptions, and tightening labor markets in the wake of the COVID-19 pandemic (Cowley et al., 2023). The resulting price inflation pushed the value of index investment in over-the-counter (OTC) agricultural swaps to $88 billion notional by December 2021, the highest level measured since before the Great Recession of 2008 (figure 1).[3] Similarly, total multi-commodity index investment, measured across the largest 21 commodities, reached a record $206 billion notional as of December 2021.[4][5] The growing size of OTC swap commodity index investment over the last two decades highlights the need for better data on the size and trader composition of these markets. Using proprietary data on commodity swaps collected by the Commodity Futures Trading Commission (CFTC), this paper explores the size and composition of agricultural swaps markets and uses the COVID-19 pandemic to examine cross-market linkages with equities markets.

The majority of commodity index investment occurs in OTC swaps markets,

[3]Notional value of agricultural multi-commodity index investment is based on authors' calculation using CFTC index swaps data for thirteen agricultural contracts: Chicago Board of Trade (CBOT) corn, soybeans, soft red winter (SRW) wheat, hard red winter (HRW) wheat, soybean meal, soybean oil, feeder cattle, live cattle, lean hogs, and Intercontinental Exchange (ICE) sugar no.11, cotton no.2, cocoa, and coffee.

[4]Total multi-commodity index investment includes 13 agricultural commodities, as well as 8 energy (e.g., New York Mercantile Exchange West Texas Intermediate (WTI) light sweet crude oil) and metal commodities (e.g., Commodity Exchange Gold).

[5]Measured in futures-equivalent contracts, we also see continued growth in OTC commodity index investment since 2007.

where institutional investors (e.g., hedge funds, pensions, endowment funds) gain passive buy-side exposure to commodity prices through swap contracts with swap dealers (CFTC, 2008). Despite the growing size of index investment through OTC commodity swaps markets, detailed data have only been collected by the CFTC since 2013 and are not publicly available. [6] As a result, studies of the effects of multi-commodity index investment on commodity markets suffer from incomplete data (Boyd et al., 2018). This paper fills this gap by estimating the size and composition of OTC agricultural swaps market and by examining whether commodity-equity linkages exist during periods of financial market stress. Understanding how the agricultural swaps and futures markets respond to equity market volatility has implications for commercial hedgers in the agricultural supply chain.

[6] The Index Investment Data are the only publicly available dataset on total commodity index investment that includes both futures and OTC swaps markets. The data series contain monthly index investment totals by commodity for the time period of December 2007 - October 2015. Details on the data can be found at: `https://www.cftc.gov/MarketReports/IndexInvestmentData/index.htm`

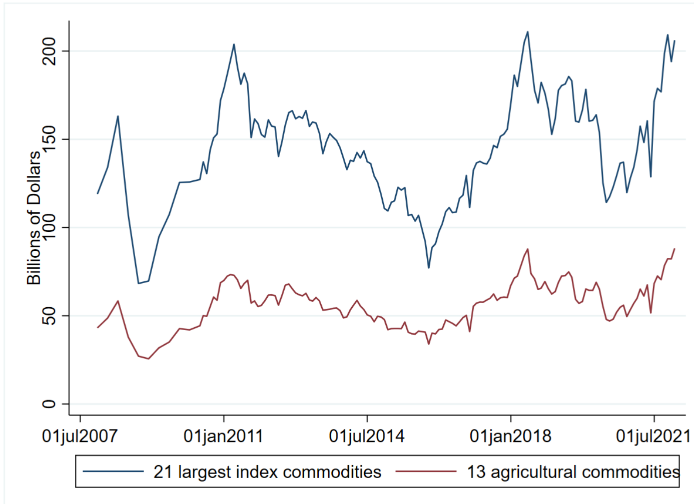

Figure 1: Total notional index investment for the 21 largest commodity swaps markets and 13 agricultural swaps markets. The monthly data series uses CFTC Index Investment Data (IID) for the period of December 2007 - October 2015, and Part 20 swaps data for the period of April 2014 - December 2021.

We examine 13 agricultural commodities traded in both OTC swaps and exchange-traded futures markets. Using proprietary data on commodity swaps reported by swap dealers to the CFTC under Part 20 regulations (hereafter referred to as "Part 20 swaps data"), we find that multi-commodity index investment in agricultural commodities represents a much larger share of open swaps (70%) as compared to its share of futures open interest (15%). Swap dealer positions in the swaps market are found to be negatively correlated with their futures hedging positions. Our empirical analysis finds evidence that agricultural swaps traders respond to shocks in financial markets, similar to traders in the futures markets. Using the spike in the Chicago Board Options Exchange Volatilty Index (VIX) in March of 2020, we find net positions of index swaps traders decrease, while commercial traders reduce their net short positions, creating a transfer of risk in three commodities (corn, SRW wheat, and sugar). This transfer of risk through offsetting swaps positions between commercial and financial index traders is similar to "convective risk flows" in futures markets (Cheng et al., 2015).

This study adds to the existing literature in several ways. First, there are few studies of OTC commodity swaps markets. Mixon et al. (2018) are the only study to use the Part 20 swaps data to examine commodity swaps markets, finding that commercial end-user open activity is greater than financial end-users in West Texas Intermediate (WTI) crude oil swaps. Our study provides a more detailed analysis of the size and composition agricultural swap markets and highlights their use for commodity index investing and for hedging by commercial traders. Second, our analysis adds to a growing literature on cross-market linkages between agricultural markets and equity markets (Bruno et al., 2017), by showing the transmission to agricultural swaps. Previous studies of agricultural futures markets and commodity-equity linkages show financial traders can propagate shocks from the financial markets during periods of financial volatility. However, the question of whether financial shocks propagate through commodity swaps markets remains underexplored. We add to this literature by showing that risk is transferred between index traders and commercial traders in agricultural swaps markets during periods of financial stress. Finally, our study contributes to recent work on the impact of COVID-19 on agricultural commodity markets

(Peng et al., 2021).

We follow a similar empirical methodology as Cheng et al. (2015), who use the VIX shock during the Great Recession of 2008 to show that financial traders will transfer risk to commercial hedgers in commodity futures during periods of market distress. The VIX captures the implied volatility of options on near-term S&P 500 futures and is considered a proxy for financial market risk. Commercial traders in futures are shown to change positions and offer liquidity to financial traders because they have greater risk absorption capacity, even when financial market distress affects hedging costs for all traders. We extend their methodology to agricultural swaps markets and use the VIX spike in early March 2020 to identify when traders in index swaps were motivated to unwind their net long positions. This position unwinding may be due to tighter financial conditions, such as increasing borrowing costs, tighter leverage constraints, and portfolio rebalancing. We find commercial traders in three swaps markets significantly reduce their net short positions and offer liquidity to index traders. This risk transfer between swaps traders allows swap dealers to net offsetting positions and reduce their hedging demand in the futures market.[7]

Our findings expand on work by Büyükşahin and Robe (2014), who find that correlations between the return on equities and commodity indices rose with greater hedge fund participation. They do not find this correlation to

[7]For the purposes of this paper, the terms "hedge," "hedging," and variations of the term means takes a position, without regard to the trader's motivation. The terms are not based on the definitions in the CFTC's regulations.

be caused by greater presence of swap dealers in futures markets. Similarly, we find that swap dealers are less responsive to equity market shocks than other financial traders. In particular, we find commodity index trader (CIT) positions from entities other than swap dealers (hereafter known as "other CITs"), a group of traders that include managed money and hedge funds, were much more responsive to the VIX shock in early 2020. Our study also complements work by Bruno et al. (2017), who examine cross-market linkages between agricultural futures and equity markets.

The Part 20 swaps data is a comprehensive, counterparty-identified position dataset reported to the CFTC under large trader reporting requirements for physical commodity swaps. Swap positions are reported by individual swap dealers following each trading day. Most studies on commodity index investment have used CFTC futures data, such as the Commitment of Traders (COT), the Supplemental COT on Commodity Index Traders (SCOT), or the Large Trader Reporting System (LTRS), to make inferences about index swaps market activity (e.g., Stoll and Whaley (2010); Sanders and Irwin (2011); Singleton (2014); Hamilton and Wu (2015); Brunetti et al. (2016)). However, these approaches require researchers to infer commodity index investment activity in swaps based on swap dealer or CIT futures positions. In agricultural commodities, CIT positions have been assumed to be a good proxy for index investment because internal swap market netting was reported to be small (CFTC, 2008). Our analysis of the Part 20 swaps data finds there is more swap market netting in agricultural markets than previously thought.

The rest of the paper is organized as follows: in the next section, we provide background information on OTC commodity swaps markets. Section 3 reviews the relevant literature. Section 4 details the Part 20 swaps data and futures data used in our analysis. Section 5 describes the size and composition of the agricultural swaps markets and compares it to the paired futures market. Section 6 presents evidence of co-movement between the equity and swaps markets, by examining position changes of agricultural swaps trader during the COVID-19 crisis. Section 7 contains a summary of our findings and a discussion of future research.

2 Background

Commodity swaps are essentially a series of forward contracts on a specific commodity with different maturity dates and the same delivery prices (Hull, 1995). However, unlike a forward contract, there is rarely any delivery in swaps. Instead, the two parties exchange cash flows at regular intervals over a specified period, with a swap dealer typically on one side of the exchange. In a non-index or single-commodity swap, commonly used by commercial traders, one leg of the swap pays a fixed amount, agreed upon at the onset, while the other leg pays a floating rate based on an underlying futures contract, such as CBOT Corn. For commercial traders, swaps may be preferred because they can be customized to account for locational or other basis risk (Popova and Simkins, 2015).

Most multi-commodity index investment occurs through the OTC commodity swaps market (CFTC, 2008).[8] CITs, such as pension funds, use multi-commodity index swaps to gain long price exposure to a weighted basket of commodities (e.g., WTI crude oil, corn, gold).[9] The index swap positions are typically in the nearby (nearest active) contract month and are rolled into the next contract month at predetermined dates. Among the most popular commodity indexes are the S&P Goldman Sachs Commodity Index (GSCI) and the Bloomberg Commodity Index (BCOM), where an index value is computed as a production-weighted average of the prices from exchange-traded futures markets (Boyd et al., 2018).

The swap dealer, which is often affiliated with a bank or other large financial institution, serves as a market maker for swap counterparties. Examples of agricultural swap counterparties include commercial traders, such as ethanol plants, hedging price risk due to being in the agricultural supply chain; and hedge funds or CITs seeking long-price exposure to a basket of commodities (CFTC, 2008). By offering swaps contracts tailored to their clients and using standardized futures contracts to hedge the resulting risk, swap dealers serve as a bridge between OTC commodity swaps and the futures markets. Due

[8]Individual investors typically use exchange-traded-funds (ETFs) and exchange-traded-notes (ETNs) to gain exposure to popular commodity indices such as the GSCI.

[9]Although many commodity swap positions could be replicated in the futures market, swaps users may find a swap preferable for several reasons, such as not having to take delivery or exit a futures position. Some other reasons swaps may be preferable to futures: 1) the tenor of exposure of a swap can be customized to match the risk that a firm needs to hedged; 2) firms have an existing relationship with a swap dealer and this may lower transactions costs in swaps markets, relative to trading futures; and 3) firms may not want to post margin to a future commission merchant.

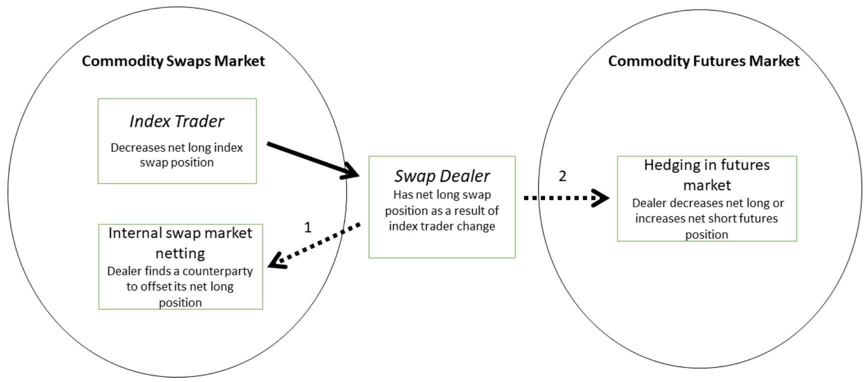

Figure 2: Swap dealers serve as a bridge between OTC swaps and exchange-traded futures. The figure shows how a swap dealer can hedge its swap book in response to a CIT decreasing its net long index swap position through: 1) internal swap market netting and 2) hedging in the futures market.

to the customized nature of swaps, dealers may rely on a combination of futures contracts, physical market positions, and other swaps to manage risk of their swap book. Figure 2 provides a visualization of how a swap dealer can hedge its swap book in response to a CIT decreasing its net long index swap position.

3 Literature Review

There is limited prior research on agricultural swaps markets, largely because of lack of publicly available data. Peterson (2014) describe the size and trading activity of agricultural swaps markets, using aggregate data from

Swap Data Repositories (SDRs). However, this analysis only measures swaps volume, not open activity (open swaps). Mixon et al. (2018) publish the first estimates of the size of OTC commodity swaps markets using the Part 20 swaps data. They calculate open interest in 29 different commodity swap markets and compare it to the respective futures market. Their analysis of WTI crude oil swaps market found that commercial activity in swaps is greater than in the paired futures market.

Financial institutions began offering a variety of commodity-index instruments to institutional investors in the early 2000s after studies showed the potential of equity-like returns and portfolio diversification benefits (Gorton and Rouwenhorst, 2006). Commodity index investment subsequently grew from near zero in 2003 to over $160 billion in 2008[10], a period known as the "financialization" period of commodity markets (Tang and Xiong, 2012). This period saw a new type of investor, known as commodity index traders, enter commodity futures markets seeking passive, long-side price exposure in order to enhance returns and diversify portfolios. There has been much academic research and public debate (Masters, 2008) about whether the influx of new commodity index investment was linked to the historically large price volatility observed between 2007-2009 in WTI crude oil and grain commodities.

The impact of commodity index investing on commodity price movements has been widely examined, with most studies finding little evidence of a

[10]This represents total index investment in U.S. commodity futures markets only, based on CFTC's Index Investment Data

price impact (e.g., Irwin and Sanders (2012); Sanders and Irwin (2017); Etienne et al. (2017)). Most studies do not find a statistical link between commodity index investment and commodity prices or returns (e.g., Irwin et al. (2009); Sanders and Irwin (2010)), particularly among agricultural commodities (Sanders and Irwin, 2011). Irwin and Sanders (2011) survey existing studies on the relationship between agricultural commodity index investment and returns, but find a lack of empirical evidence that there is causal relationship. The CFTC's SCOT on commodity index trader activity is used as a proxy for commodity index investment in many studies, but this method neglects swap market activity not visible in the futures data (e.g., Stoll and Whaley (2010); Buyuksahin and Harris (2011); Hamilton and Wu (2015)). A recent study by Da et al. (2023) examines daily autocorrelation in returns and finds commodity index trading propagates nonfundamental noise in indexed commodity prices.

Recent studies show the effects of financialization have persisted, with higher correlations found between commodity returns and stock market returns than before the financialization period of the early 2000s (e.g.,(Kang et al., 2023)). Studies of commodity-equity linkages in agricultural futures show that correlations with financial markets are typically stronger during periods of world business cycle shocks (Bruno et al., 2017). Financial institutions are more likely to transmit negative price shocks across different markets due to portfolio rebalancing and leverage constraints when there are limits to arbitrage (Vayanos et al., 2010). Cheng et al. (2015) examine how shocks to the equities markets during the Great Recession of 2008 impact the risk absorption capacity of financial traders. They use large increases in the VIX as a proxy for equities market volatility, isolating when financial traders are subject to tighter financial constraints, causing them to unwind long positions in the futures markets and transfer risk to commercial traders.

The role of financial intermediaries in transmitting or mitigating price shocks is an ongoing area of research. Intermediary pricing theory emphasizes the role that risk appetite and binding financial constraints can have on financial institutions during periods of financial crisis, causing them to reduce their futures exposure (He and Krishnamurthy, 2018). Mixon and Onur (2020) show that commodity swap dealer risk appetite varies with financial conditions and the strength of its balance sheet. They show that the amount of residual risk (e.g., swaps positions that are unhedged in futures) decreases with worsening financial conditions, as well as dealer intermediation services and liquidity provision. Swap dealers that hedge bespoke swaps contracts using standard, liquid instruments face basis risk due to differences between these two instruments (e.g., tenor, locational basis).

4 Data

4.1 Part 20 swaps data

The commodity swaps positions analyzed in this paper are non-public data that come from the CFTC's Large Trading Reporting for Physical Commodity

Swaps.[11][12][13] Reporting entities, primarily comprised of swap dealers, submit daily positions to the CFTC related to their activity in swaps that are paired to 46 physical commodity futures contracts. The swaps are considered "paired" if they settle using either the price of one of the 46 futures contracts (e.g., CBOT soybeans) or the price of the same commodity for delivery at the same location(s) as one of the contracts.[14] Each individual swap contract involves a swap dealer and counterparty. In U.S.- based commodity swaps, the swap dealer is typically either a large bank or company, required to be registered with the CFTC.[15] All swap dealer positions are reported, along with all swap counterparty positions with holdings of greater than 50 futures-equivalent contracts.[16]

The Part 20 swaps data include such fields as the swap dealer name, swap counterparty name[17], long and short open interest measured in futures-

[11]In 2011, the CFTC introduced new rules for reporting these swaps under Part 20 of CFTC's regulations. These rules were revised in 2015 and earlier data is not directly comparable. More information about the CFTC's Large Trader Swaps Reporting is available on the CFTC website: `https://www.cftc.gov/sites/default/files/idc/groups/public/@newsroom/documents/file/ltrguidebook062215.pdf`.

[12]These data only include swaps that are under the jurisdiction of the CFTC. While we observe all dealer positions, less than 15% of daily open swaps activity of counterparties is not reported. Swap dealer reports include identifying counterparty swap data as described in this section, but counterparty names may be masked. Accordingly, certain counterparties are excluded from disaggregated analysis. Dealers are not required to report key elements of swap positions.

[13]While individual market participants cannot be publicly identified based on regulatory data, several representative entities have publicly stated their participation in swap markets.

[14]A complete list of the 46 paired futures contracts are displayed in table 1.

[15]While the term swap dealer is generically used, the swap dealers who report to the CFTC are only those that meet the regulatory definition. In addition to bank-affiliated entities, reporting dealers include firms such as Cargill Inc., and BP Energy Co..

[16]See B for a detailed discussion of futures-equivalent contracts.

[17]While the universe of CFTC registered swap dealers is known, swap counterparties are

equivalent contracts, swap notional amount, whether the swap is part of a commodity index, whether the swap has optionality (i.e., is a swaption), and the tenor of exposure. The tenor of exposure is the futures-equivalent contract month of the swap (e.g., December 2018 CBOT corn) and determines the price of the floating leg. Swaptions are reported as delta-adjusted short and long positions. For a description of how the futures-equivalent contracts and delta adjustment measures for swaps are calculated and details about how multi-commodity index swaps are disaggregated into their constituent parts for analysis, see B.

The index swap information contained within the Part 20 swaps data can be viewed as a more detailed version of the IID series, a publicly available dataset of the commodity index activity of swap dealers and major swap participants in commodity futures markets that was published by the CFTC from December 2007 through October 2015. Figure 3 provides visual evidence that net index positions of swap dealers in CBOT SRW wheat from both the IID and Part 20 swaps data are very similar during the period of June 2014 through October 2015.[18] A similar overlap between the IID and Part 20 index swaps position data is observed in the other commodities used in our study, giving us confidence in the data reliability.

not always identifiable, and thus cannot be categorized as a certain type of trader (e.g., financial).

[18] In the figure, we have omitted Part 20 swaps data from 2013 because there were some significant reporting errors. Reporting of Part 20 swap positions improved considerably by 2014.

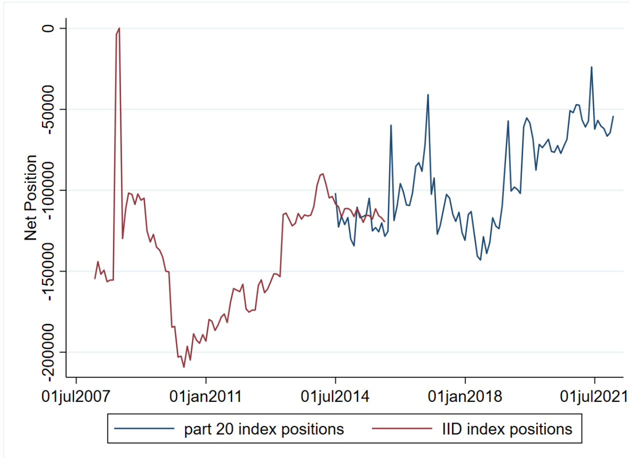

Figure 3: Monthly net index positions of swap dealers in CBOT SRW wheat using the IID positions data (December 2007 - October 2015) and Part 20 swaps data (June 2014 - December 2021).

To make the Part 20 swaps data comparable with the futures positions reported in the SCOT, we manually classify each account in the swap data using the name of the swap counterparty. We create three swap trader groups: index swap trader, commercial trader, and other financial trader. Other financial traders include banks and hedge funds that use non-index swaps, as well as dealer to dealer swaps. Index swap and other financial traders include banks, asset management funds, managed futures funds, insurance companies, and pension funds. Commercial swaps traders, who almost exclusively use non-index swaps, include agricultural cooperatives, ethanol plants, and grain elevators. Our three swap trader categories are therefore analogous to the SCOT trader categories: CITs, commercials, and noncommercials.

Since swap dealers hedge much of their swap book in the futures market, index swap trader activity should be linked to the CIT activity in futures (after swap market netting). We note that CIT positions are a noisy measure of index swap activity because of swap dealer netting, and how CITs are classified in the SCOT. In the next section, we discuss how we decompose the CIT positions into swap dealer and other CITs.

To measure the size of the swaps market, we calculate average daily open swaps measured in futures-equivalent contracts. This allows us to compare the swaps market directly with the paired futures market (measured as open interest). We calculate average daily open swaps by summing all long and short open positions of swap dealer counterparties in a given week and divide by the number of reporting days in that week. This method helps to smooth out irregularities in reporting; for instance, some foreign swap dealers do not report on business holidays in their home country. Average daily net positions are created in a similar way as average daily open swaps, but instead we subtract total short positions from total long positions for all counterparties in a commodity. We then assign these net swap positions to a specific trader category (e.g., commercial trader) based on our manual classification scheme.

4.2 Futures data

Our futures position data come from both the publicly available Commitment of Traders Supplement on Commodity Index Traders (SCOT) report and the non-public Large Trader Reporting System (LTRS).[19] The weekly SCOT report details the positions of traders in commodity futures indexes. The report, published on Fridays, is a snapshot of trader positions in 13 agricultural futures markets on Tuesday. It breaks out CIT positions, as well as commercial, non-commercial, and non-reportable trader positions.[20][21] These classifications allow us to compare similar groups of traders in the swaps and futures markets.

The CIT position data is a noisy measure of index activity, as it includes non-index activity from traders primarily engaged in index trading. In addition, the CIT position data capture the activity of traders who are not swap dealers hedging their index swaps book. To better understand the index trading behavior of swap dealers, we disaggregate CIT positions using account-level data on each trader's daily positions from the LTRS. CIT positions are split into two trader categories: dealer CITs and other CITs. Dealer CITs should capture passive commodity index positions held by swap dealers, while other CITs will have more actively traded index positions, held by other financial entities, such as hedge funds.[22]

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[19] The Commodity Index Trader Supplement data set can be found here:`https://www.cftc.gov/MarketReports/CommitmentsofTraders/HistoricalCompressed/index.htm`

[20] The CIT category includes pensions funds that previously were classified as noncommercials in the Disaggregated Commitment of Traders (DCOT) report, as well as swap dealers who would have previously been categorized as commercials (CFTC, 2008).

[21] We also include non-reportable SCOT positions in our measures of futures open interest. However, we omit this trader group in our regression analysis.

[22] For a brief summary of the differences between dealer CITs and other CITs see B.

4.3 Futures prices

Commodity futures prices are taken from daily market price data that futures exchanges report to the CFTC. This price series can easily be obtained through public sources. We use prices from the nearest to expiration futures contract until the first day of the expiration month, when the price series rolls into the next contract month.

5 Agricultural Swaps Market – Size and Participants

We begin by examining the size and composition of the thirteen agricultural commodity swaps markets in our study. These commodities are: CBOT corn, soybeans, SRW wheat, HRW Wheat, soybean oil, soybean meal, CME live cattle, lean hogs, feeder cattle, and ICE sugar no. 11, cotton no. 2, cocoa, and coffee. Together, these 13 swaps markets represent more than $95 billion dollars[23] of activity by commercial agricultural firms, money managers, banks, hedge funds, and passive multi-commodity index investors. The four largest swaps markets based on swap notional are: soybeans, corn, SRW wheat, and sugar (table 1).

[23]This is the average daily notional value of all 13 swaps markets for the period 2016-2021

Table 1: Market size comparisons for agricultural swaps and futures markets (2016-2021 daily average)

Commodity	Notional swaps ($B)	Open swaps (1000 Contracts)	Open interest (1000 Contracts)	Swaps % of Open interest	Swaps (% index)	Futures (% index)
Soybeans	16.1	318.0	960.1	33.1	56.7	13.0
Corn	15.0	755.5	2002.1	37.7	67.5	13.8
SRW Wheat	10.8	391.8	552	71.0	76.5	19.3
Sugar	10.6	644.6	1039.6	62.0	63.8	14.9
Soybean Meal	7.3	222.4	471.7	47.2	52.7	14.0
Live Cattle	7.3	160.3	382.8	41.9	82.8	17.1
Coffee	7.2	149.0	305.1	48.8	69.3	12.3
Cotton	5.5	147.8	291.4	50.7	64.4	16.4
Soybean Oil	5.0	235.9	507.3	46.5	68.0	14.3
Lean Hogs	4.4	157.2	311.7	50.4	88.1	17.3
HRW Wheat	2.7	106.4	278.5	38.2	84.6	14.6
Cocoa	2.1	88.1	288.7	30.5	79.2	12.7
Feeder Cattle	1.1	15.0	56.5	26.5	87.5	15.2
Total	95.1	3392.0	7502			
Average	7.3	260.9	577	45.0	72.4	15.0

The size of agricultural swaps markets relative to their paired futures market varies considerably. Corn is the largest market based on futures-equivalent contracts, with an average of 755,000 open contracts, but this represents only 37% of average futures open interest.[24] Four of the swaps markets are at least 50% as large at their paired futures market: SRW wheat (71%), sugar (62%), cotton (51%), and lean hogs (50%). The remaining swaps markets comprise between 27% and 50% of open interest in their paired futures market. The relatively large size of SRW wheat and sugar swaps markets may reflect the composition of traders. We note that SRW wheat has one of the highest shares of index investment activity (85% of open swaps) and sugar has the highest share of commercial trading activity (25%) among

[24]Soybeans are the largest agricultural swaps market by notional, whereas corn is the largest by futures-equivalent contracts. The difference in ranking reflects the fact that the average price of a soybean contract was $50,628, while the average price of a corn contract was $19,854.

these swaps markets, shown below in figure 4.

Index investment represents the majority of OTC agricultural swaps activity. Index swaps activity represented 72% of all open swaps and $68.9 billion in notional value from 2016 to 2021. This contrasts with the futures market, where CIT activity constitutes about one-sixth of open interest, ranging from 12% of coffee to 19% of SRW wheat open interest. Sanders et al. (2010) note that between 2006 and 2008 CIT positions represented no more than 10% to 20% of agricultural futures open interest and between 20% and 40% of long-only positions. Index trader open activity in agricultural swaps varies from 53% of soybean meal to 88% of lean hogs (figure 4). Other swaps markets where more than three-quarters of open swaps are represented by index traders include feeder cattle, live cattle, HRW wheat, cocoa, and SRW wheat.

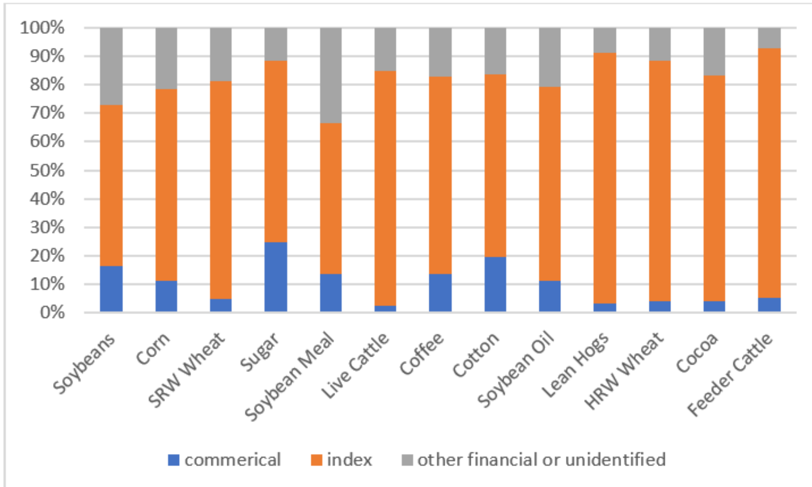

Figure 4: Share of open swaps represented by commercial, index, and other financial or unidentified traders in agricultural swaps markets, 2016-2021 average

The composition of the market helps explain why index trading dominates agricultural swaps market activity. While commercial traders represent the largest share of open interest in futures markets, financial traders, including index traders and other financial traders, are responsible for the majority of open swaps activity. Financial traders account for 80% of corn swaps activity, 79% of soybean activity, and between 68% and 91% of open swaps activity for other crop commodities. This contrasts with the WTI crude oil swaps market, where Mixon et al. (2018) find that commercial end-user activity is larger than financial end-user. Agricultural swaps markets also have lower levels of commercial trader activity when compared to the paired futures market. On average, commercial trader activity represents 10% of open swaps activity. This compares to an average of 36% of open interest among commercial traders in agricultural futures markets. The four commodities with the largest share of commercial activity in swaps are sugar, coffee, cotton, and soybeans.

The lower level of commercial activity observed in swaps is likely due to a couple of factors. Capital requirements for swaps market participants limits their use to traders of a certain size. Commercial traders that use agricultural swaps are more likely to have customized hedging needs for which a standardized futures contract would not be well-suited (e.g., because of basis risk or timing of production). Such commercial traders include ethanol plants, grain merchandisers, and cooperatives. Additionally, some commercial traders are foreign entities with an existing swap dealer relationship but no access to an Futures Commission Merchant (FCM), or they simply have a preexisting relationship with a swap dealer that can offer better pricing than futures.

5.1 Trends in swaps activity

Despite the greater concentration of index traders in agricultural swaps markets, there are clear similarities in patterns of open activity with the paired futures market. Figure 5 shows time series trends of average open activity in both swaps and futures for SRW wheat. A visual inspection suggests there is positive correlation and co-movement present between the swaps and futures market.

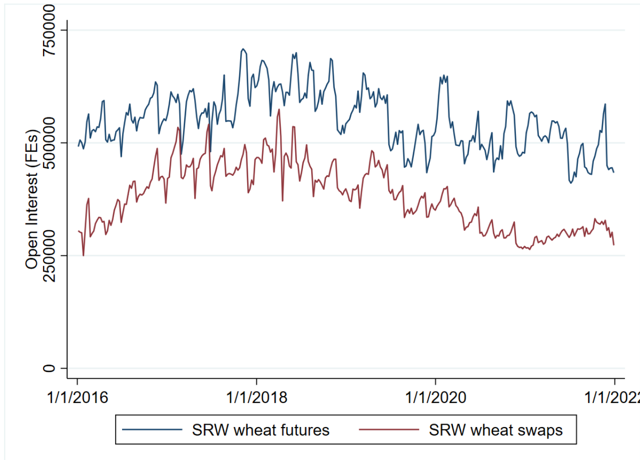

Figure 5: Trends in open interest and open swaps in SRW wheat, 2016-2021

Table 2 shows correlations of average daily open swaps and open interest for all 13 agricultural commodities. We observe correlations as high as 0.73 for soybeans in the period 2020 to 2021.[25] Cotton, corn and SRW wheat swaps markets open activity all show pairwise correlations with futures open interest of 0.5 or higher.[26]

[25]We separate the data into pre-COVID period (2016 - 2019) and COVID period (2020-2021) to account for any structural changes in the series.

[26]Pearson pairwise correlations are based on first-differences in open activity, after testing for stationarity using a 5% level of significance.

Table 2: Pearson pairwise correlation coefficients of average daily futures open interest and open swaps. Correlations are shown in two periods: pre-COVID and COVID shock. Pairwise correlations are based on first-differences after testing for stationarity at 5% level of significance.

Commodity	Jan 5, 2016 - Jan 21, 2020	Jan 28, 2020 - Dec 28, 2021
Corn	0.651***	0.535***
Soybeans	0.675***	0.730*
SRW Wheat	0.477***	0.534***
HRW Wheat	0.207***	0.337***
Soybean Oil	0.330***	0.311***
Soybean Meal	0.337***	0.479***
Cotton	0.583***	0.625***
Sugar	0.320***	0.196**
Coffee	0.291***	0.203**
Cocoa	0.244***	0.089
Feeder Cattle	0.128*	0.243**
Lean Hogs	0.211***	0.245**
Live Cattle	0.469***	0.426***
Average	0.379	0.381

Notes: asterisks denote significance level, *** 1%, ** 5%, * 10%.

Commercial and index trader swap positions are found to vary over time and by commodity. In figure 6 we show the net swaps positions of commercial and index swap traders in corn from 2016-2021. Index swaps traders are shown to be net long, while commercial trader positions vary from net long, on average, with a net short position observed at several points in the time series. We note the apparent drop in net long index positions in early 2020 as the COVID pandemic affected financial markets, while commercial trader positions became more net long around the same time. We explore this event in more detail in the empirical section.

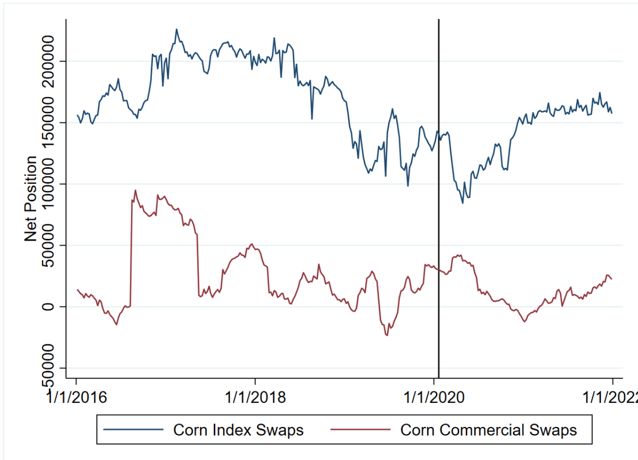

Figure 6: Net positions of Commercial and Index Swaps traders in Corn, 2016-2021

5.2 Swap dealer positions in swaps and futures

We explore the relationship between swap dealer CIT positions (in futures) and their positions in the swaps market. As noted above, the majority of a agricultural swaps activity comes from index swaps, where swap dealers have a net short position against the aggregate net long positions of commodity index investors. However, dealer's positions also reflect commercial activity, which dealers can internally net before hedging the remaining risk in the futures market. Swap dealers typically hedge their index swap book using the nearby futures contract because it is the most liquid, rolling their index positions into the next contract month in a predictable manner.[27]

We use swap dealer CIT positions (a subset of all CIT positions) as a

[27] An example is the Goldman Roll, which takes place on the fifth to ninth business day of the contract expiration month.

proxy measure of swap book hedging in futures by swap dealers. A swap dealer's hedge ratio will vary with their risk appetite (Mixon and Onur, 2020), including the strength of its balance sheet and general economic conditions. As a result, a dealer's hedge ratio may be higher during periods of greater market volatility or weaker economic conditions. A dealer's risk appetite can increase when its balance sheet is stronger, resulting in lower hedge ratios, and possibly more proprietary positions in the futures market.[28]

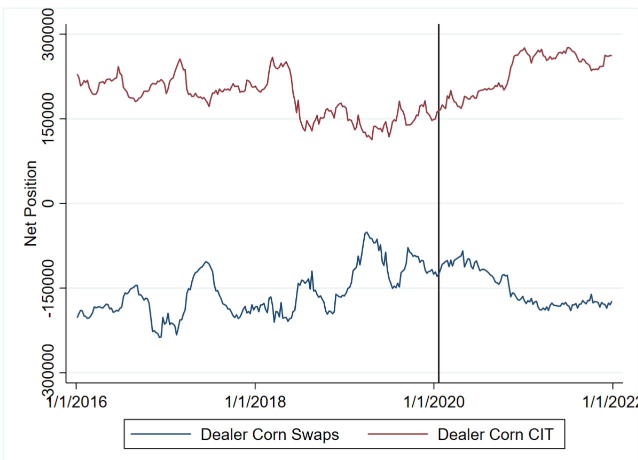

Figure 7: Net swaps positions and net CIT positions of swap dealers in corn, January 6, 2016 - December 28, 2021. The vertical line falls on January 21, 2020, the approximate beginning of the COVID-19 pandemic.

[28]Our measure of swap dealer CIT positions includes dealer proprietary positions.

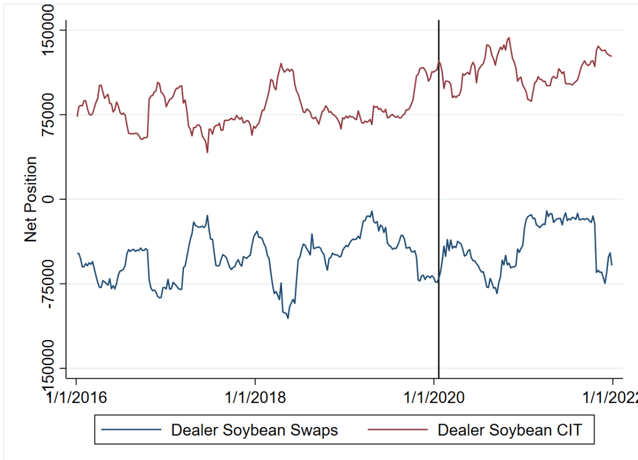

Figure 8: Net swaps positions and net CIT positions of swap dealers in soybeans, January 6, 2016 - December 28, 2021. The vertical line falls on January 21, 2020, the approximate beginning of the COVID-19 pandemic.

In figures 7 and 8 we display a time series plot of swap dealer net swap positions and swap dealer net CIT positions in corn and soybeans from 2016 to 2021. As expected, a visual inspection suggests that swap dealer net CIT positions are negatively correlated with their aggregate net swap positions. Generally, as the aggregate dealer swap book becomes more net short, the aggregate dealer CIT position in the paired futures market tends to become more net long. We calculate pairwise correlations for dealer net swaps positions and net CIT positions for all 13 agricultural commodities in table 3. Pairwise correlations are based on first-differences to ensure stationarity of each series. To account for the greater financial market volatility around the COVID-19 pandemic, we break our sample into two periods, a pre-COVID period (January 5, 2016- January 14, 2020), and a COVID shock period

(January 21, 2020 - December 28, 2021).

Table 3: Pearson correlation coefficients of average daily swap dealer net swaps and net CIT positions. Correlations are shown in both pre-COVID and COVID shock periods. Pairwise correlations are based on first-differences after testing for stationarity at 5% level of significance.

Commodity	Jan 5, 2016 - Jan 21, 2020	Jan 28, 2020 - Dec 28, 2021
Corn	-0.140**	-0.295***
Soybeans	-0.424***	-0.411***
SRW Wheat	-0.235***	-0.528***
HRW Wheat	-0.348***	-0.245***
Soybean Oil	-0.122*	-0.001
Soybean Meal	-0.167**	-0.342***
Cotton	-0.367***	-0.533***
Sugar	-0.143**	0.152
Coffee	-0.211***	-0.520***
Cocoa	-0.357***	-0.655***
Feeder Cattle	-0.234***	-0.438***
Lean Hogs	-0.179**	-0.475**
Live Cattle	-0.216***	-0.510***
Average	-0.242	-0.369

Notes: asterisks denote significance level, *** 1%, ** 5%, * 10%.

Pairwise correlations are found to be negative and significant in all 13 commodities, with exceptions in sugar and soybean oil in the COVID shock period. Correlation coefficients vary from near zero for sugar to -0.66 for cocoa in the COVID period. Overall, we see that dealer net CIT positions and net swaps positions are weakly negatively correlated, with an average correlation of -0.24 in the pre-COVID period and -0.37 in the COVID period. The higher average correlation in the latter period suggests changes in swap dealer CIT positions were more closely tied to changes in their swaps book. This may reflect a reduction in dealer risk appetite following the increased financial market volatility in early 2020.

6 Empirical methods

Our empirical analysis examines co-movements between agricultural derivatives markets and equity markets in two ways. First, we examine whether a large increase in the VIX affects swap and futures returns during the COVID shock period. Second, we test whether the same spike in the VIX affects trader positions in agricultural swaps and futures.

Using methods similar to Cheng et al. (2015), we use the large spike in the VIX during the COVID-19 pandemic to identify when financial traders had an incentive to unwind net long index swaps and futures positions (figure 9). The assumption is that financial traders have a greater incentive to decrease their positions in commodity futures and swaps during periods of high equity market volatility for a variety of reasons, including: capital and leverage constraints, portfolio re-balancing, and tighter credit conditions. Cheng et al. (2015) show that commercial traders can facilitate this unwinding of net long positions by decreasing their own net short futures positions, even if commercials also have reduced risk capacity, so long as their risk capacity is greater than the financial traders.

We separate our sample into two periods: pre-COVID and COVID shock. Our treatment period (COVID shock) begins on the week of January 21, 2020, the day after the first case of COVID-19 was confirmed by the U.S. Centers for Disease Control.[29] This time period captures the highest observed

[29]CDC COVID-19 timeline: `https://www.cdc.gov/museum/timeline/covid19.html`

values of the VIX since the beginning of the Great Recession in November of 2008. The time period before January 21, 2020 is considered pre-COVID or the control period.

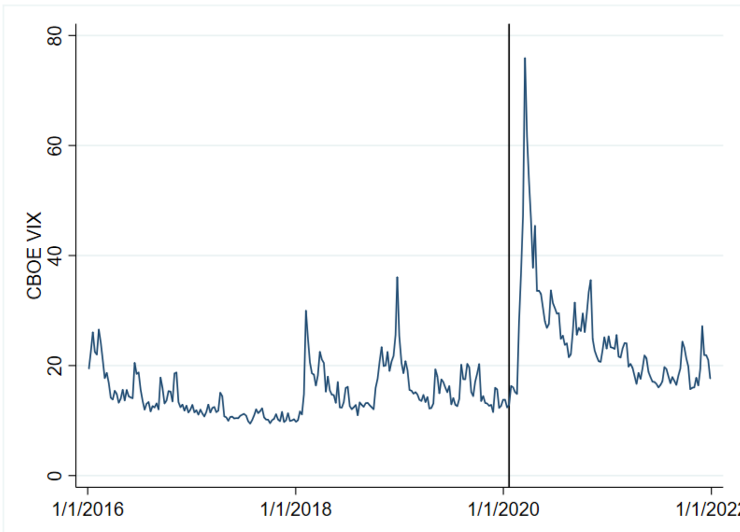

Figure 9: Average CBOE VIX measured at weekly level. The vertical line represents January 21, 2020, the day the first U.S. COVID-19 case was confirmed, and the beginning of our treatment period.

We note that the COVID pandemic was an unprecedented event that affected not only the financial and commodity markets, but many other aspects of the world economy. The slowdown in international trade affected U.S. grain farmers who depend on international markets for output sales. There was uncertainty about how long governments would shut down their economies. These events undoubtedly affected the hedging and marketing decisions of commercial producers in agricultural markets. In summary, the COVID pandemic was quite different and much more complex than previous financial market shocks. While we believe the spike in the VIX in early 2020 is still a good proxy for financial trader risk-absorption capacity, we readily acknowledge that other economic events caused by the pandemic are likely correlated with it.

Our analysis covers the period between January 5, 2016 and December 28, 2021, giving a total of 313 weekly observations. Table 2 displays summary statistics for average daily implied swaps and futures returns. Tables 4 and 3 display summary statistics on average daily net positions of index and commercial traders in swaps and CIT, commercial, and noncommercial traders in the futures markets. Index traders and CITs are found to be net long in both swaps and futures. Commercial futures traders are net short, while commercial swaps traders in swaps are found to be net short in 6 of 13 markets: soybeans, cotton, sugar, coffee, lean hogs and live cattle. The composition of commercial traders in the swaps markets may explain the heterogeneity in observed net positions. Commercial swaps traders include more intermediaries (e.g., ethanol plants, grain millers, grain elevators, meat packers) that use commodities as inputs as compared with futures.

6.1 Swaps and futures returns

We estimate a model for swaps and futures returns in 13 agricultural commodities. Newey-West estimation methods with four lags are used to correct for autocorrelation. Each model is separately estimated in the pre-COVID and COVID shock period, corresponding to lower and higher periods of equity volatility. The regression model for agricultural futures or swaps returns on the i^{th} commodity, in week t, is specified as:

$$Returns_{i,t} = \beta_0 + \beta_1 \Delta VIX_{i,t} + \beta_2 \Delta VIX_{i,t-1} + \mathbf{\Gamma X}_{i,t-1} + \epsilon_{i,t} \tag{1}$$

where Δ is the first-difference operator and ϵ is the error term, assumed to be i.i.d $\sim N(0, \sigma^2)$. We include both a contemporaneous and lagged first-difference of the VIX. Our parameter of interest is the contemporaneous first-difference in the VIX (β_1).

We include a vector of control variables that capture commodity returns, changes in U.S. trade policy and monetary policy uncertainty, U.S. credit conditions, inflation expectations, and demand for global commodities. The returns variable corresponds to either implied swaps or futures returns, depending on the trader type. Returns are based on the nearest-to-expire futures contract. The price series rolls into the next contract month at the beginning of the expiration month to ensure we track the indexed contract. Implied swaps returns are calculated using our measure of implied swaps prices. To calculate an implied swaps price, we use the swap notional value and number of futures-equivalent contracts from the Part 20 swaps data. For details on how implied swaps prices are calculated, see A.

The U.S. trade policy and U.S. monetary policy uncertainty data come from the Economic Policy Uncertainty (EPU) database.[30] These are monthly indices based on work by Baker et al. (2016) and are constructed using many sub-indexes derived from the Access World News database of over 2,000 US newspapers. We measure the corporate spread between Moody's Baa bonds and the 10-year U.S. Treasury Constant Maturity using data from the Federal Reserve Bank of St. Louis.[31] This provides a measure of credit conditions in the U.S. economy. A measure of monthly inflation expectations or inflation compensation also comes from the St.Louis Federal Reserve Economic Data (FRED). We use an updated version of the Kilian index of global real economic activity in commodity markets (Kilian, 2009) using data published by the Federal Reserve Bank of Dallas.[32] This is a monthly index derived from dollar-denominated global bulk shipping rates and is viewed as a proxy for the volume of shipping in global commodities markets.[33]

In table 4 we report estimates of β_1 for all 13 agricultural swaps and futures returns, across both the pre-COVID and COVID shock periods. The coefficients are reported as the change in returns, measured in standard deviations (SD), caused by a 1-SD increase in the VIX.

[30] Economic Policy Uncertainty website link: `https://www.policyuncertainty.com/index.html`

[31] `https://www.stlouisfed.org/`

[32] `https://www.dallasfed.org/`

[33] Because our model uses data at the weekly frequency, data based on a monthly index are repeated for each week within a month.

Table 4: Effect of 1 SD increase in VIX on returns in nearby futures contract and implied returns on swaps linked to nearby contract

Left panel: Jan 5, 2016 - Jan 21, 2020; Right panel: Jan 28, 2020 - Dec 28, 2021

	Swaps	Futures	Swaps	Futures
CBOT Corn	0.040	0.069	-0.305***	-0.242***
CBOT Soybeans	-0.118***	-0.118***	-0.333***	-0.333***
CBOT SRW Wheat	-0.025	-0.001	-0.191	-0.181
CBOT HRW Wheat	-0.013	-0.032	-0.143	-0.117
CBOT Soybean Oil	-0.164**	-0.159**	-0.359***	-0.424***
CBOT Soybean Meal	-0.074	-0.082	-0.111	- 0.111
ICE Cotton	-0.214***	-0.265***	-0.192**	-0.193**
ICE Sugar	-0.088	0.073	-0.269**	-0.276**
ICE Coffee	-0.042	-0.003	-0.240**	-0.248**
ICE Cocoa	-0.053	-0.064	-0.325***	-0.324***
CME Feeder Cattle	-0.093	-0.072	-0.529***	-0.477***
CME Lean Hogs	-0.058	-0.035	-0.232***	-0.149**
CME Live Cattle	-0.127*	-0.092*	-0.337***	-0.332***
Avg. effect	-0.079	-0.060	-0.274	-0.258
Average R^2	4.6%	4.3%	16.7%	15.7%
Obs	206	206	102	102

Note: asterisks denote significance level, *** 1%, ** 5%, * 10%

The model results shown in table 4 confirm that the large increase in the VIX in early 2020 was significantly associated with negative commodity returns for swaps and futures in 10 of the 13 agricultural markets. Averaged across all 13 commodities, we find a 1-SD increase in the VIX is associated with a 0.27-SD decrease in returns on swaps and 0.26-SD decrease in returns on futures. There is a marked difference when we examine this period with the pre-COVID period. In the latter, we find that increases in the VIX are associated with a statistically negative effect in 4 out of 13 commodities. We argue this result provides some preliminary evidence that shocks in the equities market were transmitted to both agricultural swaps and futures markets.

6.2 Swaps and futures trader net positions

We turn our attention to the response of swaps and futures positions to changes in the VIX. Swap dealers are the key intermediary in the swaps markets. When a financial shock causes a large change in the net position of a swap dealer's swap book, the swap dealer has two main hedging options. The dealer can hedge this swap position change in the paired futures market or find willing swap counterparties to offset or net the position change. In some instances, a dealer may use both options to keep a risk neutral swap book. Previous studies have not been able to observe whether internal swap market netting occurs. By examining both the Part 20 swaps data and paired futures data for these markets, we hope to see a more complete picture of how risk is transferred to traders with greater risk appetite during periods of market distress.

We estimate a net positions model similar to Cheng et al. (2015). Newey-west covariance estimation methods with four lags are used to correct for autocorrelation. As in the regression 1, we estimate the positions model in both the pre-COVID and COVID shock periods. The regression model for the j^{th} trader with a swaps or futures net position in the i^{th} commodity in week t is specified as:

$$\Delta Net\,position_{i,j,t} = \alpha_0 + \alpha_1 \Delta VIX_{i,j,t} + \alpha_2 \Delta VIX_{i,j,t-1} + \mathbf{\Psi X}_{i,t-1} + \phi_{i,t} \tag{2}$$

where Δ is the first-difference operator and ϕ is the error term, assumed to be i.i.d $\sim N(0, \sigma^2)$. The right-hand side control variables are the same as the returns model, shown above in equation 1. The swaps net position regression model uses implied swaps returns based on the Part 20 swaps data. The futures net position model uses futures returns based on the nearby month futures contract, rolled into the next contract month at the beginning of the expiration month.

Table 5: Effect of 1-SD increase in VIX on the net position of various traders in agricultural futures and swaps markets, January 21, 2020 - December 28, 2021

	Swaps Index	Swaps Comm.	CIT	Futures Comm.	Futures Noncomm.
CBOT Corn	-0.127*	0.307***	-0.168	0.203**	-0.100
CBOT Soybeans	0.014	0.035	-0.237***	0.162**	-0.090
CBOT SRW Wheat	-0.124*	0.147*	-0.065	0.217	-0.188
CBOT HRW Wheat	-0.134*	0.070	-0.309**	0.120	0.053
CBOT Soybean Oil	0.139	0.061	-0.264***	0.263**	-0.235**
CBOT Soybean Meal	0.033	0.076	0.004	-0.126*	0.180***
ICE Cotton	-0.271***	0.009	-0.226**	0.301***	-0.251***
ICE Sugar	-0.198**	0.329**	-0.084	0.155*	-0.175**
ICE Coffee	-0.041	-0.089	-0.194**	0.115	-0.034
ICE Cocoa	0.011	0.395***	-0.324***	0.302***	-0.215***
CME Feeder Cattle	0.069	-0.061	-0.367***	0.230**	-0.073
CME Lean Hogs	0.176*	-0.046	-0.084	0.104	0.026
CME Live Cattle	-0.189	0.102	-0.302***	0.305***	-0.214*
Avg. effect	-0.049	0.103	-0.201	0.181	-0.101
Avg. effect (OI weighted)	-0.076	0.151	-0.172	0.177	-0.110
Average R^2	14.6%	9.6%	18.8%	14.9%	11.8%
Obs	102	102	102	102	102

Note: asterisks denote significance level, *** 1%, ** 5%, * 10%

The parameter of interest in our model is α_1, the effect of the contemporaneous weekly change in the VIX on the weekly change in the net positions of index and commercial traders. Estimates, shown in table 5, reflect the change in net positions of each trader based on a one standard deviation increase in the VIX for the treatment period containing the COVID-19 pandemic.[34] The

[34] We also estimate regressions with shorter treatment period for the COVID-19 shock

parameter estimates for the control variables have been omitted for brevity.[35]

Averaging across all 13 swaps markets, a 1-SD increase in the VIX is associated with a 0.05-SD decrease in net long positions of index traders and a 0.10-SD decrease in net short positions of commercial traders.[36] We find evidence of convective risk flows in three swaps markets: corn, SRW wheat, and sugar. We also find evidence of convective risk flows in eight agricultural futures markets: corn, soybeans, SRW wheat, HRW wheat, soybean oil, sugar, and cotton. Noncommercials net positions decrease significantly in response to the VIX in five futures markets, while CIT net positions decrease in eight.[37]

We hypothesize that we observe convective risk flows in three swaps markets (corn, sugar and SRW wheat) for two reasons. First, they represent three of the four largest swaps markets in our study, measured in futures-equivalent contracts. Second, these three swaps markets also have the greatest number of financial traders in our dataset, and they each have over 100 commercial traders.[38] These two facts contribute to lower search costs for

to financial markets (i.e., the first six months of 2020) and find similar results, with a slightly larger VIX marginal effect in both swaps and futures. These results are available from the authors upon request.

[35]Parameter estimates for the control variables are shown for corn swaps and futures positions by trader type in appendix tables 5 and 6. Estimates for the remaining commodities are available from the authors upon request.

[36]Similar results were found when we estimate the regressions using a Seemingly Unrelated Regressions (SUR) framework, similar to Sanders and Irwin (2011).

[37]The finding of convective risk flow in CBOT corn is not apparent in table 5, but we later show other CITs did significantly reduce net long positions during COVID. This finding is shown below in table 7.

[38]Trader counts are measured as average daily number of unique financial and commercial swap counterparties across 2016-2021.

swap dealers, allowing them to find a willing counterparty to offset its net long position after index traders unwind their positions during this volatile period. In other words, these swaps markets provide a greater opportunity for convective risk flows between index and commercial traders.[39]

Table 6: Effect of 1-SD increase in VIX on the net position of various traders in agricultural futures and swaps markets, January 5, 2016 - January 14, 2020

	Swaps Index	Swaps Comm.	CIT	Futures Comm.	Futures Noncomm.
CBOT Corn	0.056	-0.011	-0.115	-0.033	0.062
CBOT Soybeans	0.070	0.054	-0.083	0.124*	-0.116*
CBOT SRW Wheat	0.094*	-0.042	0.020	0.015	-0.015
CBOT HRW Wheat	-0.020	0.046	-0.077	-0.011	0.046
CBOT Soybean Oil	0.018	0.128	0.051	0.055	-0.077
CBOT Soybean Meal	-0.003	0.054	0.034	0.017	-0.036
ICE Cotton	0.064	0.246**	-0.084	0.253***	-0.248***
ICE Sugar	0.108	-0.002	-0.087	0.008	0.029
ICE Coffee	0.037	-0.124**	-0.069	-0.022	0.056
ICE Cocoa	0.020	0.068	-0.074	0.073	-0.040
CME Feeder Cattle	0.044	0.081	-0.097**	0.095	-0.054
CME Lean Hogs	0.091	0.017	0.053	-0.029	0.045
CME Live Cattle	0.030	0.059*	0.030	0.097*	-0.137*
Average effect	0.047	0.044	-0.038	0.049	-0.037
Avg. effect (OI weighted)	0.048	0.023	-0.056	0.029	-0.015
Average R^2	5.0%	4.6%	6.5%	14.7%	13.5%
Obs	206	206	206	206	206

Note: asterisks denote significance level, *** 1%, ** 5%, * 10%

Table 6 reports estimates of α_1 for the five swaps and futures trader groups in the pre-COVID period. Our analysis finds evidence of convective risk flows in only three commodity futures markets during this period: soybeans, live cattle, and cotton futures. We do not find any evidence of convective risk flows in the swaps markets. Index traders positions in both swaps and futures

[39]Interestingly, we do not find convective risk flows in soybean swaps, the third largest swaps market when measured in futures-equivalent contracts. A possible explanation is that soybean swaps markets had already been affected by the rising number of COVID cases in China in mid-February of 2020. China is the world's largest importer of U.S. soybeans. Other agricultural commodities were found to respond to the resulting equity market volatility later, in March of 2020 (Peng et al., 2021).

show few significant changes associated with the VIX. The average VIX effect on net position changes for all traders are substantially lower than in the COVID shock period. The lack of strong evidence of a commodity-equity linkage in swaps or futures is consistent with the lower levels of financial market volatility observed in the pre-COVID period.

6.3 Swap dealers and other commodity index traders

CITs have been documented to play a role in commodity-equity co-movements (Büyükşahin and Robe, 2014). Although swap dealers make up a large share of CIT open interest, there are other traders mixed into this broad index category. As discussed in the data section, we disaggregate the CIT category into two groups: dealer CITs and other CITs. We note that the other CIT category is comprised of many traders that are classified as managed money or hedge funds. This suggests they may have more short-term oriented trading strategies, a very different motivation than swap dealers that are hedging long, passive index investment. We run separate regressions for dealer CITs and other CITs using the net positions regression model in equation 2. Results are shown in table 7.

Table 7: Effect of 1-SD increase in VIX on the dealer CIT and other CIT net positions in agricultural futures. Left panel: Jan 5, 2016 - Jan 14, 2020; Right panel: Jan 21, 2020 - Dec 28, 2021

	Dealer CITs	Other CITs	Dealer CITs	Other CITs
CBOT Corn	0.020	-0.165	0.011	-0.278***
CBOT Soybeans	-0.060	-0.047	-0.176*	-0.162***
CBOT SRW Wheat	-0.009	0.059	-0.182	0.185***
CBOT HRW Wheat	-0.063	-0.039	-0.207	-0.224**
CBOT Soybean Oil	0.047	0.030	-0.212**	-0.170
CBOT Soybean Meal	0.034	0.018	-0.036	0.035
ICE Cotton	-0.103	0.019	-0.095	-0.243**
ICE Sugar	0.013	-0.138**	0.092	-0.224**
ICE Coffee	-0.030	-0.055	-0.211**	-0.075
ICE Cocoa	-0.020	-0.084	-0.041	-0.337***
CME Feeder Cattle	-0.114**	-0.012	-0.123	-0.364***
CME Lean Hogs	0.034	0.031	0.023	-0.128
CME Live Cattle	-0.008	0.039	-0.128**	-0.174
Average effect	-0.020	-0.026	-0.099	-0.166
Average effect (OI weighted)	-0.005	-0.091	-0.064	-0.174
Average R^2	5.0%	5.5%	10.9%	18.3%
Obs	206	206	102	102

Note: asterisks denote significance level, *** 1%, ** 5%, * 10%

We find that net positions of other CITs were much more responsive to the VIX than dealer CITs. Other CITs decreased their net long positions significantly in seven commodities, compared to four commodities for dealers CITs. Using the open interest weighted estimate of the VIX effect, we find the average effect of a 1-SD increase in the VIX on net positions for other CITs is nearly three times greater than the effect for dealer CITs (-0.17 vs. -0.06). The average VIX response for other CITs is also greater than it is for noncommercials (-0.17 vs. -0.11), demonstrating the wide variation in trading motivations within the aggregate CIT category.

Our analysis reveals that while swap dealer CIT positions generally decreased in response to the spike in the VIX, the average decrease was slightly less than the average index swaps trader (-0.06 vs. -0.08), and much less than noncommercials or other CITs. We note that swap dealers did not significantly decrease their net long CIT positions in the three commodities where convective risk flows occurred in swaps (corn, SRW wheat, and sugar). The resulting internal swap market netting between index and commercial traders helps swap dealers offset the risk in their swap book, decreasing their futures hedging demand. This highlights the important role played by traders with greater risk absorption capacity (e.g., commercials) in both swaps and futures markets during periods of financial distress.

7 Conclusion

Our study brings visibility to the previously opaque agricultural swaps markets by using proprietary data on thirteen agricultural swaps markets reported to the CFTC. In total, the these swaps markets represent close to $100 billion notional activity of commodity index investment and commercial hedging activity. Many of these swap markets are quite sizable in relation to their paired futures market. However, significant differences are found between agricultural swaps and futures markets. Index traders represent the majority of open activity in swaps but are a much smaller share of paired futures. The net positions of index swap traders and CITs in the paired futures market are negatively correlated, consistent with hedging behavior of swap dealers in the futures market in relation to swaps activity.

Our empirical analysis provides novel evidence of commodity-equity linkages in OTC agricultural swaps markets. We find changes in returns and trader net positions were significantly affected by the spike in the VIX during the early months of the COVID-19 pandemic. Our findings are consistent with previous work on convective risk flows in commodity futures markets Cheng et al. (2015), but provide a more complete picture of how risk is transferred between traders with different risk absorption capacities in both swaps and futures during periods of financial volatility. We document that index swaps traders reduced net long positions in response to tightening financial conditions, while commercial swaps traders reduced net short positions, resulting in convective risk flows in three of the four largest agricultural swaps markets (corn, SRW wheat, and sugar). The internal netting of swaps positions allowed swap dealers to reduce their hedging demand in the futures market.

In future research we will examine other Part 20 swaps markets, including the paired energy and metals contracts. We expect many of these swap markets respond to financial market shocks in a similar manner as agricultural swaps. Swaps play a large role in hedging for commercial traders in WTI crude oil markets (Mixon et al., 2018) and we plan to explore whether this extends to other energies (e.g., Natural Gas). We also plan to examine whether price discovery always occurs in the paired futures market or whether commodity swaps activity can affect futures prices as well.

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A Appendix

Part 20 physical commodity swaps covered futures contracts

Table 1: Part 20 physical commodity swaps covered futures contracts

Chicago Board of Trade ("CBOT") Corn	ICUS Coffee C
CBOT Ethanol	ICUS Cotton No.2
CBOT Oats	ICUS Frozen Concentrated Orange Juice
CBOT Rough Rice	ICUS Sugar No. 11
CBOT Soybean Meal	ICUS Sugar No. 16
CBOT Soybean Oil	Kansas City Board of Trade ("KCBT") Wheat
CBOT Soybeans	Minneapolis Grain Exchange ("MGEX") Wheat
CBOT Wheat	NYSELiffe ("NYL") Gold, 100 Troy Oz.
Chicago Mercantile Exchange ("CME") Butter	NYL Silver, 5000 Troy Oz.
CME Cheese	New York Mercantile Exchange ("NYMEX") Cocoa
CME Dry Whey	NYMEX Brent Financial
CME Feeder Cattle	NYMEX Central Appalachian Coal
CME Hardwood Pulp	NYMEX Coffee
CME Lean Hogs	NYMEX Cotton
CME Live Cattle	NYMEX Crude Oil, Light Sweet
CME Milk Class III	NYMEX Gasoline Blendstock (RBOB)
CME Non Fat Dry Milk	NYMEX Hot Rolled Coil Steel
CME Random Length Lumber	NYMEX Natural Gas
CME Softwood Pulp	NYMEX No. 2 Heating Oil, New York Harbor
COMEX ("CMX") Copper Grade #1	NYMEX Palladium
CMX Gold	NYMEX Platinum
CMX Silver	NYMEX Sugar No. 11
ICE Futures U.S. ("ICUS") Cocoa	NYMEX Uranium
Diversified Commodity Index	

Implied swaps prices

We use the Part 20 swaps data to calculate daily implied swaps prices for swaps linked to the nearby contract month. Part 20 swaps data do not provide details on the overall tenor of a swap but do include a “tenor of exposure” for the futures-equivalent contract. The tenor of exposure is the futures-equivalent contract month that determines the floating-leg price, which determines the net payment flows to the swap fixed-price payer.

We calculate the average implied swaps price for the i^{th} commodity, on reporting day t as:

$implied\,swaps\,price_{i,t} =$

$$\frac{total\ notional_{i,t}}{total\ futures\ equivalent\ contracts_{i,t}} x \frac{one\ futures\ equivalent\ contract}{contract\ unit} \tag{3}$$

where the total notional is measured in U.S. dollars. Our measures uses the total notional and futures-equivalent contracts on swaps with a tenor of exposure of three months or less, so that our swaps price is tied to the nearby futures contract. Contract unit is the standardized contract size that is unique to each futures contract (e.g., 5,000 bushels of corn for CBOT Corn). For example, a CBOT corn swap worth $40,000 in notional and equal to two futures-equivalent contracts has an implied swaps price of $4.00 per bushel.

Table 2: Weekly commodity returns for swaps and nearby futures, expressed in basis points. Time period is January 5, 2016 - December 28, 2021.

Commodity	Obs	Mean	S.D.	Mean	S.D.
		Swaps		Futures	
Corn	312	0.002	0.034	0.002	0.028
Soybeans	312	0.002	0.025	0.002	0.025
SRW Wheat	312	0.003	0.041	0.002	0.035
HRW Wheat	312	0.003	0.044	0.003	0.039
Soybean Oil	312	0.003	0.032	0.003	0.031
Soybean Meal	312	0.002	0.031	0.002	0.028
Cotton	312	0.002	0.032	0.002	0.035
Sugar	312	0.002	0.041	0.001	0.033
Coffee	312	0.003	0.047	0.003	0.044
Cocoa	312	$1e^{-4}$	0.039	-$2e^{-5}$	0.035
Feeder Cattle	312	$4e^{-4}$	0.030	$4e^{-4}$	0.028
Lean Hogs	312	0.003	0.061	0.002	0.043
Live Cattle	312	$7e^{-4}$	0.034	$2e^{-4}$	0.027

Table 3: Average daily net futures positions of commodity index traders (CITs), commercial traders, and noncommercial traders. Positions are reported in futures-equivalent contracts. T=313 weeks, January 5, 2016 - December 28, 2021.

Commodity	Obs	Mean	S.D.	Mean	S.D.	Mean	S.D.
		CITs		Commercial		Noncommercial	
Corn	313	322724.0	558289.0	-305812.3	210552.0	-11946.9	189805.7
Soybeans	313	143512.2	27480.3	-127325.4	116704.9	13916.4	97521.1
SRW Wheat	313	123421.6	16334.5	-54817.3	50073.2	-62005.2	51785.8
HRW Wheat	313	51621.4	10535.7	-49346.4	33027.1	-3900.0	27449.5
Soybean Oil	313	103100.0	17374.4	-130770.0	62098.9	17890.9	51879.0
Soybean Meal	313	83477.8	13315.2	-112251.6	57815.6	10213.6	46094.4
Cotton	313	72556.4	7932.5	-119260.2	52431.8	41766.7	45053.8
Sugar	313	218283.7	32231.3	-273035.6	160545.4	28130.8	142205.4
Coffee	313	45445.6	12748.9	-39170.8	45722.6	-12435.5	40509.5
Cocoa	313	30613.5	10920.3	-33269.2	28028.79	-1866.6	24767.6
Feeder Cattle	313	12433.1	2510.5	-2904.6	4122.3	-1089.9	7125.6
Lean Hogs	313	78465.5	9396.2	-89149.9	29226.4	25066.2	25532.8
Live Cattle	313	115019.2	21063.0	-140024.9	44248.0	44283.1	37742.7

Table 4: Average daily net swaps positions of index swaps traders and commercial swaps traders. Positions are reported in futures-equivalent contracts. T=313 weeks, January 5, 2016 - December 28, 2021.

Commodity	Obs	Mean	S.D.	Mean	S.D.
		Index		Commercial	
Corn	313	163354.8	33382.4	21967.7	25859.1
Soybeans	313	63594.9	10891.4	-27435.9	14731.2
SRW Wheat	313	71469.3	15017.2	9153.8	18172.6
HRW Wheat	313	23195.9	4639.7	1345.0	2133.5
Soybean Oil	313	42783.1	8386.5	2239.4	4580.1
Soybean Meal	313	39712.0	10490.6	814.1	5356.3
Cotton	313	31005.7	7312.9	-8742.1	6220.1
Sugar	313	117248.9	12173.0	-50608.1	60166.1
Coffee	313	19405.0	4706.6	-98012.5	335066.9
Cocoa	313	10272.1	4619.4	1069.3	2897.1
Feeder Cattle	313	3787.0	1382.4	17.6	275.4
Lean Hogs	313	4853.5	7396.4	-4282.2	4095.2
Live Cattle	313	46931.0	13859.1	-2061.7	1423.2

Table 5: Parameter estimates for the control variables in CBOT corn position change regressions, by trader category. T=206, pre-COVID period: Jan 5, 2016 - Jan 21, 2020

Variable	Swaps Index	Swaps Comm.	CIT	Futures Comm.	Futures Noncomm.	SD CIT	Other CIT
D.VIX	182.405	-35.601	-506.505	-597.540	1069.712	71.823	-578.328
LD. VIX	0.646	71.235	-162.974	250.476	-2.352	185.369	-348.343
L. Returns	68252.8***	-29814.8*	80544.67***	-494002.6***	570077.2***	10460.55	70084.12***
LD. Trade Policy	-9.357*	1.324	3.902	36.498	-36.402	-1.77	5.672
LD. Monetary Policy	29.034	11.294	71.069	-332.507*	293.523*	78.94**	-7.87
LD.BAA10Y	-50.077	-4664.91	1165.382	2529.214	3927.231	-1725.124	2890.508
LD. Inflation Compensation	-0.280	3.139	-1.272	1.58	-9.119	-7.275	6.003
LD. Killian Index	36.443	-30.827	-55.625	-113.276	73.033	1.738	-57.362
Constant	-81.308	-41.42	-359.825	-49.825	86.15	43.02	-402.845
R^2	6.5%	1.3%	10.1%	12.3%	17.3%	4.9%	10.0%
Observations	206	206	206	206	206	206	206

Notes: asterisks denote significance level, *** 1%, ** 5%, * 10%.
Weekly returns are based on nearby futures prices for futures positions and implied swaps prices for swaps positions.
Standard errors are based on Newey-West method with 4 lags.

Table 6: Parameter estimates for the control variables in CBOT corn position change regressions, by trader category. T=102, COVID period: Jan 28, 2020 - Dec 28, 2021

Variable	Swaps Index	Swaps Comm.	CIT	Futures Comm.	Futures Noncomm.	SD CIT	Other CIT
D.VIX	-153.43*	184.221***	-257.6	1239.632**	-563.535	14.113	-271.71***
LD. VIX	-251.153	49.454	-305.06***	335.879	-182.478	-177.982	-127.073*
L. Returns	18163.1	-10748.9	33600.92*	-153308.3**	116797.4*	1156.1	32444.83**
LD. Trade Policy	-13.193	1.452	-20.462	-64.908*	106.807***	-20.696	0.234
LD. Monetary Policy	-48.022**	-8.532	69.80*	-207.936***	135.947**	28.889	40.9**
LD.BAA10Y	-1585.514	3622.288	-5174.316	16606.2	9107.37	-2844.5	-2329.82
LD. Inflation Compensation	-1.853	0.847	-1.876	9.191	-8.677	-0.781	-1.095
LD. Killian Index	-21.851	5.796	-48.077	94.296	64.55	-49.204	1.127
Constant	895.811	-411.645	2220.414**	-8020.983*	7779.882	1252.575	967.839*
R^2	14.9%	15.3%	21.2%	12.6%	8.3%	9.0%	19.6%
Observations	102	102	102	102	102	102	102

Notes: asterisks denote significance level, *** 1%, ** 5%, * 10%.
Weekly returns are based on nearby futures prices for futures positions and implied swaps prices for swaps positions.
Standard errors are based on Newey-West method with 4 lags.

B Data Appendix

Swap data for this paper were reported under the Large Trader Reporting for Physical Commodity Swaps. Data are reported for each dealer and counterparty position along with characteristics of the swap or swaption. For each swap, data include the index or underlying commodity, futures equivalent month, swaption strike price, and swaption expiration date, among other identifiers. For complex swaps or swaptions, this may include hundreds or thousands of rows. To make the data tractable for analysis, we aggregate swaps and swaptions to a unit of analysis for each underlying commodity, dealer and counterparty pair, futures-equivalent month, and swaption indicator. We measure only market-facing swaps in our analysis. Interaffiliate trades, those between two parts of the same parent company, were excluded from the analysis. Dealer to dealer swaps were reported by both parties the aggregate positions were reduced by half to adjust for double counting of these trades.

Futures Equivalent positions

Futures-equivalence is a methodology that allows for the conversion of disparate derivatives contracts into consistent measures of size, direction, and expiration. Essentially, the futures-equivalent positions generated from a swap would be the portfolio of futures contracts that would most closely provide the price exposure of that swap in terms of size, direction, and expiration. For example, a swap with a notional size of 250,000 bushels of CBOT corn would be reported with a position size of 50 CBOT corn contracts since one futures contract is 5,000 bushels.

According to CFTC regulation, swap dealers are required to report their positions in both nominal and future-equivalent terms. According to CFTC guidelines, “the futures-equivalent positions generated from a swap would be the portfolio of futures contracts that would most closely provide the price exposure of that swap.” For swaps that trade on a designated contract market (DCM), this is a straightforward conversion. For swaps not traded on a DCM, the CFTC guidebook states that, “If the swap pricing refers to a spot or short-term forward price series, then it is appropriate to convert the notional quantity of the swap into futures equivalent positions of the futures contract that will deliver at the same time as the cash market transactions in that price series.”

Delta-adjusted Swaptions

Swaptions are reported in non-delta-adjusted positions along with a delta factor. Authors calculated delta-adjusted futures-equivalent positions by multiplying the delta factor with the non-adjusted position.

Index Positions

Guidance by the CFTC allows swap dealers to report index positions either identified by index name and total notional value or split into individual constituent parts. Index swaps identified by their name or ticker symbol were disaggregated into underlying futures positions according to the yearly weights published by the Bloomberg Commodity Index (BCOM) and S&P Goldman Sachs Commodity Index (SPGSCI). Materials published by Bloomberg and S&P informed the calculation of components for sub-indexes and weighted and capped indexes. For swaps that were not reported by an index ticker, the vast majority of swaps were reported as either "IndexOrBasket" or "Other". While a small fraction were reported as locational basis swaps, the resultant dataset categorizes all swaps as either index or non-index swaps.

For instance, over the reference period, commodity indices were approximately 6% corn. If a dealer's position for a particular swap was $100 million notional long and zero short, the relevant portion for corn would be $6 million long. If, on the day being analyzed, the settlement price was $4 / bushel, given 5,000 bushes per corn contract, each contract has a price of $20,000. Therefore the index position is equivalent to 300 corn contracts.

Dealer and Other CITs

When we examine dealer CITs and other CITs more closely, there are clear differences. About 10% of long and 3% of short futures open interest is held by entities other than swap dealers who register as CIT traders with the CFTC (other CITs). These traders are generally classified as Managed Money (63% of long OI) or Other Reportables (33% of long OI). In corn and soybeans, a majority of positions are held on behalf of institutional clients, either through managed accounts or commodity pools.[40] In those commodities, a little over 10% of positions are from issuers of ETFs, another 10% from investment banks or non-US commercial banks, with smaller percentages from pension or mutual funds.

[40] A commodity pool typically combines participant contributions and allocates them in the commodity markets. They are similar to a hedge fund, but in the commodity space.