Commodity Futures Speculation in China

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Abstract

The burst of stock market bubbles recently along with renewed regulations stirred Chinese investors away from stocks into the rapidly emerging commodity markets. Enormous inflows of capital raised concerns about the impact of speculative activities in these markets. Using a broad sample of 30 commodities from 2004 to 2017, this paper investigates whether the increased presence of speculators in recent years destabilize the commodity futures market in China. Our findings suggest that speculative activities in the most heavily traded commodities, on an aggregate level, do not cause increase in the volatility of the broad market nor do they elevate the cross-market correlations with traditional assets. However, we find evidence that speculation increases the volatility of commodities in a dynamic long-short setting. In this setting, we show that increased presence of speculators causes the correlations to increase with stocks and decrease with macroeconomic activities. Our findings suggest additional regulations on passive long-only or other index-like investors are unwarranted, as they add liquidity and facilitate the price discovery and risk transfers in these markets.

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1. Introduction

Global commodity markets have been through a ‘roller-coaster’ ride from 2004 to 2014. Fuelled by a series of de-regulation since the beginning of the millennium, investors piled into commodity-related investments, drove up major price benchmarks to all-time-highs prior to the global financial crisis. With increased regulatory curbs, major players including global investment banks exited in the commodity business, leading to the price collapse globally from 2010 to 2014. Commonly accepted as the result of “financialization”, the recent boom and bust cycle of commodity markets have sparked intense academic and policy debates around the effect of speculation in commodity futures. Proponents of speculation posit that speculation adds liquidity to the market, decreases risk premium or lowers the cost of hedging and deduces volatility in the long-run (Brunetti, Büyükşahin, & Harris, 2016; Büyükşahin & Harris, 2011; Irwin, Sanders, & Merrin, 2009; Kim, 2015; Miffre & Brooks, 2013). On the other hand, studies have found speculation leads to increase short-term volatility, and is responsible for the frequenting of price bubbles and increased degree of integration with financial markets such as stocks and bonds (Cheng, Kirilenko, & Xiong, 2014; Tang & Xiong, 2012).

The commodity futures markets in China have experienced unprecedented growth in the last two decades. Enormous surges in trading volumes have propelled Chinese exchanges among the world’s top ten commodity exchanges in terms of the number of trading lots. Trading activities by Chinese investors now present significant influences on the pricing dynamics of several commodities traded internationally (Bloomberg, 2018). While part of the surge can be traced back to the rapid economic expansion, another driving factor behind the sharp growth is the massive inflow of speculative capital, referred to by mainstream media as the “speculation mania” (FT, 2016; WSJ, 2016). Although there has been no evidence of “financialization” in China, the “speculation mania” shares similar roots with the recent financialization of commodity futures in the US. This paper aims to shed light on the effect of speculation in the rapidly emerging commodity markets in China. The findings of this paper are of particular interest to the regulators, as evidence against speculation will support the recent regulatory curbs imposed. However, contrary evidence will suggest that further regulation could be potentially harmful, particularly in terms of price discovery and risk transfer.

The literature to date appears to agree that the presence of long-only index investors do not destabilize (i.e. increase volatility) commodity markets in the US (Hamilton & Wu, 2015; Irwin & Sanders, 2012a). These findings generally hold for dynamic long-short speculators. For example, Büyükşahin and Harris (2011) find little evidence to support that hedge funds and other non-commercial (speculator) position changes Granger-cause price changes. They show that price changes even precede their position changes. Furthermore, Miffre and Brooks (2013) conclude that long-short speculators do not cause changes in the volatilities of the portfolios they hold or changes in the conditional correlations between these portfolios and traditional assets. More recently, Brunetti *et al*. (2016) examine the relationship between changes in the net positions of hedge funds in corn, crude oil, natural gas, and volatility. They conclude that hedge funds actually stabilize prices by decreasing volatility.

The literature on commodity futures speculation in China is of paucity. On the one hand, the lack of extant studies can be attributed to the history and experience of the market; on the other hand it also presents a major limitation in our understanding of the behavior of commodity prices in China. Fan and Zhang (2018) conduct an extensive overview and document several institutional characteristics unique to China. First, the Chinese market is dominated by individual/retail investors (over 90% market share). These individual/retail investors may act as *speculators* or *hedgers*. Second, although the authorities have clearly defined individuals with foreign citizenship as eligible investors to trade on certain commodity products in a recent proposal, direct participation by foreign individual investors is currently prohibited without the approval of Qualified Foreign Institutional Investor (QFII) or RMB Qualified Foreign Institutional Investor (RQFII) quotas.[1] Third, stringent price limit[2] and positions limit[3] apply. While these limits are designed to curb excessive speculation and prevent the distortion of spot prices, they also create a "limit-to-arbitrage" in the front end of the futures curve, thereby creating two separate markets each reflects distinct pricing dynamics. Overall, they conclude Chinese commodity futures market remains segmented from the US. The findings by Fan and Zhang (2018) suggest that one cannot simply draw

[1] See www.csrc.gov.cn/pub/newsite/flb/flfg/bmgz/qhl/201507/t20150731_281991.html.

[2] For instance, "Dalian Commodity Exchange Administrative Measures for Risk Management" states that the daily price limit for all commodity futures contracts during non-delivery months is 4% within the settlement price of previous trading day, while it becomes 6% in the delivery month.

[3] For example, the maximum number of positions that non-futures company member and retail investors can hold between the first trading day of the contract and the 15th calendar day of the month prior to the delivery month is 2000. This quota then reduces to 600 for the remaining calendar days of that month. Only 200 long or short positions are granted to non-futures company members during the delivery month, while the retail investor is prohibited to trade any commodity's contract in the delivery month.

inferences on the effect of speculation in China based on the prior literature without recognizing these unique characteristics.

To date only a few studies have attempted to tackle the issue of commodities speculation in China. Using a trade-by-trade dataset, Zhao and Wan (2018) find informational volatility is far below the transitory volatility, indicating that the trading volume is primarily motivated by speculative noise rather than fundamental information. However, the aim focus of Zhao and Wan (2018) is to compare the effects of institutional and individual trading on intraday price processes. While Li, Chavas, Etienne, and Li (2017) show evidence of speculative bubbles in most agricultural commodity futures markets from 2006-2014, their main contribution is identifying the macroeconomic determinants of price bubbles. More recently, using Granger causality tests, Bohl, Siklos, and Wellenreuther (2018) conclude rise in speculation increases the volatility of agricultural commodity futures. They employ daily measures of speculation and hedging ratios to test whether increase in speculative activities in *individual* markets impact the volatility of *individual* markets.

The existing literature in Chinese commodity futures generally suffers from several drawbacks. First, studies tend to focus only on one or two sectors of the commodity markets. This limits one's ability to draw inferences to the aggregate market as a whole. More importantly, almost all studies fail to recognize the notorious position limits around the front end of the futures curve. Unlike the US, where the nearest to maturity contracts are generally the most liquid, the vast majority of trading volume in the Chinese market is around the third and fourth nearest to maturity contracts (see Fan and Zhang, 2018). This is cumbersome particularly for studies examining the effect of speculation in China, since the trading volume on the front contracts represents less than one third of the total volume traded. In this study, we employ the third nearest to maturity contracts on a broad sample of 30 commodities. We investigate the effect of speculation by both the long-only and long-short speculators using a dynamic portfolio setting proposed in Miffre and Brooks (2013). However, unlike the US market, there is no CFTC equivalent data repository available in China. Thus, to fully capture both hedgers and speculators activities in the market, we first employ the hedging and speculation ratio proposed by Garcia, Leuthold, and Zapata (1986) and Bohl *et al.* (2018)[4], to

[4] In addition to rolling methodology and sector coverage, our approach is superior to Bohl *et al*. (2018) for several reasons. First, hedging and speculation ratio in our long-only portfolio presents stronger statistically power in the causality test, which help shed light on the aggregate effect of long-only speculation. Second, we explicitly account for the dynamic switches on a monthly basis by long-short speculators, while they focus only on individual agricultural markets. As noted also by the authors, speculators trade actively where they go in and out of different commodity markets multiple times even during one trading day.

measure the degree of hedging and speculative pressures. Subsequently, we test whether changes in hedging and speculation ratios granger cause increases in volatility of long-only and long-short portfolios as well as their correlations with traditional assets and macroeconomic activities in China.

Our paper presents three key contributions to the commodity futures literature. First, consistent with recent evidence in the US, we find that speculative activities in 20 of the most heavily traded commodities do not cause increase in the volatility of the broad commodity market in China (Etienne, Irwin, & Garcia, 2017; Sanders & Irwin, 2017). The same finding holds whether trading activities are measured by hedging ratio or speculation ratio. Furthermore, we show that speculative activities in these markets on an aggregate level do not elevate cross-correlations between commodities and traditional assets such as stocks and bonds. Since the Chinese commodity market is believed to be segmented from the US due to unique institutional settings and regulations, along with the fact that this market is characterized as one of the most speculative in the world, our findings may be viewed as an out-of-sample test for the role of index investors in destabilizing markets.

Second, consistent with Bohl *et al*. (2018), we find that increased presence of speculators (measured by speculation ratio) can led to the increase in the volatility of commodities in a dynamic long-short setting.[5] Specifically, we demonstrate that long-short speculators who trade based on momentum and term structure do not destabilize the market, but speculators who trade based on the volatility signal increase the volatility of the portfolios they trade, as well as the correlation with stocks. Nevertheless, our findings suggest that speculators who trade based on the hedgers' hedging pressure signal can cause the price volatility and correlations with conventional assets and macroeconomic variables to decrease China.[6] These results do not support the previous findings on the role of long-short investors in the US (Brunetti *et al*., 2016; Miffre & Brooks, 2013). Consistent with the findings on long-only aggregate markets, we find the impact of hedging activities (measured by hedging ratio) is rather limited, suggesting that hedgers' activities do not destabilize the market in China.

[5] In this setting, investors are assumed to process a higher level of sophistication, thus are better informed than the long-only speculators. We implement systematic long-short strategies to mimic the behaviour of these speculators. Proven to be successful by previous studies, this includes term structure, momentum, hedging pressure and volatility.

[6] These seemingly contradictory results suggest that a definitive conclusion is rather difficult to reach as one cannot accurately measure the extent how these two effects neutralize each other.

Third, our findings are also related to the literature on commodity price bubbles. Li, Zhang, and Zhou (2017) conclude that economic growth, money supply and inflation have positive effects on price bubbles in China. In this paper, we show that increased presence of more sophisticated long-short speculators in fact elevate the correlations between commodity futures and macroeconomic activities in China, suggesting that effect of key economic variables on commodity prices may have become stronger. Furthermore, Brooks, Prokopczuk, and Wu (2015) argue that extreme price movements in commodity markets are not caused by pure speculation. The authors examine a large sample of commodities in the US from all sectors and find evidence of speculative bubbles only for crude oil and feeder cattle. They conclude that additional regulations on speculators are unnecessary. However, our findings suggest that regulation in China is a balancing act between liquidity and market stability. Though at the very least, we recommend the China Securities Regulatory Commission (CSRC) not to impose additional regulations on passive long-only or other index-like commodity investors in China, because their participation adds liquidity to the market and facilitates the price discovery and risk transfers.

The remainder of the paper proceeds as follows. Section 2 discusses the literature on speculation and financialization. Section 3 describes the data and sample selection. Section 4 details the methodologies employed, followed by results in Section 5. The paper concludes in Section 6.

2. Related Literature

A large number commodities across several sectors experienced a boom and bust cycle from 2007 to 2008, in which the price volatility of many commodities spiked (Cheng & Xiong, 2014a). According to the Commodity Futures Trading Commission (CFTC) (2008) staff report, the investment inflows to various commodity futures indexes increased from $15 billion in 2003 to over $200 billion in 2008. With the large expansion of commodity derivatives trading, the increasing presence of financial investors has led to a growing concern of general public, policy makers, and market participants as to whether the increased financialization process in the futures markets causes excessive price fluctuations. The financialization of commodity markets identifies the increasing role of financial motives, financial markets and actors in the operation of commodity markets (Flassbeck, Bicchetti, Mayer, & Rietzler, 2011).[7]

There is an ongoing debate in academia on whether the financialization of commodity markets is the driving force behind the destabilization of the market. The discussions can be categorized by the potential destabilizing role of net-long commodity index traders (CITs) and long-short speculators (such as commodity trading advisors (CTAs). From the perspective of CITs, the results are mixed. One side of the argument states that the index investments have caused an increase in commodity futures volatility and correlations with other asset classes (Tang & Xiong, 2012).[8] This argument is backed by the Masters Hypothesis, which claims that unprecedented buying pressure in recent years from commodity index investors created massive bubbles in commodity prices in 2007-2008.[9] Gilbert (2010b) finds a significant relationship between index fund trading and price changes in three commodities, crude oil, aluminum, and copper. In a subsequent work, Gilbert (2010a) show that index-based investment in agricultural futures markets is seen as the major channel through which macroeconomic and monetary factors generated the 2007-2008 food price rises. In particular, the index activity was driven in part by the rapid economic growth in China. Singleton (2013) also finds that index investment flows are important determinant of price changes along with several other conditional variables. In addition, Tang and Xiong (2012) find that the financialization process of commodity markets helps explain the large increase in the price volatility of non-energy commodities around 2008. However, as pointed out by Cheng *et al*. (2014), in times of distress, CITs, by reducing their net long exposures, fail to provide the insurance that short hedger demand. Meanwhile, they transmit outside shocks to commodity markets.

On the other hand, a large amount of literature argues that the Masters Hypothesis does not hold in reality. This line of research uses time-series regression tests, such as Granger causality tests, to investigate the relationship between price movements and index

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[7] Investors can gain commodity exposure through a number of investment vehicles, such as commodity index traders (CITs), exchange traded products (ETPs), mutual funds, commodity trading advisors (CTAs) and commodity based company stocks (Jensen & Mercer, 2011).

[8] CIT describes as “an entity that conducts futures trades on behalf of a commodity index fund or to hedge commodity index swap positions.” Commodity index products such as exchange-traded funds and exchange traded notes build on passive, long-only, fully collateralized commodity futures positions taken by CITs.

[9] The Masters Hypothesis was proposed by hedge fund manager Michael W. Master, who argues that massive buy-side from index funds created a bubble in commodity prices. As a result, commodity prices, and crude oil prices in particular, far exceeded fundamental values at the peak. The term “The Masters Hypothesis” is used as a short-hand label of this argument.

positions. For example, Irwin *et al*. (2009) show little evidence that the 2006-2008 boom and bust in commodity prices was driven by speculative bubble. Irwin, Garcia, Good, and Kunda (2011) show that rolling of positions by index funds or the initiation of large index position do not contribute to an expansion of the price spread. Further, by showing no causal links between daily returns and volatility in the crude oil and natural gas futures markets, Irwin and Sanders (2012b) reject the Master Hypothesis in commodity futures markets. Sanders and Irwin (2011a) focus on a group of 14 grain, livestock, soft and energy futures markets. The system of Granger causality tests fail to reject the null hypothesis that trader positions do not lead market returns. In addition, there is a consistent tendency to reject the null hypothesis that index trader positions do not lead market volatility.

Subsequently, Sanders and Irwin (2011b) employ new data from 2004 to 2005 and show a large increase in commodity index position occurred in select grain futures markets. However, the increased index participation took place well in advance of the 2007-2008 price spikes. The Granger causality test fails to find any causal linkages between commodity index activity and grain futures prices. Sanders, Irwin, and Merrin (2010) also show that index fund positions were relatively stable percentage of total open interest during 2006-2008 commodity price boom. Stoll and Whaley (2010) indicate that commodity index rolls have little futures price impact, and inflows and outflows from commodity index investment do not cause futures prices to change.

Another strand of research is related more to our work, which focuses on whether long-short investors are to blame for the observed price changes. Similar to the results of the index investments, the findings based on long-short investors thus far are also inconclusive. Studies by Till (2009) and Sanders *et al.* (2010) support the argument that long-short speculators are not blame for excessive price impact in 2006-2008 as rising in speculation is merely a response to increase in hedging demand. Likewise, Miffre and Brooks (2013) use a battery of trading strategies and test whether long-short speculators destabilize the US market. Their results conclude that long-short speculators do not cause changes in the volatilities of the portfolios they hold or changes in the conditional correlations between these portfolios and traditional assets. In addition, finding of Büyükşahin and Harris (2011) show little evidence to support that hedge funds and other non-commercial (speculator) position changes Granger-cause price changes. Moreover, price changes even precede their position changes. Hamilton and Wu (2015) find no evidence that the positions of traders in agricultural contracts identified by the CFTC as following an index strategy can help predict returns on the near futures contracts.

Furthermore, several empirical studies show that speculations are not responsible for excessive price fluctuations and increase in co-movements with other asset classes. Instead, speculative trading helps reduce the volatility level (Brunetti & Büyüksahin, 2009; Brunetti et al., 2016; Kim, 2015). Brunetti *et al.* (2016) use data from 2005-2009 that uniquely identify categories of traders to test how speculators such as hedge funds and swap dealers relate to volatility and price changes. Their results show that speculators' activity does not destabilize financial markets. To the contrary, hedge fund position actually decreases the volatility in corn, crude oil, and natural gas futures. Additionally, swap dealer activity is largely unrelated to contemporaneous volatility. Similar results are also concluded by Brunetti and Büyüksahin (2009), which suggest that speculative trading in futures market reduces volatility level rather than destabilizing the market.

Kim (2015) examines how increased speculator participation in the commodity futures market affects market outcomes, including trades' price impacts, price volatility, and market quality. The analysis finds no evidence that speculators destabilize the commodity spot market. Instead, speculators contribute to lower price volatility, enhanced price efficiency, and better liquidity in the commodity markets. More importantly, the author finds that speculators either have no effect or stabilize prices during periods of large price movement. However, Büyüksahin, Haigh, and Robe (2010) find hedge funds active in both equity and commodities. More recently, Büyükşahin and Robe (2014) indicate the correlation between return rates of investible commodity and equity indices rises amid greater participation by speculators generally. In particular, hedge funds in particular, hold positions in both equity and commodity futures markets.

All of the existing studies above concentrate on markets in the US and studies focusing on Chinese commodity futures appear to be of paucity. At the early stage, the studies are primarily focused on the broad market developments (Williams, Peck, Park, & Rozelle, 1998). With the rapid market development, the studies switched to market efficiency and linkage with mature commodity markets, such as the US (Fung, Tse, Yau, & Zhao, 2013; Fung & Tse, 2010; Xin, Chen, & Firth, 2006). With the growing importance of Chinese commodity futures contract play in the global context, recent studies have examined the *performance of investment strategies* (Li *et al.*, 2017; Fan and Zhang, 2018), *forecasting power of volatilities* (Jiang *et al.*, 2017; Tian *et al.*, 2017), *pricing implications* (He, Jiang, &

Molyboga, 2017; Mo, Gupta, Li, & Singh, 2017) and the *diversification potential* (Hammoudeh *et al.*, 2014). In comparison to the US commodity markets, there are several unique institutional settings in the Chinese markets and one of the most striking characteristics is the fact that more than 95% of the participants are retail or individual investors. Unsurprisingly, the composition of participants is similar in the domestic stock market according to studies by Li and Wang (2010) and Ng and Wu (2007). The domestic stock market in China has experienced extreme volatilities in the past decade. Since retail investors are known to be less informed compared to institutional investors, and given the lessons learned in the stock market, the commodity futures market in China is likely to be extremely speculative. Motivated by this gap in the literature, we examine whether speculators' activity in the Chinese futures market destabilize the prices and cross-market correlations.

3. Data

3.1 Commodity Futures

We obtain the entire history of Chinese commodity futures from Datastream International covering the period of January 1992 to May 2017. The initial sample contains more than 4,000 contracts, however only a few commodities were traded in the early part of the sample. We closely follow Fan and Zhang (2018) in constructing our final sample. From February 2004 to May 2017, our sample covers 30 commodities from five sectors, namely industrials (Cotton, PTA, Flat Glass, Natural Rubber, LLDPE, PVC, Metallurgical Coke and Coking Coal), metals (Aluminium, Gold, Copper, Lead, Steel Rebar, Steel Wire Rod, Zinc and Silver), grains (Sugar, Strong Gluten Wheat, Common Wheat, No.1 Soybean, No.2 Soybean and Corn), oilseeds (Rapeseed Oil, Rapeseed Meal, Rapeseed, Soybean Meal, Palm Olein and Soybean Oil) and energies (Methanol and Fuel Oil). We download daily settlement price (expressed in local currency-RMB), open interest (number of positions), trading volume (number of contracts traded and counted as two-side) and lot size.

To compile continuous return series and the corresponding trading volume and open interests, we follow Miffre and Brooks (2013). For m^{th} nearest to maturity return series (m=1, 2, 3, 4), we assume investors hold m^{th} nearest contract until the last trading day of the month prior to delivery month. We first compute the daily (monthly) returns for each contract and roll the returns as aforementioned. To ensure futures returns are computed based on the same contract, we compile the continuous returns series after computing the returns of each contract. This procedure is reiterated to construct the m^{th} nearest trading volume and open interest series.

[Insert Figure 1 Here]

Figure 1 illustrates the monthly average trading volume across the futures curve. Based on our sample of 30 commodities, the third nearest contracts clearly stand out as the most actively traded contracts. Since we are interested in examining the effect of speculation in these markets, it is imperative to focus on the third nearest contracts. For robustness, we also conduct tests based on the 4^{th} nearest contracts, which are the second most actively traded on the futures curve. Trading volumes on the 3^{rd} and 4^{th} nearest contracts alone account for almost half of the total trading volumes.

[Insert Table 1 Here]

Table 1 reports the summary statistics on the final sample. First, the findings suggest that Chinese commodity markets perform poorly at individual commodity level, as only 8 out of 30 commodities yield positive monthly average returns on the front-contract exposure.[10] This finding is consistent with that of the US market by Erb and Harvey (2006). Second, it appears that the traditional risk-return trade-off does not hold well. For example, although soybean meal delivers the highest mean return (0.99%) on front contract, its standard deviation (6.94%) is relatively low compared to metallurgical coke which reveals the highest volatility (10.63%) and the second lowest return of -1.14% per month on average. Third, the average open interests by commodity reveal that trading activities are not concentrated on only a few commodities or sectors. No.2 soybean meal is the least liquid instrument and steel rebar is the most heavily traded commodity.

3.2 Traditional Assets and Macroeconomic Variables

To test the effect of speculation on cross-market correlation, we obtain data on traditional assets and macroeconomic variables in China. The stock market is proxied by the CSI 300 index, which consists of the top 300 stocks traded on the Shanghai and Shenzhen stock

[10] Among the 8 commodities, soybean meal is the only one that shows significance at 10% level. Further, although there are 6, 8 and 7 commodities exhibiting positive monthly average returns on 2^{nd}, 3^{rd} and 4^{th} nearby contracts respectively, only soybean meal on the 2^{nd} nearest series is statistically different from zero.

exchanges. Bond returns are measured by the Barclays China aggregate Index which covers fixed-rate treasury, government and corporate bonds.

The RMB effective exchange rate index (REER) is attained from the Bank for International Settlements. Inflation shock is the difference between actual and forecast inflation estimated by Bloomberg. China GDP growth rate is collected from Bloomberg, formatted to monthly frequency. Economic Climate Index (ECI) is obtained from Datastream International. The ECI is an official macroeconomic indicator observed by the China National Bureau of Statistics (NBS) and used as an alternative proxy for economic growth in China. Producer Price Index (PPI) is also obtained from Datastream to represent domestic inflation. Term spread is calculated by using 10-year government bond yield minus the one-year government bond yield. The government bond yield is obtained from Wind Financial (the Chinese equivalent of Bloomberg), which provides historical reference data, real time market data and historical intraday data covering stocks, bonds, futures, foreign exchanges, funds and indexes in China.

[Insert Figure 2 Here]

Figure 2 illustrates the performance of the broad commodity market and stocks normalized at February 2004. Figure 2 also plots the evolution of open interest growth and economic growth. While the commodity market clearly underperformed stocks during most of the sample period, the open interest of commodity futures increased steadily and rapidly particularly following stock market sell-offs. Since the overall economic growth slowed down post to the Global Finance Crisis (GFC), the explosive growth in commodity futures open interests clearly cannot be fully attributed to aggregate economic activities. This highlights the possibility that large amount of growth in open interests may be due to speculative activities.

4. Methodology

4.1 Hedging and Speculative Ratios

Miffre and Brooks (2013) employ CFTC's commitments of trader reports to measure the hedging and speculative pressure. Since no such data is available in China, we take an alternative approach. We apply the following ratios proposed by Garcia *et al*. (1986) and Lucia and Pardo (2010) as proxies for hedgers' hedging pressure (HHP) and speculators' hedging pressure (SHP).

$$Ratio_{i,t}^{Hedge} = \frac{\Delta OI_{i,t}}{Vol_{i,t}} \quad (1)$$

$$Ratio_{i,t}^{Spec} = \frac{Vol_{i,t}}{OI_{i,t}} \quad (2)$$

where $OI_{i,t}$ and $\Delta OI_{i,t}$ represent the monthly open interest and the change of open interest for commodity i at time t, and $Vol_{i,t}$ denotes the total monthly volume of commodity i at time t. The volume is measured as the number of contracts traded whereas the open interest is measured as the total number of long and short positions taken. Due to the aforementioned unique position limits in China, considerable jumps exist in the continuous time-series of both ratios. For example, trading volume (open interest) may shrink substantially from the third to the second trading month prior to expiration, resulting in occasional but large changes in hedging or speculation ratios.

Early studies have documented a connection between these ratios and commodity futures prices and volatilities. For example, Streeter and Tomek (1992) analyse the agricultural commodities in US markets and discover a positive relationship between speculation ratio and the returns volatility of soybeans. More recently, Bohl *et al.* (2018) conclude a positive impact of the speculation ratio on returns volatility in Chinese commodity futures market. The core assumption behind the two ratios is that hedgers hold positions longer than speculators. Consequently, speculators should have more influence on trading volume as they are more likely to trade frequently. While hedgers' impact is primarily reflected on open interest, as the outstanding contracts at the end of each month should be held by hedgers (Bessembinder & Seguin, 1993; Leuthold, 1983).

In theory, a higher hedging ratio indicates that hedgers dominate the market relative to speculators for a given commodity, whereas a higher speculation ratio suggests more trades are triggered by speculators. However, this notion is not bullet-prove. Practitioners have long argued that open interest (volume) is in fact more associated with speculators (hedgers). Cheng and Xiong (2014b) also state that hedgers frequently change their positions over time for reasons unrelated to output fluctuations, which effectively means speculation. Nevertheless, reflective of unique institutional settings in China, it is extremely difficult to distinguish hedgers from speculators, since almost the entire market is classified as retail or individual accounts.[11] For this reason, we employ both the hedging and speculation ratio to measure the dynamics of speculative pressure in the Chinese market.

4.2 Long-short Strategies

To simulate the trading activities of market participants, we employ four long-short strategies that have been studied extensively in the literature. The literature in the US market has unveiled that hedge funds and CTAs exploit past returns and term structure in their portfolio formation (Baltas & Kosowski, 2013; Fung & Hsieh, 1997). Similarly, Li *et al*., (2017) and Fan and Zhang (2018) find that in a market dominated by individul investors, trend-following and momentum strategies generate persistent profits in China. In addition to term structure and momentum strategies, we implement hedging pressure and volatility strategies, as they are also found to be profitable in the front end of the futures curve (Fan & Zhang, 2018).

The *term structure* strategy is motivated by the Hedging Pressure Hypothesis (Cootner, 1960) and the Theory of Storage (Working, 1949). A variety of studies have documented that long-short portfolios constructed based on "roll-yield" generate statistically and economically significant profits (Erb & Harvey, 2006; Fuertes, Miffre, & Rallis, 2010; Gorton, Hayashi, & Rouwenhorst, 2013; Yang, 2013). We define the sorting signal as:

$$Roll_{i,t} = log(F_{it,Front}) - log(F_{it,2}) \tag{3}$$

where $F_{it,Front}$ and $F_{it,2}$ represent the futures prices on the nearest and the second-nearby contracts. A positive (negative) roll-yield indicates a backwardated (contangoed) market. Consequently, the term structure strategy simultaneously holds long (short) positions in commodities within the top (bottom) quartile measured by $Roll_{i,t}$. The rebalancing takes place at the end of each month.

The second long-short strategy used to mimic trading activities in China is the *momentum* strategy. In the commodities literature, momentum is viewed as an alternative proxy for backwardation and contango cycle, although Bianchi, Drew, and Fan (2016) argue that anchoring behaviour of investors explain a large portion of the returns variations. Fan and Zhang (2018) report persistent economic returns by momentum strategies along the

[11] According the 2013 China Futures Association Annual Report, investors with total invested funds below 1 million RMB are classified as individual/retail investors which accounted for 98.96% of total market participants.

futures curves in the Chinese market over the period 2004-2017. We define the momentum signal as:

$$MOM_{i,t} = \sum_{j=0}^{11} r_{i,t-j} \tag{4}$$

where $MOM_{i,t}$ represents returns of commodity *i* in the past 12 months at time *t*. The strategy takes long (short) positions in the top (bottom) quartile of commodities in terms of past returns.

The third strategy documented by Fan and Zhang (2018) to be profitable in China is the *hedging pressure* strategy. Basu and Miffre (2013) document statistically significant profits for hedgers' hedging pressure (HHP) and speculators' hedging pressure (SHP) strategies. Since no CFTC-equivalent positions data are collected for the Chinese market. we follow Fan and Zhang (2018) who employ hedging and speculation ratios to construct hedging pressure portfolios. They find sizeable profits to the hedgers' hedging pressure strategy. The sorting signals employed for HHP and SHP strategies are identical to those specified in Eq (1) and (2). The HHP strategy takes long (short) positions in commodities in the lowest (highest) quartile of hedging ratio. Similarly, the SHP strategy takes long (short) positions in commodities with the highest (lowest) speculation ratio.

We implement the *volatility* strategy as a final approach to mimic the dynamics of long-short speculators. Szymanowska, de Roon, Nijman, and van den Goorbergh (2014) construct a long-short portfolio that buy (sell) commodities that are relatively more (less) volatile. They find statistically significant profits in the US. Fan and Zhang (2018) confirm the success of the volatility strategy on the front end of the futures curve in the Chinese market. Following these studies, we define the volatility signal as:

$$CV_{i,t} = \frac{{\sigma^2}_{i,t}}{\left|\mu_{i,t}\right|} \tag{5}$$

where $CV_{i,t}$ gauges the relative standard deviation of commodity *i* during the past 3 years at time *t*. The volatility strategy takes long (short) positions in the top (bottom) quartile commodities sorted by the *CV*.

The long-short strategies implemented in the present paper are designed to capture dynamic speculative activities, which are otherwise difficult to capture using static metrics. Since the third nearest contract exhibit the highest trading volume and open interest in the aggregate market, we focus on the third contract instead of the front contracts on the futures curve. For robustness reasons, we also conduct analysis on the fourth nearest contracts, and find qualitatively similar results.

4.3 Volatility and Correlations

The generalised autoregressive conditional heteroskedasticity GARCH (1, 1) model is used to derive the time-varying volatility series. The model is specified as follows.

$$R_{c,t} = aX + \varepsilon_{c,t}, \varepsilon_t^2 | \Omega_{t-1} \sim N\,(0, \sigma_t^2) \tag{6}$$

$$\sigma_{c,t}^2 = \alpha_0 + \alpha_1 \sigma_{c,t-1}^2 + \beta_1 \varepsilon_{c,t-1}^2$$

where $R_{c,t}$ is the return of the passive long-only, long, short or long-short commodity portfolios at time *t*; $\varepsilon_{c,t}$ is the error term; *X* is the mean of $R_{c,t}$. The conditional variance $\sigma_{c,t}^2$ is modelled as a linear function of its own lagged one conditional variance (the GARCH term) and the last period's squared errors (the ARCH term); α_0 is the intercept term and the coefficient estimators are represented by α_1 and β_1 and α_0, α_1 and β_1 are such that $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$.

When measuring the co-movement between commodity (*c*) and the traditional assets and macroeconomic variables (*j*), the Asymmetric Dynamic Conditional Correlation (ADCC)-GARCH model is used. We follow Cappiello, Engle, and Sheppard (2006) procedure in two steps. The first step is to estimate returns in a univariate asymmetric GARCH (1,1) process. In the second stage, we model the correlation coefficients based on the residuals that have been normalized from the first stage as follows:

$$Z_{cj,t} = \frac{\varepsilon_{cj,t}}{\sigma_{cj,t}}$$

$$Z_{cj,t} \sim N(0, q_{cj,t}) \tag{7}$$

$$\lambda_{cj,t} = \max[0, -Z_{cj,t}]$$

$$q_{cj,t} = (1 - a - b - k)\bar{\rho}_{cj} + a z_{c,t-1} z_{j,t-1} + b q_{cj,t-1} + k \lambda_{c,t-1} \lambda_{j,t-1}$$

where $Z_{cj,t}$ is the normalized residual; $q_{cj,t}$ is the conditional variance for the normalized residual and $\bar{\rho}_{cj}$ is the unconditional correlation coefficients between the two return seires. Then, the dynamic conditional correlation coefficient between commodity portfolios (*c*) and traditional assets or macroeconomic variables (*j*) is defined as:

$$\rho_{cj,t} = \frac{q_{cj,t}}{\sqrt{q_{c,t}}\sqrt{q_{j,t}}} \tag{8}$$

4.4 Granger-causality Tests

To test whether the speculative activities destabilize the volatility of commodities, we employ the Granger-causality test based on regressions of the following form:

$$\triangle\, \delta_{c,t} = \alpha \triangle \delta_{c,t-1} + \beta' X_{t-1} + \varepsilon_t \tag{9}$$

where $\triangle\, \delta_{c,t}$ represents the changes in the annualized volatility of the passive long, dynamic long, short and long-short portfolios. $\beta = [\beta_0, \beta_1]$; the null hypothesis that $\beta_0 = 0$ is then tested using a Granger-causality test. X is a vector of explanatory variables, with up to 4 lags.

We have two groups of causality tests based on Equation (9). For the first group, the dependent variable is the volatility of the passive long-only portfolio (AVG). The independent variables include the changes in speculators' hedging pressure ($\triangle\, AVG20SHP$) and the changes in hedgers' hedging pressure ($\triangle\, AVG20HHP$) on top 20 most liquid contracts. The second group of causality tests is conducted on dynamic long, short and long-short portfolios constructed based on, roll-yield, hedging/speculative pressure, momentum and volatility signals. The dependent variable is the volatility of these dynamic portfolios, and the independent variables include the changes in speculators' hedging pressure ($\triangle\, \overline{SHP}$) and changes in hedgers' hedging pressure ($\triangle\, \overline{HHP}$) within these portfolios. It is important to note that, $\triangle\, \overline{SHP}$ and $\triangle\, \overline{HHP}$ are computed on monthly by averaging the SHPs and HHPs on commodities selected by each long-short strategy. This is a dynamic process as the composition of long-short portfolios can vary significantly over time.

There are a total of four sets of null hypotheses we are testing. The first null hypothesis is that changes in AVG20HHP or AVG20SHP do not Granger cause changes in the volatility of passive long-only portfolio. The second null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for constituents of the long portfolio do not Granger-cause a change in the volatility of corresponding dynamic long portfolio. The third null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for the constituents of the short portfolios do not Granger-cause a change in the volatility of dynamic short portfolio. The fourth and final null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for the constituents of the long-short portfolios do not Granger-cause a change in the volatility of dynamic long-short portfolios.

Subsequently, the Granger causality tests are employed to investigate whether speculative activities destabilize the cross-market correlations between the commodity portfolio (c) and the traditional assets and macroeconomic variables (j). The Granger-causality test can be specified as follows:

$$\triangle \rho_{c,j,t} = \alpha \triangle \rho_{c,j,t-1} + \beta' X_{t-1} + \varepsilon_t \tag{10}$$

where $\triangle \rho_{c,j,t}$ represents the changes in the annualized time-varying correlation of the passive long, dynamic long, short and long-short portfolios with traditional assets or macroeconomic variables. $\beta = [\beta_0, \beta_1]$; the null hypothesis that $\beta_0 = 0$ is then tested using a Granger-causality test. X is a vector of explanatory variables, with lags up to 4.

Similarly, we conduct two groups of causality tests based on equation (10). The independent variables employed are identical to those examined for volatilities in equation (9). For the effect of speculation on cross-market correlation, we are testing four sets of null hypotheses. The first null hypothesis is that changes in AVG20HHP and AVG20SHP do not Granger cause changes in the correlation of passive long-only portfolio with traditional assets or macroeconomic variables. The second null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for the constituents of the long portfolio do not Granger-cause changes in the correlation of corresponding dynamic long portfolio. The third null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for the constituents of the short portfolios do not Granger-cause a change in the correlation of dynamic short portfolio. The fourth and final null hypothesis is that the changes in the speculators' and hedgers' hedging pressure ratios for the constituents of the long-short portfolios do not Granger-cause a change in the correlation.

Two robustness tests are conducted. Following Irwin and Sanders (2011), Brunetti *et al.* (2016) and Büyükşahin and Robe (2014), the first robustness test employs levels of conditional volatility and correlation as dependent and independent variables instead of their changes. As volatilities and correlations do not depend solely on past values and traders' positions, the second robustness test augments with the first lag in one business cycle variable, term spread. The results for these two robustness tests are presented under the labels Test 1 and Test 2, respectively.

5. Empirical Results

5.1 Performance of long-short strategies

Table 2 reports the performance of long-short strategies and the long-only portfolios. Panels A, B and C report the long, short and long-short portfolios, respectively. Panel D reports the performance of long-only portfolios covering the broad market as well as commodity sectors. The findings reveal that passive long-only investments do not generate statistically significant economic profits in the sample period examined. This not only applies to the broad market but also commodity sectors. The findings presented in Table 2 suggest that only term structure and momentum strategies report statistically significant profits with the former reporting a monthly return of 1.15% and 1.39%, receptively. Besides, it appears that the long and short legs are equally important for the success of term structure and momentum strategies.

Furthermore, the findings presented in Table 2 suggest that HHP, SHP and volatility strategies do not deliver significant profits when implemented on the 3rd nearest contracts. These findings are consistent with Fan and Zhang (2018), in which they test the performance of 12 long-short strategies on the first through to the fourth nearest contracts on the futures curve. Since these unprofitable strategies are successful on the front contracts, we continue our analysis with all five strategies in order to capture additional investment styles by different speculators. The granger causality results will be elaborated in the following subsections.

5.2 Causality Tests for Passive Long Only Portfolio

Table 3 reports the results on whether speculative activities increase volatility of the broad market and commodity sectors. Two sets of regressions are conducted to examine whether the changes in the speculators' and hedgers' hedging pressure ratios on the top 20 most traded commodities lead to increase in the volatility of equally-weighted portfolio (Panel A) and commodity sector portfolios (Panel B). We focus on the top 20 commodities because they represent the highest trading intensity, hence better reflects the speculative activities of market participants. We present estimates and the corresponding *t*-statistics for β_1 based on equation (9), *p*-values for null hypothesis of Granger causality are in parentheses. We also report the mean variance inflation factor to mitigate concerns about multicollinearity and endogeneity. To capture the possibility of a delayed reaction, we report *p*-values from Granger-causality tests for up to four lags.

Overall, the findings presented in Table 3 suggest that neither hedgers' nor speculators' activities in the top 20 most traded commodities increase the volatilities of the broad market and commodity sectors, in a passive long-only setting. In fact, hedger's activities (measured by hedgers' hedging pressure ratio) actually lead to decreases in the volatility of energy commodities. This finding implies that additional regulation should not be imposed onto the passive, index-like investors in the Chinese commodity futures markets, as they do not destabilize commodity market volatilities. We now proceed to test whether these speculative activities cause changes in the cross-market correlations between the broad market and traditional assets and macroeconomic movements.

[Insert Table 3 Here]

Table 4 reports the results on causality test for cross-market correlations between the broad market portfolio with movements in traditional assets and macroeconomic variables. We employ a suite of variables to gauge these movements. For traditional assets in China, we employ the CSI300 index (CSI300), Shanghai composite index (SH), Shenzhen composite index (SZ) and Barclays China aggregate bond index (BOND). As for macro variables, we consider RMB real effective exchange rate (REER), CPI Shock (CPIS), gross domestic product (GDP), economic climate index (ECI) and producer price index (PPI). Panel A reports the results on speculators' hedging pressure (SHP) whereas Panel B reports the results on hedgers' hedging pressure (HHP) ratios. Once again, we focus only on the top 20 most traded commodities for the SHP and HHP ratio calculations. We also present *p*-values from Granger-causality tests with one-lag and four lags under the headings p(1) and p(4), respectively.

[Insert Table 4 Here]

The results in Panel A indicate that β_1 is not significant at the 10% level for all correlation pairs. In the meantime, it appears that speculative activities (as measured by SHP) do not cause changes in the correlations. The Chinese commodity futures market is characterized by extreme speculative behaviour, in which speculative activity presumably exceeds hedging demand. However, when speculative activities are measured by hedgers' hedging pressure ratio (HHP) in Panel B, we still fail to find any significant causality results. If the HHP ratio is interpreted as a measurement for hedger's hedging pressure, this result would imply that hedgers' activity (in a passive long-only setting) has no influence on the correlation of the broad commodity market with traditional assets and macroeconomic variables. Overall, the findings presented in Table 4 suggest that the increased presence of speculative activates does not impact the risk-sharing function of commodity futures in China.

5.3 Causality Tests for Volatilities of Long-short Portfolios

To further examine the impact of speculation, we construct dynamic portfolios to mimic the trading behavior of long-short investors in Chinese markets. These investors are assumed to process a higher level of sophistication, thus are better informed than the long-only speculators. As a result, we implement systematic long-short strategies proven to be successful in China, and examine whether the volatility and correlations of these dynamic portfolios are affected by increased level of speculation in recent years.

[Insert Table 5 Here]

Table 5 reports the causality results on volatilities. We consider long, short and long-short portfolios based on term structure, HP, momentum and volatility strategies. Coefficients, *t*-statistics and *p*-values on the *F*-test of the null hypothesis are reported. Panel A reports the results on SHP ratios and Panel B reports HHP ratios. To capture the possibility of a delayed effect, *P*-values from Granger-causality tests with first lag (p1) and four lags (p4) are also reported.

The results in Panel A reveal that increases in the SHP ratio increase the volatility of some but not all portfolios. For the long portfolios, changes in the SHP ratios cause increases in the volatility of commodities traded by momentum and volatility strategies, but cause decreases in the volatility of commodities traded by the hedgers' HP strategy. These patterns do not hold for the short portfolios. In a long-short setting however, increases in SHP ratios appear to only increase the volatility of commodities traded by the volatility strategy, but decrease the volatility of commodities traded by hedgers' HP strategy. The absence of significance by the momentum strategy in long-short portfolio implies that long-short momentum speculators do not destabilize the volatility of commodities. Contrary to Miffre and Brooks (2013), findings in Panel A suggest that speculative activities in China can lead to increases in the volatility of commodities, i.e. in a dynamic setting.

Panel B reports the results on hedgers' HP ratios. None of the portfolios show significant coefficients, indicating that increase in HHP ratios neither increase nor decrease the volatility of commodities. Consistent with regression results, we fail to reject the null hypothesis that hedgers' activities do not Granger-cause changes in the volatility. Once again, our findings suggest that hedgers' activities (as measured by HHP) do not destabilize the market in China. Besides, two robustness checks are implemented. Following Brunetti *et al.* (2016) and Büyükşahin and Robe (2014). We first test whether the results hold if we replace the changes in conditional volatility and conditional correlation in Equations (9) and (10) by using levels. Second, we include an additional control variable, the first lag of the term spread in China, to capture the potential influence from business cycles. *P*-values from the Granger-causality tests are reported in the last two columns (Test1 and Test2). These results are consistent with our main findings.

5.4 Causality Tests for Correlations of Long-short Portfolios

We now proceed to investigate whether speculative activities in long-short portfolios granger-cause changes in correlations with both conventional assets and macroeconomic variables.

[Insert Table 6 Here]

From Panels A through to D, Table 6 presents the causality test for speculative activities (measured by SHP ratios) with conditional correlation with conventional assets including CSI300 index, Shanghai composite index, Shenzhen composite index and Barclays China aggregate bond index, respectively. For the dynamic long portfolios, the results show that commodities traded by the term structure and HHP strategies consistently report negative loadings on the correlation with stocks.[12] This indicates that dynamic long speculators who trade based on roll-yields and HHP signals deceases the correlations between commodity futures and stocks. Furthermore, findings also reveal that commodities traded by the momentum and volatility strategies report positive loadings on the correlation with stocks, indicating that dynamic long speculators who trade based on past returns and volatility signals lead to increase in the correlation with stocks. These findings are generally consistent for the short portfolios. In a long-short setting, while the results hold for HHP and volatility strategies, speculators who trade based on term structure and momentum no longer have impact on the correlation with stocks. Turning to bonds, our results suggest that speculative

[12] Although $L.\beta_1$ and $L.\beta_2$ are statistically insignificant, the $\beta_1$is statistically significant at 5% with lag 3.

activities in commodities traded by the HHP strategy also decrease the correlation with bonds. No other significance are observed.

It comes to our attention that the Granger-Causality coefficients on the short portfolios of HHP and SHP strategy exhibit relatively extreme numbers, compared to those of other strategies. As discussed before, the HHP (SHP) strategy employs the hedging (speculation) ratio to sort commodities. Therefore, their short portfolios, by design, are more likely to highly concentrate on commodities with “extreme” speculation and hedging ratios, relative to the strategies which do not sort commodities based on these two ratios. Due to this reason, a scaling difference will continue to be present in subsequent analyzes.

The *p*-values indicates the null hypotheses that change in the speculators’ hedging pressure do not Granger-cause change in correlations can be rejected in many cases. More specifically, changes in SHP ratio granger-cause the changes in correlations with stocks. Moreover, the majority of the causality relationships is detected in the dynamic long portfolios. In addition, for results of correlation with bond index, only three solitary causality relationships are found in long portfolio and long-short portfolio based on term structure and Hedgers’ HP strategies. Robustness checks using level and term spread data confirm the significance of causality relationships for long-short Hedgers’ HP and volatility trading strategies. Overall, our results clearly show that speculation granger-causes changes in correlations with conventional assets in a dynamic long-short setting.

We carry on the analysis with correlations to macroeconomic variables. Macroeconomic variables signal the aggregate trends and determine the current behavior of the overall economy. Previous studies show that commodity futures prices are positively related to inflation and negatively related to exchange rates (Erb and Harvey, 2006; Szymanowska *et al*., 2014). Thus, we examine whether increased speculation in China has altered these correlations. We also extend the analysis to GDP growth rate, economic climate and producer purchase indicators to better capture the movements of the macro-economy in China.

[Insert Table 7 Here]

Table 7 presents the Granger causality results for speculators’ hedging pressure ratios and correlation with exchange rate (REER), inflation shock (CPIS), country economy (GDP), economic growth (ECI) and domestic inflation (PPI) in China, through Panels A to E, respectively. Several interesting results emerge from Table 7. First, we find that speculations in commodities traded by SHP strategy load negatively (positively) on the correlation with CPIS and ECI (REER) for dynamic long portfolios, suggesting that increases in long positions of speculators actually decrease (increase) the correlation with inflations (exchange rates). Second, we find that dynamic long speculators in momentum strategy causes the correlation with GDP growth to decrease. These results indicate that increase in the long positions of speculators destabilize commodity market by influencing the correlations with macroeconomic variables. The causality tests show consistent results suggesting that speculators granger-cause changes in correlations with macroeconomic variables. In addition, it is worth noting that *p*-values on the fourth lag in the long portfolios imply a possible delayed effect. This means that the impact of speculation on the correlation could take up to four months to take effect.

When taking a closer look at the short positions, four portfolios present significant coefficient estimates. These are SHP, momentum, volatility and HHP strategies. β_1 of all significant results show a negative relationship with macroeconomic variables. A negative loading indicates that speculators increasing their short positions increases the correlation with macroeconomic variables. This is also supported by the Granger causality results. Lastly, in a long-short setting, we find that long-short speculators who trade based on HHP increase the correlation with exchange rates, decrease the correlation with GDP growth, ECI and PPI. Furthermore, we find that momentum traders decrease correlation with exchange rates, and also decrease the correlation with the ECI. Two robustness checks followed by Brunetto *et al.* (2011) and Büyüksahin and Robe (2010) are consistent with those previously reported. Overall, findings presented in Table 7 are contrary to those of Miffre and Brooks (2013), suggesting that dynamic long-short speculators destabilize the correlations of commodities with macroeconomic variables in China.

Nevertheless, given the fact that more than 90% of the market participants in China are individual investors, it is rather difficult to distinguish speculators from hedgers without the relevant positions data. Consequently, as part of our effort to gain further robustness, we also examine whether speculative activities proxied by hedgers' hedging pressure ratio Granger-cause changes in correlations with traditional assets and macroeconomic activities. These results are presented in Tables 8 and 9.

[Insert Table 8 Here]

Table 8 reports the results as to whether hedgers' activities (proxied by hedgers' HP ratios) increase cross-market linkages for long, short and long-short portfolios. The first and second lag of the coefficient estimates are reported along with associated *t*-statistics (in parentheses). *P*-values represent the results for the null hypothesis on whether changes in hedgers' hedging pressure Granger-cause the changes in correlation with traditional assets. *P*-values with up to four lags are reported. Interestingly, unlike the results for speculative activities, hedgers' activities appear to only affect the correlations with bonds, but not with stocks. More specifically, in the dynamic long portfolio, HHP ratio of the SHP strategy is positively related to the correlation with bonds at 5% level. In the short portfolios, changes in hedger's activities are significant only for the momentum strategy. Finally, in a dynamic long-short portfolio, momentum also shows negative significance at 4th lag, indicating that hedgers actually decreases the commodities' correlation with bonds. Overall, the results presented in Table 8 suggest that hedgers' participation does not destabilize commodities correlations with stocks and bonds even in a dynamic long-short setting.

[Insert Table 9 Here]

Table 9 presents the results for tests of whether the hedgers' activities (measured by hedgers' HP ratio) alter the correlation with macroeconomic activities. The first and fourth lags as well as the corresponding *t*-statistics (in parentheses) are reported. *P*-values is the *F*-test result for the null hypothesis that changes in the hedging pressure of hedgers do not Granger-cause the change in correlations with macroeconomic variables. First, in the dynamic long portfolios, we find weak significance in hedger's activities and correlation with GDP growth and ECI. These loadings are not consistent in the short portfolios. In a long-short setting, we fail to find consistent loadings or causality relationships. Overall, findings presented in Table 9 suggest that hedgers' activities do not have an impact on the commodities correlations with macroeconomic variables.

6. Conclusions

This paper examined the impact of speculation on volatility and cross-market correlations in the Chinese commodity futures market. We first tested the influence of speculative activities in the top 20 most heavily traded commodities and found that speculation does not increase or decrease the volatility of the broad market. We demonstrated that speculative activities in these markets do not elevate cross-correlations between commodities and traditional assets such as stocks and bonds. Subsequently, we made different assumptions about the level of sophistication and examined the role of better informed, long-short dynamic speculators. In such a setting, we found evidence that speculative activities as measured by speculation ratio increase the volatility of commodities. Our results suggest that increased presence of dynamic long-short speculators have the potential to increase the cross-correlations with stocks and destabilize the correlation with macroeconomic activities. Based on our findings, we recommend the CSRC and other relevant authorities not to impose additional regulations on passive long-only or other index-like commodity investors in China, as the participation by these "speculators" adds liquidity to the market and facilitate the price discovery and risk transfers.

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Table 1 Summary statistics

Exchange	Commodity	Mean				SD				Sharpe				Open interest
		m=1	*m=2*	*m=3*	*m=4*	*m=1*	*m=2*	*m=3*	*m=4*	*m=1*	*m=2*	*m=3*	*m=4*	*m*={1,2…12}
ZCE	Sugar	-0.07%	-0.19%	-0.35%	-0.31%	5.70%	5.54%	5.82%	5.96%	-0.0127	-0.0348	-0.0595	-0.0512	765451
	Cotton1	-0.17%	-0.16%	-0.20%	-0.15%	5.31%	5.10%	5.20%	5.17%	-0.0311	-0.0319	-0.0381	-0.0283	262554
	PTA	-0.64%	-0.75%	-0.77%	-0.52%	7.51%	7.23%	7.27%	6.85%	-0.0846	-0.1039	-0.1061	-0.0765	613244
	Methanol	-1.07%	-0.62%	-0.76%	-0.41%	7.83%	7.04%	6.60%	6.61%	-0.1365	-0.0887	-0.1157	-0.0618	255095
	Glass	0.77%	0.82%	0.26%	-0.04%	7.48%	4.78%	5.12%	4.55%	0.1026	0.1709	0.0508	-0.0079	429546
	Rapeseed Oil	-0.50%	-0.36%	-0.19%	-0.45%	5.15%	5.69%	6.18%	6.36%	-0.0971	-0.0638	-0.0314	-0.0715	162580
	Strong Wheat	-0.80%	-0.58%	-0.56%	-0.42%	3.46%	3.04%	2.87%	2.98%	-0.2301	-0.1904	-0.1946	-0.1407	166074
	Common Wheat	-1.35%	-0.77%	-0.47%	-0.28%	3.73%	2.92%	2.77%	2.75%	-0.3607	-0.2648	-0.1692	-0.1005	12122
	Rapeseed Meal	0.96%	0.97%	0.95%	0.80%	8.05%	6.61%	6.49%	5.91%	0.1193	0.1464	0.1465	0.1358	1030157
	Rapeseed	-0.33%	-0.42%	-0.87%	-0.51%	3.51%	3.71%	4.31%	5.00%	-0.0934	-0.1127	-0.2020	-0.1018	3207
SHFE	Aluminium	-0.18%	-0.22%	-0.27%	-0.23%	4.48%	4.34%	4.34%	4.38%	-0.0393	-0.0509	-0.0613	-0.0519	262320
	Gold	0.10%	0.08%	-0.23%	0.53%	5.69%	5.57%	5.63%	5.50%	0.0184	0.0144	-0.0408	0.0968	139406
	Copper	0.86%	0.94%	0.77%	0.71%	8.21%	8.36%	8.52%	8.64%	0.1047	0.1120	0.0900	0.0824	379522
	Fuel Oil	-0.94%	-0.49%	-0.06%	-0.60%	9.39%	8.32%	7.93%	8.08%	-0.1000	-0.0591	-0.0072	-0.0738	47363
	Lead	-0.31%	-0.26%	-0.18%	-0.17%	5.87%	5.82%	5.78%	5.73%	-0.0522	-0.0442	-0.0307	-0.0304	24196
	Steel Rebar	-0.65%	-0.62%	-0.53%	-0.29%	8.16%	7.01%	6.73%	6.76%	-0.0796	-0.0889	-0.0783	-0.0430	1834366
	Natural Rubber	-0.64%	-0.41%	-0.40%	-0.46%	8.79%	9.10%	9.33%	9.30%	-0.0727	-0.0455	-0.0429	-0.0498	195368
	Steel Wire Rod	-0.94%	-0.44%	-0.16%	-0.63%	4.41%	5.14%	5.32%	4.78%	-0.2127	-0.0863	-0.0307	-0.1323	3540
	Zinc	-0.41%	-0.52%	-0.48%	-0.47%	7.78%	7.86%	7.97%	8.02%	-0.0524	-0.0659	-0.0608	-0.0582	280650
	Silver	-1.08%	-0.98%	-0.88%	-0.72%	6.91%	7.02%	7.11%	7.23%	-0.1570	-0.1400	-0.1241	-0.1000	481588
DCE	No1 Soybean	-0.35%	-0.01%	0.30%	0.14%	4.73%	4.26%	4.70%	4.85%	-0.0741	-0.0019	0.0644	0.0284	406705
	No2 Soybean	0.73%	0.31%	0.47%	0.25%	5.94%	4.57%	4.72%	5.27%	0.1222	0.0673	0.0985	0.0477	1877
	Corn	-0.38%	-0.12%	-0.03%	-0.16%	3.77%	3.20%	2.92%	3.19%	-0.1005	-0.0390	-0.0098	-0.0509	774718
	LLDPE	0.30%	-0.08%	-0.18%	-0.34%	8.22%	8.27%	8.30%	9.14%	0.0365	-0.0101	-0.0213	-0.0369	317716
	Soybean Meal	0.99%	0.88%	0.66%	0.53%	6.94%	6.20%	6.29%	6.16%	0.1431	0.1413	0.1053	0.0860	1479079
	Palm Olein	-1.03%	-1.41%	-0.80%	-0.50%	6.70%	7.85%	7.54%	7.49%	-0.1539	-0.1790	-0.1060	-0.0672	440463
	PVC	-0.88%	-0.33%	-0.31%	-0.42%	4.62%	5.02%	5.27%	4.95%	-0.1906	-0.0647	-0.0597	-0.0848	79326
	Soybean Oil	-0.09%	-0.14%	0.08%	0.07%	6.78%	6.48%	6.46%	6.38%	-0.0138	-0.0209	0.0118	0.0107	599591
	Coke	-1.14%	-1.08%	-1.09%	-0.49%	10.63%	9.24%	9.20%	9.13%	-0.1074	-0.1167	-0.1180	-0.0535	162309
	Coal	0.87%	-0.79%	0.32%	-0.27%	9.23%	7.30%	8.42%	7.87%	0.0947	-0.1083	0.0381	-0.0338	229404

Notes: The table presents summary statistics on m^{th} maturity contracts (m=1,2,3,4). ZCE, SHFE and DCE represent the Zhengzhou Commodity Exchange, Shanghai Futures Exchange and Dalian Commodity Exchange, respectively. Mean, SD and Sharpe represent average return, standard deviation and Sharpe ratio of each commodity per month. The last column reports the average total open interest per month for each commodity. The sample period covers February 2004 to May 2017.

Table 2 Performance of strategies

	Mean	*t*-stat	SD	Sharpe
Panel A: Long portfolios				
Term Structure	0.63%	1.32	5.97%	0.1051
HHP	-0.35%	-1.13	3.92%	-0.0903
SHP	-0.27%	-0.59	5.72%	-0.0470
Momentum	0.85%	1.70	6.04%	0.1403
VOLA	-0.31%	-0.59	5.79%	-0.0534
Panel B: Short portfolios				
Term Structure	-0.52%	-1.71	3.83%	-0.1364
HHP	-0.05%	-0.15	4.38%	-0.0123
SHP	-0.15%	-0.52	3.53%	-0.0415
Momentum	-0.54%	-1.55	4.25%	-0.1281
VOLA	0.00%	-0.01	3.39%	-0.0006
Panel C: Long-short portfolios				
Term Structure	1.15%	3.01	4.79%	0.2398
HHP	-0.30%	-1.04	3.61%	-0.0833
SHP	-0.07%	-0.18	4.47%	-0.0147
Momentum	1.39%	3.10	5.43%	0.2564
VOLA	-0.31%	-0.67	5.04%	-0.0610
Panel D: Long-only portfolios				
AVG	-0.12%	-0.36	4.06%	-0.0296
Energies	-0.09%	-0.15	7.15%	-0.0123
Grains	-0.16%	-0.70	2.86%	-0.0561
Industrials	-0.37%	-0.78	5.90%	-0.0624
Metals	0.11%	0.25	5.58%	0.0201
Oilseeds	0.07%	0.16	5.85%	0.0124

Notes: The table presents summary statistics of long, short and long-short portfolios of dynamic strategies in Panels A, B and C, respectively. Panel D reports the performance of long-only portfolios constructed based on the broad market and commodity sectors. The term structure strategy sorts commodities based on roll-yields. Hedgers' hedging pressure (HHP) and speculators' hedging pressure (SHP) strategies sort commodities based on hedging and speculation ratios introduced by Bohl *et al*. (2018). The hedging ratio is the change of open interest divided by volume, while the speculation ratio is computed as volume divided by open interest. Momentum strategy exploits past 12-month returns. Volatility strategy utilizes the coefficient of variation of past 36-month returns. All signals are based on the 3rd nearest contracts with the exception of roll-yield, which is computed using the first and second nearest contracts. AVG represents an equally-weighted market portfolio. All portfolios are rebalanced monthly. Mean, *t*-stat, SD and Sharpe are returns, *t*-statistics, standard deviations and Sharpe ratios per month, respectively. The sample period covers February 2004 through May 2017.

Table 3 Volatility of Passive Long Portfolios

	Passive Long Only Portfolio				
	$L.\beta_1$	t(β_1)	VIF	p(1)	p(4)
Panel A: Broad Market					
$\Delta AVG20SP$	-0.0644	(-0.92)	1.74	0.36	0.42
$\Delta AVG20HP$	0.0016	(0.27)	2.28	0.79	0.96
Panel B: Commodity Sectors					
B1. Energies					
$\Delta AVG20SP$	-0.0330	(-0.13)	1.91	0.90	0.54
$\Delta AVG20HP$	-0.0531**	(-2.58)	2.45	0.01	0.08
B2. Grains					
$\Delta AVG20SP$	0.0262	(1.58)	1.65	0.12	0.46
$\Delta AVG20HP$	0.0017	(1.02)	2.19	0.31	0.81
B4. Industrials					
$\Delta AVG20SP$	0.1210	(0.87)	1.72	0.39	0.47
$\Delta AVG20HP$	0.0110	(0.96)	2.26	0.34	0.78
B3. Metals					
$\Delta AVG20SP$	0.0018	(0.06)	1.71	0.95	0.58
$\Delta AVG20HP$	0.0002	(0.09)	2.19	0.93	0.99
B5. Oilseeds					
$\Delta AVG20SP$	-0.0707	(-1.34)	1.67	0.18	0.10
$\Delta AVG20HP$	0.0008	(0.18)	2.25	0.86	0.89

Notes: This table presents the results of Granger Causality tests on the volatility of the commodity market portfolios. The dependent variables (DV) are the changes in volatility of passive long only portfolio (Panel A) and commodity sectors (Panel B). The independent variables (IVs) are the changes in the hedgers' hedging pressure ratio ($AVG20HP_{c,t}$) and speculators hedging pressure ratios ($AVG20SP_{c,t}$) on the top 20 most actively traded commodities, respectively. The models are specified as Equation (9). β_1 denotes the coefficient estimates of the change in conditional volatility on the first lag of the IV. The corresponding *t*-statistics and mean variance inflation factor (VIF) are reported in parentheses. *p(L)* is the *p*-value of the *F*-statistic that tests the null hypotheses that changes in IVs do not Granger-cause change in the conditional volatility of the passive long-only portfolios. *L* represents the number of lags. The sample period covers February 2004 through to May 2017.

Table 4 Correlations of Passive Long Portfolios

DV: Correlations	Passive Long Only Portfolio				
	$L.\beta_1$	t(β_1)	VIF	p(1)	p(4)
Panel A: Speculators' HP Ratio					
A1. Conventional Assets					
CSI300	-0.5000	(-0.88)	3.61	0.38	0.45
SH	-0.0861	(-0.38)	2.39	0.71	0.72
SZ	-0.0120	(-0.11)	1.81	0.92	0.86
BOND	0.0241	(0.26)	1.65	0.79	0.66
A2. Macroeconomic Variables					
REER	0.2570	(0.73)	2.02	0.47	0.00
CPIS	-0.0265	(-0.28)	1.62	0.78	0.74
GDP	-0.2100	(-1.03)	1.66	0.31	0.90
ECI	-0.0301	(-0.23)	1.71	0.82	0.65
PPI	0.0517	(0.83)	1.80	0.41	0.37
Panel B: Hedgers' HP Ratio					
B1. Conventional Assets					
CSI300	-0.0018	(-0.08)	3.80	0.94	0.97
SH	-0.0019	(-0.10)	2.90	0.92	1.00
SZ	-0.0023	(-0.24)	2.37	0.81	1.00
BOND	0.0086	(1.13)	2.29	0.26	0.10
B2. Macroeconomic Variables					
REER	-0.0093	(-0.31)	2.49	0.76	0.41
CPIS	0.0000	(0.00)	2.24	1.00	0.99
GDP	-0.0124	(-1.38)	2.53	0.17	0.02
ECI	0.0024	(0.21)	2.35	0.83	0.66
PPI	0.0004	(0.09)	2.27	0.93	0.95

Notes: This table presents the results of Granger Causality tests on cross-market correlations. The dependent variable is the time-varying correlations of passive long-only broad market portfolio with conventional assets as well as macroeconomic variables. The independent variables (IVs) include speculators' hedging pressure (Panel A) and hedgers' hedging pressure ratios (Panel B) on top 20 most actively traded commodities, respectively. Based on Equation (10), we test whether each IV Granger-cause changes in the correlation between broad commodity market and conventional assets and macro variables. We use the CSI300 index (CSI300), Shanghai composite index (SH), Shenzhen composite index (SZ) and Barclays China aggregate bond index (BOND) to gauge the movements of conventional assets. Real effective exchange rate (REER), CPI Shock (CPIS), gross domestic product (GDP), economic climate index (ECI) and producer price index (PPI) are used to capture the macroeconomic activities. β_1 denotes the coefficient of the first lag of the IV. The corresponding *t*-statistics and mean variance inflation factor (VIF) are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause change in the cross-market correlation of the commodity market portfolio. *L* denotes the number of lags. The sample period covers February 2004 to May 2017.

Table 5 Volatility of Long-short Portfolios

DV: Volatility	Long Portfolio				Short Portfolio				Long-Short Portfolio				Test1	Test2
	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)		
Panel A: Speculators' HP ratio														
Term Structure	-0.1240	-0.2580	0.61	**0.00**	0.0004	-0.0002	0.62	0.92	-0.0001	0.0002	0.93	1.00	0.98	0.93
	(-0.52)	(-0.89)			(0.49)	(-0.26)			(-0.083)	(0.136)				
HHP	-0.0471*	-0.0483	**0.06**	**0.00**	0.0680	0.1160	0.30	**0.10**	-0.456***	-0.436***	**0.00**	**0.00**	**0.00**	**0.00**
	(-1.88)	(-1.50)			(1.04)	(1.40)			(-6.750)	(-4.528)				
SHP	-0.0213	0.0149	0.24	0.20	0.4280	0.0869	0.44	0.58	-0.1240	-0.1360	0.20	0.42	0.46	0.59
	(-1.18)	(0.70)			(0.78)	(0.14)			(-1.282)	(-1.216)				
Momentum	0.454***	0.726***	**0.01**	**0.00**	0.0330	-0.0025	0.44	0.89	0.0414	-0.1440	0.79	0.52	0.48	0.53
	(2.75)	(3.99)			(0.64)	(-0.04)			(0.263)	(-0.715)				
VOLA	1.617***	2.729***	**0.00**	**0.00**	0.1610	0.0968	0.25	0.80	3.392***	4.708***	**0.00**	**0.00**	**0.00**	**0.00**
	(2.97)	(4.46)			(1.16)	(0.60)			(3.129)	(3.936)				
Panel B: Hedgers' HP ratio														
Term Structure	-0.0035	0.0070	0.79	0.87	0.0003	0.0001	0.65	0.90	0.0000	0.0001	0.99	1.00	1.00	1.00
	(-0.27)	(0.46)			(0.46)	(0.09)			(-0.01)	(0.05)				
HHP	-0.0002	0.0000	0.75	1.00	-2.0670	-3.0710	0.46	0.58	-0.0001	-0.0005	0.93	0.99	1.00	0.99
	(-0.32)	(-0.04)			(-0.74)	(-0.89)			(-0.09)	(-0.27)				
SHP	-0.0028	0.0036	0.79	0.83	-0.0006	-0.0006	0.35	0.71	0.0060	0.0121	0.55	0.53	0.47	0.52
	(-0.26)	(0.26)			(-0.95)	(-0.74)			(0.60)	(0.98)				
Momentum	0.0023	0.0066	0.62	0.54	0.0006	0.0017	0.84	0.89	0.0085	-0.0018	0.21	0.27	0.28	0.23
	(0.50)	(1.12)			(0.20)	(0.50)			(1.27)	(-0.22)				
VOLA	0.0003	0.0055	0.98	0.98	0.0002	0.0002	0.83	0.82	0.0015	0.0056	0.92	1.00	1.00	0.99
	(0.03)	(0.36)			(0.21)	(0.18)			(0.10)	(0.30)				

Notes: This table presents the results for Granger Causality tests. The dependent variable (DV) is the volatility of long, short and long-short portfolios. The independent variables (IVs) include speculators' hedging pressure (Panel A) and hedgers' hedging pressure ratios (Panel B) on commodities included in the long-short dynamic strategies. Panel A tests whether the increased presence of speculators (measured by speculators' hedging pressure ratio) Granger-cause changes in the volatility of commodity futures portfolio. Panel B tests whether hedgers' activities (measured by hedgers' hedging pressure ratio) Granger-cause changes in the volatility of commodity futures portfolio. β_1 denotes the coefficient estimates of the change in conditional volatility on the first lag of the IVs. The corresponding *t*-statistics are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause change in the volatility of commodities in dynamic long, short and long-short portfolios. *L* denotes the number of lags. The last two columns report *p*-values from two Granger-causality tests with four lags as robustness tests; the first test uses the levels of, instead of the changes in volatility as dependent variables. The second test augments Equation (9) with the first lag of term spread. The sample period covers February 2004 through May 2017.

Table 6 Speculators’ Hedging Pressure: Correlations of Long-short Portfolios with Conventional Asset

DV: Correlations	Long Portfolio				Short Portfolio				Long-short Portfolio				Test1	Test2
IV: SHP	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)		
Panel A: CSI300														
Term Structure	-0.1420*	-0.1470	**0.06**	**0.00**	0.0032	0.0029	0.41	0.71	-0.0024	0.0014	0.84	0.98	0.98	0.96
	(-1.91)	(-1.61)			(0.820)	(0.743)			(-0.20)	(0.11)				
HHP	-0.657***	-0.4030	**0.00**	**0.00**	4.158***	3.839**	**0.00**	**0.01**	-0.8000**	-1.0670**	**0.05**	**0.00**	**0.00**	**0.00**
	(-2.98)	(-1.37)			(3.571)	(2.556)			(-2.01)	(-2.30)				
SHP	-0.0501	-0.0763	0.71	0.76	21.0800***	15.1300**	**0.00**	**0.01**	-0.4320**	-0.2830	**0.05**	**0.08**	**0.08**	**0.08**
	(-0.37)	(-0.46)			(3.36)	(2.19)			(-2.01)	(-1.14)				
Momentum	0.9770*	0.9520*	**0.06**	0.32	-0.0513	-0.0843	0.74	0.99	0.0772	0.4360	0.89	0.78	0.78	0.76
	(1.88)	(1.67)			(-0.33)	(-0.46)			(0.14)	(0.64)				
VOLA	-0.8030	-0.1080	0.20	0.34	3.9280**	1.6180	**0.03**	0.20	2.1780***	1.9160**	**0.00**	**0.01**	**0.01**	**0.01**
	(-1.29)	(-0.16)			(2.25)	(0.81)			(3.13)	(2.50)				
Panel B: SH														
Term Structure	-0.1320	-0.1030	0.12	**0.00**	0.0032	0.0025	0.41	0.75	0.0004	0.0036	0.97	1.00	0.98	0.92
	(-1.55)	(-1.00)			(0.82)	(0.63)			(0.03)	(0.30)				
HHP	-0.5000**	-0.2930	**0.01**	**0.00**	1.4930***	1.8620***	**0.00**	**0.05**	-0.5600*	-0.9350**	**0.08**	**0.00**	**0.00**	**0.00**
	(-2.48)	(-1.13)			(2.93)	(2.89)			(-1.76)	(-2.33)				
SHP	0.0539	0.1260*	0.33	0.22	10.3900**	3.9580	**0.01**	**0.02**	-0.0429	-0.0723	0.61	0.83	0.86	0.88
	(0.98)	(1.91)			(2.49)	(0.83)			(-0.51)	(-0.72)				
Momentum	1.2670**	1.3070**	**0.02**	0.11	-0.0464	-0.0669	0.83	1.00	-0.1120	-0.0068	0.87	1.00	0.99	1.00
	(2.32)	(2.17)			(-0.21)	(-0.24)			(-0.20)	(-0.01)				
VOLA	2.6160***	2.4250**	**0.01**	**0.04**	4.5130**	1.4660	**0.04**	0.22	2.5580***	2.4310**	**0.00**	**0.01**	**0.02**	**0.02**
	(2.81)	(2.21)			(2.04)	(0.58)			(3.05)	(2.51)				
Panel C: SZ														
Term Structure	-0.1710*	-0.2490**	**0.08**	**0.00**	0.0050	0.0007	0.21	0.48	0.0013	0.0050	0.91	0.99	0.98	0.88
	(-1.74)	(-2.08)			(1.258)	(0.180)			(0.109)	(0.434)				
HHP	-0.3710**	-0.2580	**0.01**	**0.00**	1.1360***	1.2620***	**0.00**	**0.04**	-0.4560	-0.9570*	0.29	**0.03**	**0.06**	**0.03**
	(-2.52)	(-1.37)			(3.06)	(2.68)			(-1.07)	(-1.81)				
SHP	-0.0137	-0.106	0.84	0.43	0.7760	0.4530	0.65	0.99	0.1550	-0.0188	0.34	0.12	**0.10**	0.12
	(-0.20)	(-1.31)			(0.45)	(0.23)			(0.96)	(-0.10)				
Momentum	1.6280***	1.1010	**0.01**	**0.09**	0.0517	0.0148	0.67	0.99	-0.1540	-0.1520	0.83	1.00	1.00	1.00
	(2.65)	(1.63)			(0.43)	(0.10)			(-0.32)	(-0.25)				
VOLA	1.5190***	1.5680**	**0.00**	**0.03**	2.2580	2.2270	0.12	0.50	1.1540***	1.1070***	**0.00**	**0.00**	**0.00**	**0.01**
	(2.92)	(2.54)			(1.56)	(1.34)			(3.44)	(2.88)				
Panel D: Bonds														
Term Structure	0.3040*	0.2200	**0.09**	**0.05**	-0.0006	-0.0010	0.66	0.95	-0.0014	-0.0099	0.84	0.57	0.53	0.57
	(1.69)	(1.00)			(-0.45)	(-0.69)			(-0.20)	(-1.46)				
HHP	-0.5780***	-0.5870**	**0.00**	**0.00**	0.2980	0.3130	0.63	0.97	-0.1680	0.4290	0.68	**0.00**	**0.00**	**0.00**
	(-2.95)	(-2.26)			(0.48)	(0.40)			(-0.41)	(0.80)				
SHP	-0.0053	0.0046	0.75	0.68	-2.0080	-2.3080	0.59	0.71	0.0443	0.0567	0.46	0.27	0.31	0.28
	(-0.32)	(0.22)			(-0.53)	(-0.54)			(0.74)	(0.76)				
Momentum	-0.7640	-0.8930	0.24	0.32	-0.0189	0.0183	0.73	0.91	-0.0875	-0.1740	0.54	0.93	0.97	0.92
	(-1.17)	(-1.27)			(-0.35)	(0.26)			(-0.44)	(-0.69)				
VOLA	1.5470	0.2480	0.21	0.70	-0.4010	0.5350	0.70	0.79	0.3020	0.8210	0.78	0.86	0.75	0.92
	(1.26)	(0.18)			(-0.38)	(0.45)			(0.28)	(0.68)				

To be continued on next page

Table 6 continued

Notes: This table presents the results for Granger Causality tests for speculators' hedging pressure and correlation with conventional assets. The dependent variable (DV) is the time-varying correlations between dynamic long-short portfolios with conventional assets. The independent variables (IVs) are speculators' hedging pressure ratios on commodities included in the long-short dynamic strategies. Panels A, B, C and D tests whether increased presence of speculators (measured by changes in the speculators' hedging pressure ratio) Granger-cause changes in the correlation of commodity futures portfolios with CSI300 index, Shanghai composite index (SH), Shenzhen composite index (SZ) and Barclays China aggregate bond index (Bond), respectively. β_1 denotes the coefficient estimates of the change in correlation on the first and second lag of the IVs. The corresponding *t*-statistics are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause change in the correlation of commodities in dynamic long, short and long-short portfolios with conventional assets. *L* denotes the number of lags. The last two columns report *p*-values from two Granger-causality tests with four lags as robustness tests; the first test uses the levels of, instead of the changes in correlations as dependent variables. The second test augments Equation (10) with the first lag of term spread. The sample period covers February 2004 through to May 2017.

Table 7 Speculators' Hedging Pressure: Correlations of Long-short Portfolios with Macrocosmic Variables

DV: Correlations	Long Portfolio				Short Portfolio				Long-short Portfolio				Test1	Test2
IV: SHP	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)		
Panel A: REER														
Term Structure	0.2370	-0.2510	0.48	**0.05**	-0.0021	0.0060	0.85	0.96	-0.0028	-0.0010	0.81	0.93	0.93	0.91
	(0.71)	(-0.62)			(-0.19)	(0.54)			(-0.24)	(-0.09)				
HHP	-0.2910	-0.1190	0.26	0.76	-1.8750	0.3840	0.11	0.12	-0.2430	0.7130	0.77	**0.06**	**0.04**	**0.06**
	(-1.14)	(-0.43)			(-1.61)	(0.26)			(-0.29)	(0.66)				
SHP	0.0925	0.3430**	0.41	**0.09**	-33.4900***	-27.3300**	**0.00**	**0.01**	0.3100	0.7480*	0.33	0.31	0.69	0.32
	(0.83)	(2.55)			(-3.52)	(-2.50)			(0.98)	(1.97)				
Momentum	-1.0770	-1.4020	0.24	0.27	-0.0855	-0.1910*	0.26	0.30	-0.4880	-2.0190***	0.27	**0.07**	**0.05**	**0.07**
	(-1.17)	(-1.42)			(-1.12)	(-1.92)			(-0.81)	(-2.61)				
VOLA	-1.6310	-1.6220	0.21	0.32	-1.2650	0.4260	0.12	**0.02**	0.1950	-0.3230	0.90	0.22	0.30	0.24
	(-1.27)	(-1.09)			(-1.59)	(0.46)			(0.12)	(-0.18)				
Panel B: CPI Shock														
Term Structure	0.2250	0.6870***	0.19	**0.00**	-0.0002	-0.0002	0.96	1.00	-0.0077	0.0006	0.17	0.73	0.80	0.63
	(1.32)	(3.48)			(-0.05)	(-0.06)			(-1.38)	(0.10)				
HHP	-0.0865	-0.3870***	0.45	**0.00**	-0.1620	-0.2410	0.51	0.74	-0.0082	-0.2300	0.97	0.48	0.52	0.47
	(-0.76)	(-2.67)			(-0.66)	(-0.77)			(-0.04)	(-0.92)				
SHP	-0.0027	-0.0702*	0.93	0.29	0.7360	2.557	0.82	0.83	-0.0161	-0.0497	0.85	0.96	0.99	0.95
	(-0.08)	(-1.82)			(0.23)	(0.69)			(-0.20)	(-0.50)				
Momentum	-0.1580	-0.4480	0.66	0.71	-0.0506	0.0166	0.54	0.92	-0.0518	-0.0814	0.75	0.58	0.62	0.58
	(-0.44)	(-1.16)			(-0.61)	(0.16)			(-0.35)	(-0.43)				
VOLA	-0.0569	-0.0660	0.93	0.98	0.1420	-1.1860	0.93	0.72	0.1450	-0.6500	0.89	0.19	0.14	0.19
	(-0.09)	(-0.09)			(0.09)	(-0.66)			(0.14)	(-0.57)				
Panel C: GDP														
Term Structure	0.0035	0.0040	0.97	0.99	0.0105	0.0034	0.27	0.03	0.0044	0.0008	0.62	0.99	0.93	0.80
	(0.04)	(0.04)			(1.10)	(0.36)			(0.50)	(0.09)				
HHP	0.1310	-0.0084	0.37	0.67	-1.0410	-0.8880	0.13	0.52	-0.4350***	-0.3060	**0.01**	**0.04**	**0.03**	**0.04**
	(0.90)	(-0.05)			(-1.53)	(-1.03)			(-2.63)	(-1.42)				
SHP	0.1380	0.1600	0.22	0.47	13.2600	-3.2080	0.13	**0.07**	0.0142	0.2680	0.93	0.39	0.39	0.42
	(1.24)	(1.11)			(1.52)	(-0.33)			(0.08)	(1.24)				
Momentum	-0.6030**	0.3680	**0.04**	**0.05**	-0.0445	-0.0162	0.40	0.73	0.0044	-0.0063	0.98	0.96	0.97	0.97
	(-2.12)	(1.18)			(-0.84)	(-0.24)			(0.14)	(-0.16)				
VOLA	-1.0050**	-0.1820	**0.03**	0.21	-2.006***	-0.6470	**0.00**	**0.04**	0.0220	-0.2060	0.94	0.88	0.77	0.83
	(-2.16)	(-0.33)			(-2.95)	(-0.82)			(0.08)	(-0.63)				
Panel D: ECI														
Term Structure	0.1610	0.1120	0.24	**0.00**	0.0001	0.0013	0.91	0.71	-0.0055	0.0054	0.61	0.93	0.91	0.66
	(1.18)	(0.69)			(0.11)	(1.04)			(-0.51)	(0.50)				
HHP	0.3960	0.4730	0.13	0.46	-0.3600	-1.6610	0.71	0.20	4.5510***	0.6840	**0.00**	**0.00**	**0.00**	**0.00**
	(1.51)	(1.42)			(-0.38)	(-1.37)			(5.52)	(0.60)				
SHP	0.0105	-0.2060**	0.88	**0.03**	4.4760	-6.6110	0.39	**0.08**	-0.0545	-0.1950	0.71	0.08	0.15	0.09
	(0.15)	(-2.47)			(0.86)	(-1.10)			(-0.37)	(-1.10)				
Momentum	-0.0217	-0.3020	0.90	0.57	-0.3580***	-0.2670*	**0.00**	**0.05**	-0.4760	-0.9120*	0.18	0.48	0.39	0.49
	(-0.12)	(-1.55)			(-3.05)	(-1.94)			(-1.30)	(-1.95)				
VOLA	0.1800	0.2510*	0.12	0.43	-0.8670	-2.288*	0.46	0.51	-0.2580	0.3030	0.38	0.60	0.81	0.50
	(1.55)	(1.84)			(-0.73)	(-1.72)			(-0.66)	(0.68)				

Panel E: PPI														
Term Structure	0.1400	0.1060	0.14	**0.03**	-0.0010	-0.0012	0.53	0.71	0.0034	0.0028	0.60	0.96	0.97	0.95
	(1.48)	(0.96)			(-0.64)	(-0.71)			(0.53)	(0.44)				
HHP	0.4740***	0.6270***	**0.00**	**0.00**	-0.6340**	-0.6220*	**0.02**	**0.07**	-0.8200*	-1.1120*	**0.08**	**0.01**	**0.01**	**0.01**
	(2.87)	(2.89)			(-2.41)	(-1.83)			(-1.79)	(-1.86)				
SHP	0.0382	0.0700	0.45	0.82	-2.5690	-3.7500	0.22	**0.05**	-0.0442	-0.0683	0.66	0.91	0.99	0.93
	(0.75)	(1.12)			(-1.24)	(-1.56)			(-0.44)	(-0.55)				
Momentum	0.4000	0.695*	0.29	0.22	-0.0898	-0.2050	0.54	0.72	-0.1210	-0.2480	0.71	**0.01**	**0.01**	**0.01**
	(1.07)	(1.72)			(-0.62)	(-1.16)			(-0.80)	(-1.41)				
VOLA	-0.1660	-0.4050	0.81	0.38	1.8770	1.2870	0.35	0.55	0.2470	0.9010	0.54	0.73	0.66	0.73
	(-0.24)	(-0.50)			(0.94)	(0.57)			(0.12)	(0.40)				

Notes: This table presents the results for Granger Causality tests for speculators' hedging pressure and correlation with macroeconomic variables. The dependent variable (DV) is the time-varying correlations between dynamic long-short portfolios with macroeconomic variables. The independent variables (IVs) are speculators' hedging pressure ratios on commodities included in the long-short dynamic strategies. Panels A, B, C, D and E tests whether increased presence of speculators (measured by changes in the speculators' hedging pressure ratio) Granger-cause changes in the correlation of commodity futures portfolios with nominal real effective exchange (REER), CPI Shock, GDP growth, Economic Climate Index (ECI) and Producer Production Index (PPI), respectively. β_1 denotes the coefficient estimates of the change in correlation on the first and second lag of the IVs. The corresponding *t*-statistics are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause change in the correlation of commodities in dynamic long, short and long-short portfolios with macro variables. *L* denotes the number of lags. The last two columns report *p*-values from two Granger-causality tests with four lags as robustness tests; the first test uses the levels of, instead of the changes in correlations as dependent variables. The second test augments Equation (10) with the first lag of term spread. The sample period covers February 2004 through May 2017.

Table 8 Hedgers' Hedging Pressure: Correlations of Long-short Portfolios with Conventional Assets

DV: Correlations	Long Portfolio				Short Portfolio				Long-short Portfolio				Test1	Test2
IV: HHP	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)		
Panel A: CSI300														
Term Structure	-0.0006	-0.0003	0.88	0.78	0.0022	0.0042	0.53	0.69	0.0004	0.0028	0.97	1.00	1.00	1.00
	(-0.15)	(-0.06)			(0.62)	(0.89)			(0.04)	(0.21)				
HHP	-0.0009	-0.0014	0.83	1.00	-31.7000	22.4000	0.52	0.76	0.0029	-0.0005	0.69	0.94	0.94	0.94
	(-0.21)	(-0.23)			(-0.65)	(0.38)			(0.40)	(-0.05)				
SHP	0.0312	0.0637	0.43	0.69	-0.0020	-0.0013	0.75	0.99	-0.0005	-0.0043	0.96	1.00	1.00	1.00
	(0.79)	(1.20)			(-0.32)	(-0.16)			(-0.05)	(-0.32)				
Momentum	-0.0033	-0.0098	0.82	0.98	-0.0058	0.0013	0.55	0.84	0.0023	0.0352	0.92	0.56	0.56	0.62
	(-0.23)	(-0.54)			(-0.60)	(0.10)			(0.10)	(1.22)				
VOLA	-0.0110	-0.0037	0.40	0.82	-0.0039	0.0009	0.71	0.89	-0.0007	-0.0004	0.94	1.00	1.00	1.00
	(-0.85)	(-0.23)			(-0.38)	(0.07)			(-0.08)	(-0.03)				
Panel B: SH														
Term Structure	-0.0013	-0.0010	0.76	0.71	0.0023	0.0039	0.53	0.74	0.0013	0.0038	0.89	1.00	1.00	1.00
	(-0.31)	(-0.20)			(0.63)	(0.81)			(0.13)	(0.29)				
HHP	-0.0013	-0.0013	0.74	1.00	-14.4100	11.7600	0.52	0.81	0.0023	-0.0007	0.70	0.96	0.98	0.97
	(-0.33)	(-0.24)			(-0.65)	(0.44)			(0.39)	(-0.09)				
SHP	0.0268	0.0554	0.42	0.71	-0.0011	-0.0002	0.83	0.98	-0.0012	-0.0040	0.90	0.99	1.00	1.00
	(0.81)	(1.26)			(-0.21)	(-0.03)			(-0.13)	(-0.36)				
Momentum	0.0013	0.0003	0.93	1.00	-0.0166	-0.0081	0.29	0.44	0.0036	0.0365	0.88	0.61	0.51	0.67
	(0.08)	(0.02)			(-1.07)	(-0.42)			(0.15)	(1.22)				
VOLA	0.0034	0.0103	0.86	0.99	-0.0012	0.0102	0.93	0.83	0.0018	0.0030	0.87	1.00	1.00	1.00
	(0.18)	(0.43)			(-0.09)	(0.61)			(0.16)	(0.21)				
Panel C: SZ														
Term Structure	0.0042	0.0057	0.45	0.83	0.0040	0.0039	0.27	0.27	0.0019	0.0058	0.84	0.99	0.99	0.99
	(0.77)	(0.89)			(1.12)	(0.81)			(0.21)	(0.46)				
HHP	0.0018	0.0015	0.56	0.71	-9.6040	7.1260	0.55	0.86	0.0013	-0.0035	0.86	0.93	0.94	0.92
	(0.58)	(0.36)			(-0.60)	(0.36)			(0.17)	(-0.35)				
SHP	0.0112	0.0124	0.77	0.91	-0.0009	-0.0012	0.67	0.23	-0.0077	-0.0092	0.65	0.99	1.00	0.99
	(0.29)	(0.24)			(-0.42)	(-0.48)			(-0.45)	(-0.43)				
Momentum	0.0054	0.0091	0.75	0.99	-0.0045	-0.0061	0.54	0.64	0.0084	0.0458*	0.69	0.29	0.23	0.34
	(0.32)	(0.42)			(-0.62)	(-0.66)			(0.40)	(1.75)				
VOLA	-0.0003	0.0047	0.97	0.98	-0.0009	-0.0020	0.92	0.99	0.0008	0.0017	0.86	0.99	1.00	0.99
	(-0.03)	(0.35)			(-0.10)	(-0.18)			(0.18)	(0.30)				
Panel D: Bonds														
Term Structure	0.0001	-0.0045	0.99	0.24	-0.0004	-0.0011	0.75	0.98	-0.0001	-0.0064	0.98	0.74	0.74	0.74
	(0.01)	(-0.45)			(-0.32)	(-0.62)			(-0.03)	(-0.87)				
HHP	-0.0046	-0.0068	0.29	0.59	-7.391	0.199	0.78	0.96	0.0020	-0.0023	0.80	0.29	0.32	0.30
	(-1.07)	(-1.16)			(-0.29)	(0.01)			(0.25)	(-0.21)				
SHP	0.0200**	0.0096	**0.04**	**0.00**	0.00464	0.000915	0.28	**0.02**	-0.0015	-0.0095	0.82	0.12	0.19	0.09
	(2.05)	(0.73)			(1.07)	(0.17)			(-0.23)	(-1.12)				
Momentum	0.0082	0.0079	0.65	0.83	-0.00879**	-0.00789*	**0.02**	**0.10**	0.0002	-0.0244**	0.98	**0.01**	**0.03**	**0.01**
	(0.46)	(0.35)			(-2.42)	(-1.71)			(0.03)	(-2.36)				
VOLA	-0.0174	-0.0127	0.50	0.97	-0.0052	-0.0076	0.40	0.83	-0.0032	-0.0061	0.81	0.39	0.39	0.38
	(-0.68)	(-0.40)			(-0.84)	(-0.95)			(-0.24)	(-0.35)				

Notes: *Notes*: This table presents the results for Granger Causality tests for hedgers' hedging pressure and correlation with conventional assets. The dependent variable (DV) is the time-varying correlations between dynamic long-short portfolios with conventional assets. The independent variables (IVs) are hedgers' hedging pressure ratios on commodities included in the long-short dynamic strategies. Panels A, B, C and D tests whether hedgers activities (measured by changes in the hedgers' hedging pressure ratio) Granger-cause changes in the correlation of commodity futures portfolios with CSI300 index, Shanghai composite index (SH), Shenzhen composite index (SZ) and Barclays China aggregate bond index (Bond), respectively. β_1 denotes the coefficient estimates of the change in correlation on the first and second lag of the IVs. The corresponding *t*-statistics are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause changes in the correlation of commodities in dynamic long, short and long-short portfolios with conventional assets. *L* denotes the number of lags. The last two columns report *p*-values from two Granger-causality tests with four lags as robustness tests; the first test uses the levels of, instead of the changes in correlations as dependent variables. The second test augments Equation (10) with the first lag of term spread. The sample period covers February 2004 through May 2017.

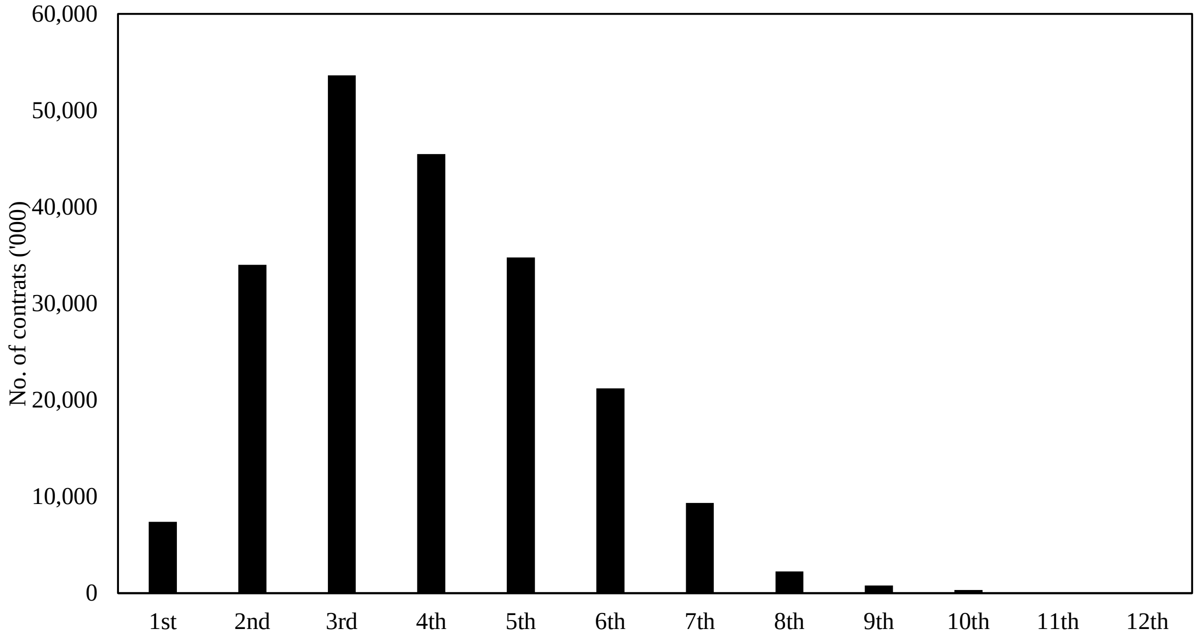
Table 9 Hedgers' Hedging Pressure (HHP): Correlations of Long-short Portfolios with Macroeconomic Variables

DV: Correlations	Long Portfolio				Short Portfolio				Long-short Portfolio				Test1	Test2
IV: HHP	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)	$L.\beta_1$	$L2.\beta_1$	p(1)	p(4)		
Panel A: REER														
Term Structure	-0.0164	-0.0148	0.32	0.90	-0.0009	0.0064	0.93	0.97	0.0013	-0.0016	0.89	0.88	0.88	0.88
	(-1.00)	(-0.76)			(-0.09)	(0.49)			(0.14)	(-0.13)				
HHP	0.0011	0.0024	0.76	0.80	21.4300	-9.8490	0.67	0.95	-0.0119	-0.0199	0.44	0.87	0.95	0.87
	(0.31)	(0.49)			(0.43)	(-0.16)			(-0.78)	(-0.97)				
SHP	0.0233	0.0648	0.74	0.65	-0.0150	-0.0009	0.20	0.47	0.0301	0.0467	0.39	0.67	0.74	0.68
	(0.34)	(0.69)			(-1.27)	(-0.06)			(0.87)	(1.06)				
Momentum	0.0137	0.0011	0.60	0.95	0.0012	0.0007	0.81	0.86	-0.0072	-0.0187	0.80	0.82	0.89	0.82
	(0.53)	(0.03)			(0.24)	(0.11)			(-0.25)	(-0.51)				
VOLA	0.0343	0.0218	0.19	0.63	0.0033	0.0087	0.50	0.51	0.0257	0.0171	0.18	0.53	0.61	0.51
	(1.33)	(0.66)			(0.69)	(1.45)			(1.34)	(0.67)				
Panel B: CPI Shock														
Term Structure	-0.0037	0.0079	0.65	0.40	-0.0003	-0.0007	0.93	1.00	-0.0053	-0.0049	0.26	0.84	0.90	0.82
	(-0.46)	(0.82)			(-0.08)	(-0.17)			(-1.14)	(-0.79)				
HHP	0.0004	0.0008	0.87	0.91	10.6000	8.0140	0.31	0.69	-0.0028	-0.0012	0.42	**0.10**	0.11	**0.10**
	(0.17)	(0.29)			(1.02)	(0.62)			(-0.81)	(-0.26)				
SHP	0.0062	-0.0019	0.75	0.46	0.00802**	0.0057	**0.05**	0.13	-0.0002	-0.0001	0.98	0.78	0.80	0.77
	(0.32)	(-0.07)			(2.00)	(1.13)			(-0.03)	(-0.01)				
Momentum	-0.0071	-0.0073	0.46	0.86	-0.0007	-0.0071	0.91	0.28	-0.00461	0.0008	0.48	0.65	0.70	0.65
	(-0.74)	(-0.60)			(-0.11)	(-0.92)			(-0.71)	(0.09)				
VOLA	-0.0094	0.0020	0.51	0.87	0.0073	0.0096	0.43	0.75	0.0108	0.0145	0.40	0.75	0.85	0.76
	(-0.67)	(0.11)			(0.79)	(0.82)			(0.84)	(0.85)				
Panel C: GDP growth														
Term Structure	-0.00701*	-0.0062	0.04	0.14	0.0034	0.0001	0.39	0.11	0.0036	0.0054	0.47	0.99	1.00	0.98
	(-1.90)	(-1.41)			(0.38)	(0.01)			(0.49)	(0.55)				
HHP	-0.0026	-0.00645**	0.29	**0.09**	15.6000	-32.0700	0.57	0.18	0.0005	0.0020	0.87	0.73	0.75	0.71
	(-1.07)	(-2.01)			(0.58)	(-0.97)			(0.16)	(0.50)				
SHP	0.0249	0.0079	0.55	0.59	-0.0086	-0.0164	0.33	0.11	0.0127	0.0162	0.17	**0.00**	**0.00**	**0.01**
	(0.59)	(0.14)			(-0.98)	(-1.49)			(1.39)	(1.41)				
Momentum	-0.0052	-0.0044	0.50	0.55	0.0005	-0.0006	0.91	**0.07**	-0.0009	-0.0009	0.50	0.95	0.96	0.95
	(-0.67)	(-0.45)			(0.12)	(-0.12)			(-0.67)	(-0.52)				
VOLA	0.0025	0.0063	0.80	0.85	-0.0033	-0.00849*	0.40	0.12	0.0058	0.00844*	**0.10**	**0.10**	0.15	0.11
	(0.25)	(0.51)			(-0.84)	(-1.72)			(1.66)	(1.78)				
Panel D: ECI														
Term Structure	0.0081	0.0096	0.23	0.23	0.0000	0.0011	0.97	0.71	-0.0033	-0.0002	0.71	0.97	0.98	0.97
	(1.21)	(1.23)			(-0.04)	(0.72)			(-0.37)	(-0.01)				
HHP	-0.0009	-0.0011	0.85	0.65	29.1600	79.6400	0.46	0.40	0.0222	0.0291	0.23	0.77	0.85	0.77
	(-0.19)	(-0.18)			(0.73)	(1.65)			(1.21)	(1.20)				
SHP	-0.0293	-0.0942*	0.48	**0.00**	0.0042	0.0072	0.50	0.20	-0.0069	-0.0154	0.66	0.62	0.51	0.62
	(-0.71)	(-1.73)			(0.67)	(0.93)			(-0.44)	(-0.78)				
Momentum	-0.0031	-0.0035	0.52	0.61	0.0051	0.0105	0.48	0.23	0.0027	-0.0335	0.87	0.12	0.13	0.12
	(-0.64)	(-0.56)			(0.71)	(1.17)			(0.17)	(-1.66)				
VOLA	-0.0010	-0.0020	0.69	0.62	0.0058	0.0049	0.39	0.78	-0.0053	-0.0068	0.28	0.43	0.58	0.46
	(-0.41)	(-0.67)			(0.87)	(0.57)			(-1.09)	(-1.05)				

Panel E: PPI														
Term Structure	-0.0084*	-0.0087*	**0.05**	0.31	0.0000	0.0000	1.00	1.00	0.0082	0.0110	0.12	0.44	0.52	0.42
	(-1.97)	(-1.68)			(0.00)	(-0.02)			(1.57)	(1.59)				
HHP	0.0003	0.0004	0.94	1.00	4.0080	5.8080	0.72	0.71	-0.0008	0.0015	0.93	0.97	0.95	0.98
	(0.08)	(0.09)			(0.35)	(0.42)			(-0.09)	(0.13)				
SHP	0.0367	0.0396	0.24	0.58	-0.0005	-0.0010	0.85	0.85	-0.0090	-0.0116	0.42	0.41	0.26	0.40
	(1.17)	(0.96)			(-0.19)	(-0.34)			(-0.81)	(-0.84)				
Momentum	-0.0063	-0.0119	0.55	0.74	0.0039	0.00453	0.57	0.96	-0.0062	-0.0065	0.32	0.84	0.93	0.88
	(-0.61)	(-0.90)			(0.56)	(0.53)			(-0.99)	(-0.84)				
VOLA	0.0007	0.0070	0.96	0.98	-0.0096	-0.0132	0.38	0.61	-0.0280	-0.0336	0.26	0.82	0.70	0.82
	(0.04)	(0.37)			(-0.89)	(-0.98)			(-1.12)	(-1.02)				

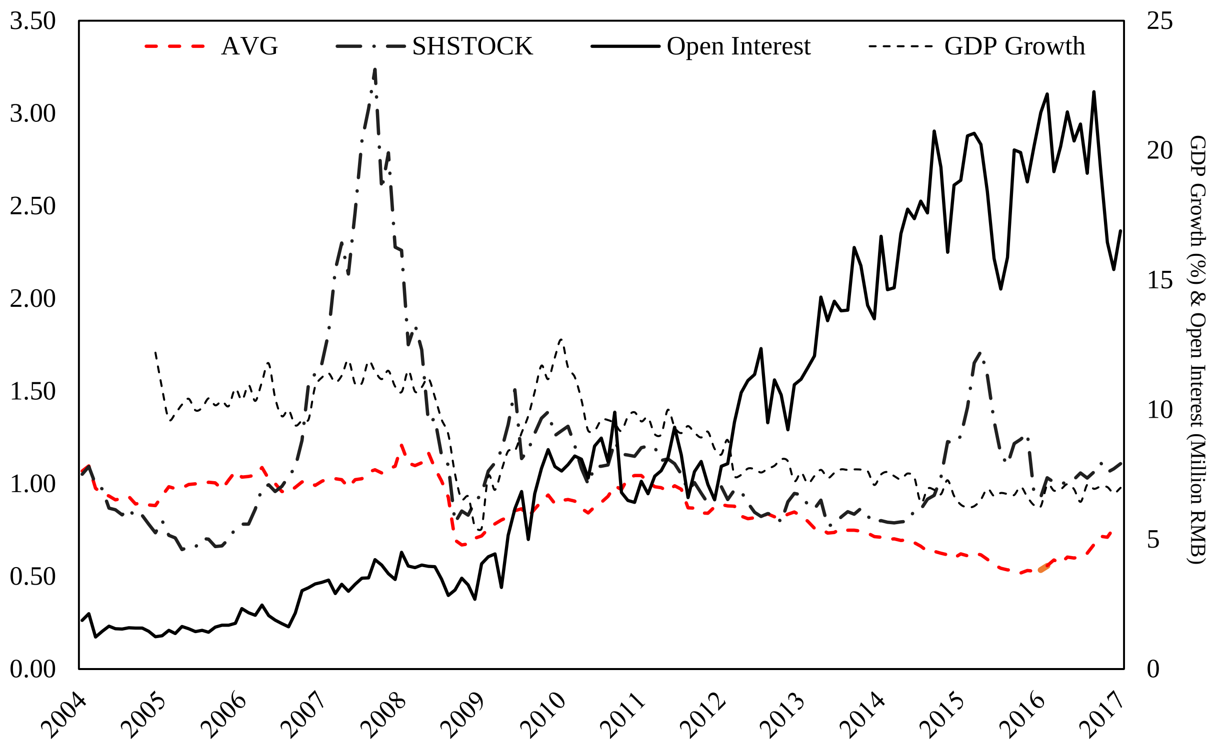
Notes: This table presents the results for Granger Causality tests for hedgers' hedging pressure and correlation with macroeconomic variables. The dependent variable (DV) is the time-varying correlations between dynamic long-short portfolios with macroeconomic variables. The independent variables (IVs) are hedgers' hedging pressure ratios on commodities included in the long-short dynamic strategies. Panels A, B, C, D and E tests whether hedgers' activities (measured by changes in the hedgers' hedging pressure ratio) Granger-cause changes in the correlation of commodity futures portfolios with nominal real effective exchange (REER), CPI Shock, GDP growth, Economic Climate Index (ECI) and Producer Production Index (PPI), respectively. β_1 denotes the coefficient estimates of the change in correlation on the first and second lag of the IVs. The corresponding *t*-statistics are reported in parentheses. *p(L)* represents is the *p*-value of the *F*-statistic that tests the null hypotheses that the IV does not Granger-cause change in the correlation of commodities in dynamic long, short and long-short portfolios with macro variables. *L* denotes the number of lags. The last two columns report *p*-values from two Granger-causality tests with four lags as robustness tests; the first test uses the levels of, instead of the changes in correlations as dependent variables. The second test augments Equation (10) with the first lag of term spread. The sample period covers February 2004 to May 2017.

Figure 1 Trading Volumes Across Futures Curves



Notes: The figure exhibits the average trading volume per month on m^{th} maturity contracts, based on a sample of 30 commodities covering February 2004 to May 2017.

Figure 2 Comparative Performance



Notes: This figure illustrates the performance of Chinese commodity futures market, stock market and economic growth. AVG represents the commodity futures market and SHSTOCK represents the Shanghai Composite Index. AVG and SHSTOCK are normalized at February 2004 with a beginning value of 1. AVG is computed based on 3rd nearby contracts. The black line exhibits the total open interest of our sample, while the black dash is the GDP growth rate. This figure covers the period from February 2004 to May 2017.