

The Untold Story of Commodity Futures in China

John Hua FAN* and Tingxi ZHANG

Department of Accounting, Finance and Economics, Griffith Business School
Griffith University

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Abstract

We investigate the behavior of commodity futures risk premia in China. In the presence of retail-dominance and barriers-to-entry, the term structure and momentum premia remain persistent, whereas hedging pressure, skewness, volatility and liquidity premia are distorted by time-varying margins and strict position limits. Furthermore, open interest, currency and inflation premia are sensitive to institutional settings. The observed premia cannot be attributed to common risks, sentiment, transactions costs or data-snooping, but are related to liquidity, anchoring, and regulation-induced limits-to-arbitrage. We highlight the distinctive features of Chinese futures markets and assess the challenges posed to theories of commodity risk premia.

JEL Classification: G13, G14, G15, G41, N25, Q02

Keywords: China; Commodity futures; Position limits; Margins; Price discovery;
Momentum; Term structure; Hedging pressure; Liquidity; Diversification

*Corresponding author. Address: Department of Accounting, Finance and Economics, Griffith Business School, Griffith University, Nathan Campus, 170 Kessels Road, Nathan, Queensland 4111, Australia. Tel: +61 (0)7 3735 3948; E-mail: j.fan@griffith.edu.au.

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1. Introduction

This paper investigates the behavior of passive long and systematic risk premia in China. Taking a deep dive into the institutional settings in comparison to the US, we document the impact of unique market characteristics on empirical design and results. Our findings contribute to the literature in several ways. First, we conduct a true out-of-sample test of existing theories in a unique environment. These findings inform the pricing of commodities in the presence of retail dominance, time-varying margin and strict position limits. Second, investors seeking new ways to improve their portfolios have embraced the idea of factor investing globally.¹ In light of the ongoing internationalization process of commodity markets in China, our findings on systematic risk premia in an emerging futures market are of immediate interests to liquid alternatives, such as hedge funds and commodity trading advisors who seek for diversification opportunities. Last but not the least, we discuss policy implications for the efficient functioning of commodity markets.

Since the beginning of the millennium, commodity futures markets in China have undergone tremendous developments. The trading volume soared from a mere 3 trillion to 227 trillion RMB over the period 2001-2010 (China Futures Association, 2015).² As of 2018, six of the world's top ten most active commodity contracts were traded in China. Furthermore, China accounted for 56% of global demand for nickel, 50% for coal, copper and steel, and 47% for aluminum and pork in 2017 (VisualCapitalist, 2018). To fulfill the economic transition, demand for commodities is expected to grow even further (FT, 2017). Along with the colossal demand, surging investor interests and the ongoing liberalization, the once extraneous market

¹ BlackRock (2018) notes the factor industry is \$1.9 trillion in Assets Under Management (AUM) and has grown organically at around 11% per year since 2011. In a survey of the world's 500 largest asset managers, 5.5% of the AUM of the firms surveyed was invested in factor-based strategies in 2016 (Willis Towers Watson, 2017). Similarly, Invesco (2017) estimated a 50% growth in proportion of AUM allocated to factor investing by 2022.

² A similar trend is observed in the growth of open interests. However, while China dominates the trading volume comparison, the year-end open interests are consistently larger in the US. Based on our selected sample estimates, the dollar or RMB open interest is roughly 3.5 times larger in the US.

in the global commodities trade has become a significant force in determining the international commodity prices (WSJ, 2016; Bloomberg, 2018b). However, the Chinese commodity futures market remains enigmatic to practitioners and academics alike due to the barriers-to-entry, state influences and unique trading rules.

One of the most striking characteristics the literature has become accustomed to, is the large presence of retail investors. By the end of 2016, more than 86% of the open interest was held by individual accounts (China Futures Association, 2016), compared to less than 15% in the US (Bhardwaj, Gorton, & Rouwenhorst, 2016). Strikingly, the average holding period of a futures contract in China is less than four hours (Citi, 2016). Individuals are known to be less informed (Griffin, Harris, & Topaloglu, 2003), and their trades are more correlated with volumes (Grinblatt & Keloharju, 2000). Furthermore, retail-dominance also induces a higher degree of positive feedback trading (De Long, Shleifer, Summers, & Waldmann, 1990) and herding (Li, Rhee, & Wang, 2017). Therefore, combined with the lack of strong legal framework (Allen, Qian, & Qian, 2006), a low level of investment risk perception and skills (Wang, Shi, & Fan, 2006), and evidence of disposition, overconfidence and representativeness (Chen, Kim, Nofsinger, & Rui, 2007), the Chinese commodity market is likely highly speculative. The predominant level of sophistication is crucial for the dynamics of risk premia (Campbell, Grossman, & Wang, 1993).

Moreover, China's socialist market economy signifies the government's constant attempt at balancing productivity and stability. By limiting the market access and maintaining a tight control over its commodity markets, a unique institutional environment is created for the formation of prices. First, direct participation by foreign investors is currently restricted,

although this is being loosened as part of the effort to internationalize these markets.³ However, historically being segregated from global investors likely caused market segmentation, limits-to-arbitrage and gradual information diffusion. For example, Yang, Yang, and Zhou (2012) find that barriers-to-entry reduces the information content of the futures prices in China. Second, directly managed by the government, the priority of the Chinese exchanges is market stability rather than the maximization of shareholders' wealth. Compared to developed markets such as the US, this fundamental difference inevitably leads to more frequent interventions and tighter regulatory controls, which are ultimately translated into unique implementations of price limits, margins and position limits. These unique settings convey significant implications for the futures price discovery and hence the dynamics of risk premia.

The paper presents four key findings. First, unlike the US markets where nearby contracts are most active, the nearest to maturity contracts in China account for less than 10% of total volume traded on the futures curve. Overlooked by the extant literature, this means inferences drawn from the nearest contracts are incomplete at best. Nonetheless, Ciner (2002) and Webb (1995) find Japanese speculators prefer deferred contracts as they believe there is more time for their futures position to become profitable. Chinese investors exhibit preferences toward longer-dated contracts with specific maturities. Exacerbated by the time-varying margins and strict position limits, speculators are involuntarily pushed away from the front end of the futures curve.⁴ As a result, a regulation-induced "limits-to-arbitrage" causes the liquidity

³ As of October 2019, foreign investors can directly trade in crude oil (from March 2018), iron ore (from May 2018), PTA (from November 2018), STR rubber (from August 2019) and fuel oil (from December 2019) markets. Products under discussions include methanol, soybeans, palm olein, LLDPE, PP, copper, aluminum, nickel, zinc, lead and tin. These markets are expected to be opened shortly. Since then, qualified foreign brokerage firms are allowed to directly trade in the exchange, instead of conducting trades via a domestic intermediary.

⁴ At the time when the paper was written, individual investors in common wheat are prohibited to hold any positions during the delivery month while non-individuals are limited to 200 contracts. In addition, a margin of 5% is applied from the first to the 15th calendar day of the month prior to the delivery month. This margin is then increased to 10% for the remaining month and 20% in the delivery month. A forced liquidation process is triggered if positions exceed the defined limit. As speculators cannot trade *sufficient* volumes in the nearest contracts, moving to a more distant contract not only maintains continuous exposures but also avoids a higher margin cost.

and volatility to be lower, and the expected returns to be higher in the nearest to delivery markets. In these markets, hedgers' ability to effectively transfer risks is impeded.

Second, passive long-only investing does not yield statistically significant profits, regardless of the time, sector or weighting schemes employed. This helps explain the relative absence of indexing instruments known to investors.⁵ In general, the performance of long-only commodities mirrors the rapid growth and recent slowdown of the Chinese economy. The absence of long-only premia suggests the theory of normal backwardation (Keynes, 1930; Hicks, 1939) does not hold well in China. Under this framework, net long speculators accrue a risk premium by assuming the price risk of net short hedgers. Even though some individual accounts may represent hedgers in disguise, the absence of long-only premia suggests that speculators overpower hedgers as a result of retail-dominance.

Third, unique institutional settings do not eliminate the risk premia. Among an exhaustive list of premia tested, term structure and momentum premia are inflated by, but are robust to, strict position limits and time-varying margins. As roll-yields and past returns are empirically linked to inventory (Gorton, Hayashi, & Rouwenhorst, 2013), our findings suggest that unique trading rules do not disrupt the pricing fundamentals underpinned by the theory of storage (Working, 1949). However, hedging pressure, volatility, liquidity and skewness premia can be distorted. Thus, we argue that the hedging pressure hypothesis (Hirshleifer, 1989) and the selective hedging hypothesis (Fernandez-Perez, Frijns, Fuertes, & Miffre, 2018) are potentially incomplete. On the other hand, we find the informational content of gross open interest, correlations with currency and inflation, are sensitive to excessive speculation,

⁵ The Nanhua Commodity Index (www.nanhua.net) covers a board range of 20 commodities and follows a construction methodology similar to the Commodity Research Bureau. The CFMMC China Commodity Futures Index (CCFI) was introduced by the China Futures Market Monitoring Center in 2015. The CCFI covers 20 commodities as of January 2018 (www.cfmmc.com/main/views/index.html).

government intervention and economic structures, respectively.⁶ Therefore, future research on commodity pricing ought to incorporate the effects of unique institutional settings.

Fourth, the term structure and momentum premia in China cannot be attributed to aggregate market risks, none-tradable macroeconomic risks or changes in market sentiments. However, illiquidity, anchoring bias and the regulation induced limits-to-arbitrage provide at least a partial explanation. Moreover, the hedging pressure premium can be adequately explained by the Bakshi, Gao, and Rossi (2019) model. While the broad commodity market in China is more intertwined with stocks than in the US, term structure, momentum and hedging pressure premia are found to offer promising diversification potential for Chinese equity exposures, though the benefit is immediate only to Chinese investors. Finally, our evidence suggests Chinese commodity prices are an important indicator of future economic growth in China. An extensive suite of robustness tests suggests our findings are consistent in the most liquid markets, randomly excluded commodity sectors, US dollar-denominated returns, a “matched” sample with the US, by altering futures return measurements, portfolio breakpoints, and cannot be subsumed by data-snooping or transactions costs.

2. Institutional Settings

2.1 A brief walk down the great wall of commodity

To better understand the dynamics of commodity futures in China, it is worthwhile to first understand its origin. The history began with a grain wholesale market established in October

⁶ Hong and Yogo (2012) posit the gross open interest is a better predictor of future economic activity and asset prices than futures prices. In their model of limited arbitrage by speculators, futures prices adjust to long or short excess hedging demand. However, the substantial presence of speculators in China suggests that risk absorption capacity is unlikely to be an issue. On the other hand, the currency premium is significant when futures returns are denominated in US dollars. The inflation premium is positive in a sample predominately made up of foodstuffs—a major component of the CPI basket in China.

1990 in Zhengzhou, the capital city of Henan Province, a major agricultural production region. Initially, the grain wholesale market only facilitated spot transactions, but quickly evolved to futures trading (Williams, Peck, Park, & Rozelle, 1998). Due to the speculative nature of inexperienced participants and the ineffective regulatory oversight, the market experienced a chaotic period in its first decade of development. After several boom and bust cycles, a market overhaul took place in 2000. The number of both the exchanges and products reduced from a peak of more than 50, to just three exchanges and nine products. A relatively steady period of development followed until the introduction of the index futures in 2010. The financial futures sparked enormous interests in futures trading, where the commodity futures markets also benefited from the soaring volume.

However, the regulators quickly introduced several policies to curb the excessive speculation in order to prevent a potential collapse. For example, starting from 2011, newly launched contracts were mainly big-scale.⁷ This fundamentally constrained speculation, and also made the Chinese market more compatible with international counterparts. Increased margins, price limits and transaction fees caused the trading lots to drop substantially (by 51%) in 2011 (see Figure 1). However, the effectiveness of such actions on speculation remains unanswered, as recent studies find higher margins can lead to a reduction in open positions and increase in volatility (Hedegaard, 2014), whereas price limits may restrict price discovery but not stop speculation (Janardanan, Qiao, & Rouwenhorst, 2019). After decades of consolidation, the Shanghai Futures Exchange (SHFE), Zhengzhou Commodity Exchange (ZCE), Dalian Commodity Exchange (DCE), along with the recently established China Financial Futures

⁷ Those small-scale commodities traded during 1994-1998 experienced over-speculation by large speculators, which drove up the market risk (Xin, Chen, & Firth, 2006). Soybean meal, one of the early contracts, was set as 10 tons per contract, while the recently launched thermal coal was designed as a big-scale contract—100 tons per contract.

Exchange (CFFEX) and the Shanghai International Energy Exchange (INE), constitute the contemporary Chinese futures markets.

Given the immaturity of the market, early studies have primarily focused on qualitative market developments (Williams *et al.*, 1998). As the market became more mature, the research attention turned to the market efficiency and linkages with the US. Fung, Leung, and Xu (2003) compare the pricing impact and information transmission between China and the US and conclude that the less regulated products in China are affected more by the US market. Xin *et al.* (2006) find that copper and aluminum futures markets in China are efficient and they attribute the efficiency to improved regulations and skills of participants. Chan, Fung, and Leung (2004) find asymmetric responses in copper, mung beans, soybeans and wheat markets. They also show that volatility is positively (negatively) linked to trading volume (open interest).

Recent studies have examined the *broad market performance* (Fung, Tse, Yau, & Zhao, 2013; Tu, Song, & Zhang, 2013), *trend-following strategies* (Li, Zhang, & Zhou, 2017), *pricing implications* (He, Jiang, & Molyboga, 2019), *volatility* (Jiang, Ahmed, & Liu, 2017; Tian, Yang, & Chen, 2017), *diversification potential* (Hammoudeh, Nguyen, Reboredo, & Wen, 2014; Liu, Tse, & Zhang, 2018), the *impact of speculation* (Fan, Mo, & Zhang, 2019; Wellenreuther & Voelzke, 2019) and *high frequency trading* (Zhao & Wan, 2018). For example, Tu *et al.* (2013) conclude that the correlation between the Chinese and the US markets has increased during the period 2000-2010. Li, Zhang, *et al.* (2017) find that trend-following strategies outperform buy and hold strategies. Moreover, Kang and Kwon (2017), He *et al.* (2019) and Ham, Cho, Kim, and Ryu (2019) document strong profitability of momentum strategies. Overall, the Chinese commodity markets have undergone remarkable developments in the past decades. While a vibrant literature exists on US and European commodities, studies on Chinese commodities are emerging rapidly.

2.2 Unique characteristics

China's socialist market economy signifies the government's constant attempt at balancing productivity and stability. Restrictive measures such as limiting the market access and maintaining tight control over the exchanges are instituted to manage its commodity futures market. Consequently, this creates a unique institutional environment for the formation of prices. The following table presents a comparative summary of key institutional settings between China and the US. The table highlights noticeable distinctions in areas of market access, participants-mix, exchange ownership and regulations. Since these unique settings have significant implications on futures price discovery, we discuss their potential impacts on research design, empirical results and form testable hypotheses in the following sections.

	China	U.S.
Regulator	China Securities Regulatory Commission (CSRC)	Commodity Futures Trading Commission (CFTC)
Self-regulation	China Futures Association	National Futures Association
Barriers-to-entry	Only qualified foreign institutions are allowed to trade; strict approval process	Foreign investors are allowed to trade
Traders	>86% open interest held by individual accounts	Institutions dominate the market
Exchanges	Public institutions	Private or listed firms
Price limits	Multi-level; unsystematic revision; increases in delivery months (DCE only)	Single or Dual-level; semi-annual revision; no limit in delivery months
Margins	Increase significantly approaching maturity; linked to price limits	Small increases approaching maturity; linked to volatility and liquidity
Position limits	Retail positions are restricted near delivery and prohibited in delivery months	Positions are restricted but not prohibited in delivery months

2.2.1 Retail-dominance

The Chinese commodities market is dominated by individual investors. Broadly speaking, the trading accounts are classified into *individuals* and *non-individuals*, where non-individuals include corporations, asset management firms and risk management entities. By the end of 2016, there were a total of 1.18 million trading accounts, of which 1.15 million (97.5%) were

individual accounts (China Futures Association, 2016). Driven by the participation of private funds and asset management companies, the number of institutional trading accounts saw a growth of 49.5% in 2016 (173.8% in 2015), however, it was still a mere 16,500 (11,500 in 2015) accounts in total.⁸ Characterized by the size of accounts, 94.01% (87.58%) of investors held a margin account below 100 thousand RMB (equivalent to USD 15,000), 5.72% (11.80%) of investors had margin account balances ranging from 100 thousand to 10 million RMB, while the remaining 0.27% (0.6%) investors possess a margin account beyond 10 million RMB, by the end of 2015 (2016). Interestingly, the total capital under management by institutional investors accounted for 38%, while the total trading volume contributed by institutions only accounted for 9.8%.

According to the theory of normal backwardation, hedgers pledge an “insurance cost” in the form of risk premia to attract speculators to take on the price risk. Thus, we form the following testable hypotheses. First, retail-dominance in China implies that there may be an insufficient number of net-short hedgers, hence leading to zero long-only risk premia in these markets. However, retail-dominance does not prevent the long-short premia. Second, in the framework of selective hedging, hedgers not only want to minimize risk but also maximize skewness. Thus, skewness preferences can cause futures contracts to be mispriced (Fernandez-Perez *et al.*, 2018). However, the key assumption is that commodity futures markets are dominated by large speculators and hedgers, with retail investors rarely participating. Therefore, we do not expect to find skewness premia in China. Third, retail-dominance is found to induce a higher degree of positive feedback trading (De Long *et al.*, 1990) and herding (Li, Rhee, *et*

⁸ Such retail-dominance is present for several reasons. First, due to an immature social security system, the household savings rate in China is among the highest in the world (Kang, Liu, & Ni, 2002). In light of strict capital outflow restrictions, along with relative scarcity of fixed-income securities, investors have historically resorted to bank deposits, stocks and properties. However, the bank deposit rates in China are often kept below market rates, and property ownership is increasingly regulated. Hence, equity is the major wealth-building instrument favored by Chinese individual investors. The emergence of commodity futures market has provided a new vehicle to channel the wealth accumulated.

al., 2017), which suggests that commodity price momentum is likely stronger compared to developed markets (Nofsinger & Sias, 1999; Demirer, Lien, & Zhang, 2015).

2.2.2 *Excessive speculation*

One of the unfavorable consequences of retail-dominance is excessive speculation.⁹ In fact, the speculative nature of Chinese individual investors is well documented. Allen *et al.* (2006) point out that the desire for quick gains combined with a lack of strong legal framework in China fostered a speculative attitude among investors. Wang *et al.* (2006) employ a 42-item questionnaire to investigate the psychological mechanisms of Chinese investors, with a sample of 1,547 individuals. They conclude that the Chinese investors are speculation-orientated, bear a low level of risk perception, investment knowledge and skills. Chen *et al.* (2007) find that Chinese investors suffer from behavioral biases such as disposition effect, overconfidence and representativeness more than the US investors do.

The primary function of a futures market is to enable the transfer of spot price risks. Although higher trading volume translates to market liquidity, a market can be over-speculative if the volume is not well justified by the size of the underlying spot market. This is evident in the Chinese market both presently and historically. For example, Williams *et al.* (1998) highlight that the open interest of mung bean futures in 1996 represents roughly three times national production. Citi (2016) shows the average holding period of a contract is less than four hours. More recently, Bloomberg (2018a) reports the trading volume of apple futures on 15th May 2018 alone is equivalent to half of the annual production worldwide (or China's annual crop).

⁹ The CSRC implicitly refers to “drastic price turbulence” and “abnormal trading volume” as indicators of excessive speculation. Thus, one can interpret “excessive speculation” as excess volatility and/or trading volume, in line with our use of the term. See http://www.csrc.gov.cn/shanxi/xxfw/sxgzjx/201605/t20160505_296971.htm.

Foreign investors, especially institutional investors, are presumed to possess a higher level of experience, rationality and information compared to Chinese investors. Thus, if allowed to participate they are expected to improve the market quality by reducing the price volatility (Li, Nguyen, Pham, & Wei, 2011). However, access to Chinese commodity futures market has been difficult for foreign investors. Currently, institutional investors who are members of (R)QFII (RMB Qualified Foreign Institutional Investor) program are allowed to invest. The membership is subject to approval and quota of the government. Foreign individual investors are only allowed to trade crude oil, iron ore and PTA contracts as of early 2019. Although the market liberalization has accelerated in recent years, Yang *et al.* (2012) find that barriers-to-entry reduces the information content of the index futures prices and the market's price discovery performance. As a consequence, barriers-to-entry along with retail-dominance hinders the market's ability to neutralize excessive speculation.

2.2.3 Exchange ownership and regulations

In addition to retail dominance and excessive speculation, the exchanges are directly managed by the government in the form of public institutions, rather than private or publicly listed firms in the US or Europe.¹⁰ This means the top priority of the exchanges is *not* to maximize the shareholders' wealth. Bai, Lu, and Tao (2006) assert that state-owned entities in China are "grossly inefficient and ill-prepared for market competition". The exchanges are responsible for organizing trading-related matters, such as managing contracts and facilitating transactions. With the political risk embedded, bureaucracy will likely impede the operational (informational) efficiency of commodity exchanges (markets) in China. Since the priority of the exchanges is to maintain market stability, it inevitably leads to more frequent interventions and tighter regulatory controls compared to developed markets. These are ultimately translated into price

¹⁰ Public institutions are fully or partly funded by the government, which historically included all public schools, universities, clinics, hospitals, libraries, performing groups, research institutes and media organizations in China.

limits, margin requirements and position limits.¹¹ As margins and price limits are found to have significant impacts on futures price discovery, it is paramount to understand these unique institutional settings before examining the performance of premia or investment strategies.

Price limits. First, the price limits in both China and the US share similarities in terms of the expansion mechanism, with three to five levels in China and only one to two levels in the US. If the initial price limit is reached, the expanded limit(s) will be applied on the following day(s), until the trading is halted. The expansion levels vary by commodities and exchanges. Second, the price limit may increase in the delivery month in China whereas no limit is applied in the US. According to the “DCE Administrative Measures for Risk Management”, the initial daily price limit for all contracts during non-delivery months is 4% within the settlement price of the previous trading day, while it becomes 6% in the delivery month.¹² This does not apply for commodities traded on the ZCE and the SHFE. Finally, price limits are systematically reset twice a year in the US to reflect the market information. However, Chinese exchanges can adjust the limits whenever they believe is necessary. While the multi-level price limits in China are designed to constrain excessive speculation and facilitate price discovery, Liu and An (2011) argue that they can adversely impact the market in terms of reflecting new information in futures prices.

Margins. First, unlike the US where margins are relatively stable, the margin requirements in China increase significantly as a contract approaches the delivery month.¹³ For the DCE, a margin of 5% is applied from the first trading day to the 15th calendar day of the

¹¹ Investors could have opted for other exchanges in the Asia-Pacific region with a more transparent legal framework and a more advanced operational infrastructure (e.g. SGX-Singapore Exchange). However, the existence of capital outflow restrictions means home-bias is not entirely discretionary.

¹² An exchange-level ordinance, drafted in accordance with the “DCE Trading Rules”, periodically reviewed to reflect the current market condition. The latest version took effect on 8th April 2019. See <http://www.dce.com.cn/dalianshangpin/fg/fz/6142914/6142922/6146604/index.html>.

¹³ All commodity futures traded in China require physical delivery for settlement. The delivery process is similar to the US. Internet Appendix II outlines a list of authorized delivery warehouses, for each commodity in our sample. As of October 2019, there are a total of 573 delivery locations across 25 provinces.

month prior to delivery, then increases to 10% for the remainder of the month. The margin is elevated to 20% when the contract enters the delivery month. For the ZCE and SHFE, a similar structure applies but the margins vary by commodities. Second, the changes in margins are determined by the market volatility and liquidity in the US, margins in China are jointly determined by the price limits. This means that if the initial price limit is reached, the required margin will increase on top of the expanded price limit. For example, assuming a copper contract has a price limit of 5% and a margin of 4%, if the closing price increases by 5%, the price limit and the margin requirement will automatically rise to 8% and 10% respectively on the next trading day. Consequently, the time-varying margin creates the incentive for speculators to stay out of the maturing contracts.

Position limits. Position limits in the delivery month are common in global futures markets; however, Chinese retail investors are prohibited to hold positions in the delivery month. Additionally, their positions are restricted in the preceding month prior to contract delivery. A forced liquidation process is triggered for non-compliance. Taking the common wheat contract as an example, the maximum number of positions that non-futures company members and retail investors can hold before the 15th calendar day of the month prior to the delivery is 2000 (600 for the remaining month).¹⁴ In the delivery month, only 200 positions are granted to non-futures company members, while a retail investor is prohibited to trade at all. Coupled with the time-varying margin requirements, the position limits imply that nearest contracts are unlikely to be the most liquid in China.

Accordingly, we form the following testable hypotheses. First, strict position limits prevent retail participation in the nearest to delivery contracts. Exacerbated by higher margin

¹⁴ Futures companies serve as the intermediaries between the exchanges and investors. Non-futures companies, registered as membership holders of exchanges, also function as intermediaries. e.g. private futures funds, risk management, asset management and securities brokerage firms. See “Administrative Measures for Futures Companies Supervision” published on 29 October 2014 by the CSRC, available from <http://www.shfe.com.cn/regulation/exchangelaw/911322933.html>

requirements approaching the delivery, most traders exit their positions before the contract enters the preceding month. Hence, the front contracts are expected to be less liquid compared to the distant contracts. Second, if the liquidity is lower on the front contracts, market volatility is also expected to be lower compared to distant contracts. Meanwhile, the absence of time-varying margin and strict position limits would suggest that spot market volatility (proxied by the nearest contracts) is higher in the US for the same commodity. Third, while the regulatory constraint creates a policy-induced limits-to-arbitrage on the front-end of the futures curve, higher margins lead to higher required returns as predicted by the margin-based asset pricing model of Gârleanu and Pedersen (2011). Therefore, we expect the risk premia to be higher on the front contracts. Finally, to accommodate the majority, most hedgers would employ contracts with higher liquidity to transfer risks. Consequently, the hedging pressure premia should only be observed on distant contracts.

In summary, the institutional environment of commodity markets presents significant implications for the formation of futures prices in China. Therefore, we aim to shed light on this gap by examining the impact of unique settings on the performance of long-only and an exhaustive list of long-short risk premia.

3. Data and Methods

3.1 Sample selection

We obtain the entire archive of Chinese commodity futures from Datastream International. From January 1992 to May 2017, we download the daily settlement price (in RMB), trading volume and open interest of 47 commodities of all maturities traded across DCE, ZCE and SHFE. This results in more than 4,000 contracts in total. We require each commodity to have at least four years of data and a minimum of 8 commodities in the cross-section to manage the

volatility of portfolios. The cleaning process resulted in a final sample of 30 commodities, covering February 2004-May 2017. Following Szymanowska, de Roon, Nijman, and van den Goorbergh (2014), we categorize commodities into five sectors in accordance with the Commodity Research Bureau (CRB), which include industrials, grains, oilseeds, energies and metals. Table 1 outlines the commodity tickers, contract size, delivery months, initial price limit, margin requirements, first- and last- contracts and their maturity dates.

To compile continuous futures returns, we closely follow Miffre and Rallis (2007) and Fernandez-Perez *et al.* (2018). We hold contracts until the last trading day of the month prior to expiration. The positions are then rolled over to the next nearest contract. We also construct returns series based on distant contracts with m^{th} maturity ($m = 2, 3$ and 4). These contracts represent the majority of the volume and open interest on the futures curves in China (as can be seen in Figure 1). When compiling the m^{th} nearest-contract returns, price changes of the m^{th} maturity contract are held up to the last day of the month before the front contract matures, along with the corresponding open interest, volume and price series. Following Fuertes, Miffre, and Rallis (2010), our long-short portfolios can be viewed as 50% collateralized. This implies a leverage factor of two, which is considerably conservative within the hedge fund industry. Our long-short portfolios would have been fully collateralized if a weighting of 0.5 was assigned to each of the long and short legs. By fully collateralizing long-short portfolio, the strategy returns and volatilities will be halved, while the risk-adjusted performance, significance of regression coefficients remain unaffected.

Table 2 reports the annualized returns (Panel A), standard deviations (Panel B), trading volume (Panel C) and the Amihud illiquidity measures (Panel D). Panel A shows that individual commodities do not perform well, as most of the commodities report large and negative returns. The returns range from 11.9% (soybean meal) to -13.7% (coking coal) on the nearest contracts and 9.6% (rapeseed meal) to -8.7% (silver) on the fourth nearest contracts.

The difference-in-mean tests reveal that the first nearby contracts report higher returns than the third nearby contracts in only three markets. Furthermore, the standard deviation ranges from as low as 9.5% (common wheat fourth nearest) to 36.8% per annum (coking coke first nearest). In line with our hypothesis, the difference-in-mean tests reveal that the front contracts in 12 out of 30 commodities report lower volatility compared to the third nearby contracts. In contrast to Duong and Kalem (2008), these results suggest that the support for the Samuelson (1965) hypothesis is mixed in China. Turning to the trading volume, Panel C clearly shows that the number of contracts traded is concentrated in the more distant maturities. Correspondingly, the Amihud illiquidity measure in Panel D suggests that the majority of commodities present sufficient liquidity on the distant contracts for the implementation of systematic strategies. The p -values suggest that volume and liquidity are indeed higher on the third nearby compared to the first nearby contracts, consistent with our hypothesis.

We put forward two potential explanations on why the long-only premia is not higher on the first nearby contracts compared to the distant. First, higher margin and position limits on the front contracts can cause the distant contracts to be overpriced, leading to a compressed basis. Thus, lower basis and spot volatility can cause backwarddated contracts to be less backwarddated and contangoed contracts to be more contangoed, whereby increasing the selling pressure while reducing the buying pressure, thus reducing the risk premia. Second, as we do not consider prices during the delivery month (when margins are the highest), the changes in margins between the first and the third nearby contracts may not be large enough to make a difference in our sample.

3.2 Macro variables and US data

To facilitate the implementation of strategies and the construction of risk adjustment models, several macroeconomic and financial variables are obtained in local currency. The RMB

effective exchange rate index is attained from the Bank for International Settlements (BIS). The Chinese unexpected inflation rate and unexpected industrial production are the difference between actual and forecasted figures. To track the movements of Chinese stocks, four indices are considered. Similar to the S&P500, the CSI300 consists of the top 300 stocks traded on the Shanghai and Shenzhen stock exchanges. To capture the broader stock market, we also consider the Shanghai Composite Index and the Shenzhen Composite Index. Furthermore, to include large- and mid-cap Chinese stocks listed in Hong Kong, US and Singapore, we employ the MSCI All China Index. The Barclays China Aggregate Index is used as a proxy for the RMB-denominated fixed income market. The index covers fixed-rate treasury, government and corporate bonds. All macro and financial data are obtained from Bloomberg.

To rule out the possibility of a sample selection bias, we construct a “matched” sample consisting of “identical” US commodities. From the Commodity Research Bureau (CRB) InfoTech CD, we obtain settlement price, open interest and volume on 14 commodities traded on US exchanges. We perform the same rolling procedures to compile futures returns at daily and monthly frequencies. Internet Appendix I provides a summary of the “matched” sample. Traders’ positions data are retrieved from the CFTC commitments of traders (CoT) report. The US effective exchange rate is obtained from the BIS, and the inflation data are from Bloomberg.

3.3 Long-short portfolios

We consider an exhaustive list of risk premia from the literature. The first strand of premia is motivated by the Theory of Storage (Kaldor, 1939), the Hedging Pressure Hypothesis (Cootner, 1960) and the Selective Hedging Practice (Stulz, 1996; Gilbert, Jones, & Morris, 2006). These premia rely on the informational content of roll-yield (Gorton & Rouwenhorst, 2006), past returns (Miffre & Rallis, 2007), net positions of hedgers (Basu & Miffre, 2013) and skewness (Fernandez-Perez *et al.*, 2018). The second group of premia is inspired by economic and

empirical intuitions, which exploits information such as value (Asness, Moskowitz, & Pedersen, 2013), open interest (Hong & Yogo, 2012), currency and inflation (Erb & Harvey, 2006), volatility and liquidity (Szymanowska *et al.*, 2014). To capture these risk premia, we construct systematic long-short portfolios through characteristic sorts. At month end, each strategy buys (sells) the commodity quartile predicted by the commodity characteristic or signal to appreciate (depreciate). Appendix A lists the definitions of sorting variables.

Term Structure (TS): The TS strategy is motivated by the theory of storage (Working, 1949; Brennan, 1958) which links the slope of the term structure with inventory levels and the benefits of owning spot commodities. Studies have shown a premium can be generated by taking long (short) positions in commodities with high (low) roll-yields (Erb & Harvey, 2006; Gorton *et al.*, 2013).

Hedging Pressure (HP): The HP strategy is motivated by the hedging pressure hypothesis (Cootner, 1960; Hirshleifer, 1990) which posits that net long (short) speculators demand compensation for taking on the price risk of net short (long) hedgers. Evidence of a hedging pressure premium can be found in De Roon, Nijman, and Veld (2000) and Basu and Miffre (2013). Due to the absence of trader positions data in China, we employ the hedging ratio proposed by Lucia and Pardo (2010) as a proxy for HP.¹⁵

Momentum (MOM): The MOM strategy buys (sells) past winners (losers) based on the cumulative performance over the most recent 12 months. The existence of the momentum

¹⁵ Due to the absence of positions data, the hedging ratio is the only tool available to measure the hedging pressure. Although we are unable to formally establish the link in the Chinese market, evidence from the US market suggests that hedging ratio produces similar results compared to hedging pressure constructed using the CFTC CoT reports (Robles, Torero, & Von Braun, 2009). Our use of the hedging ratio is based on the assumption that hedgers hold positions longer than speculators. This is generally supported by the exchange statistics. In theory, a higher hedging ratio suggests more trades are triggered by hedgers. Thus, in a cross-sectional setting, we interpret a higher hedging ratio as a signal for a higher hedging pressure relative to other commodities. We acknowledge that hedging ratio is an imperfect measure of HP. Nevertheless, HP constructed using the CoT data are also heavily criticized for its ambiguity in trader group classifications (Briese, 2012; Cheng & Xiong, 2014; Fan *et al.*, 2020). Thus, we employ the hedging ratio to conduct a “bottom-line” test and draw inferences on the hedging pressure hypothesis in China.

premium is documented extensively in the literature (Miffre & Rallis, 2007; Bianchi, Drew, & Fan, 2015; Bakshi *et al.*, 2019).

Volatility (VOLA): The VOLA strategy is motivated by the theory proposed by Dhume (2011), where commodities with high spot volatility correlate positively with durable consumption growth. Since these commodities cannot act as a hedge against intertemporal risk, investors demand compensation for holding these assets. Studies have shown a volatility premium can be generated by buying (selling) commodities with high (low) volatility (Gorton *et al.*, 2013; Szymanowska *et al.*, 2014).

Open Interest (OI): The OI strategy is motivated by the findings of Hong and Yogo (2012), in which unexpected changes in OI predict commodity futures returns. An open interest premium can be generated by buying (selling) commodities with high (low) changes in OI (Szymanowska *et al.*, 2014).

Liquidity (LIQ): The LIQ strategy is empirically motivated as investors demand compensations for holding commodities with relatively low liquidity. Szymanowska *et al.* (2014) employ the Amivest measure (Marshall, Nguyen, & Visaltanachoti, 2012) and show that a liquidity premium can be generated in US commodity futures.

Currency and Inflation (FX/INF): The FX and INF strategies are motivated by the empirical fact that commodities prices are negatively correlated with the US\$ effective exchange rate and positively correlated with inflation shocks (Gorton & Rouwenhorst, 2006; Bhardwaj *et al.*, 2016). Using regression beta as signals, Szymanowska *et al.* (2014) demonstrate that an FX premium can be generated by buying (selling) commodities with low (high) FX beta, and an INF premium can be generated by buying (selling) commodities with high (low) sensitivity to inflation shocks.

Skewness (SKEW): The SKEW strategy is motivated by investors' preferences for skewness under cumulative prospect theory and selective hedging practices. Fernandez-Perez *et al.* (2018) demonstrate that a skewness premium can be generated by buying (selling) commodities with the most negative (positive) skewness.

Value (VAL): The VAL strategy is inspired by Asness *et al.* (2013). Using a long-term mean reversion measure, high-value, cheap or long-term loser commodities are found to outperform the long-term winner commodities.

4. Results

4.1 Passive long-only

Table 3 reports the performance of long-only investments in the broad market and sectors. The market is represented by an equally weighted portfolio of 30 commodities in the sample and rebalanced monthly. Since the majority of the trading volumes are on the third and fourth nearest contracts, we construct portfolios based on the first to fourth nearest contracts (also see Figure 1). Panel A reports the results over the sample period 2004-2017, whereas Panel B extends the sample to market inception. The findings in Table 3 suggest that regardless of time, sector and maturity specifications, long-only portfolios in China do not generate significant economic profits. Most notably, grains saw statistically significant losses on the first and second nearest contracts. These results can be better visualized in Figure 2.

Figure 2 illustrates the cumulative performance of the broad market and sectors based on the third nearest contracts. In addition to equal weights, we also employ alternative weighting schemes taking into account the impacts of trading volume and open interest. Regardless of schemes, passive long-only investments in the broad market or sectors deliver poor economic returns. Specifically, industrials are the worst performers followed by energy

commodities, which lost more than half of their values since 2004. Notably, grains have outperformed the rest of the market under all weighting schemes. In the meantime, metals, oilseeds and energies exhibit non-synchronized growth with the broad market from 2004 leading to the global financial crisis (GFC). Over the last 5 years, all sectors have declined by varying degrees, although the decline is less pronounced in grains. This decline can be attributed to the excess supply and the slowed demand experienced by the Chinese economy.

Our findings clearly suggest the rejection of the null hypothesis of non-zero risk premium. The theory of normal backwardation suggests that speculators receive a risk premium as compensation for taking on the price risk of hedgers. However, since more than 97% of the trading accounts are individual-based, the absence of long-only premia in China may be viewed as evidence of speculators overpowering hedgers.¹⁶ It seems plausible that speculators demand liquidity from each other, because the long-only risk premia are largely negative across commodities. Nevertheless, one may still raise the question why are there so few hedgers in these markets? The answer traces back to the origin of the Chinese futures market.

The former vice chairman of the CSRC highlights the fundamental difference between the US and Chinese commodity futures markets. The former was established in the 1870s as a result of the market demand, while the latter was directly propelled by the government as one of the measures to liberalize the economy in the early 1990s, during which the private sector was emerging. Put alternatively, the US commodity futures markets were founded to meet the producers' demands, whereas the Chinese markets were set up because the government believed it was necessary. Consequently, the number of corporates engaged in futures trading is relatively small, and futures trading is still recognized as a speculative game and complex to

¹⁶ We acknowledge the limitation of this conjecture, as a classification independent of the business purpose could present a mixture of hedgers and speculators. One is unable to definitively distinguish the trading purpose of individual and non-individual traders. Besides, it is also probable that traders (companies) transact for hedging purpose with an account registered under an individual name.

understand by majority of the producers (China Futures, 2019). However, instead of focusing solely on “excessive speculation”, we stress the fact that hedgers in China have not had the time to complete the “learning process”. Overall, the findings on long-only premia suggest that the theory of normal backwardation does not hold well in China. We now move on to the performance of long-short strategies.

4.2 Long-short strategies

Table 4 reports the performance of 10 long-short strategies on first (Panel A), second (Panel B), third (Panel C) and fourth (Panel D) nearest contracts. Following the literature, we first focus on the nearest contracts, as these contracts are often regarded as proxies for spot returns.

4.2.1 Nearest contracts with strict position limits

Under Panel A, only three out of 10 long-short strategies yield statistically significant profits on the nearest contracts. Most notably, the momentum strategy returns an astonishing 21.94 percent (10.97 percent if fully collateralized) per annum on average. This is followed by the term structure and volatility strategies, with annualized profits of 15.91 and 10.53 percent, respectively. In the presence of strict position limits and increased margins, commodities with higher past returns, roll-yields and spot price volatility systematically outperform commodities with lower past returns, roll-yields and spot price volatility (Erb & Harvey, 2006; Miffre & Rallis, 2007; Szymanowska *et al.*, 2014; Fuertes, Miffre, & Fernandez-Perez, 2015). At face value, the large momentum premium indicates strong price persistency in these markets. Gorton *et al.* (2013) demonstrate that past returns, roll-yields and volatilities are empirically related to inventory levels. Taken together, our results suggest that Chinese commodity futures behave according to the predictions of the Theory of Storage (Working, 1949).

However, these position limits and margins have significant impact on the behavior of market participants. For example, while we expect the skewness premia to be statistically

indifferent from zero, the skewness strategy reports significant losses. The skewness strategy is motivated by investors' preferences for positive skewness under the cumulative prospect theory and the selective hedging practice. Fernandez-Perez *et al.* (2018) document a sizeable premium in the US by taking long (short) positions in the most negatively (positively) skewed commodities. On the contrary, we find that commodities with higher skewness outperform those with lower skewness, suggesting that position limits cause the skewness preferences to reverse. Alternatively, this may be explained by the level of sophistication of the market participants.

Due to strict position limits and higher margins, only the “true” hedgers remain in the front contract during the delivery month. From the perspective of the hedger, it is more favorable for commodities to be sold at a higher price for a producer, and to be bought at a lower price for a user, at delivery. Therefore, producers (users) with net-short (net-long) positions may prefer contracts with positive (negative) skewness, because such contracts could deliver large upward (downward) price movements favored by hedgers, despite a relatively small probability. Consequently, such “lottery-like” behavior can cause positively (negatively) skewed commodities to become over-sold (over-bought) in the front markets. Meanwhile, we find that relatively illiquid commodities underperform the more liquid ones (almost significant at 10%), suggesting that traders do not receive a compensation for bearing liquidity risks, but instead they pay a price to hold illiquid commodities.

Strategies that do not report significant profits also present important findings. First, the results on value suggest that the reversion of long-term losers to winners is relatively weak in China, though returns to the value strategy are positive and generally consistent with Asness *et al.* (2013). Second, commodities with a higher (lower) inflation beta and lower (higher) currency beta are expected to earn higher (lower) returns relative to commodities with lower (higher) inflation beta and higher (lower) currency beta. It is plausible the absence of the FX

premium is due to known issues surrounding the RMB data. The Chinese government has long been criticized for intervening the RMB currency markets to maintain tight control over the value of the RMB.¹⁷ Proven to be considerable forces on both the onshore and offshore RMB markets, these intervention activities may contaminate the informational content embedded in the correlation with commodity prices. We test this hypothesis and explore alternative explanations for the inflation results in the following sections.

Finally, Hong and Yogo (2012) find that open interests not only predict commodity returns but also the real economy. In their model of limited arbitrage by speculators, futures prices adjust to long or short excess hedging demand. The core assumption made by Hong and Yogo (2012) is that open interest will rise due to increasing hedging demand fueled by the anticipation of higher economic activities. However, in light of retail dominance and speculative trading, risk absorption capacity is unlikely to be an issue in China. Thus, the predictability of gross open interests is questionable in such settings. Recall the China Futures Association 2015 report, though capital under management by institutional investors constituted 44% of the market, it only contributed to 15.3% of the total trading volume (China Futures Association, 2015). Overall, findings in Panel A suggest that Chinese commodity futures prices behave very differently to the US.

4.2.2 Distant contracts with alleviated limits

We re-evaluate the performance of all strategies on the second, third, and fourth nearest contracts through Panels B to D. Consistent with our hypotheses, we find that that long-short premia are higher on front contracts and gradually deteriorate towards distant contracts. Position limits and time-varying margins create a regulation-induced “limits-to-arbitrage” in

¹⁷ Zhang and Pan (2004) use adjusted foreign reserves as a proxy for exchange rate intervention by the government to estimate the “actual” exchange rate and find the RMB would have appreciated by 15-22% against US dollar if there was no government intervention during 1996-2003.

the nearest contracts, and also lead to higher expected returns. Notably, the momentum profits have declined significantly relative to term structure, while the term structure premium is relatively stable across the curve.

Why are higher premia on the front contracts only present in a long-short but not long-only setting? We put forward the following explanations. Higher margins and position limits pushed the return spread of past winners and losers (or high vs low basis commodities) to become larger, although the term structure premia on the front is not statistically larger than that on distant contracts. This increases the momentum premia even when long-only premium is non-existent. Meanwhile, traders overreact to abundance (underreact to scarcity) signals due to lower spot volatility and compressed basis, leading them to over-sell in the spot market. Such overreaction pushes the price down while underreaction to scarcity induces a delayed response. On the other hand, overreaction to past returns will push the price of winner commodities even higher, and losers' prices even lower. Eventually, these mispricings are corrected at the new equilibrium. However, exacerbated by strict position limits which make arbitrage difficult, such systematic errors cause the long-short returns spread to become larger in the spot market. On the distant market, the overreaction is arguably stronger given the higher volumes. However, when position limits are alleviated, the returns decline as the market's ability to detect mispricing becomes less impaired, while the expected return also becomes lower due to lower margins. Thus, more efficient arbitrage reduces the long-short returns spread. Overall, margin-induced overreaction, position limit-induced limits-to-arbitrage both contribute to the higher long-short premia observed on the front contracts. Consequently, momentum profits reported by previous studies are likely "inflated".

Meanwhile, several new findings emerge from Panels B to D. First, the volatility premium is no longer significant, suggesting that investors are only compensated for taking on spot price volatility risks when position limits are at the strictest. When these limits are

alleviated or when liquidity is more abundant, investors no longer receive such compensation in the second nearest contracts and beyond. This finding suggests that the compensation for high volatility in China is induced by the position limits, not the commodity's inability to hedge against intertemporal risks. Second, consistent with our hypothesis, while the hedging pressure premium is insignificant on the nearest contracts, it becomes statistically significant on the third nearest contracts, with an annual average return of 8.11%. This suggests that the front contracts do not effectively facilitate the risk-transfer between hedgers and speculators. As a contract approaches maturity, the position limit initiates and the margin requirement increases significantly. Thus, most hedgers and speculators look beyond the nearest contracts to avoid a higher cost. However, hedgers who wish to stay hedged before taking delivery must bear additional costs. Finally, the significance of skewness and liquidity premia disappears on distant contracts, suggesting that skewness and Amihud liquidity are not priced in the cross-section (Boons & Prado, 2019). Overall, findings presented in Table 4 suggest that position limits and time-varying margins have significant impacts on the trading behavior of market participants, causing the price dynamics to vary considerably across the futures curve.

Figure 3 illustrates the cumulative returns of one RMB invested in term structure, hedging pressure and momentum strategies, benchmarked against the passive long-only portfolio (AVG). We plot the cumulative performance of the third nearest contracts, as they are a more realistic representation of investment performance. Momentum generates the highest terminal value of 6.12 RMB versus 4.96 and 2.54 for term structure and hedging pressure strategies, respectively. Momentum suffered considerable losses following the GFC. Notably, the persistence of momentum post-2010 is in sharp contrast with the previous literature (Bianchi *et al.*, 2015; Bianchi, Drew, & Fan, 2016), signaling a segmented market.

4.3 Comparison with the US

Since more than half of the commodities in our sample are not traded in the US, this raises comparability concerns. To rule out the possibility that the observed results are due to sample selection, we select 14 comparable commodities traded in both markets and re-examine the performance of all strategies in this “matched” sample. Panel A of Table 5 reports the results on Chinese markets whereas Panel B reports the US results. We employ the first and the third nearby contracts, since they reveal the highest trading volume on average in China and the US, respectively. We also report the performance on the term premia as per Szymanowska *et al.* (2014). Internet Appendix III details the estimation of spot and term premia. In addition, the cross-country correlations for each strategy are presented in Panel C.

Consistent with previous results, term structure, momentum and volatility strategies remain profitable on the front and third nearest contracts. Interestingly, the inflation strategy now reports 14.27% per annum return with a t -statistics of 2.83 on the third nearest contracts, suggesting that these 14 commodities are more closely associated with inflation. This is not surprising since most of them are food-related products. RBA (2017) stresses that the variations in China’s CPI are primarily affected by food which constitutes roughly 30% of the CPI basket. Besides, the value premium becomes remarkably stronger, suggesting that long-term reversal is more pronounced among foodstuffs. However, the hedging pressure premia is no longer significant on the third nearest contracts, suggesting that the predictive power of hedging pressure is not uniform across sectors. Furthermore, the skewness and liquidity premia are consistently negative and statistically significant on the nearest contracts. In line with Szymanowska *et al.* (2014), the term premia for seven out of 10 strategies exhibit the opposite signs against the spot premia (see Internet Appendix IV for results on the spot and term premia).

To mitigate concerns that the observed results are due to differences in exchange rates, we also employ the US dollar-denominated prices within the Chinese sample. We find the majority of the results remain consistent, with the exception of the FX strategy. When the

returns are measured in US dollars, the FX strategy reports statistically significant profits of 9.23% ($t=1.88$) on the third nearest contracts. This supports our argument that the failure of FX strategy is attributable to the government intervention of the RMB. These results are not reported in the paper but are available upon request.

Turning to the US results, the performance is generally poor. The hedging pressure strategy, constructed using the CoT report, reveals the strongest results. The predictability of hedging pressure is consistent with Basu and Miffre (2013), with an annual mean return of 16.65% ($t=2.75$). We also tested the hedging pressure signal in Appendix A but did not find any significant results.¹⁸ Whether the hedging ratio is a good proxy for hedging pressure is beyond the scope of the current paper, but these differences highlight the uniqueness of the Chinese market. The term structure and momentum strategies report inferior performance in the US sample. This is not surprising, as discussed in Bhardwaj *et al.* (2016), commodity markets have become more contangoed in the most recent decade. Given that momentum strategy implicitly buys (sells) the backwardated (contangoed) commodities, the imbalance between backwardated and contangoed markets contribute to the failure of these long-short strategies. Moreover, Bianchi *et al.* (2016) also document a noticeable decline in momentum profits. They argue that previously successful strategies tend to become less profitable due to the increased competition among market participants.

Furthermore, the value strategy reports a mean return of 13.01% p.a., stronger than those reported by Asness *et al.* (2013). Surprisingly, however, alternative risk premia strategies such as open interest, liquidity, FX, inflation and skewness do not report statistically significant profits in our US sample. This is in sharp contrast with Szymanowska *et al.* (2014) and

¹⁸ Within the framework of the hedging pressure hypothesis, two conditions must be met for the ratio-based HP strategy to be feasible. First, hedgers should hold positions longer than speculators. Second, when speculators are outnumbered by hedgers, hedgers must be net short in those markets. However, Cheng and Xiong (2014) reveal that US hedgers frequently change their positions. This violates the first condition and could help explain why ratio-based HP strategy does not deliver significant profits in the US.

Fernandez-Perez *et al.* (2018), who report seemingly robust profits using a longer time-series and a larger cross-section of commodities. This clearly suggests that alternative premia are sensitive to sample- and time-specifications, but it also implies that the recent “financialization” has had an enduring impact on commodity markets in the US. Moreover, consistent with our hypothesis, retail-dominance causes momentum to be significantly stronger in China.

As for the cross-country correlations in Panel C, the majority of the results are insignificant at the 5% level. However, we observe a low level of cross-country correlations on hedging pressure, momentum and FX premia on the third nearest contracts. Although neither the hedging pressure nor the FX strategy reports significant profits in the US and China, the positive correlations suggest the existence of commonalities. Particularly for the momentum strategy, as the cross-country correlation is also significant on the first nearest contracts. Furthermore, the spreading returns based on liquidity signal reveal negative cross-country correlations, confirming that the liquidity risk dynamics are distinct between the US and China. Overall, the findings presented in Table 5 highlight the uniqueness of the Chinese markets.

In Internet Appendix I, we conduct a direct side-by-side comparison of the “matched” sample. Overall, the findings suggest that the Chinese commodity markets are indeed different from the US. Unlike the results on a portfolio level, the majority of the commodities in China seem to be significantly correlated with their US counterparts on an individual contract level, with average correlations of 0.46 and 0.52 based on the front and the third nearest contracts, respectively. However, one may be misled by the moderate levels of returns correlations between two markets. The differences can be uncovered by comparing the term structure, hedging pressure and other price dynamics. First, on average, we do not find statistically significant term premia in individual commodities in China (Panel A). Second, we find significant differences in basis, spot volatility, hedging pressure, past returns, value and skewness characteristics (Panels B and C). Third, while spot volatility, past returns and value

are somewhat correlated, basis, hedging pressure and skewness of the same commodities remain largely different. These findings reinforce our results on systematic long-short risk premia and indicate that Chinese commodity futures market is segmented from the US.

Our study can also be viewed as a true out-of-sample test on risk premia in commodity futures, given the market segmentation from the US. The findings present several implications to existing theories and empirics developed for the US market. First, in the presence of barriers to entry and retail-dominance, only term structure and momentum premia are robust to the influence of strict position limits, multileveled price limits and time-variant margins. This suggests that excessive speculation does not eliminate the risk premia, and that unique settings do not disrupt the pricing fundamentals underpinned by the theory of storage (Working, 1949). Second, we show that hedging pressure, volatility, liquidity and skewness premia can be distorted by position limits. When these limits are alleviated, volatility, liquidity and skewness premia are statistically indifferent from zero, while the hedging pressure premia becomes positive and significant. Therefore, our hedging pressure and skewness results imply that the hedging pressure hypothesis (Cootner, 1960) and the selective hedging practice (Fernandez-Perez *et al.*, 2018) theories are potentially incomplete. Third, the absence of open interest, FX and inflation premia suggests the information content embedded in futures open interest, and correlations with currency and inflation are sensitive to excessive speculation, government intervention and economic structures. As a result, future research ought to explicitly account for these unique settings. We now move on to investigate the dynamics of the premia observed.

4.4 Returns analysis

4.4.1 Correlations

We first examine the Pearson correlations among long-only and long-short strategies. Table 6 reports correlations on the nearest contracts (Panel A) and third nearest contracts (Panel B).

Panel A reveals that among the significant premia, volatility is not correlated with term structure and momentum premia. Term structure and momentum premia are positively correlated, as has been confirmed by Fernandez-Perez *et al.* (2018) and Bakshi *et al.* (2019). Fuertes *et al.* (2010) estimate an average correlation of 0.32, our estimate of 0.47 suggests that term structure and momentum premia are more closely intertwined in China.

Furthermore, despite the absence of statistical significance, returns to unprofitable strategies exhibit significant correlations. First, the value premia are negatively correlated with term structure and momentum. This is consistent with Asness *et al.* (2013), in which they argue that the opposite exposures to liquidity risk are the primary driver of the negative correlation. Second, although the FX premium is statistically insignificant, it reports significant correlations with term structure, volatility, open interest and liquidity premia, implying that the value of RMB indeed plays an important role in Chinese commodity futures. Finally, the skewness premium appears to be unrelated to any premia, suggesting that skewness is not presently priced in China. These results are largely consistent on the third nearest contracts (in Panel B) with alleviated position limits, with one notable exception. The hedging pressure premium is now positively correlated with liquidity and value premia, and negatively correlated with volatility, open interest and FX premia. While the negative relation between hedging pressure and volatility is consistent with the previous literature, these results once again highlight that the risk-transfer mechanism varies significantly between the front and distant contracts. Moreover, the positive correlation of hedging pressure and liquidity implies that commodities with larger presence of hedgers also tend to be less liquid.

As for the interaction between long-only and long-short premia, the market portfolio appears to be correlated with term structure, volatility, open interest and FX strategies on both front and the third nearest contracts, although the hedging pressure and inflation premia

(liquidity) are only correlated with the market portfolio on the third (first) nearest contracts. We now move on to investigate the sources of returns.

4.4.2 *Decomposing long-short portfolios*

Table 7 reports the performance of quartile portfolios for term structure, hedging pressure, momentum and volatility premia. First, when strategies are implemented on the nearest contracts, the return spreads on term structure and momentum premia are large. This suggests that the profits are not short sided, although the significance in short portfolios appears to be stronger than those in the long portfolios, particularly for the term structure premia. These findings are consistent with the previous literature (Fuertes *et al.*, 2010; Bianchi *et al.*, 2015). Second, it appears that the volatility premia on the nearest contracts are largely sourced from the short portfolio, suggesting that commodities with the lowest spot price volatility significantly underperform those with the highest spot price volatility. These findings are consistent on the third nearest contracts.

To address the concerns that our observed profits are compensation for high transaction costs, we compute the net returns. Following Fuertes *et al.* (2010), we first compute the portfolio turnover for all quartile portfolios and long-short portfolios and then apply a round trip transaction cost of 0.086% (Marshall *et al.*, 2012). It is evident that portfolio turnovers vary across strategies, with the highest average turnover reported by the hedging pressure and the lowest being observed in the volatility premia. Interestingly, portfolio turnovers for momentum are considerably lower compared to the US, suggesting that winner (loser) commodities remain as winners (losers) over longer periods of time. This also helps to shed light on the weaker performance of the value premia. As a result, the profits to the long-short strategies are too large to be subsumed by transaction costs. Overall, findings presented in Table 7 highlight the importance of long-short positions in capturing risk premia in Chinese commodity futures.

4.4.3 Risks adjustments

To examine whether the long-short premia can be explained by risk-taking, we employ commodity-specific (Panel A) and standard risk (Panel B) factors in Table 8. Panel A reports the regression results of long-short portfolios in a three-factor model proposed by Bakshi *et al.* (2019). Bakshi *et al.* (2019) demonstrate that market, carry and momentum factors are sufficient to describe the cross-sectional variations of commodity futures returns in the US. AVG represents the broad commodity market risk and CARRY is constructed by taking long positions in the five most backwardated commodities and short positions in the five most contangoed commodities. MOM is identical to our momentum premia. Results on both the first and the third nearest contracts are reported.

We first show that the term structure premium loads positively on MOM and AVG, but the intercepts remain significant. This suggests that the term structure premia cannot be fully explained by bearing systematic risks such as the broad market and momentum factors. When regressed on CARRY and AVG, momentum loads positively on CARRY but not AVG, with larger intercepts. This suggests that the predictability of momentum is stronger compared to the term structure, and double-sorting or integration will likely improve the risk-adjusted performance of momentum and term structure strategies. Furthermore, we find that the Bakshi *et al.* (2019) model cannot adequately explain the dynamics of the volatility strategy on the nearest contracts. While the hedging pressure (volatility) premium loads negatively (positively) on the AVG, neither strategies are related to CARRY or MOM. However, these loadings are not consistent on the third nearest contracts where the model explains their return variations relatively well. In particular, the hedging pressure premia is found to be positively related to momentum. Overall, carry and momentum factors cannot fully explain the long-short premia.

Our findings are supported by He *et al.* (2019), who find a three-factor model is not able to fully explain the cross-sectional return variations in China.¹⁹

Following Bianchi *et al.* (2016), we conduct additional risk adjustments by employing a six-factor model in Panel B. We augment the model to reflect the market dynamics in China by employing the CSI 300 as the stock market risk (STOCK), Barclays China Aggregate index as a proxy for the bond market (BOND), the sample of commodities in this study as the representative of commodity market factor (AVG), as well as the China unexpected inflation rate (INFSHOCK), RMB effective exchange rate index return (FX), and unexpected industrial production (UIP). Similar to the three-factor model, these broad market and macroeconomic risks are poor at explaining the returns dynamics of long-short portfolios. While the AVG remains significant across the board, more than half of the intercepts remain largely significant and the R^2 's are generally low. This is with the exception of the HP strategy on the third nearest contracts. The hedging pressure premia is negatively related to the unexpected changes in industrial production.

Although macroeconomic shocks appear to be largely insignificant at explaining the long-short premia, we further investigate the lead-lag relationship through a vector autoregression (VAR) framework. Motivated by Hong and Yogo (2012), we focus on whether risk premia can help gauge the macroeconomic quantities three months ahead. Panel C reports the results on the first lag. Once again, we observe divergent results between the nearest and third nearest contracts. Nevertheless, our findings unveil a consistent positive lead-lag relationship for TS and MOM with the industrial production (IP), while the relationship with inflation is relatively weak. Interestingly, MOM not only exhibits consistent predictability on

¹⁹ He *et al.* (2019) employ a three-factor model similar to our study but replace the MOM factor with a time-series momentum factor (TSMOM). For robustness, they also test a three-factor model with the MOM factor, but do not attain any improvements in cross-sectional pricing.

the IP but also the unexpected IP. This is not entirely surprising as our sample is primarily consists of industrial and chemical commodities. Meanwhile, HP on the third nearest contracts is found to negatively predict both the IP and inflation. These findings suggest that commodity prices in China indeed contain important insights about the Chinese economy.

Overall, the findings presented in Table 8 suggest that the profitability of long-short strategies in China cannot be attributed to commodity-specific, broad markets nor non-tradable macroeconomic risks; however, long-short risk premia can help gauge the movement of Chinese economy in the near term.

4.4.4 Liquidity, behavioral and sentiment factors

Previous studies have demonstrated that the liquidity risk explains the momentum profits across asset classes (Sadka, 2006; Asness *et al.*, 2013; Daskalaki, Kostakis, & Skiadopoulos, 2014). Recently, Bianchi *et al.* (2016) document that momentum can be largely explained by the anchoring behavior of investors, proxied by the 52-week high. Motivated by these findings, we employ the Amihud Illiquidity factor (AI) and the 52-week high momentum factor (HMOM) in search for an alternative source of observed profits. Table 9 reports these regression results.

Panel A shows that the AI factor alone is unable to explain any premia. However, we find that the term structure and volatility premia exhibit negative exposure to liquidity risks. This confirms that lower liquidity (or higher illiquidity) signals *lower* (as oppose to higher) expected returns. Panel B reports the results on the behavioral factor. Consistent with Bianchi *et al.* (2016), the momentum premia is indeed related to the 52-week high momentum in China, with relatively high R^2 s. Since the intercepts remain large and significant, anchoring bias provides at least a partial explanation for the remarkable profits generated by the momentum strategy. Consistent with our hypothesis, this behavioral bias likely has been amplified in China

due to the retail-dominance (Li, Zhang, *et al.*, 2017). However, we fail to detect any significant relationship between the anchoring bias and other types of premia.

In addition to liquidity and behavioral factors, sentiment has been found to be a significant component that influences the broad financial markets. Studies have documented the connections of sentiments with stock returns (Baker & Wurgler, 2007) and commodity futures returns (Gao & Süß, 2015; Bianchi *et al.*, 2016). Motivated by these findings, we employ the CBOE Crude Oil Volatility Index (OVX) and AlphaShares Chinese Volatility Index (CHIX) as proxies for market sentiment in China. The OVX measures the market expectation of 30-day volatility of crude oil prices. CHIX measures the implied volatility of options on the FTSE Xinhua China 25 and Hang Seng indices. The results presented in Panels C and D suggest that our observed premia cannot be subsumed by changes in market sentiments. Overall, the findings presented in Table 9 suggest that illiquidity and behavioral factors provide at least a partial explanation for the profitability of long-short strategies in China. Moreover, we find that higher liquidity (or lower illiquidity) leads to higher expected returns.

4.5 Potential for diversification

We now proceed to examine whether long-only and long-short strategies can serve as effective tools for diversification and inflation hedging in China. Figure 4 illustrates the pairwise correlations of strategy returns on the third nearest contracts with stocks, bonds and changes in unexpected inflation. First, commodities and stocks boast a significant positive correlation of 42.8%. Although Basu and Miffre (2013) also estimate a positive correlation between long-only commodity portfolios and the S&P500, the magnitude is much lower. Moreover, correlations of 9.1% and -3.6% are documented with the unexpected inflation and the bond market, respectively. Yet neither of them is significantly different from zero. This contradicts with the notion that passive commodity vehicles can hedge unexpected inflations (Erb &

Harvey, 2006; Gorton & Rouwenhorst, 2006). However, it may be premature to conclude that the commodity futures in China fail to hedge inflation at the current stage, as Gorton and Rouwenhorst (2006) argue that the inflation-hedging increases at longer horizons.

Nevertheless, for most of the long-short strategies, a zero correlation with the macro and financial variables cannot be rejected at the 5% level, highlighting their diversification advantage over long-only investments. Moreover, the term structure strategy shows a statistically significant correlation of 26.4% with the stock market, considerably lower than the long-only portfolio. Interestingly, the hedging pressure strategy reveals a negative correlation with the CSI 300, making it a prime candidate for hedging against adverse movements in Chinese stocks. Overall, findings presented in Figure 4 suggest that long-short strategies are promising for portfolio diversification but not for inflation hedging in China.

Since correlations can be time-dependent, we compute dynamic correlations to address the concerns that unconditional correlations may lead to false conclusions about diversification. Figure 5 exhibits the time-varying correlation between the successful strategies and the Chinese stock market. The correlations are estimated using the ADCC-GARCH model of Cappiello, Engle, and Sheppard (2006). Consistent with previous discussions, the hedging pressure strategy exhibits relatively lower and negative correlations with the stock market compared to the other strategies. Moreover, the correlation between the momentum strategy and stocks is most volatile. Consistent with the previous literature, correlations are generally higher in periods of market stress in China.²⁰ To add another dimension to the diversification potential over time, Figure 6 illustrates the performance across market conditions measured by the CSI300. On average, most strategies perform better (worse) during stock market growth (crisis)

²⁰ In addition to the bear markets globally in 2008-2009 and 2011-2012, the Shanghai stock market fell 30 percent in July 2015. The index fell again on 24 August 2015 ("Black Monday") by 8.48 percent. In January 2016, the market experienced another steep sell-off of 18 percent, and trading was halted on 4 January and 7 January 2016.

periods. Confirming the correlation results, the broad market is in sync with the CSI300 from crisis to growth periods, whereas the hedging pressure reveals a reversed pattern. Moreover, the momentum strategy delivers the strongest performance when the market state is neutral, suggesting that momentum is sensitive to market states.

4.6 Robustness tests

We conduct an extensive suite of robustness tests including re-estimating long-short premia in the most liquid markets and randomly selected commodity sectors, by varying portfolio breakpoints and testing the likelihood of data-snooping.

To examine whether market liquidity impacts the long-short premia, we exclude the 10 least liquid commodities, sorted by the average trading volume over the sample period (Internet Appendix V). Since the liquidity strategy fails to deliver statistically significant returns, we expect strategies to perform better or at least unaffected when implemented in a more liquid sample. As a result, successful strategies (with the exception of volatility) indeed experience improvements in risk-adjusted returns. The weakened volatility premia imply that compensations to spot price volatility risk are limited to relatively more illiquid commodities. Furthermore, the performance generally deteriorates when position limits and margins are alleviated. While this is consistent with the full sample, the economic profits of momentum strategy remain strong both quantitatively and statistically. This implies that market liquidity matters less to momentum compared to the term structure strategy.

To examine whether the strategy performances are driven by specific sectors, we re-evaluate the performance of strategies by excluding an entire sector of commodities at a time (Internet Appendix VI). While most of the unsuccessful strategies remain insignificant, several interesting dynamics emerge. First, the volatility strategy fails to deliver significant returns when grains or oilseeds are excluded, suggesting that the volatility premia is largely driven by

grains or oilseeds commodities. Second, term structure and momentum premia are unaffected by sector specifications. Notably, the momentum premia are stronger when grains are excluded, suggesting that grains commodities are less prone to price continuation. Overall, the term structure and momentum premia are not due to concentrated allocations to specific commodities, but the volatility premium is sector-specific. These findings are better illustrated in Figure 7, which depicts the percentage of total trades each strategy assigns to every sector.

Finally, we conduct the data-snooping test using the White (2000) Reality Check (RC) and Hansen (2005) Superior Predictive Ability (SPA) test (Internet Appendix VII). The null hypothesis is that the average performance of the benchmark is as small as the minimum average performance across the strategies tested. We perform five groups of tests with block lengths of 2, 10 and 20 months. Within each block length, stationary and circular bootstraps are performed based on 10,000 replications. Overall, our results consistently suggest the success of strategies is not a result of data mining.

5. Conclusion

This paper examined the behavior of long-only and an exhaustive list of long-short risk premia in Chinese commodity futures. In the presence of retail-dominance, time-variant margins and strict position limits, the long-only premia are non-existent, whereas cross-sectional term structure and momentum premia are statistically and economically persistent. These premia cannot be attributed to aggregate market risks, none-tradable macroeconomic risks, market sentiments, currency or sample selection, transactions cost and data-snooping. However, illiquidity, anchoring bias, and regulation-induced limits-to-arbitrage provide a partial explanation. We also demonstrated that systematic strategies offer superior diversification benefits for Chinese stocks. Overall, the paper highlights the distinctiveness of the Chinese

markets compared to the US. However, as China accelerates the liberalization of its capital markets, it remains to be seen whether such dissociation would continue in the future.

Our findings present several policy implications. First, we urge the CSRC to re-classify traders in accordance with their business purposes, in addition to individual and non-individual trading accounts. Similar to the CFTC, the classification may include but not limited to producers, processors, manufacturers, swap dealers and professional-managed money. Second, in order to definitively assess the efficient functioning of derivative markets, we highlight the need to collect and make available the positions data for futures and options contracts in each trading category to improve transparency. Third, as the evidence suggests, the hedging cost is escalated in the front contracts, we call for the exchanges to gradually loosen the position limits and margin requirements approaching delivery months, to better facilitate the effective transfer of risk. Last but not the least, sophisticated institutional investors provide liquidity to hedgers and other speculators, facilitate the efficient discovery of prices and the stabilization of market volatility. Thus, we restate the importance of institutional participation both domestically and internationally in addressing the potential perils of excessive speculation.

Data Availability Statement:

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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- [Macroeconomic data]; Not publicly available; data set can be acquired by paying a data license fee in *Bloomberg*.
- [Commitment of Traders reports]; Publicly available; data set can be obtained from Commodity Futures Trading Commission (CFTC) website (<https://www.cftc.gov/data>).

Appendix A Sorting variables

Premia	Acronym	Signals	Definition	References
Term Structure	TS	$Roll_{i,t} = \text{LN}(F_{i,t,Front}) - \text{LN}(F_{i,t,2})$	$F_{i,t,Front}$ represents the price of the front contract for commodity i at time t , and $F_{i,t,2}$ denotes the price of the second nearest contract of commodity i at time t	Erb & Harvey (2006); Gorton & Rouwenhorst (2006); Bakshi <i>et al.</i> (2019)
Hedging Pressure	HP	$Ratio_{i,t}^{Hedge} = \frac{ \Delta OI_{i,t} }{Vol_{i,t}}$	$\Delta OI_{i,t}$ denotes the change of monthly open interest for commodity i at time t , and $Vol_{i,t}$ denotes the total monthly volume of commodity i at time t . The hedging ratio ranges from 0 to 1.	Bessembinder (1992); De Roan <i>et al.</i> (2000); Basu & Miffre (2013)
Momentum	MOM	$MOM_{i,t} = \left(\frac{1}{12}\right) \sum_{j=0}^{11} r_{i,t-j}$	$r_{i,t-j}$ denotes the log return of commodity i in the month $t-j$.	Erb & Harvey (2006); Miffre & Rallis (2007); Asness <i>et al.</i> (2013)
Volatility	VOLA	$CV_{i,t} = \frac{\sigma_{i,t}^2}{ \mu_{i,t} }$	$\sigma_{i,t}^2$ denotes the variance of front contract (daily return) for commodity i at time t over the past 36 months, and $ \mu_{i,t} $ represents the absolute value of the prior 36-month average daily return at time t .	Dhume (2011); Szymanowska <i>et al.</i> (2014); Fernandez-Perez, Fuertes, & Miffre (2019).
Open Interest	OI	$\Delta OI_{\Delta i,t} = OI_{i,t} - OI_{i,t-1}$	$OI_{i,t}$ represents the aggregate open interests along the futures curve of commodity i at time t	Hong & Yogo (2012); Szymanowska <i>et al.</i> (2014)
Liquidity	LIQ	$Amivest_{i,t} = \frac{1}{D} \sum \frac{Vol_{i,d}}{ r_{i,d} }$	$Vol_{i,d}$ and $r_{i,d}$ denote the daily RMB volume and return of commodity i at time d , respectively. D is the number of days in the past 2 months	Marshall <i>et al.</i> (2012); Szymanowska <i>et al.</i> (2014)
Currency	FX	$\beta_{i,t}^{FX} = \frac{Cov(r_{i,t(42)}, r_{FX,t(42)})}{Var(r_{FX,t(42)})}$	$r_{i,t(42)}$ is the prior 42 monthly returns of commodity i at time t , $r_{FX,t(42)}$ represents the prior 42 monthly effective RMB exchange index returns at time t . $Cov(r_{i,t(42)}, r_{FX,t(42)})$ denotes the covariance and $Var(r_{FX,t(42)})$ is the variance of $r_{FX,t(42)}$.	Erb & Harvey (2006); Szymanowska <i>et al.</i> (2014)
Inflation	INF	$\beta_{i,t}^{INF} = \frac{Cov(r_{i,t(42)}, r_{c,t(42)})}{Var(r_{c,t(42)})}$	$r_{i,t(42)}$ is the prior 42 monthly returns of commodity i at time t , $r_{INF,t(42)}$ represents the prior 42 monthly unexpected inflation rates at time t . $Cov(r_{i,t(42)}, r_{INF,t(42)})$ denotes the covariance and $Var(r_{INF,t(42)})$ is the variance of $r_{INF,t(42)}$.	Bodie & Rosansky (1980); Erb & Harvey (2006); Gorton & Rouwenhorst (2006); Szymanowska <i>et al.</i> (2014)
Skewness	SKEW	$Skew_{i,t} = \frac{\frac{1}{D} \sum_{d=1}^D (r_{i,d} - \mu_{i,t})^3}{\sigma_{i,t}^3}$	$r_{i,d}$ denotes the daily return of commodity i at time d , $\mu_{i,t}$ represents the prior 12-month average daily return of commodity i at time t , $\sigma_{i,t}$ stands for the standard deviation of the past 12-month daily return at time t , and D is the number of days in the past 12 months	Fernandez-Perez <i>et al.</i> (2018)
Value	VAL	$Value_{i,t} = \ln \frac{\frac{1}{D} \sum_{d=1}^D F_{i,d}}{F_{i,t}}$	$value_{i,t}$ is the log of the average daily price of commodity i from 3.5 to 4.5 years ago divided by the price at time t , and D is the number of days between 3.5 and 4.5 years ago	Asness <i>et al.</i> (2013); Fernandez-Perez <i>et al.</i> (2019)

Table 1 Contracts specification

This table reports symbols, contract size, delivery month, price limit, margin requirements on our sample of 30 commodities traded on DCE, SHFE and ZCE. For each commodity, the table outlines the first and last maturity and their corresponding dates in the sample. *indicates monthly contract of the recent 3 consecutive months and consecutive even months contracts within the recent 13 months. **indicates all months but excluding the month for the Chinese New Year holiday. *** indicates delivery months of 1,3,5,7,9,11, and all months after the 2018 May contract.

Exchange	Sector	Commodity	Symbol	Contract Size	Delivery Month	Price Limit	Margin	First Contract	First Price Date	End Contract	End Price Date
DCE	Grains	No.1 Soybean	A	10 Tons/Contract	1,3,5,7,9,11	±4%	5%	2003 Mar	2002/03/29	2017 May	2017/04/28
DCE	Grains	No.2 Soybean	B	10 Tons/Contract	***	±4%	5%	2005 July	2004/12/31	2017 May	2017/04/28
DCE	Grains	Corn	C	10 Tons/Contract	1,3,5,7,9,11	±4%	5%	2005 Jan	2004/09/30	2017 May	2017/04/28
DCE	Industrial	LLDPE	L	5 Tons/Contract	all	±4%	5%	2007 Oct	2007/07/31	2017 June	2017/05/31
DCE	Industrial	PVC	V	5 Tons/Contract	all	±4%	5%	2009 Sep	2009/05/29	2017 June	2017/05/31
DCE	Industrial	Metallurgical Coke	J	100 Tons/Contract	all	±4%	5%	2011 Sep	2011/04/29	2017 June	2017/05/31
DCE	Industrial	Coking Coal	JM	60 Tons/Contract	all	±4%	5%	2013 July	2013/03/29	2017 June	2017/05/31
DCE	Oil Seeds	Soybean Meal	M	10 Tons/Contract	1,3,5,7,8,9,11,12	±4%	5%	2000 Nov	2000/07/31	2017 May	2017/04/28
DCE	Oil Seeds	RBD Palm Olein	P	10 Tons/Contract	all	±4%	5%	2008 Jan	2007/10/31	2017 June	2017/05/31
DCE	Oil Seeds	Soybean Oil	Y	10 Tons/Contract	1,3,5,7,8,9,11,12	±4%	5%	2006 Mar	2006/01/31	2017 May	2017/04/28
SHFE	Energy	Fuel Oil	FU	50 Tons/Contract	**	±5%	8%	2005 Jan	2004/08/31	2017 June	2017/05/31
SHFE	Industrial	Natural Rubber	RU	10 Ton/Contract	1,3,4,5,6,7,8,9,10,11	±3%	5%	1995 Sep	1995/07/31	2017 June	2017/05/31
SHFE	Metal	Aluminum	AL	5 Tons/Contract	all	±3%	5%	1994 Feb	1993/11/30	2017 June	2017/05/31
SHFE	Metal	Gold	AU	1 Kilogram/Contract	*	±3%	4%	2008 June	2008/01/31	2017 June	2017/05/31
SHFE	Metal	Copper	CU	5 Tons/Contract	all	±3%	5%	1993 June	1993/05/31	2017 June	2017/05/31
SHFE	Metal	Lead	PB	5 Tons/Contract	all	±4%	5%	2011 Sep	2011/03/31	2017 June	2017/05/31
SHFE	Metal	Steel Rebar	RB	10 Tons/Contract	all	±3%	5%	2009 Sep	2009/03/31	2017 June	2017/05/31
SHFE	Metal	Steel Wire Rod	WR	10 Ton/Contract	all	±5%	7%	2009 Sep	2009/03/31	2017 June	2017/05/31
SHFE	Metal	Zinc	ZN	5 Tons/Contract	all	±4%	5%	2007 July	2007/03/30	2017 June	2017/05/31
SHFE	Metal	Silver	AG	15 Kilograms/Contract	all	±3%	4%	2012 Sep	2012/05/31	2017 June	2017/05/31
ZCE	Energy	Methanol	MA	10 Tons/Contract	all	±4%	5%	2012 Mar	2011/10/31	2017 June	2017/05/31
ZCE	Grains	White Sugar	SR	10 Tons/Contract	1,3,5,7,9,11	±4%	6%	2006 May	2006/01/31	2017 May	2017/04/28
ZCE	Grains	Strong Gluten Wheat	WH	20 Tons/Contract	1,3,5,7,9,11	±4%	5%	2003 May	2003/03/31	2017 May	2017/04/28
ZCE	Grains	Common Wheat	PM	50 Tons/Contract	1,3,5,7,9,11	±4%	5%	1994 Jan	1993/12/31	2017 May	2017/04/28
ZCE	Industrial	Cotton No.1	CF	5 Tons/Contract	1,3,5,7,9,11	±4%	5%	2004 Nov	2004/06/30	2017 May	2017/04/28
ZCE	Industrial	PTA	TA	5 Tons/Contract	all	±4%	5%	2007 Feb	2006/12/29	2017 June	2017/05/31
ZCE	Industrial	Flat Glass	FG	20 Tons/Contract	all	±4%	5%	2013 Mar	2012/12/31	2017 June	2017/05/31
ZCE	Oil Seeds	Rapeseed Oil	OI	10 Tons/Contract	1,3,5,7,9,11	±4%	5%	2007 July	2007/06/29	2017 May	2017/04/28
ZCE	Oil Seeds	Rapeseed Meal	RM	10 Tons/Contract	1,3,5,7,8,9,11	±4%	5%	2013 May	2012/12/31	2017 May	2017/04/28
ZCE	Oil Seeds	Rapeseed	RS	10 Tons/Contract	7,8,9,11	±4%	5%	2013 July	2012/12/31	2016 Nov	2016/10/31

Table 2 Summary statistics

This table reports the summary statistics. We compute annualized returns (Panel A), standard deviations (Panel B), trading volume (Panel C) and Amihud illiquidity for returns on m^{th} nearest to maturity contracts, where $m = 1, 2, 3$ and 4. Trading volume (expressed in thousands) is the monthly average number of contracts traded. The Amihud illiquidity (AI) measure is defined as Amihud (2002), where AI is the ratio of returns by turnover (=price x contract size x volume) in RMB. AI is expressed in basis point per one-million-RMB trade. *Diff* reports the difference between the front and the third nearest contracts. *Sig* denotes the p -values of the difference-in-mean tests. Bold indicates significance at 10% or better. The sample period covers February 2004 to May 2017.

Sectors	Commodities	m^{th} nearest contract						m^{th} nearest contract					
		1 st	2 nd	3 rd	4 th	Diff	Sig	1 st	2 nd	3 rd	4 th	Diff	Sig
Panel A: Annualized returns (%)													
Energy	Methanol	-12.8	-7.5	-9.2	-4.9	-4.10	0.69	27.1	24.4	22.9	22.9	-1.32	0.12
	Fuel Oil	-11.3	-5.9	-0.7	-7.2	-10.05	0.93	32.5	28.8	27.5	28.0	-0.43	0.36
Grains	Sugar	-0.9	-2.3	-4.2	-3.7	3.75	0.07	19.7	19.2	20.2	20.6	-0.92	0.00
	Strong Wheat	-9.5	-6.9	-6.7	-5.0	-2.18	0.81	12.0	10.5	9.9	10.3	0.84	0.98
	Common Wheat	-16.1	-9.3	-5.6	-3.3	-11.63	1.00	12.9	10.1	9.6	9.5	1.91	1.00
	No.1 Soybean	-4.2	-0.1	3.6	1.7	-6.59	0.98	16.4	14.8	16.3	16.8	-1.37	0.00
	No.2 Soybean	8.7	3.7	5.6	3.0	3.18	0.25	20.6	15.8	16.3	18.3	1.47	0.97
	Corn	-4.6	-1.5	-0.3	-1.9	-4.61	0.95	13.1	11.1	10.1	11.0	0.23	0.73
Oilseeds	Rapeseed Oil	-6.0	-4.4	-2.3	-5.5	-1.60	0.66	17.8	19.7	21.4	22.0	-9.09	0.15
	Rapeseed Meal	11.5	11.6	11.4	9.6	0.63	0.47	27.9	22.9	22.5	20.5	0.72	0.88
	Rapeseed	-3.9	-5.0	-10.5	-6.1	5.47	0.18	12.2	12.9	14.9	17.3	-3.06	0.00
	Soybean Meal	11.9	10.5	7.9	6.4	5.10	0.06	24.1	21.5	21.8	21.3	-0.23	0.28
	Palm Olein	-12.4	-16.9	-9.6	-6.0	-3.68	0.74	23.2	27.2	26.1	25.9	0.65	0.77
	Soybean Oil	-1.1	-1.6	0.9	0.8	-0.19	0.52	23.5	22.5	22.4	22.1	1.69	1.00
Industrial	Cotton	-2.0	-2.0	-2.4	-1.8	0.14	0.48	18.4	17.7	18.0	17.9	-1.18	0.00
	Flat Glass	9.2	9.8	3.1	-0.4	5.33	0.29	25.9	16.5	17.7	15.8	3.45	1.00
	Natural Rubber	-7.7	-5.0	-4.8	-5.6	-1.12	0.67	30.5	31.5	32.3	32.2	-2.07	0.00
	LLDPE	3.6	-1.0	-2.1	-4.0	5.47	0.12	28.5	28.6	28.8	31.7	-1.13	0.03
	PVC	-10.6	-3.9	-3.8	-5.0	-5.98	0.87	16.0	17.4	18.2	17.2	-0.57	0.26
	PTA	-7.6	-9.0	-9.3	-6.3	2.06	0.15	26.0	25.1	25.2	23.7	-2.16	0.08
	Coking Coke	-13.7	-12.9	-13.0	-5.9	0.17	0.49	36.8	32.0	31.9	31.6	0.70	0.65
	Coking Coal	10.5	-9.5	3.8	-3.2	7.84	0.21	32.0	25.3	29.2	27.3	-0.99	0.27
Metal	Aluminum	-2.1	-2.7	-3.2	-2.7	1.13	0.14	15.5	15.0	15.0	15.2	-0.83	0.00
	Gold	1.3	1.0	-2.8	6.4	1.40	0.24	19.7	19.3	19.5	19.0	1.16	0.99
	Copper	10.3	11.2	9.2	8.5	1.64	0.07	28.4	28.9	29.5	29.9	-0.97	0.00
	Lead	-3.7	-3.1	-2.1	-2.1	-0.08	0.52	20.3	20.2	20.0	19.8	-0.40	0.05
	Steel Rebar	-7.8	-7.5	-6.3	-3.5	-3.90	0.84	28.3	24.3	23.3	23.4	0.42	0.84
	Steel Wire Rod	-11.3	-5.3	-2.0	-7.6	-9.53	0.96	15.3	17.8	18.4	16.5	-3.79	0.00
	Zinc	-4.9	-6.2	-5.8	-5.6	1.04	0.14	26.9	27.2	27.6	27.8	-0.50	0.00
	Silver	-13.0	-11.8	-10.6	-8.7	-0.27	0.58	23.9	24.3	24.6	25.1	-0.04	0.45
Panel C: Trading volume													
Energy	Methanol	391	3034	4301	4374	-4710	0.04	917.6	777.6	335.5	723.3	576.3	0.03
	Fuel Oil	100	655	965	87	-1016	0.00	211.7	57.7	151.1	160.3	24.7	0.38
Grains	Sugar	932	3739	7263	6005	-6382	0.00	1.8	1.8	2.2	2.4	-0.6	0.79
	Strong Wheat	70	364	830	681	-776	0.00	43.2	20.7	31.6	33.7	-2.9	0.66
	Common Wheat	9	20	64	50	-56	0.02	240.5	101.0	68.2	106.9	131.1	0.05
	No.1 Soybean	287	1229	2253	1553	-1992	0.00	6.0	9.1	12.3	27.1	-6.2	0.98
	No.2 Soybean	2	3	16	11	-14	0.09	476.3	265.7	197.8	328.3	268.0	0.01
	Corn	477	1205	2439	1895	-2087	0.00	7.4	3.8	5.3	3.4	2.4	0.06
Oilseeds	Rapeseed Oil	178	548	762	260	-643	0.00	122.8	79.4	88.4	126.7	33.9	0.24
	Rapeseed Meal	3314	11125	13786	8051	-10388	0.00	18.6	10.9	6.2	5.1	12.8	0.06
	Rapeseed	2	2	64	0	-70	0.06	293.8	484.1	89.2	442.4	203.4	0.05
	Soybean Meal	809	3490	6478	6238	-5776	0.00	23.3	13.0	6.6	8.4	16.8	0.03
	Palm Olein	71	833	1286	1916	-1046	0.00	283.0	243.3	111.8	117.5	176.0	0.02
	Soybean Oil	193	1039	2574	2819	-2354	0.00	62.0	53.0	28.8	33.0	30.1	0.04
Industrial	Cotton	246	1186	2199	1200	-1982	0.00	1.1	0.7	1.3	0.7	-0.2	0.61
	Flat Glass	206	1343	3581	3281	-3390	0.00	453.4	224.6	118.3	156.7	350.6	0.12
	Natural Rubber	460	1985	3262	3439	-2799	0.00	1.1	1.3	1.4	2.1	-0.4	0.86
	LLDPE	181	1941	2558	2396	-2403	0.00	183.3	114.5	101.2	82.6	60.5	0.17
	PVC	77	313	461	257	-380	0.01	445.3	583.5	548.0	689.8	-87.1	0.64
	PTA	324	3094	3296	3344	-3005	0.00	28.1	22.6	22.9	44.7	5.5	0.26
	Coking Coke	115	614	1090	2114	-921	0.00	135.4	68.4	100.4	92.9	39.1	0.21
	Coking Coal	91	798	1455	1524	-1432	0.00	446.9	987.5	618.7	427.6	-180.9	0.71
Metal	Aluminum	210	956	873	248	-687	0.00	0.1	0.0	0.0	0.0	0.0	0.00
	Gold	131	273	473	496	-361	0.01	8.1	4.7	2.5	4.3	5.3	0.00
	Copper	452	2489	3164	1453	-2735	0.00	0.0	0.0	0.0	0.0	0.0	0.00
	Lead	107	178	31	4	54	0.98	0.5	0.7	41.2	38.2	-40.7	0.85
	Steel Rebar	503	4334	9063	12210	-8578	0.00	4.8	2.4	3.1	2.2	1.6	0.12
	Steel Wire Rod	18	8	9	2	12	0.86	1038.5	1297.1	1454.6	747.0	-518.4	0.81
	Zinc	415	2904	3351	1282	-3008	0.00	0.1	0.0	0.0	0.2	0.1	0.00
	Silver	1577	2764	3983	4189	-2661	0.06	0.9	2.3	2.9	5.5	-2.0	1.00
Panel D: Amihud illiquidity													

Table 3 Performance of long-only investments

This table reports the performance of the broad market and sectors. Panel A reports the results over the sample period from February 2004 to May 2017 whereas Panel B reports the extended sample from 1992. AVG represents the broad market of 30 commodities. Energy, Grains, Industrials, Metals and Oilseeds report the performance of each commodity sector as classified in Table 2. All portfolios are equally-weighted and rebalanced monthly. For each portfolio, we report returns on m^{th} nearest to maturity contracts, where $m = 1, 2, 3$ and 4. Not all commodities started trading prior to our sample period in 2004.

	AVG	Energy	Grains	Industrials	Metals	Oilseeds
<i>Panel A: 2004-2017</i>						
<i>First nearest contract (m=1)</i>						
Annualized arithmetic mean	-0.0285	-0.0859	-0.0551	-0.0349	0.0125	0.0276
<i>t</i> -statistics	-0.84	-1.15	-2.06	-0.67	0.24	0.55
Annualized volatility	0.1234	0.2616	0.0974	0.1908	0.1886	0.1817
Sharpe Ratio	-0.2306	-0.3283	-0.5661	-0.1831	0.0664	0.1519
<i>Second nearest contract (m=2)</i>						
Annualized arithmetic mean	-0.0219	-0.0313	-0.0341	-0.0387	0.0169	0.0036
<i>t</i> -statistics	-0.61	-0.44	-1.32	-0.73	0.33	0.07
Annualized volatility	0.1311	0.2549	0.0934	0.1932	0.1883	0.1965
Sharpe Ratio	-0.1673	-0.1228	-0.3647	-0.2004	0.0899	0.0182
<i>Third nearest contract (m=3)</i>						
Annualized arithmetic mean	-0.0139	-0.0105	-0.0193	-0.0442	0.0135	0.0087
<i>t</i> -statistics	-0.36	-0.15	-0.70	-0.78	0.25	0.16
Annualized volatility	0.1407	0.2478	0.0990	0.2043	0.1934	0.2026
Sharpe Ratio	-0.0987	-0.0426	-0.1944	-0.2162	0.0696	0.0430
<i>Fourth nearest contract (m=4)</i>						
Annualized arithmetic mean	-0.0124	-0.0329	-0.0187	-0.0487	0.0179	-0.0012
<i>t</i> -statistics	-0.31	-0.47	-0.62	-0.86	0.33	-0.02
Annualized volatility	0.1449	0.2491	0.1072	0.2044	0.1935	0.2020
Sharpe Ratio	-0.0855	-0.1323	-0.1745	-0.2383	0.0925	-0.0059
<i>Panel B: 1992-2017</i>						
<i>First nearest contract (m=1)</i>						
Annualized arithmetic mean	-0.0299	-0.0859	-0.0906	-0.0202	0.0042	0.0419
<i>t</i> -statistics	-1.24	-1.15	-3.36	-0.44	0.12	0.89
Annualized volatility	0.1182	0.2616	0.1299	0.2126	0.1670	0.1930
Sharpe Ratio	-0.2527	-0.3283	-0.6970	-0.0952	0.0250	0.2169
<i>Second nearest contract (m=2)</i>						
Annualized arithmetic mean	-0.0234	-0.0313	-0.0590	-0.0419	0.0030	0.0135
<i>t</i> -statistics	-0.89	-0.44	-2.29	-0.87	0.09	0.28
Annualized volatility	0.1282	0.2549	0.1233	0.2246	0.1706	0.1989
Sharpe Ratio	-0.1823	-0.1228	-0.4785	-0.1866	0.0179	0.0680
<i>Third nearest contract (m=3)</i>						
Annualized arithmetic mean	-0.0172	-0.0105	-0.0253	-0.0530	-0.0023	0.0261
<i>t</i> -statistics	-0.62	-0.15	-0.90	-1.05	-0.06	0.53
Annualized volatility	0.1347	0.2478	0.1339	0.2310	0.1753	0.2013
Sharpe Ratio	-0.1278	-0.0426	-0.1889	-0.2293	-0.0132	0.1294
<i>Fourth nearest contract (m=4)</i>						
Annualized arithmetic mean	-0.0179	-0.0329	-0.0106	-0.0555	-0.0072	0.0207
<i>t</i> -statistics	-0.62	-0.47	-0.37	-1.07	-0.19	0.42
Annualized volatility	0.1396	0.2491	0.1375	0.2334	0.1797	0.1990
Sharpe Ratio	-0.1280	-0.1323	-0.0773	-0.2378	-0.0399	0.1040

Table 4 Performance of long-short strategies

This table reports the performance of ten long-short strategies. Panels A through to D report results based on m^{th} nearest to maturity contracts, where $m = 1, 2, 3$ and 4 , respectively. For each strategy, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the top (bottom) quartile. All portfolios are equally weighted and rebalanced monthly. The term structure signal is based on the roll-yield from the front to the next nearest contract. The hedging pressure strategy sorts commodities based on hedging ratio—the change of open interest divided by volume. The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on prior 3-year daily returns. The open interest signal is computed as the change of monthly open interests of the entire curve. The liquidity signal is the Amivest measure as defined by Amihud (2002), computed as the average ratio of monthly turnover to absolute return in the past 2 months using daily returns. The FX signal is the regression beta of commodity returns on the RMB effective exchange rate index, with a rolling window of 42 months. The inflation signal is the regression beta of commodity returns on unexpected inflation with a rolling window of 42 months. The skewness signal is computed as the Pearson skewness based on the past 12-month daily return. Finally, the value signal is the log of the average daily prices from 3.5 to 4.5 years ago divided by the price at each time t . The sample period covers February 2004 through to May 2017.

	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness	Value
<i>Panel A: First nearest contract ($m=1$)</i>										
Annualized arithmetic mean	0.1591	0.0285	0.2194	0.1053	-0.0367	-0.0684	0.0477	0.0222	-0.0958	0.0748
t -statistics	3.24	0.73	4.13	2.43	-0.94	-1.43	0.83	0.44	-2.32	1.13
Annualized volatility	0.1790	0.1416	0.1866	0.1394	0.1421	0.1736	0.1805	0.1599	0.1453	0.1961
Sharpe Ratio	0.8891	0.2010	1.1757	0.7555	-0.2582	-0.3942	0.2645	0.1387	-0.6596	0.3814
Sortino Ratio	1.0041	0.3219	2.1373	1.1409	-0.3579	-0.5722	0.2890	0.2039	-0.9312	0.7939
Skewness	-1.7586	-0.0058	0.1996	-0.3185	-0.5605	0.0855	-1.5333	-0.1431	0.1775	1.6645
Kurtosis	14.4057	3.1096	4.1832	4.6964	3.8109	4.2825	12.0713	4.4294	4.1239	11.2184
99% VaR(Cornish-Fisher)	0.2705	0.1269	0.2070	0.1344	0.1092	0.1655	0.2329	0.1504	0.1375	0.3281
<i>Panel B: Second nearest contract ($m=2$)</i>										
Annualized arithmetic mean	0.1753	0.0273	0.1738	0.0689	-0.0558	0.0290	0.0104	-0.0005	0.0270	0.0857
t -statistics	3.94	0.74	3.59	1.59	-1.52	0.60	0.17	-0.01	0.71	1.42
Annualized volatility	0.1614	0.1341	0.1695	0.1390	0.1326	0.1759	0.1873	0.1514	0.1335	0.1791
Sharpe Ratio	1.0860	0.2035	1.0252	0.4959	-0.4210	0.1646	0.0555	-0.0031	0.2024	0.4784
Sortino Ratio	1.3365	0.3665	1.8392	0.6107	-0.5369	0.2523	0.0571	-0.0046	0.2984	1.0848
Skewness	-1.2063	0.3781	0.4011	-1.1411	-1.0737	0.0942	-2.2592	0.1091	-0.3505	2.3314
Kurtosis	11.6339	3.5553	5.2736	9.4102	9.9717	5.5141	14.1756	4.1316	4.0679	15.8853
99% VaR(Cornish-Fisher)	0.2152	0.1381	0.2067	0.1581	0.1464	0.1910	0.2792	0.1487	0.1159	0.3426
<i>Panel C: Third nearest contract ($m=3$)</i>										
Annualized arithmetic mean	0.1379	0.0811	0.1671	0.0485	-0.0311	0.0088	0.0153	0.0477	0.0152	0.0992
t -statistics	3.01	2.06	3.10	1.07	-0.95	0.22	0.26	1.00	0.42	1.61
Annualized volatility	0.1660	0.1421	0.1882	0.1440	0.1183	0.1457	0.1842	0.1475	0.1272	0.1812
Sharpe Ratio	0.8308	0.5709	0.8880	0.3370	-0.2628	0.0605	0.0830	0.3232	0.1197	0.5476
Sortino Ratio	0.8823	1.0223	1.5867	0.3916	-0.3922	0.1024	0.0919	0.5486	0.1707	1.2821
Skewness	-2.3344	1.4611	0.2985	-1.5046	0.0817	0.2074	-1.6907	0.1588	-0.5253	2.4826
Kurtosis	20.2724	12.2774	4.4897	11.8426	5.8944	3.4807	10.1077	3.8560	3.8952	16.4701
99% VaR(Cornish-Fisher)	0.3288	0.2510	0.2129	0.1845	0.1268	0.1415	0.2117	0.1482	0.1033	0.3488
<i>Panel D: Fourth nearest contract ($m=4$)</i>										
Annualized arithmetic mean	0.1169	-0.0078	0.1526	0.0478	-0.0553	-0.0137	0.0081	0.0200	-0.0098	0.0980
t -statistics	2.57	-0.21	2.75	1.02	-1.64	-0.42	0.15	0.41	-0.25	1.57
Annualized volatility	0.1639	0.1348	0.1932	0.1480	0.1211	0.1173	0.1718	0.1517	0.1377	0.1826
Sharpe Ratio	0.7129	-0.0576	0.7901	0.3227	-0.4570	-0.1167	0.0471	0.1315	-0.0715	0.5369
Sortino Ratio	0.7469	-0.1013	1.3665	0.3787	-0.6244	-0.1819	0.0517	0.1915	-0.1066	1.1867
Skewness	-2.0513	0.4482	0.2071	-1.3812	-0.3862	-0.1116	-1.6516	-0.1599	-0.1580	2.5280
Kurtosis	16.3461	4.1660	4.1648	11.1886	8.4230	2.8749	9.4287	4.8733	3.6408	16.0866
99% VaR(Cornish-Fisher)	0.2719	0.1435	0.2082	0.1827	0.1331	0.0965	0.1887	0.1464	0.1191	0.3447

Table 5 Comparison between the US and China

This table reports the performance of long-short strategies in a “matched” sample of 14 commodities in China (Panel A), the US (Panel B), and the cross-country correlations (Panel C). For each strategy, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the high (low) quartile. All portfolios are equally weighted and rebalanced monthly. The term structure signal is based on the roll-yield from the front to the next nearest contract. In the Chinese sample, hedging pressure sorts commodities based on the hedging ratio—the change of open interest divided by volume. In the US sample, the HP signal is the average ratio of hedgers’ net short positions to total hedgers’ positions in the past 12 months (CFTC). The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on the prior 3-year daily returns. The open interest signal is the change of monthly open interests on the entire curve. The liquidity signal is the Amivest measure as defined by Amihud (2002), computed as the average ratio of monthly turnover to absolute return in the past 2 months using daily returns. The FX signal is the regression beta of commodity returns on the RMB effective exchange rate index, with a rolling window of 42 months. The inflation signal is the regression beta of commodity returns on unexpected inflation with a rolling window of 42 months. The skewness signal is computed as the Pearson skewness based on the past 12-month daily return. Finally, the value signal is the log of the average daily prices from 3.5 to 4.5 years ago divided by the price at each time t . The third block reports the spreading return assumes simultaneously taking a long position on the m^{th} (>1) contracts and short positions on the nearby contract (Szymanowska *et al.*, 2014). The sample period for both markets covers February 2004 through to May 2017. * in Panel C denotes significance at 5% level or better.

	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness	Value
<i>Panel A: China</i>										
<i>First nearest contract ($m=1$)</i>										
Annualized arithmetic mean	0.1179	-0.0050	0.2206	0.1324	0.0050	-0.0854	0.0396	-0.0135	-0.1133	0.1738
t -statistics	2.18	-0.11	3.71	2.47	0.10	-1.68	0.69	-0.23	-2.27	2.44
Annualized volatility	0.1972	0.1701	0.2086	0.1720	0.1737	0.1849	0.1805	0.1885	0.1753	0.2107
Sharpe Ratio	0.5979	-0.0295	1.0574	0.7699	0.0285	-0.4620	0.2195	-0.0719	-0.6463	0.8251
<i>Third nearest contract ($m=3$)</i>										
Annualized arithmetic mean	0.0985	0.0149	0.1649	0.0900	0.0136	-0.0375	0.0756	0.1427	0.0254	0.1999
t -statistics	1.79	0.33	3.02	1.67	0.35	-0.74	1.41	2.83	0.56	3.18
Annualized volatility	0.1978	0.1639	0.1904	0.1721	0.1335	0.1816	0.1669	0.1567	0.1582	0.1853
Sharpe Ratio	0.4977	0.0908	0.8661	0.5228	0.1016	-0.2064	0.4529	0.9107	0.1606	1.0788
<i>Spreading returns ($m=3$)</i>										
Annualized arithmetic mean	-0.0075	-0.0006	-0.0462	-0.0151	-0.0032	0.0089	-0.0228	-0.0148	0.0096	0.0173
t -statistics	-0.39	-0.04	-2.28	-0.73	-0.14	0.48	-0.91	-0.63	0.69	0.78
Annualized volatility	0.0699	0.0515	0.0706	0.0658	0.0806	0.0671	0.0776	0.0732	0.0488	0.0645
Sharpe Ratio	-0.1079	-0.0118	-0.6550	-0.2295	-0.0391	0.1322	-0.2944	-0.2023	0.1971	0.2679
<i>Panel B: The US</i>										
<i>First nearest contract ($m=1$)</i>										
Annualized arithmetic mean	0.0672	0.1665	0.1046	-0.0829	0.0029	-0.0098	-0.0443	0.0181	0.0416	0.1301
t -statistics	1.08	2.75	1.59	-1.43	0.05	-0.19	-0.68	0.25	0.72	1.89
Annualized volatility	0.2276	0.2099	0.2307	0.1851	0.2160	0.1918	0.2044	0.2271	0.2017	0.1906
Sharpe Ratio	0.2951	0.7935	0.4534	-0.4479	0.0136	-0.0513	-0.2170	0.0795	0.2064	0.6829
<i>Third nearest contract ($m=3$)</i>										
Annualized arithmetic mean	0.0377	0.0785	0.0785	-0.0109	0.0178	-0.0016	-0.0726	0.0596	-0.0397	0.0907
t -statistics	0.73	1.59	1.28	-0.22	0.33	-0.03	-1.22	0.96	-0.72	1.52
Annualized volatility	0.1887	0.1707	0.2154	0.1585	0.1899	0.1714	0.1877	0.1960	0.1933	0.1650
Sharpe Ratio	0.1998	0.4598	0.3642	-0.0690	0.0935	-0.0093	-0.3868	0.3042	-0.2055	0.5497
<i>Spreading returns ($m=3$)</i>										
Annualized arithmetic mean	-0.0143	-0.0367	-0.0046	0.0426	0.0047	0.0030	0.0089	-0.0101	-0.0133	-0.0043
t -statistics	-1.06	-3.12	-0.36	3.80	0.44	0.27	0.80	-0.70	-1.17	-0.36
Annualized volatility	0.0495	0.0408	0.0450	0.0359	0.0370	0.0410	0.0353	0.0454	0.0401	0.0333
Sharpe Ratio	-0.2893	-0.8998	-0.1012	1.1877	0.1266	0.0739	0.2534	-0.2216	-0.3330	-0.1290
<i>Panel C: Cross-country correlations</i>										
<i>First nearest contract ($m=1$)</i>										
Pearson's correlation	0.0425	-0.0131	0.3516*	0.0230	0.1172	0.0376	0.0672	0.0243	0.1118	0.1718
<i>Third nearest contract ($m=3$)</i>										
Pearson's correlation	0.1318	0.2155*	0.3275*	0.0695	0.0495	-0.0129	0.2747*	-0.0384	0.1109	0.0950
<i>Spreading returns ($m=3$)</i>										
Pearson's correlation	0.0156	0.0501	-0.1427	-0.0212	0.0945	-0.2024*	-0.1112	-0.0890	0.0764	-0.0367

Table 6 Correlations of strategies

This table presents the Pearson correlation. Panel A reports the first nearest to maturity contracts whereas Panel B reports the third nearest contracts. To construct strategy portfolios, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the top (bottom) quartile. All portfolios are equally weighted and rebalanced monthly. AVG is the equally weighted market portfolio of all commodities sampled. The term structure signal is based on the roll-yield from the front to the next nearest contract. The hedging pressure signal is the change of open interest divided by volume. The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on prior 3-year daily returns. The open interest signal is the change of monthly open interests of the entire curve. The liquidity signal is the Amivest measure as defined by Amihud (2002), computed as the average ratio of monthly turnover to absolute return in the past 2 months using daily returns. The FX signal is the regression beta of commodity returns on the RMB effective exchange rate index, with a rolling window of 42 months. The inflation signal is the regression beta of commodity returns on unexpected inflation with a rolling window of 42 months. The skewness signal is the Pearson skewness based on the past 12-month daily return. The value signal is the log of the average daily prices from 3.5 to 4.5 years ago divided by the price at each time t . The sample period covers February 2004 through to May 2017. *denotes significance at 5% level or better.

	AVG	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness
<i>Panel A: First nearest contract (m=1)</i>										
Term Structure	0.3980*									
Hedging Pressure	-0.2368	-0.1267								
Momentum	0.2689	0.4673*	-0.0498							
Volatility	0.4361*	0.2639	-0.0817	0.1445						
Open Interest	0.3368*	0.1120	-0.1517	-0.0697	0.1744					
Liquidity	-0.4152*	-0.2184	0.2001	-0.2757	-0.2054	-0.1443				
FX	0.6226*	0.4475*	-0.1493	0.0200	0.4930*	0.3872*	-0.5278*			
Inflation Shocks	0.2075	-0.2077	-0.0285	-0.1587	0.1124	0.0833	0.0453	0.1304		
Skewness	-0.0584	-0.0315	-0.0794	-0.0505	0.0235	-0.0263	0.0277	-0.0968	0.0719	
Value	-0.0423	-0.4474*	-0.0964	-0.3641*	-0.1897	-0.0759	-0.0189	-0.0216	0.4009*	0.0651
<i>Panel B: Third nearest contract (m=3)</i>										
Term Structure	0.4591*									
Hedging Pressure	-0.4198*	-0.1541								
Momentum	0.2573	0.4467*	0.0622							
Volatility	0.4725*	0.4402*	-0.4832*	0.1308						
Open Interest	0.3656*	0.2139	-0.2987*	-0.0724	0.2676					
Liquidity	-0.2565	-0.1264	0.3328*	-0.1361	-0.2590	-0.0610				
FX	0.6142*	0.5206*	-0.3181*	-0.0510	0.4373*	0.3967*	-0.3999*			
Inflation Shocks	0.6098*	0.2643	-0.2197	0.0766	0.3182*	0.2636	-0.2731	0.5241*		
Skewness	-0.0577	-0.0408	0.0689	0.0741	-0.0067	-0.0763	-0.0550	-0.0748	0.2209	
Value	-0.2742	-0.5365*	0.4338*	-0.3806*	-0.4521*	-0.2373	-0.0558	-0.2731	0.0307	0.2026

Table 7 Decomposing long-short strategy returns

This table reports the performance of quartile portfolios for term structure, hedging pressure, momentum and volatility strategies. The term structure signal is based on the roll-yield from the front to the next nearest contract. The hedging pressure signal is the change of open interest divided by volume. The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on prior 3-year daily returns. Portfolio turnover is estimated following Fuertes *et al.* (2010). The transaction cost is based on Marshall *et al.* (2012) of 0.086%. The sample period covers February 2004 through to May 2017.

	<i>First nearest contract (m=1)</i>					<i>Third nearest contract (m=3)</i>				
	Q1	Q2	Q3	Q4	L-S	Q1	Q2	Q3	Q4	L-S
Term Structure										
Annualized arithmetic mean	-0.0902	-0.0846	-0.0187	0.0689	0.1591	-0.0627	-0.0561	-0.0130	0.0752	0.1379
<i>t</i> -statistics	-2.77	-2.13	-0.43	1.28	3.24	-1.71	-1.34	-0.29	1.32	3.01
Annualized volatility	0.1185	0.1448	0.1594	0.1961	0.1790	0.1327	0.1518	0.1606	0.2066	0.1660
Sharpe Ratio	-0.7611	-0.5844	-0.1172	0.3516	0.8891	-0.4724	-0.3696	-0.0808	0.3640	0.8308
Skewness	0.1385	-1.5115	-0.2338	-2.2903	-1.7586	0.3370	-1.5845	-0.5048	-2.3509	-2.3344
Kurtosis	3.0586	10.1581	5.8269	17.9179	14.4057	4.8093	10.7171	5.5657	19.0136	20.2724
Portfolio Turnover	5.8929	7.7477	7.1403	6.4591	6.1760	5.8929	7.7477	7.1403	6.4591	6.1760
Net Return					0.1485					0.1273
Hedging Pressure										
Annualized arithmetic mean	-0.0559	-0.0309	-0.0093	-0.0274	0.0285	-0.0393	-0.0274	-0.0398	0.0418	0.0811
<i>t</i> -statistics	-1.24	-0.71	-0.26	-0.70	0.73	-0.83	-0.57	-0.91	1.09	2.06
Annualized volatility	0.1635	0.1576	0.1313	0.1426	0.1416	0.1705	0.1749	0.1592	0.1385	0.1421
Sharpe Ratio	-0.3416	-0.1959	-0.0709	-0.1920	0.2010	-0.2305	-0.1564	-0.2502	0.3020	0.5709
Skewness	-0.8427	-0.0797	-0.0585	-1.5840	-0.0058	-1.0495	-2.0923	-1.7621	0.2545	1.4611
Kurtosis	8.2819	7.5533	3.4108	12.6302	3.1096	8.6554	14.7000	15.3652	3.8278	12.2774
Portfolio Turnover	8.2413	8.8764	8.4778	8.3861	8.3717	7.4118	8.1497	8.7088	8.1125	7.7622
Net Return					0.0142					0.0677
Momentum										
Annualized arithmetic mean	-0.0992	-0.0632	-0.0075	0.1202	0.2194	-0.0654	-0.0013	-0.0135	0.1017	0.1671
<i>t</i> -statistics	-2.61	-1.95	-0.16	2.13	4.13	-1.55	-0.03	-0.31	1.69	3.10
Annualized volatility	0.1337	0.1136	0.1684	0.1983	0.1866	0.1473	0.1429	0.1528	0.2094	0.1882
Sharpe Ratio	-0.7420	-0.5562	-0.0447	0.6063	1.1757	-0.4439	-0.0093	-0.0882	0.4859	0.8880
Skewness	-0.1082	0.2815	-2.9240	-0.2729	0.1996	-0.5550	-0.8747	-1.7779	-0.2653	0.2985
Kurtosis	5.0310	3.7031	25.1664	5.5433	4.1832	7.2530	8.6591	12.8271	5.9367	4.4897
Portfolio Turnover	2.3491	5.0439	4.4620	2.2355	2.2923	2.6832	5.3246	4.6689	2.3516	3.7571
Net Return					0.2155					0.1606
Volatility										
Annualized arithmetic mean	-0.0711	-0.0195	-0.0234	0.0343	0.1053	-0.0225	0.0038	-0.0050	0.0260	0.0485
<i>t</i> -statistics	-2.26	-0.38	-0.47	0.72	2.43	-0.67	0.07	-0.09	0.49	1.07
Annualized volatility	0.1009	0.1640	0.1601	0.1526	0.1394	0.1079	0.1690	0.1781	0.1688	0.1440
Sharpe Ratio	-0.7042	-0.1190	-0.1464	0.2245	0.7555	-0.2087	0.0224	-0.0283	0.1541	0.3370
Skewness	0.5579	-0.5986	-0.6136	-0.4562	-0.3185	0.9368	-0.9302	-0.9148	-1.4799	-1.5046
Kurtosis	3.9551	6.4202	6.5832	5.6247	4.6964	5.4497	7.5363	7.7109	10.6690	11.8426
Portfolio Turnover	1.4355	4.0798	4.3291	2.6215	2.0285	1.4355	4.0798	4.3291	2.6215	2.0285
Net Return					0.1018					0.0450

Table 8 Risks adjustments

This table reports regression results on the three-factor (Bakshi *et al.*, 2019) model and a six-factor (Fuertes *et al.*, 2010; Bianchi *et al.*, 2016) model in Panels A and B, respectively. Panel C reports the results of lead-lag relationships (measured by a VAR model with up to three lags) between each premium and macroeconomic quantities. Results on m^{th} nearest to maturity contracts are reported, where $m=1$ and 3. AVG is an equally-weighted portfolio of 30 commodities in our sample, rebalanced monthly. CARRY is constructed by taking long (short) positions in the five most backwardated (contangoed) commodities. MOM is constructed by taking long (short) positions in past 12-month winner (loser) commodities. STOCK and BOND denote Chinese equity and bond markets, proxied by the CSI 300 and Barclays China aggregate index, respectively. FX denotes returns on the RMB effective exchange rate index. INFSHOCK and UIP denote unexpected inflation rate and unexpected industrial production in China, computed as the difference between the actual and consensus figures from Bloomberg. The t -statistics (in parentheses) are estimated using the Newey and West (1987) procedure (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. The sample period covers February 2004 through to May 2017.

	Term Structure (TS)		Hedging Pressure (HP)		Momentum (MOM)		Volatility (VOLA)	
	$m=1$	$m=3$	$m=1$	$m=3$	$m=1$	$m=3$	$m=1$	$m=3$
<i>Panel A: Commodity-specific risks</i>								
AVG	0.471*	0.484**	-0.371***	-0.433***	0.267	0.190	0.452***	0.368**
	(1.67)	(2.10)	(-4.52)	(-3.38)	(1.47)	(1.07)	(3.55)	(2.45)
CARRY			0.022	-0.121	0.339***	0.371**	0.036	0.238*
			(0.23)	(-0.98)	(3.48)	(2.56)	(0.38)	(1.81)
MOM	0.356***	0.291***	0.022	0.162**			0.023	-0.027
	(4.35)	(3.79)	(0.32)	(2.48)			(0.24)	(-0.30)
Constant	0.007**	0.008**	0.002	0.005	0.014**	0.010**	0.009**	0.003
	(2.00)	(2.33)	(0.67)	(1.55)	(2.50)	(2.06)	(2.20)	(0.61)
Observations	148	146	148	146	148	146	124	122
Adj. R2	0.310	0.355	0.082	0.238	0.138	0.131	0.173	0.257
<i>Panel B: Standard risks</i>								
STOCK	0.053	0.070**	-0.040	0.019	-0.018	-0.042	-0.003	0.000
	(1.30)	(2.41)	(-1.06)	(0.45)	(-0.32)	(-0.77)	(-0.09)	(0.01)
BOND	0.322	0.215	0.079	0.665	1.143	1.372*	0.252	0.377
	(0.41)	(0.29)	(0.17)	(1.36)	(1.44)	(1.68)	(0.51)	(0.68)
AVG	0.535**	0.520***	-0.340***	-0.423**	0.429**	0.430***	0.531***	0.468**
	(2.05)	(2.66)	(-3.37)	(-2.45)	(2.40)	(2.75)	(3.71)	(2.38)
INFSHOCK	0.337	-0.287	-1.355	-0.160	1.039	-0.028	-0.469	-0.535
	(0.24)	(-0.30)	(-1.28)	(-0.16)	(0.64)	(-0.03)	(-0.46)	(-0.54)
FX	-0.098	-0.028	-0.362	-0.103	-0.239	0.001	0.152	-0.254
	(-0.29)	(-0.09)	(-1.35)	(-0.45)	(-0.50)	(0.00)	(0.77)	(-1.15)
UIP	0.178	0.052	0.223	-0.346**	-0.212	-0.268	-0.146	-0.072
	(0.69)	(0.22)	(1.16)	(-2.17)	(-0.58)	(-0.92)	(-0.89)	(-0.52)
Constant	0.013***	0.011**	0.004	0.004	0.016***	0.010*	0.009**	0.004
	(2.68)	(2.39)	(1.20)	(1.16)	(2.70)	(1.71)	(2.23)	(0.87)
Observations	148	146	148	146	148	146	124	122
Adj. R2	0.164	0.243	0.117	0.205	0.063	0.070	0.158	0.196
<i>Panel C: Lead-lag relationship</i>								
IP	8.632***	8.886***	-1.382	-8.272**	6.350***	6.153***	3.685	4.775*
	(3.15)	(3.01)	(-0.40)	(-2.34)	(3.23)	(3.13)	(1.31)	(1.71)
UIP	4.932**	3.991	-3.753	-2.667	5.607***	5.726***	-0.031	2.378
	(2.10)	(1.58)	(-1.24)	(-0.89)	(3.04)	(3.09)	(-0.01)	(0.89)
INF	1.806*	1.851*	0.345	-2.837**	0.294	0.291	-0.069	-0.066
	(1.90)	(1.80)	(0.28)	(-2.34)	(0.32)	(0.33)	(-0.05)	(-0.05)
INFSHOCK	1.017*	0.824	-0.404	-2.639***	0.150	-0.059	-0.224	0.189
	(1.71)	(1.28)	(-0.53)	(-3.62)	(0.32)	(-0.13)	(-0.35)	(0.29)

Table 9 Liquidity, behavioral and sentiment factors

This table reports factor loadings of strategy returns on liquidity, anchoring bias and market sentiments. Panel A reports regression results on Amihud illiquidity (AI), computed as the ratio of monthly return to RMB volume in absolute term based on the front-contract and the 3rd nearest contracts accordingly. The RMB volume is scaled to the nearest 1 million RMB. Panel B reports loadings on the 52-week high momentum (HMOM), a proxy of anchoring bias as proposed by Bianchi *et al.* (2016). The 52-week high momentum signal is the ratio of the current price to the highest price in the past 12 months. HMOM is constructed by taking long (short) positions in commodities that are nearest (furthest) to their 52-week highs. Panel C reports the results on OVX, which denotes the CBOE crude oil volatility index that measures the market expectation of 30-day volatility of crude oil prices. Panel D reports loadings on CHIX, which denotes the AlphaShares Chinese volatility index that measures the implied volatility of options on the FTSE Xinhua China 25 and Hang Seng indices. We report results on m^{th} nearest to maturity contracts, where $m=1$ and 3. The t -statistics (in parentheses) are estimated using the Newey and West (1987) procedure (***) $p<0.01$, (**) $p<0.05$, (*) $p<0.1$). The sample period covers February 2004 through to May 2017.

	Term Structure		Hedging Pressure		Momentum		Volatility	
	$m=1$	$m=3$	$m=1$	$m=3$	$m=1$	$m=3$	$m=1$	$m=3$
<i>Panel A: Amihud illiquidity</i>								
AI	-0.354*	-0.417**	0.178	0.049	-0.131	-0.353	-0.302*	-0.028
	(-1.90)	(-2.41)	(0.78)	(0.24)	(-0.57)	(-1.28)	(-1.74)	(-0.12)
Constant	0.017***	0.015***	0.000	0.006	0.020***	0.017***	0.013***	0.004
	(2.90)	(3.28)	(0.06)	(1.53)	(2.62)	(3.04)	(2.65)	(0.77)
Observations	159	157	159	157	148	146	124	122
R2	0.012	0.019	0.005	0.000	0.002	0.011	0.014	0.000
<i>Panel B: Anchoring</i>								
HMOM	-0.002	-0.057	-0.109	0.190	0.420***	0.619***	-0.180	-0.241
	(-0.01)	(-0.30)	(-1.60)	(1.61)	(3.24)	(4.70)	(-1.41)	(-1.46)
Constant	0.013***	0.012***	0.005	0.004	0.014***	0.008**	0.010***	0.006
	(2.81)	(3.55)	(1.43)	(1.48)	(3.42)	(2.43)	(2.78)	(1.49)
Observations	147	145	147	145	147	145	124	122
R2	0.000	0.004	0.021	0.072	0.171	0.382	0.049	0.081
<i>Panel C: OVX</i>								
OVX	-0.005	-0.023	0.007	0.053	0.048	0.033	-0.039	-0.043
	(-0.11)	(-0.54)	(0.35)	(1.47)	(1.53)	(1.28)	(-1.32)	(-1.14)
Constant	0.009	0.008*	0.003	0.005	0.015***	0.009**	0.009**	0.004
	(1.62)	(1.76)	(0.83)	(1.33)	(2.78)	(2.15)	(2.31)	(0.94)
Observations	120	118	120	118	120	118	120	118
R2	0.000	0.006	0.001	0.044	0.026	0.012	0.022	0.025
<i>Panel D: CHIX</i>								
CHIX	-0.026	-0.017	0.007	0.012	0.002	0.012	-0.041**	-0.041*
	(-1.01)	(-0.78)	(0.28)	(0.45)	(0.09)	(0.43)	(-2.05)	(-1.79)
Constant	0.013**	0.011***	0.002	0.007*	0.018***	0.014***	0.008**	0.004
	(2.59)	(2.83)	(0.69)	(1.91)	(3.32)	(2.93)	(2.29)	(0.84)
Observations	159	157	159	157	148	146	124	122
R2	0.008	0.004	0.001	0.003	0.000	0.002	0.035	0.035

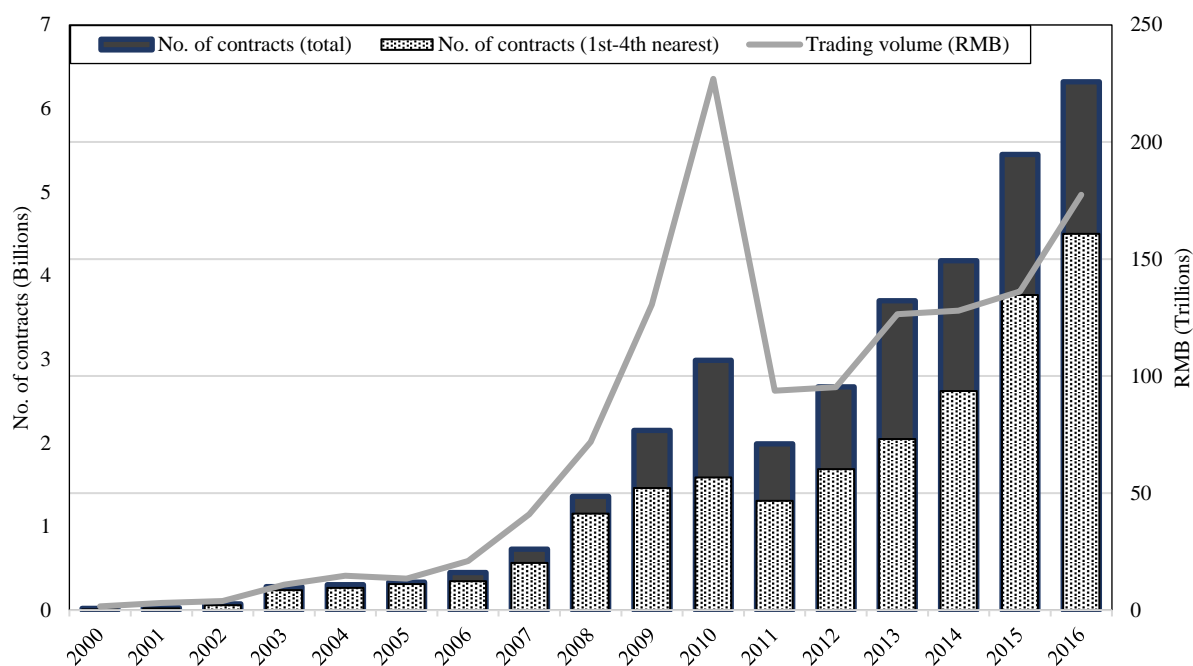


Figure 1 Annual trading volumes

This figure illustrates the annual trading volume of commodity futures in China. The line plot exhibits the total trading volume (expressed in trillions of RMB) of 48 commodity futures contracts which progressively entered the market. The solid bar plot represents the total number of contracts traded across the futures curve based on our sample of 30 commodities whereas the patterned bars plot the number of contracts from 1st to 4th nearest to maturity contracts. Data on annual RMB trading volume are obtained from the China Futures Association.

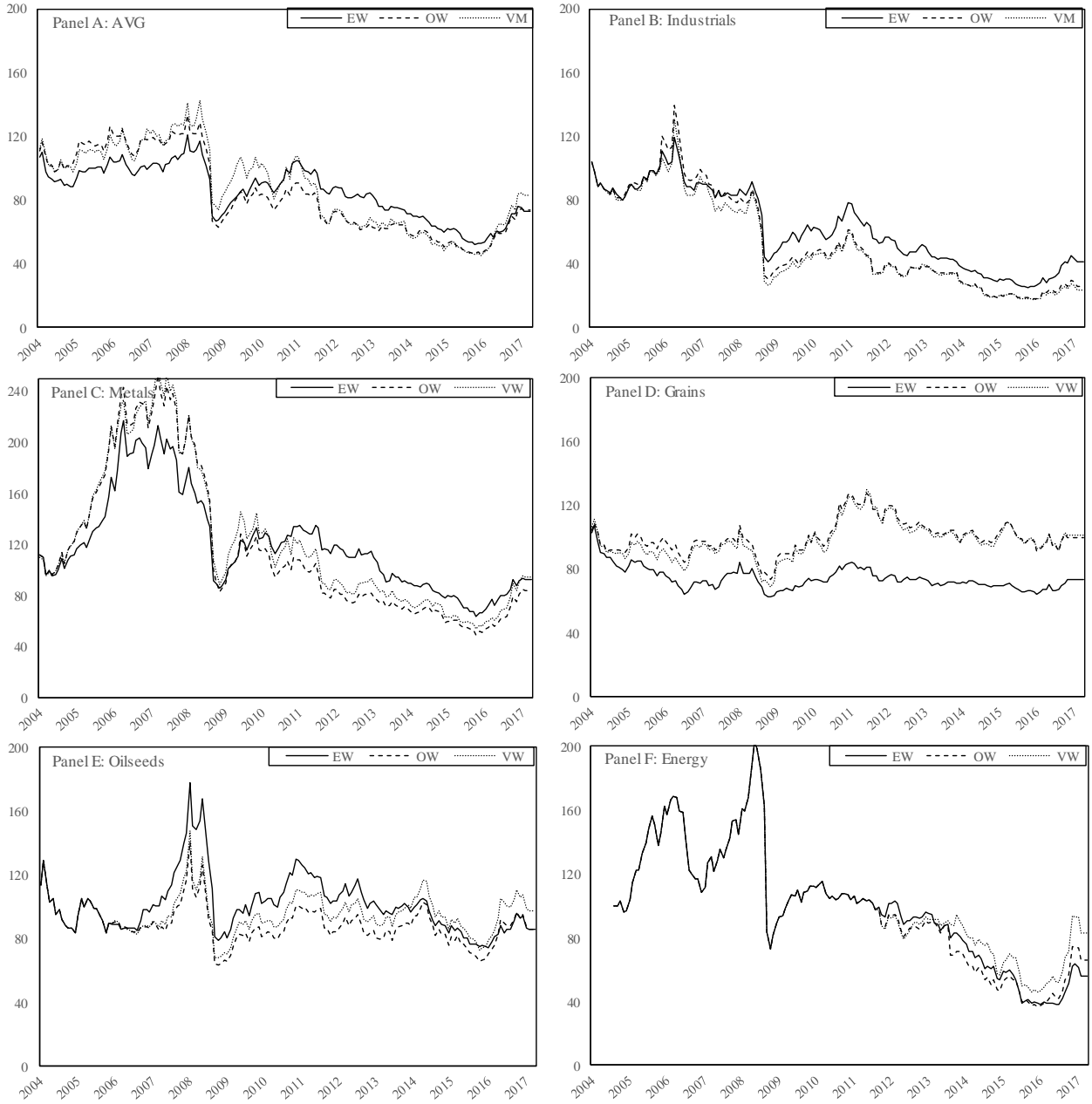


Figure 2 Performance of passive long-only investments

This figure illustrates the cumulative performance of the passive long-only commodity portfolios in China. Panel A exhibits the broad market performance (AVG). Panels B through to F illustrate the performance of industrials, metals, grains, oilseeds and energies, respectively. Within each panel, we construct equal-weighted, open interest- and volume-weighted portfolios, respectively. The unit value index (UVI) at time t is computed as $UVI_t = UVI_{t-1} (1 + R_t)$, with an initial value of 100. R_t denotes the index return at time t . For equally-weighted portfolios, $R_t = \frac{1}{N} \sum r_{t,i}$ where N is the number of commodities at time t and $r_{t,i}$ is the return of commodity i at time t . For open interest- and volume-weighted portfolios, the $R_t = \frac{\sum a_{t,i} r_{t,i}}{A_t}$ where $a_{t,i}$ denotes the open interest or volume of commodity i at time t and A_t is the open interest of all commodities at time t . All the portfolios are constructed based on the third nearest to maturity contracts. The sample period covers 2004 through to 2017.

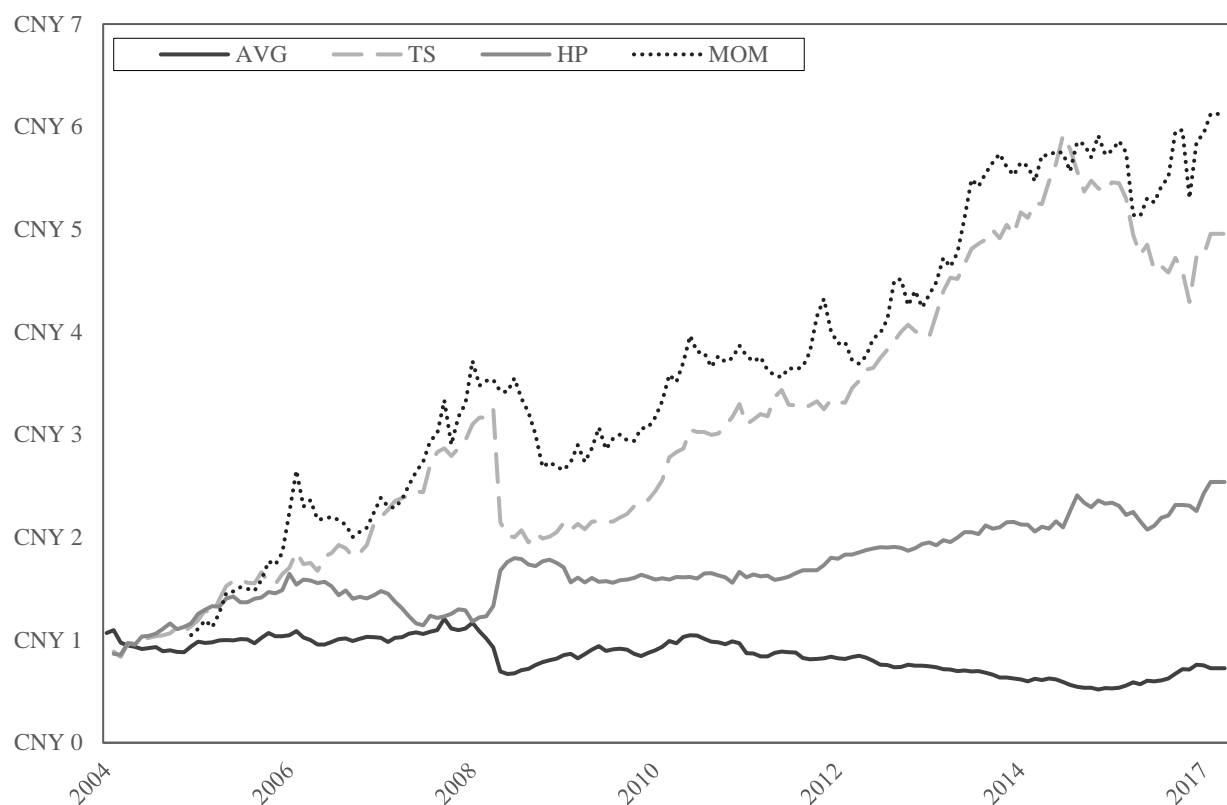


Figure 3 Cumulative returns

This figure illustrates the future value of 1 RMB invested in long-only and long-short strategies. AVG denotes the equally-weighted portfolio of 30 commodities. To construct strategy portfolios, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the top (bottom) quartile. All portfolios are equally weighted and rebalanced monthly. The term structure signal is the roll-yield from the front to the next nearest contract. The hedging pressure signal is the change of open interest divided by volume. The momentum signal is past 12-month returns. All portfolios are evaluated based on the third nearest contracts. The sample period covers February 2004 through to May 2017.

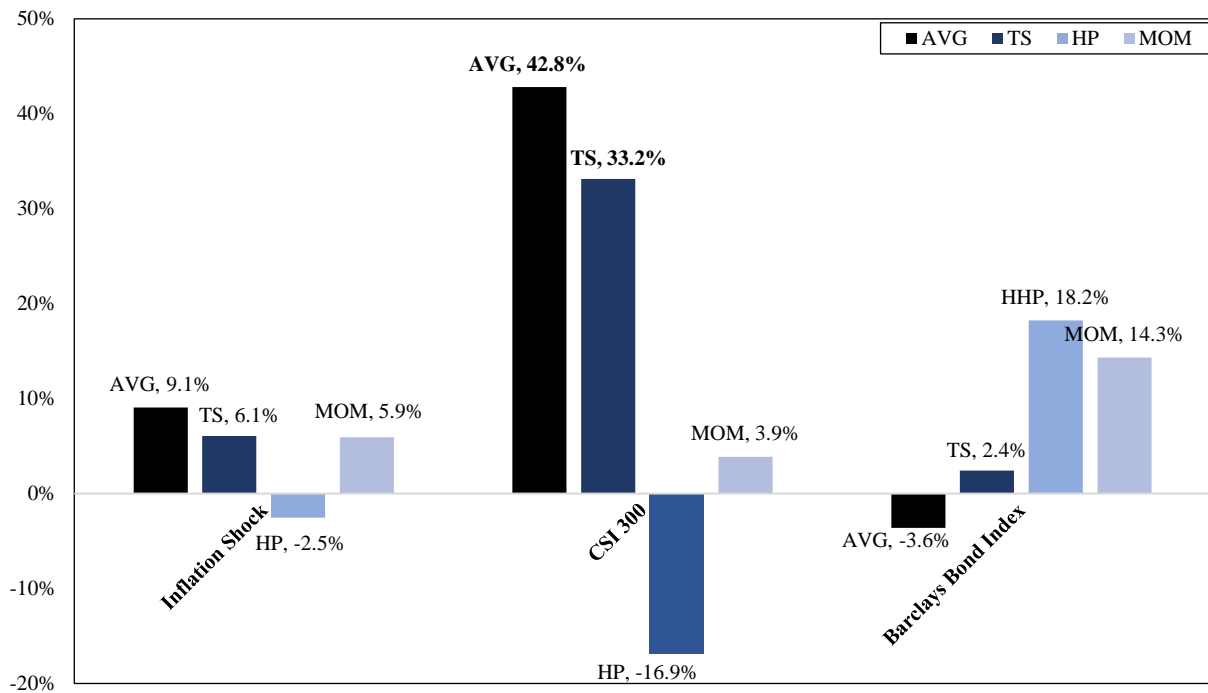


Figure 4 Correlations with stocks, bonds and inflation

This figure illustrates the pairwise correlations of strategy returns with equity, bond returns and changes in unexpected inflation. The inflation shock is the difference between actual and forecasted inflation estimated by Bloomberg. The CSI 300 consists of top 300 stocks traded on the Shanghai and Shenzhen stock exchanges. The Barclays China Aggregate Index covers fixed-rate treasury, government and corporate bonds. AVG denotes the equally-weighted portfolio of 30 commodities. TS, HP and MOM denote the term structure, hedging pressure and momentum strategies, respectively. All portfolios are evaluated based on the third nearest contracts. The sample period covers February 2004 through to May 2017. Bold indicates significance at 5% level or better.

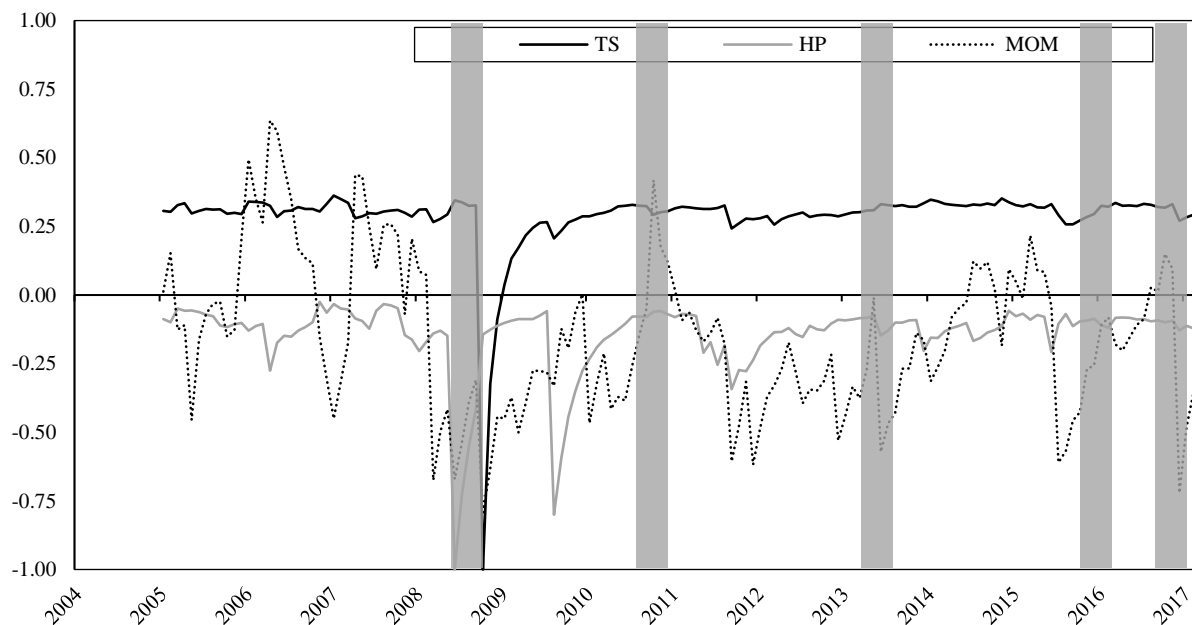


Figure 5 Time-varying correlation

This figure illustrates the dynamic correlations between long-short strategies returns and the CSI 300. The correlations are estimated using the ADCC-GARCH (1,1) model. TS, HP and MOM denote the term structure, hedging pressure and momentum strategies, respectively. The shaded areas represent periods of stock market stress. The sample period covers February 2004 through to May 2017.

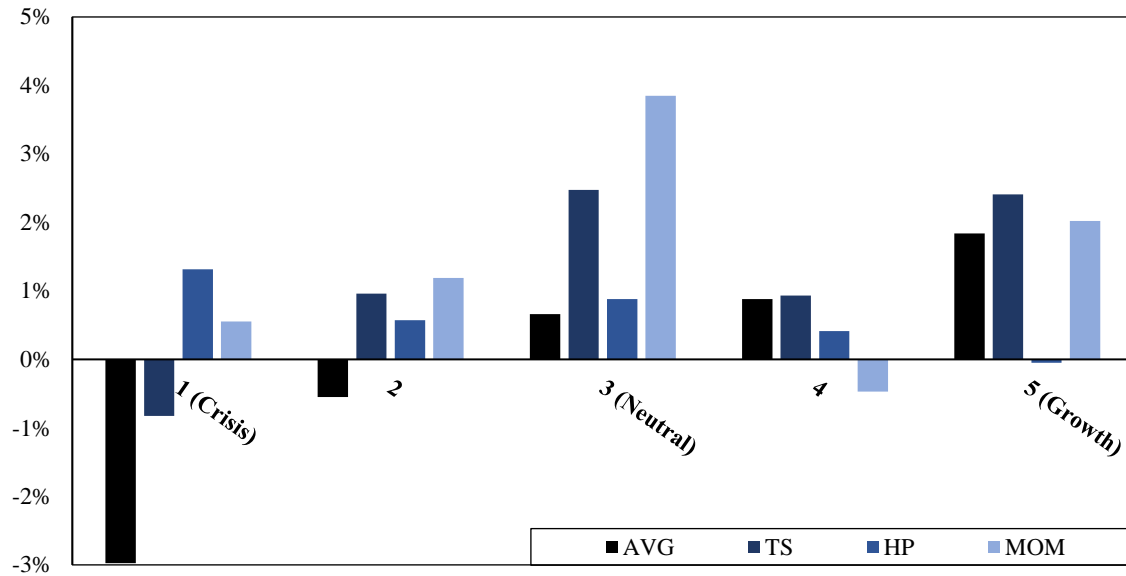


Figure 6 Extreme market conditions

This figure demonstrates the performance of long-only and long-short strategies under five different market conditions measured by the CSI300 index whose returns are sorted into quintiles (Q1-5). Crisis (Growth) represents periods when the CSI300 reported the lowest (highest) average monthly return. AVG denotes the equally weighted portfolio of 30 commodities. TS, HP and MOM denote the term structure, hedging pressure and momentum strategies, respectively. All commodity portfolios are evaluated based on the third nearest contracts. The sample period covers February 2004 through to May 2017.

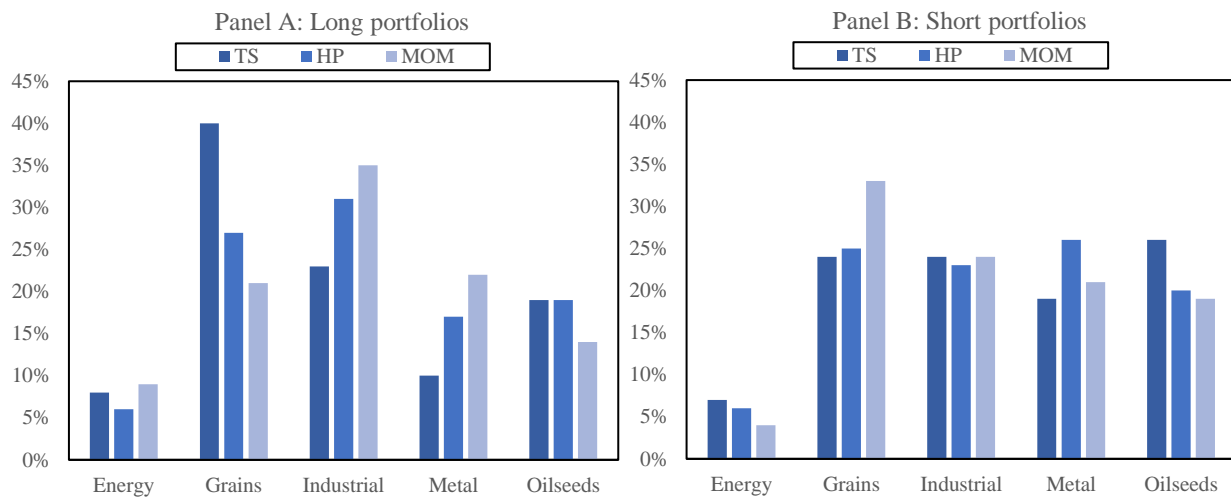


Figure 7 Percentage of total trades

This figure illustrates the percentage of total trades of long-short strategies. Panel A exhibits long portfolios whereas Panel B exhibits short portfolios. TS, HP and MOM denote the term structure, hedging pressure and momentum strategies, respectively. All strategies are evaluated based on the third nearest contracts. The sample period covers February 2004 through to May 2017.

Internet Appendix

The Untold Story of Commodity Futures in China

John Hua Fan* and Tingxi Zhang

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*Corresponding author. Address: Department of Accounting, Finance and Economics, Griffith Business School, Griffith University, Nathan Campus, 170 Kessels Road, Nathan, Queensland 4111, Australia. Tel: +61 (0)7 3735 3948; Fax: +61 (0)7 3735 7760; E-mail: j.fan@griffith.edu.au.

Appendix I Matched sample of Chinese and US commodities

This table reports a side-by-side comparison between China and the US markets. Panel A reports the returns on the nearest and the third nearest markets. Term premia is the spreading returns between the third and the first nearest contracts. Panel B reports the basis, spot volatility and hedging pressure. The basis is measured using the first and the second nearest contracts. The spot volatility is computed as the monthly average 3-year rolling standard deviation. The hedging pressure is proxied through the speculation ratio for both US and Chinese markets. Panel C reports the price based characteristics such as past returns, value and skewness, computed using signals discussed in the manuscript. Hedging pressure, past returns, value and skewness are computed using the first (third) nearest contracts for the US (China). We report the difference-in-mean (*Diff*) and Pearson correlations (*Corr*). * indicate statistical significance at 10% or better. *N* denotes the number of overlapping observations in both markets. For soybean and wheats, we use the same commodity in the other market to measure the difference and correlations.

China	US	CN	US	Diff	Corr.	N	CN	US	Diff	Corr.	N	CN	US	Diff	Corr.	N
<i>Panel A: Risk premia</i>		1st Nearby (%)					3rd Nearby (%)					Term premia (%)				
Corn	Corn	-0.38	0.05	-0.43	0.11	151	-0.03	0.32	-0.35	0.35*	147	0.21	0.12*	0.09	-0.11	147
No.1 Soybean	Soybean	-0.35	0.92	-1.27*	0.48*	159	0.30	0.79	-0.48	0.67*	155	0.27*	-0.15	0.42*	-0.05	155
No.2 Soybean		0.73		-0.35	0.43*	148	0.47		-0.48	0.62*	144	-0.23		-0.08	0.08	144
Coal	Coal	0.09	-1.22	1.31	0.11	44	-0.11	-1.46	1.35	0.16	44	-0.25	-0.14	-0.11	-0.09	44
Strong Wheat	SRW Wheat	-0.80	-0.69	-0.11	0.18*	159	-0.56	-0.28	-0.28	0.26*	155	0.10	0.19*	-0.09	-0.01	155
Common Wheat	HRW Wheat	-1.35	-0.19	-1.16	0.10	159	-0.47	-0.03	-0.43	0.19*	153	0.54*	0.05	0.49*	-0.04	153
	HRS Wheat		0.63	-1.98*	0.09	159		0.23	-0.69	0.17*	153		-0.29*	0.83*	0.02	153
Soybean Meal	Soybean meal	0.99	1.53	-0.53	0.63*	159	0.66	1.21	-0.55	0.75*	154	-0.21	-0.28*	0.07	-0.04	154
Soybean Oil	Soybean oil	-0.09	0.07	-0.16	0.71*	135	0.08	0.16	-0.08	0.86*	131	-0.05	0.00	-0.04	0.06	131
Cotton	Cotton	-0.17	0.42	-0.59	0.51*	154	-0.20	0.33	-0.52	0.64*	150	-0.01	-0.05	0.04	0.17*	150
Sugar	Sugar	-0.07	-0.31	0.24	0.48*	135	-0.35	0.24	-0.58	0.48*	131	-0.16	0.23*	-0.39*	-0.14*	131
Fuel Oil	Heating oil	-0.94	-0.13	-0.81	0.38*	142	-0.06	0.19	-0.25	0.45*	151	0.39	0.10*	0.30	0.09	140
Gold	Gold	0.10	0.32	-0.22	0.91*	109	-0.23	0.24	-0.47	0.60*	95	-0.08	0.03	-0.11	-0.12	91
Copper	Copper	0.86	1.05	-0.19	0.89*	160	0.77	0.99	-0.22	0.92*	158	-0.02	-0.06*	0.04	-0.07	158
Silver	Silver	-1.08	-0.78	-0.30	0.88*	59	-0.88	-0.54	-0.34	0.70*	57	0.02	0.04	-0.02	-0.21	55
	Average	-0.18	0.12	-0.44	0.46		-0.04	0.17	-0.29	0.52		0.04	-0.02	0.10	-0.03	
<i>Panel B: Commodity characteristics</i>		Basis (%)					Spot Volatility (%)					Hedging Pressure (%)				
Corn	Corn	-0.93	-1.94	1.01	-0.01	150	0.62	1.93	-1.31*	-0.09	116	7.2	9.5	-2.2*	-0.11	147
No.1 Soybean	Soybean	-0.53	0.43	-0.95*	0.14*	157	0.87	1.57	-0.70*	0.82*	122	8.6	8.1	0.5	0.07	155
No.2 Soybean		0.73		0.43	0.21*	147	1.20		-0.38*	0.86*	113	12.0		4.1*	-0.08	136
Coal	Coal	-0.57	-0.54	-0.03	-0.08	43	1.29	0.73	0.56*	0.11	8	6.5	2.5	4.0*	-0.03	31
Strong Wheat	SRW Wheat	-2.06	-2.77	0.72	0.09	157	0.69	2.12	-1.43*	-0.11	122	10.7	10.4	0.3	-0.14*	152
Common Wheat	HRW Wheat	-2.79	-1.61	-1.19*	0.04	157	0.84	1.92	-1.08*	0.01	122	13.5	15.0	-1.5	-0.03	131
	HRS Wheat		-0.08	-2.72*	-0.01	157		1.80	-0.96*	0.17*	122		16.0	-2.5	0.07	131
Soybean Meal	Soybean meal	1.38	1.24	0.14	0.13	157	1.15	1.79	-0.64*	0.87*	122	9.0	9.8	-0.8	0.02	154
Soybean Oil	Soybean oil	-0.19	-0.74	0.55	-0.32*	134	1.26	1.50	-0.24*	0.97*	100	10.9	10.9	0.0	-0.08	130
Cotton	Cotton	-0.20	-0.90	0.69	0.25*	153	0.82	1.79	-0.97*	0.72*	120	7.7	21.3	-13.7*	0.14*	150
Sugar	Sugar	-0.37	-1.04	0.67	0.23*	134	0.98	2.05	-1.07*	0.84*	100	4.2	6.7	-2.5*	0.14	130
Fuel Oil	Heating oil	-1.24	-0.63	-0.61	0.07	142	1.60	1.90	-0.30*	0.40*	118	8.9	7.5	1.4	-0.16*	142
Gold	Gold	-0.02	-0.07	0.05	-0.04	109	1.16	1.17	-0.01	0.86*	77	7.7	9.4	-1.6	-0.08	95
Copper	Copper	0.48	0.20	0.28*	0.25*	159	1.42	1.88	-0.46*	0.98*	123	5.4	11.9	-6.6*	0.15*	158
Silver	Silver	-0.40	-0.10	-0.29*	-0.29*	58	1.26	1.72	-0.46*	0.86*	25	8.0	8.1	-0.1	0.16	57
	Average	-0.48	-0.61	-0.08	0.04		1.08	1.70	-0.63	0.55		8.6	10.5	-1.4	0.00	
<i>Panel C: Price-based characteristics</i>		Past returns (%)					Value (%)					Skewness				
Corn	Corn	-1.11	0.87	-1.99	0.46*	136	-15.8	-4.9	-10.9	0.84*	94	0.029	0.082	-0.05	0.26*	136
No.1 Soybean	Soybean	3.28	11.95	-8.66*	0.79*	143	-13.2	-15.7	2.5	0.87*	102	-0.085	-0.080	-0.01	0.39*	143
No.2 Soybean		4.16		-9.39*	0.79*	133	-3.7		7.3*	0.89*	91	-0.251		-0.18*	0.19*	133
Coal	Coal	-15.71	-15.24	-0.46	-0.18	33						-0.119	-1.609	1.49	-0.09	32
Strong Wheat	SRW Wheat	-6.51	-6.72	0.21	0.33*	143	-18.9	-2.5	-16.4*	0.41*	102	-0.209	0.182	-0.39*	-0.18*	143
Common Wheat	HRW Wheat	-5.06	0.31	-5.37	0.10	143	-20.0	-1.6	-18.4*	0.49*	102	-0.341	0.179	-0.52*	-0.19*	143
	HRS Wheat		11.19	-16.24*	0.16*	143		-2.5	-17.5*	0.45*	102		0.394	-0.74*	0.09	143
Soybean Meal	Soybean meal	7.78	20.26	-12.47*	0.79*	143	-6.8	-21.8	15.0*	0.89*	102	-0.024	0.088	-0.11*	0.45*	143
Soybean Oil	Soybean oil	-0.57	1.08	-1.65	0.93*	120	12.1	8.5	3.6	0.95*	78	-0.239	0.159	-0.40*	0.27*	120
Cotton	Cotton	-3.41	6.39	-9.80*	0.86*	139	-1.7	-8.5	6.8	0.88*	98	-0.165	-0.075	-0.09	0.19*	140
Sugar	Sugar	-1.83	-0.64	-1.19	0.66*	120	-17.6	-7.6	-10.0	0.92*	78	0.016	0.003	0.01	0.71*	120
Fuel Oil	Heating oil	-3.89	-1.22	-2.67	0.74*	140	2.9	5.5	-2.6	0.81*	98	-0.227	0.080	-0.31*	-0.06	140
Gold	Gold	-0.74	5.26	-6.00*	0.94*	99	2.0	3.1	-1.1	0.99*	56	-0.216	-0.248	0.03	0.83*	99
Copper	Copper	7.41	15.60	-8.20*	0.93*	146	5.1	1.0	4.1	0.88*	105	-0.267	-0.048	-0.22*	0.33*	146
Silver	Silver	-13.93	-11.02	-2.91	0.93*	47	34.7	28.2	6.4	0.94*	5	-0.101	-0.155	0.05	0.76*	47
	Average	-2.15	2.72	-5.79	0.61		-3.14	-1.43	-2.22	0.79		-0.157	-0.075	-0.095	0.26	

Appendix II Delivery warehouses

This table presents the number of authorized warehouses for delivery for each commodity in our sample. These warehouses across 25 provinces/municipalities, namely, Shanghai (SH), Jiangsu (JS), Zhejiang (ZJ), Guangdong (GD), Jiangxi (JX), Shandong (SD), Tianjin (TJ), Henan (HN), Chongqing (CQ), Yunnan (YN), Hainan (HAN), Xinjiang (XJ), Hubei (HUB), Hebei (HEB), Anhui (AH), Guangxi (GX), Beijing (BJ), Liaoning (LN), Shaanxi (SAX), Fujian (FJ), Sichuan (SC), Neimeng (NM), Shanxi (SX), Jilin (JL) and Heilongjiang (HLJ). * indicates municipalities.

Exchange	Sector	Commodity	SH*	JS	ZJ	GD	JX	SD	TJ*	HN	CQ	YN	HAN	XJ	HUB	HEB	AH	GX	BJ*	LN	SAX	FJ	SC	NM	SX	JL	HLJ	Total
DCE	Grains	No.1 Soybean																		6			1		1	7	15	
DCE	Grains	No.2 Soybean		1				3												3							7	
DCE	Grains	Corn																		9			1		6	3	19	
DCE	Industrial	LLDPE	6	2	5	5		3	4		1																26	
DCE	Industrial	PVC	6	3	4	4																					17	
DCE	Industrial	Metallurgical Coke		2				4	3							7								5			21	
DCE	Industrial	Coking Coal		1				2	2							3								2			10	
DCE	Oil Seeds	Soybean Meal		11		9		3	4																		27	
DCE	Oil Seeds	RBD Palm Olein		9		5			5																		19	
DCE	Oil Seeds	Soybean Oil		9	1			5	5							2											22	
SHFE	Energy	Fuel Oil	1		2	5																					8	
SHFE	Industrial	Natural Rubber	9					8	2			1	2														22	
SHFE	Metal	Aluminum	13	8	5	5		3	3	6	2																45	
SHFE	Metal	Gold																									39	
SHFE	Metal	Copper	13	5	2	2	1																				23	
SHFE	Metal	Lead	6	2	3	3			3																		17	
SHFE	Metal	Steel Rebar	2	4	3	1			1																		11	
SHFE	Metal	Steel Wire Rod		3	2				2																		7	
SHFE	Metal	Zinc	10	4	4	4																					22	
SHFE	Metal	Silver	2																								2	
ZCE	Energy	Methanol		13		3		2		1						2						1		2			24	
ZCE	Grains	White Sugar		3	1	2		4	2	1		3			1	4		8	2	2	2						35	
ZCE	Grains	Strong Gluten Wheat		2				2		5						4					1						14	
ZCE	Grains	Common Wheat		2				2		5						3	1				1						14	
ZCE	Industrial	Cotton No.1		5	1			4		4				3	2	1	1										21	
ZCE	Industrial	PTA		10	10															2		1					23	
ZCE	Industrial	Flat Glass			1			4							3	8									1		17	
ZCE	Oil Seeds	Rapeseed Oil		5		2					1				2		2	3			1	3	3				22	
ZCE	Oil Seeds	Rapeseed Meal		2		2									3		2	3				3	1				16	
ZCE	Oil Seeds	Rapeseed		2											3		2						1				8	

Appendix III Alternative returns measurements

Following Szymanowska *et al.* (2014), we measure holding, short roll, spreading and excess holding.

Holding represents holding a contract i at time t until its maturity. For an m^{th} ($m=1,2,3,4$) exposure, holding means to hold the m^{th} contract until maturity, then roll over to the next m^{th} contract. We define the holding return as

$$r_{t \rightarrow t+n}^{(n)} = \ln P_{t+n} - \ln P_t \quad (A1)$$

Where $r_{t \rightarrow t+n}^{(n)}$ represents the return of buying a futures contract maturing in n periods at time t and holding it until time $t+n$ (maturity). P_{t+n} and P_t denote the prices at which the contract is sold at time $t+n$ and bought at time t .

Short Roll represents buying a contract maturing in the next period for n consecutive periods. Therefore, short roll return for n periods can be written as

$$Short\ roll = \sum_{j=1}^n r_{t+j}^{(1)} \quad (A2)$$

An n -period short roll return can be interpreted as the sum of the return of investing a one-period contract during this n -period time. The concept of “one-period contract” in Szymanowska *et al.* (2014) does not necessarily refer to a contract maturing in the next month but corresponds to the m^{th} series exposure in this paper. $r_{t+j}^{(1)}$ stands for the return of a futures contract that is the nearest to maturity along the curve at time $t+j$. Similarly, $r_{t+j}^{(m)}$ represents the return of an m^{th} contract at time $t+j$. It is important to clarify the difference between the rolling procedure behind holding and short roll (the technique applied in the main body of the paper). The holding roll is to maintain a position regardless the contract’s status on the curve, while our rolling (or short roll) constantly ensures the contract property of being the m^{th} nearest contract is valid. Therefore, holding strategy implemented on the nearest contract is the same as the short roll strategy applied to front contract, which implies there are no term premia in the nearby contract.

Spreading Return is a proxy for term premia. Since no term premia exist in the front contract, we will take the third nearby contract as an example. First, spreading return is based on the short roll. As defined by Szymanowska *et al.* (2014), spreading is a combination of taking long position(s) on distant contract(s) and short position(s) on nearby contract(s). To isolate the term premia from an investment on the third nearest contracts, we long the third nearest and short the second nearest contract. This implicitly suggests a time-varying risk embedded in the term premia, since the term structure may not be perfectly linear. Ultimately, spreading return for m^{th} exposure can be expressed as

$$Spreading = \frac{1}{m} \sum_{m=1}^n \sum_{j=1}^n (r_{t+j}^m - r_{t+j}^1) \quad (A3)$$

Where $\frac{1}{m}$ scales the term premia earned at different points of futures curve to per unit of maturity.

Excess holding is an alternative measurement for term premia. It is the difference between m^{th} holding and m^{th} short roll. Recall that holding strategy does not involve rolling before the maturity, m^{th} holding will evolve from m^{th} short roll to the 1st short roll as maturity approaches from a short-roll perspective. As a result, excess holding is earning the term premia from m^{th} , $(m-1)^{th}$ to 2nd consecutively, until it becomes the nearby contract. In contrast, the spreading return earns $\frac{1}{m}$ of each of the m^{th} term premia at each point in time. Excess holding can be written as

$$Excess\ holding = r_{t \rightarrow t+n}^{(n)} - \sum_{j=1}^n r_{t+j}^{(1)} \quad (A4)$$

Appendix IV Decomposing risk premia

This table reports results based on alternative return measurements including holding return (Panel A), shot roll (Panel B), spreading return (Panel C) and excess holding return (Panel D). The sorting signals used to construct long-short portfolios remain the same as our main results. Holding return is calculated in the way that holds m^{th} contract until maturity instead of rolling over to the next m^{th} contract. Short roll is the same as our main result. Spreading return derives from a strategy that buys m^{th} (>1) contract and shorts the nearby contract at each period, while the excess return is the difference between holding and short roll returns. Appendix II provides a formal description of all return metrics.

	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness	Value
<i>Panel A: Holding</i>										
Mean	0.2002	0.0552	0.2036	<i>Second nearest contracts (m=2)</i>		0.0041	0.0262	0.0085	-0.0589	0.0593
<i>t</i> -statistics	4.40	1.45	3.96	0.0954	-0.0548	0.08	0.42	0.16	-1.42	0.96
				<i>Third nearest contracts (m=3)</i>						
Mean	0.1810	-0.0058	0.1932	0.0802	-0.044	0.0103	-0.0134	0.0446	-0.0202	0.1046
<i>t</i> -statistics	4.20	-0.13	3.82	1.85	-1.14	0.26	-0.20	0.94	-0.51	1.76
				<i>Fourth nearest contracts (m=4)</i>						
Mean	0.1717	0.0446	0.1692	0.0785	-0.0264	-0.0302	0.0273	0.0513	-0.0627	0.0940
<i>t</i> -statistics	4.02	0.82	3.19	1.78	-0.70	-0.76	0.40	1.04	-1.60	1.65
<i>Panel B: Short roll</i>										
Mean	0.1753	0.0273	0.1738	<i>Second nearest contracts (m=2)</i>		-0.0070	0.0104	-0.0005	0.0270	0.0857
<i>t</i> -statistics	3.94	0.74	3.59	0.0689	-0.0558	-0.15	0.17	-0.01	0.71	1.42
				<i>Third nearest contracts (m=3)</i>						
Mean	0.1379	0.0811	0.1671	0.0485	-0.0311	-0.021	0.0153	0.0477	0.0152	0.0992
<i>t</i> -statistics	3.01	2.06	3.10	1.07	-0.95	-0.47	0.26	1.00	0.42	1.61
				<i>Fourth nearest contracts (m=4)</i>						
Mean	0.1169	-0.0078	0.1526	0.0478	-0.0553	-0.0434	0.0081	0.0200	-0.0098	0.0980
<i>t</i> -statistics	2.57	-0.21	2.75	1.02	-1.64	-1.31	0.15	0.41	-0.25	1.57
<i>Panel C: Spreading</i>										
Mean	0.0053	0.0027	-0.0283	<i>Second nearest contracts (m=2)</i>		-0.0127	-0.0040	-0.0078	0.0103	-0.0010
<i>t</i> -statistics	0.52	0.28	-2.66	-0.0155	-0.0129	-1.10	-0.33	-0.48	1.21	-0.08
				<i>Third nearest contracts (m=3)</i>						
Mean	-0.0040	0.0068	-0.0412	-0.0301	-0.0071	0.0125	-0.0290	-0.0349	0.0072	0.0171
<i>t</i> -statistics	-0.29	0.53	-2.68	-2.06	-0.53	0.92	-1.39	-1.90	0.62	0.96
				<i>Fourth nearest contracts (m=4)</i>						
Mean	-0.0114	0.0098	-0.0313	-0.0379	-0.0089	0.0400	-0.0265	-0.0258	0.0291	0.0087
<i>t</i> -statistics	-0.72	0.59	-1.58	-1.95	-0.53	2.66	-1.28	-1.21	1.79	0.39
<i>Panel D: Excess holding</i>										
Mean	0.0179	0.0331	0.0298	<i>Second nearest contracts (m=2)</i>		-0.0306	0.0090	0.0060	-0.0787	-0.0266
<i>t</i> -statistics	0.76	0.74	1.16	0.0220	0.0072	-1.06	0.29	0.15	-2.99	-1.10
				<i>Third nearest contracts (m=3)</i>						
Mean	0.0512	-0.0856	0.0288	0.0395	-0.0038	-0.0057	-0.0081	0.0027	-0.0347	0.0051
<i>t</i> -statistics	2.14	-2.06	1.05	2.16	-0.24	-0.15	-0.27	0.09	-1.05	0.20
				<i>Fourth nearest contracts (m=4)</i>						
Mean	0.0450	0.0466	0.0056	0.0263	0.0249	-0.0221	0.0290	0.0348	-0.0437	0.0134
<i>t</i> -statistics	1.96	0.84	0.21	1.40	1.33	-0.53	0.85	0.82	-1.21	0.45

Appendix V Market liquidity

This table reports the performance of long-short strategies executed on a restricted sample of the top 20 most liquid commodities. We eliminate 10 most illiquid commodities with the lowest average trading volume. Panel A reports results on the first nearest to maturity contract whereas Panel B reports the third nearest contract. For each strategy, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the top (bottom) quartile. All portfolios are equally weighted and rebalanced monthly. The term structure signal is based on the roll-yield from the front to the next nearest contract. The Hedging pressure signal is the change of open interest divided by volume. The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on prior 3-year daily returns. The open interest signal is computed as the change of monthly open interests of the entire curve. The liquidity signal is the Amivest measure is computed as the average ratio of monthly turnover to absolute return in the past 2 months using daily returns. The FX signal is the regression beta of commodity returns on the RMB effective exchange rate index, with a rolling window of 42 months. The inflation signal is the regression beta of commodity returns on unexpected inflation with a rolling window of 42 months. The skewness signal is computed as the Pearson skewness based on the past 12-month daily return. Finally, the value signal is obtained by taking the log of the average daily prices from 3.5 to 4.5 years ago divided by the price at each time t . The sample period covers February 2004 through to May 2017.

	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness	Value
<i>Panel A: First nearest contract (m=1)</i>										
Annualized arithmetic mean	0.1895	0.0098	0.2193	0.0704	-0.0338	0.0206	-0.0708	-0.0369	-0.0917	0.0165
<i>t</i> -statistics	3.71	0.22	3.46	1.56	-0.72	0.39	-1.02	-0.60	-1.77	0.24
Annualized geometric mean	0.1726	-0.0028	0.1958	0.0599	-0.0485	0.0029	-0.0961	-0.0554	-0.1085	-0.0033
Annualized volatility	0.1857	0.1602	0.2223	0.1454	0.1699	0.1901	0.2173	0.1931	0.1822	0.2053
Annualized downside volatility	0.1086	0.0889	0.1227	0.0961	0.1219	0.1190	0.1918	0.1350	0.1269	0.1083
Sharpe Ratio	1.0204	0.0612	0.9864	0.4838	-0.1988	0.1083	-0.3259	-0.1911	-0.5032	0.0806
Sortino Ratio	1.9041	0.1108	1.9791	0.7561	-0.2728	0.1745	-0.3575	-0.2686	-0.6925	0.1539
Skewness	0.1675	0.3559	0.9417	-0.0134	-0.5772	0.5855	-1.2530	0.2866	-0.2111	1.5780
Kurtosis	4.2658	3.2766	8.8849	3.8806	4.2150	5.7942	8.1232	7.9165	3.6290	10.3465
Max monthly gain	0.1982	0.1563	0.3756	0.1361	0.1152	0.2259	0.1692	0.2466	0.1236	0.3216
Max monthly loss	-0.1734	-0.0951	-0.1840	-0.1053	-0.1813	-0.1650	-0.3128	-0.2264	-0.1966	-0.1360
99% VaR(Cornish-Fisher)	0.203	0.1592	0.3441	0.1410	0.1355	0.2310	0.2123	0.2451	0.1483	0.3270
% of positive months	0.6352	0.4528	0.6351	0.5968	0.5127	0.4747	0.4831	0.4576	0.4324	0.4717
Maximum Drawdown	-0.2917	-0.4981	-0.3399	-0.2035	-0.5346	-0.5363	-0.6604	-0.4667	-0.8342	-0.4044
Drawdown Length (months)	4	82	12	4	89	95	16	23	117	44
Max Run-up (consecutive)	0.5410	0.1020	0.5717	0.3430	0	0.4068	0	0.2306	0.3750	0.3216
Run-up Length (months)	9	1	3	5	0	3	0	2	7	1
Max 12M rolling return	0.6805	0.3859	0.9828	0.5451	0.2640	0.4851	0.6626	0.3541	0.6002	0.4008
Min 12M rolling return	-0.2569	-0.3847	-0.3988	-0.1772	-0.3230	-0.3826	-0.7574	-0.3512	-0.5736	-0.3508
<i>Panel B: Third nearest contract (m=3)</i>										
Annualized arithmetic mean	0.1171	0.0195	0.2137	0.0596	0.0003	-0.0125	-0.0621	0.0686	-0.0195	0.0454
<i>t</i> -statistics	2.17	0.40	3.38	1.34	0.01	-0.26	-1.02	1.13	-0.40	0.69
Annualized geometric mean	0.098	0.0046	0.1903	0.0496	-0.0143	-0.0276	-0.0814	0.0511	-0.0337	0.0274
Annualized volatility	0.1955	0.1742	0.2205	0.1417	0.1671	0.1739	0.1896	0.1891	0.1691	0.1946
Annualized downside volatility	0.1326	0.1114	0.1318	0.0896	0.1308	0.1166	0.1728	0.1205	0.0911	0.1144
Sharpe Ratio	0.5989	0.1117	0.9691	0.4206	0.0018	-0.0721	-0.3276	0.3629	-0.1156	0.2334
Sortino Ratio	0.9319	0.1763	1.7902	0.6837	0.0022	-0.1070	-0.3494	0.5876	-0.2125	0.4054
Skewness	-0.2542	0.6379	0.5856	-0.0629	-1.1542	0.2026	-1.6807	0.3151	0.1314	1.3984
Kurtosis	5.3689	8.1748	6.9385	3.6362	11.1395	4.7034	8.4204	6.1396	2.8691	11.2215
Max monthly gain	0.2008	0.2676	0.3409	0.1200	0.1656	0.1989	0.0993	0.2129	0.1622	0.3149
Max monthly loss	-0.2362	-0.1835	-0.1632	-0.1039	-0.2925	-0.1322	-0.2678	-0.1957	-0.1106	-0.1629
99% VaR(Cornish-Fisher)	0.1979	0.2413	0.3008	0.1322	0.2026	0.1810	0.1898	0.2274	0.1512	0.3245
% of positive months	0.5796	0.5478	0.6301	0.5984	0.4872	0.4872	0.4741	0.5086	0.5274	0.5385
Maximum Drawdown	-0.3455	-0.5003	-0.3480	-0.2340	-0.5079	-0.6080	-0.5535	-0.3788	-0.6835	-0.3495
Drawdown Length (months)	18	19	13	7	59	101	16	56	81	22
Max Run-up (consecutive)	0.3705	0.2040	1.0239	0.2596	0.1830	0.1337	0	0.3498	0.2469	0.0549
Runup Length (months)	2	2	11	3	3	1	0	3	3	1
Max 12M rolling return	0.7017	0.5357	1.0862	0.3903	0.3537	0.2946	0.2598	0.6594	0.4692	0.3605
Min 12M rolling return	-0.3323	-0.5182	-0.3937	-0.2414	-0.3964	-0.5407	-0.4657	-0.2279	-0.3155	-0.2956

Appendix VI Commodity sectors

This table reports the performance of long-short strategies after removing one commodity sector at a time. Panels A through to E reports the strategy returns on non-industrials, non-metals, non-grains, non-oilseeds and non-energy sample of commodities, respectively. The results are based on the first nearest to maturity contracts. For each strategy, we sort commodities into quartiles based on the respective signal. At the end of each month, we take long (short) positions in commodities within the top (bottom) quartile. All portfolios are equally weighted and rebalanced monthly. The term structure signal is based on the roll-yield from the front to the next nearest contract. The Hedging pressure signal is the change of open interest divided by volume. The momentum signal is the past 12-month returns. The volatility signal is the coefficient of variation computed based on prior 3-year daily returns. The open interest signal is computed as the change of monthly open interests of the entire curve. The liquidity signal is the Amivest measure is computed as the average ratio of monthly turnover to absolute return in the past 2 months using daily returns. The FX signal is the regression beta of commodity returns on the RMB effective exchange rate index, with a rolling window of 42 months. The inflation signal is the regression beta of commodity returns on unexpected inflation with a rolling window of 42 months. The skewness signal is computed as the Pearson skewness based on the past 12-month daily return. Finally, the value signal is obtained by taking the log of the average daily prices from 3.5 to 4.5 years ago divided by the price at each time t . The sample period covers February 2004 through to May 2017.

	Term Structure	Hedging Pressure	Momentum	Volatility	Open Interest	Liquidity	FX	Inflation Shocks	Skewness	Value
<i>Panel A: Excluding industrials</i>										
Annualized arithmetic mean	0.1490	-0.0125	0.1979	0.1310	-0.0481	-0.0926	0.0713	0.0299	-0.0629	0.0551
t -statistics	3.10	-0.32	3.60	2.70	-1.08	-1.83	1.38	0.59	-1.33	0.95
Annualized volatility	0.1748	0.1418	0.1929	0.1559	0.1614	0.1834	0.1618	0.1588	0.1665	0.1722
Sharpe Ratio	0.8525	-0.0884	1.0255	0.8406	-0.2980	-0.5049	0.4407	0.1882	-0.3776	0.3202
Sortino Ratio	1.2010	-0.1402	1.7109	2.0495	-0.3706	-0.7031	0.5621	0.2790	-0.5185	0.4818
Skewness	-0.6112	0.0812	-0.0305	0.6377	-0.9620	-0.1451	-0.9402	-0.2832	-0.0154	0.1042
Kurtosis	5.3305	3.0150	4.7128	3.4483	6.2343	3.9249	7.0441	3.9459	3.5595	5.2988
<i>Panel B: Excluding metals</i>										
Annualized arithmetic mean	0.1143	0.0205	0.202	0.0959	-0.0116	-0.0427	0.0603	-0.0324	-0.1501	0.1121
t -statistics	2.19	0.44	3.54	1.99	-0.27	-0.99	1.23	-0.56	-3.53	1.68
Annualized volatility	0.1897	0.1709	0.2006	0.1552	0.1557	0.1561	0.1541	0.1808	0.1491	0.1989
Sharpe Ratio	0.6026	0.1200	1.0073	0.6180	-0.0746	-0.2737	0.3913	-0.1795	-1.0062	0.5637
Sortino Ratio	0.7033	0.2011	1.7856	1.0934	-0.1011	-0.3523	0.5252	-0.2414	-1.3976	0.9405
Skewness	-1.6390	0.6887	0.0552	-0.0500	-0.5333	-0.5779	-0.6040	-0.3039	0.2101	0.2999
Kurtosis	11.7901	6.7587	3.8173	3.7822	3.5153	4.9509	7.0171	4.1607	4.0029	5.0551
<i>Panel C: Excluding grains</i>										
Annualized arithmetic mean	0.1511	-0.0041	0.2826	0.0469	-0.0224	-0.0070	-0.0755	-0.0332	-0.1123	-0.0111
t -statistics	2.82	-0.08	4.51	0.78	-0.44	-0.11	-1.05	-0.52	-1.95	-0.14
Annualized volatility	0.1952	0.1888	0.2199	0.1922	0.1832	0.2253	0.2251	0.1974	0.2025	0.2306
Sharpe Ratio	0.7741	-0.0220	1.2850	0.2442	-0.1224	-0.0313	-0.3356	-0.1684	-0.5545	-0.0479
Sortino Ratio	1.3825	-0.0318	2.8781	0.2757	-0.1554	-0.0448	-0.3435	-0.2659	-0.7226	-0.0900
Skewness	0.3703	-0.1688	1.0107	-1.2760	-0.9247	0.0169	-1.2765	0.1421	-0.3877	2.2113
Kurtosis	5.3088	4.0784	7.8091	7.0641	6.6164	8.0951	7.5985	3.2981	3.9091	15.5523
<i>Panel D: Excluding oilseeds</i>										
Annualized arithmetic mean	0.1279	0.0555	0.1973	0.0742	0.0090	-0.0635	0.0555	0.0468	-0.0674	0.0519
t -statistics	2.12	1.32	3.53	1.52	0.22	-1.16	0.90	0.85	-1.67	0.75
Annualized volatility	0.2196	0.1535	0.1962	0.1565	0.1475	0.1986	0.1935	0.1729	0.1417	0.2064
Sharpe Ratio	0.5822	0.3618	1.0055	0.4740	0.0608	-0.3200	0.2870	0.2704	-0.4754	0.2514
Sortino Ratio	0.6225	0.5833	1.6111	0.7140	0.0863	-0.4845	0.3331	0.3661	-0.7672	0.4244
Skewness	-2.5593	-0.1803	-0.0405	-0.4020	-0.3952	0.7427	-1.5169	-0.5414	0.5542	1.3451
Kurtosis	21.0226	3.0555	4.1638	4.0643	4.7446	7.6727	12.0799	4.3068	5.0154	10.0371
<i>Panel E: Excluding energy</i>										
Annualized arithmetic mean	0.1761	0.0119	0.2320	0.1186	-0.0332	-0.0478	0.0413	0.0310	-0.1068	0.0718
t -statistics	3.82	0.31	4.35	2.56	-0.83	-1.05	0.76	0.66	-2.66	1.09
Annualized volatility	0.1676	0.1377	0.1872	0.1488	0.1452	0.1656	0.1700	0.1474	0.1412	0.1959
Sharpe Ratio	1.0506	0.0864	1.2393	0.7972	-0.2289	-0.2885	0.2427	0.2100	-0.7564	0.3668
Sortino Ratio	1.0975	0.1354	2.3952	1.2563	-0.3267	-0.4263	0.2945	0.2828	-1.0170	0.8735
Skewness	-2.2467	-0.0626	0.4056	-0.2494	-0.4913	0.1157	-1.1403	-0.5719	-0.0872	1.8683
Kurtosis	18.2023	3.1350	4.4570	4.3625	3.8379	4.3355	8.3086	5.8068	3.7910	11.2500

Appendix VII Data-snooping test

This table reports the Reality Check (White, 2000) and SPA (Hansen, 2005) test. The parameter q is the geometric distribution that determines the block-length in the bootstrap process, where the block-length is computed as $1/q$. For each test, the bootstrap is replicated 10,000 times. The stationary and circular bootstraps are based on Politis and Romano (1994) and Politis and Romano (1992) respectively. Only the statistically significant strategies are tested. Panel A reports all strategies as a group against a zero-mean return benchmark. Panel B reports all strategies against the passive long-only benchmark (AVG), an equally weighted portfolio of 30 commodities in the sample. Panels C through E report each strategy against the AVG. Significant p -values indicate that the strategy outperforms the benchmark.

Bootstrap dependence	Bootstrap method	Reality check Consistent p -values	SPA test Consistent p -values
<i>Panel A: All strategies versus zero-mean-return benchmark</i>			
$q=0.05$	Stationary	0.0010	0.0020
	Circular	0.0000	0.0000
$q=0.1$	Stationary	0.0020	0.0050
	Circular	0.0000	0.0020
$q=0.5$	Stationary	0.0020	0.0020
	Circular	0.0000	0.0000
<i>Panel B: All strategies versus AVG</i>			
$q=0.05$	Stationary	0.0010	0.0010
	Circular	0.0020	0.0000
$q=0.1$	Stationary	0.0050	0.0000
	Circular	0.0030	0.0010
$q=0.5$	Stationary	0.0020	0.0010
	Circular	0.0050	0.0040
<i>Panel C: Term structure strategy versus AVG</i>			
$q=0.05$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
$q=0.1$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
$q=0.5$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
<i>Panel D: Momentum strategy versus AVG</i>			
$q=0.05$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
$q=0.1$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
$q=0.5$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
<i>Panel E: Volatility strategy versus AVG</i>			
$q=0.05$	Stationary	0.0000	0.0000
	Circular	0.0000	0.0000
$q=0.1$	Stationary	0.0000	0.0000
	Circular	0.0010	0.0010
$q=0.5$	Stationary	0.0020	0.0000
	Circular	0.0010	0.0020