A Practical Look at Commodity Risk Factors in China

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Abstract

This paper examines the cross-sectional momentum, carry and basis-momentum risk premia in the Chinese markets, employing a variety of contract rolling methods and portfolio weighting schemes which have not been previously integrated into a single study. We first document the strong profitability of the momentum and carry strategy, which is consistent with previous literature. We then confirm the success of basis-momentum in the Chinese markets and its maturity-specific nature. The observed risk premia are robust to various contracts rolling and portfolio weighting methods. Rank weight and strength weight methods do not significantly improve the momentum and carry strategy performance, compared to the equal weight method. We show that the momentum effect can be improved when the most advantageous contracts along the futures curve are selected. The examined risk premia are exposed to downside risk, and are generally higher during market up-states. Overall, our findings highlight the pervasiveness of commodity risk premia that not only exist in the academic papers, but also survive under a stricter and more practical framework.

Keywords: China, Commodity Futures, Momentum, Carry, Basis-momentum, Portfolio, Contract Rolling

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1 Introduction

With substantial development in the past 30 years, the Chinese commodity futures markets have become an important force in global commodities trade. Established in the early 1990s, the Chinese markets experienced a chaotic decade due to lack of regulation and excessive speculation. Entering the 21st century, both regulator and exchanges committed to improve market transparency and build an effective regulatory framework, which had helped make the Chinese market one of the most active and influential futures markets in the world with a variety of commodity futures products. Some of these products are unique, some are directly competing and jointly pricing the global commodity prices with those traded in developed markets, and some are ranked the world top 3 traded instruments. Given that commodities are an essential component of an economy and China plays a significant role in global economy, it is our great curiosity to probe into the Chinese commodity markets at this time when China is experiencing slower growth and ongoing tension with its largest trading partner, the US, who also dominates the world economy.

This paper aims to investigate two barely addressed yet unique and important matters to commodity futures studies in the context of Chinese markets, namely, the rolling of futures contracts and portfolio weights. The purpose of rolling futures contracts is to construct a time-series return which is the fundamental element in calculating risk and return in the risk premium and asset pricing literature. Moreover, in practice, investors have to rollover their positions from the expiring contract to the next available one, in order to constantly maintain commodity exposures for hedging or speculating purpose. There are several rolling methods applied in the literature. They are all developed upon the same prerequisite, that is, the rolling method should construct a sample which can represent the market in terms of liquidity. However, we notice that although the liquidity concern is resolved, different rolling methods could lead to distinct return series which correspond to different underlying assets. Therefore, it is challenging to draw inferences from different studies. This is of significance for the risk premia literature, as the risk premia derived from different rolling methods might not be comparable. The arguably incomparable risk premia further raise a question-to what extent do rolling methods impact the documented risk premia? To investigate this question, we set the experiment in the Chinese markets. Apart from the economic significance of Chinese markets as mentioned earlier, the unique market structure characteristics make the Chinese markets an intriguing place for conducting this research.

There are several unique characteristics observed in the Chinese commodity futures markets. Two of them are directly relevant to this study. First, due to position limits and forced liquidation rule, individual investors who represent more than 90% of the market share in terms of the number of trading accounts are either prohibited or strictly limited to trade the nearest to delivery futures contracts. As a result, the nearby contracts only account for approximately 10% of total market open interest and 3% of total market trading volume. Consequently, if one follows most of the studies on developed markets to employ the nearest contracts as the main sample in China, any conclusions drawn will be incapable of representing the entire Chinese markets, and incomparable to that of the developed market literature. Second, it is interesting that Chinese investors have a strong preference towards certain maturities and seem to deliberately skip some maturities. Although most commodities have futures contracts available each month, only half or less than half of them are traded actively. For example, gold futures have monthly maturities, however, it is only June and December contracts that collectively dominate the trading activities of this market. Moreover, for quite a few monthly-available commodities, investors only trade the odd or even months contracts. Therefore, simply holding one contract to maturity (or one/two months before maturity) will only be academically investable but less likely feasible in practice in the Chinese markets. Stated differently, the observed risk premium deriving from a rolling method that does not reflect the market conditions may misguide industry practitioners. This, once again, highlights the importance and relevance of our study. There are a number of Chinese studies addressing the contact rolling issue (Liu, Chng, & Xu, 2014; Jiang, Ahmed, & Liu, 2017; Yang, Göncü, & Pantelous, 2018). Each of these researches has designed a rolling method to match the Chinese market characteristics. However, to what extent the rolling method can impact the results remains unresolved in the Chinese literature, and only has been discussed at a minimum in the developed market literature. For example, Mouakhar and Roberge (2010) and de Groot, Karstanje, and Zhou (2014) propose an "optimal-roll" approach to strategically roll positions to the most advantageous contracts based on roll yield. Moreover, Miffre and Rallis (2007) test the sensitivity of the momentum premium to different rolling dates and rolling distances. Further, Mou (2010) discover an arbitrage opportunity arising from an earlier roll approach relative to the index roll. Following these studies, this paper will proceed with the analysis regarding rolling of futures contracts.

The second goal of this paper is to incorporate a variety of portfolio weight schemes into the examination of risk premia in the Chinese futures markets. When it comes to risk premia, most studies opt to conduct analysis at the portfolio level. This inevitably involves a weighting design. The majority of the commodity risk premia literature apply equal weights, such as Miffre and Rallis (2007) and Szymanowska, de Roon, Nijman, and van den Goorbergh (2014). The only difference within equal weight studies is the choice of the breakpoint, which could depend on the sample size. Moreover, some other studies exploit rank weight in the portfolio construction to mitigate the impacts by extremes (Koijen, Moskowitz, Pedersen, & Vrugt, 2018). There also exists the volatility weighted portfolio construction approach, which is utilised to adjust the risk profile of the portfolio (Moskowitz, Ooi, & Pedersen, 2012; Moreira & Muir, 2017), and the strength weight (Fan, Fernandez-Perez, Fuertes, & Miffre, 2019). Each of these portfolio construction methods has seen considerable development in the literature. However, a direct comparison on risk premia generated by different portfolio construction methods has not gained much research attention. One attempt in this regard is from Asness, Moskowitz, and Pedersen (2013) who simultaneously investigates the value and momentum premia using equal weight and rank weight methods. Considering this missing piece in the puzzle, we will jointly examine how risk premia in Chinese commodity futures markets respond to alternative rolling of futures contracts and portfolio weights.

Speaking of the commodity risk premia, the seminal theoretical frameworks are the *Theory of Normal Backwardation (Keynes, 1930; Hicks, 1939), Hedging Pressure Hypothesis (Cootner, 1960)* and *Theory of Storage (Working, 1933, 1949).* Inspired by these theories, various risk premia have been documented in commodity markets, such as carry/roll yield (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006), hedging pressure (Basu & Miffre, 2013), momentum (Miffre & Rallis, 2007; de Groot et al., 2014) and skewness (Fernandez-Perez, Frijns, Fuertes, & Miffre, 2018a). In addition, some other risk premia are also attained based on economic intuitions. Evidences of this type of risk premia include volatility (Dhume, 2011), open interest (Hong & Yogo, 2012), value (Asness et al., 2013), time-series momentum (Moskowitz et al., 2012), basis-momentum (Boons & Prado, 2018), liquidity, inflation and currency betas

(Szymanowska et al., 2014). Although the Chinese commodity futures markets are relatively young compared to the developed markets, it has gained a lot of attentions rapidly in recent years. There are several risk premia studies in the Chinese market. For example, Kang and Kwon (2017) investigate the momentum effect in China; Yang et al. (2018) examine momentum and reversal premium; a basket of trend following strategies are tested by Li, Zhang, and Zhou (2017); Fan and Zhang (2018) explore 12 risk factors that have been studied extensively based on developed markets in the Chinese commodity futures markets. To answer the question raised in the paper, we will focus on roll yield- and momentum-driven risk premia, as aforementioned Chinese studies demonstrate that these two types of premia are the most robust ones in China.

This study makes four contributions to the literature. First, we find that the carry, momentum and basis-momentum premia are not affected by contract rolling methods. The strong profitability of carry and momentum is consistent with previous literature on Chinese commodity futures markets. However, for the momentum strategy, our finding is different from Miffre and Rallis (2007) who document a less statistically and economically significant profit when contracts are rolled differently in the US market. This study, for the first time in the literature, examines the risk premium using four different rolling methods, namely, conventional roll, maximum volume roll, dynamic maximum volume roll and gradual roll. Also, this is the first study testing basis-momentum in the Chinese markets, which is proven to be profitable under all rolling methods, with the exceptions of the second and fourth nearest contracts in the context of the conventional roll. This finding highlights that the basis-momentum premium contains a maturity-specific component, which is consistent with Boons and Prado (2018).

Second, we find the portfolio weighting methods do not fundamentally impact the risk premia in the Chinese commodity futures markets. The robustness of the momentum strategy in China under rank- and equal-weight approaches is consistent with the findings in the US market by Asness et al. (2013). Furthermore, this study, for the first time, investigates the impacts of three portfolio weight schemes on commodity risk premium in the Chinese markets. Although the magnitude of premiums varies under equal weight, rank weight and strength weight, the significance of carry, momentum and basis-momentum profits remains persistently large. Interestingly, rank weight and strength weight do not considerably improve the risk-return profile of all three long-short strategies, comparing to equal weight. Rank weight is most effective on momentum and carry, while strength weight outperforms the other two on basis-momentum in terms of risk-adjusted return. Therefore, we can conclude that portfolio weight schemes neither impact the significance of risk premia, nor necessarily result in profound improvements.

Third, inspired by de Groot et al. (2014), the three rolling-driven momentum strategies can deliver statistically and economically significant profits and are robust to different contract rolling and portfolio weighting methods in the Chinese markets, which is consistent with their results in the US markets. The three rolling-driven momentum strategies are *high roll-yield (HRMOM)*, *high momentum (HMMOM)* and *all contracts (ALLMOM)*. The HRMOM strategy buys (sells) the contracts with the highest (lowest) roll yield for winner (loser) commodities, while the HMMOM strategy takes long (short) positions on the contracts with the highest (lowest) momentum for backwardated (contangoed) commodities. The ALLMOM strategy reshuffles the sample into winner and loser groups. The winner (loser) group consists of the winner (loser) contract of each commodity, and only the top (bottom) quartile candidates in the winner (loser) group will be bought (sold). In contrast with our second contribution, it appears the rank weight scheme outperforms equal and volatility weight methods on these rolling-driven strategies in terms of risk-adjusted return and maximum drawdown.

Fourth, the robustness analysis suggests the risk premia in China is partially exposed to downside risk, and could be pushed upwards during market up-states measured by the business cycle and market volatility. The exposure to downside risk is consistent with Koijen et al. (2018). The overall outperformance during market upturns is in line with Levine, Ooi, Richardson, and Sasseville (2018), although the difference between market up- and down-states is less significant compared to the US markets.

The remainder of the paper proceeds as follows. Section 2 presents a review of the relevant literature. Section 3 describes the data sources employed in this study. Section 4 elaborates methodologies regarding construction of long-short portfolios, rolling of futures contracts and portfolio weights. This is followed by Section 5 where empirical results will be presented and discussed. Section 5 provides concluding remarks.

2 Literature review

2.1 Commodity investing

Commodity investment is recognised for its “equity-like” returns, diversification benefits and ability to hedge against inflation (Erb & Harvey, 2006). Although the financialization literature has shown a gradual deterioration of these three characteristics (Tang & Xiong, 2012; Cheng & Xiong, 2014), the importance of commodities in alternative investing remains unchanged. Another appealing feature of commodity assets is the lower transaction costs in futures markets (Locke & Venkatesh, 1997; Marshall, Nguyen, & Visaltanachoti, 2012). *Theory of Normal Backwardation* (Keynes, 1930; Hicks, 1939), *Hedging Pressure Hypothesis (HPH)* (Cootner, 1960) and *Theory of Storage (TS)* (Working, 1933, 1949) are the pillars that established the commodity literature, rationalise return predictors whereby a variety of systematic long-short strategies have developed.

The commodity-specific predictors are roll yield and hedging pressure, which are derived from TS and HPH, respectively, and have been proven to be priced factors (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Basu & Miffre, 2013). The former argues that the shape of the term structure contains information on expected returns, while the latter implies that the holding positions of hedgers and speculators predict future performance. The ‘roll yield’, sometimes, is also referred to as ‘carry’ which has been examined across multi-assets (Koijen et al., 2018). There are other long-short strategies not directly motivated but somehow indirectly intertwined with commodity theories. For example, momentum and skewness strategies are found to be possibly underpinned by the *Theory of Storage* and *Hedging Pressure Hypothesis* (Deaton & Laroque, 1992; Miffre & Rallis, 2007; Fernandez-Perez et al., 2018a).

Apart from commodity theories, economic intuitions also have enriched the commodity investing literature. The idea from Dhume (2011) arguing that futures returns represent compensation for bearing the volatility of the spot market legitimise a long-short allocation based on volatility. Moreover, in the wake of the examination of liquidity proxies in commodity markets by Amihud (2002), cross-sectionally buying the illiquid and selling liquid assets has been empirically validated. Furthermore, given the fact that commodities can be used to hedge inflation and is negatively correlated with exchange rates (Bodie & Rosansky, 1980; Erb & Harvey, 2006), regression betas on unexpected inflation and the change in exchange rates are exploited in constructing long-short portfolios. In addition, Moskowitz et al. (2012) examine time-series momentum across equity, commodity, bond and currency futures, and find the past 12-month return of each asset can predict its future return. Boons and Prado (2018) propose a new return predictor called 'basis-momentum' which captures the supply-demand imbalance between speculators and intermediaries. Further, Hong and Yogo (2012) explore the predictability of open interest in commodity futures, and document a positive relation between open interest and returns. Lastly, the value effect in the commodity markets has been tested by Asness et al. (2013).

Building on the aforementioned individual strategies, two types of studies have extended the commodity investing literature. The first group of studies examine all the discovered systematic risk factors in the same sample (Szymanowska et al., 2014; Fernandez-Perez, Fuertes, & Miffre, 2018b), while the second strand of literature attempts to achieve a higher risk-adjusted performance through combining more than one trading signal, such as integrating momentum and roll yield (Fuertes, Miffre, & Rallis, 2010; de Groot et al., 2014), jointly testing momentum and the reversal effect (Bianchi, Drew, & Fan, 2015) and a triple-sorted strategy incorporating momentum, term structure and idiosyncratic volatility (Fuertes, Miffre, & Fernandez-Perez, 2015).

Thus far, the commodity futures literature has evolved dramatically both in breadth and depth for developed markets. However, the commodity markets in China are less familiar to the world. The next section will review the Chinese commodity literature to date.

2.2 Commodities in China

The literature on Chinese commodity markets is relatively underdeveloped compared to that of US/European markets. Considering the tremendous commodity consumption in China and the government's initiatives to liberalise and internationalise its overall capital markets, the Chinese commodity markets have sparked substantial interest among scholars and practitioners in recent years.

The early China-related studies primarily focus on the market development which can trace back to the reform of the food ration system and grain market liberalisation in the 1980s (Williams, Peck, Park, & Rozelle, 1998; Rozelle, Park, Huang, & Jin, 2000; Park, Jin, Rozelle, & Huang, 2002; Peck, 2002). These studies are of importance as they aid in understanding the characteristics of modern Chinese commodity markets. For example, it is partially believed that Chinese market participants' trading preferences on specific maturities originate from the seasonality feature of the agricultural products launched in the early days.

After a decade of operations, academics began to investigate the interaction between Chinese and other international commodity markets. Fung, Leung, and Xu (2003) document the dominant role of US markets in commodities (copper and soybean) that are less regulated, while the commodities (wheat) that are subject to tighter restrictions in China appear to be segmented from its US equivalents. In a later study by Fung, Liu, and Tse (2010) focusing on metallurgical futures traded in both markets, they conclude that the two markets are cointegrated and efficient. Further, Fung, Tse, Yau, and Zhao (2013) compare 16 commodities across China, US, UK, Japan and Malaysia markets and argue that the Chinese commodity futures markets are informationally-efficient and driven by domestic factors. In a co-dependency research, Gong and Zheng (2016) demonstrate the aluminium futures contracts traded in China and UK are more correlated during market downturns.

Another strand of Chinese literature specialises on volatility analysis. Chan, Fung, and Leung (2004) find asymmetric effects of return on volatility, which implies negative returns impact volatility more than positive return. In addition, they confirm a positive (negative) relation between volatility and trading volume (open interest), which is also supported by Bohl, Siklos, and Wellenreuther (2017) who document a positive relation between speculative activities (estimated using information from open interest and trading volume) and volatility. In terms of volatility forecasting, Jiang et al. (2017) investigate three volatility forecasting models and find the ARFIMA (Autoregressive Fractionally Integrated Moving Average) model deliver the best estimates in the Chinese markets.

In addition, there are studies pioneering the relation between the Chinese commodity and stock markets. Hammoudeh, Nguyen, Reboredo, and Wen (2014) report evidence indicating a low and positive correlation between the two markets and suggest that commodity futures provide portfolio diversification benefits to stock portfolios in China. Moreover, Liu, Tse, and Zhang (2018) argue that the Chinese commodity and stock markets are exposed to different risks, and diversification benefits can be earned by including specific commodity futures into a stock portfolio. Further, Zhang, Ding, and Scheffel (2018) confirm the connection between Chinese stock and commodity markets by demonstrating how policies imposed on the stock market impact the commodity markets.

Recently, the trading strategy and asset pricing literature have been extended to the Chinese commodity futures markets. Kang and Kwon (2017) and Li et al. (2017) employ momentum and trend following strategies, all of which are proven to be statistically and economically significant. Yang et al. (2018) investigate the momentum and reversal effect in China, and also synthesise a momentum-reversal double-sorted portfolio. Fan and Zhang (2018) examine 12 systematic long-short strategies and several well-established pricing models and risk factors, and conclude the observed risk premia cannot be adequately explained by these models/factors. He, Jiang, and Molyboga (2018) also use a three-factor model to explain the spot and term premium of three long-short strategies.

2.3 Rolling of futures contracts and portfolio weighting

To the best of our knowledge, there is no well-developed literature centring on the rolling of futures contracts and portfolio weighting in the context of commodity futures markets. This section will deliver a brief review on the literature that is most relevant to our paper.

First, with regard to the rolling of futures contracts, there is no standard way in the literature. Most of the studies simply assume investors hold a contract until a specific time, which usually is the last trading day of the preceding month, then roll to the next nearest contract. We refer this type of rolling as 'conventional roll' throughout this study. Because each commodity has multiple maturities that can be traded at the same time, we often see studies compile m^{th} ($m=1, 2, 3,\ldots n$) nearest series returns, and set the 1$^{\text{st}}$ nearest as the main sample and apply the others in a robustness analysis. What underpins the conventional roll is that the front nearby contracts attract most of the liquidity in the developed markets. It is also the liquidity argument that divides the literature on this matter. For example, Szymanowska et al. (2014) only hold a futures contract until the last trading day of month *T-2* (*T* = maturity) instead of month *T-1*. This is because they observed a decline in open interest starting from 6 weeks before maturity for most of the sample constituents. Furthermore, Asness et al. (2013) strictly refine the sample to be the most liquid on each day, which means the rollover process for each commodity can take place on any day instead of a predefined date applied across all commodities in the sample. Further, there is the GSCI index roll (de Groot et al., 2014), which refers to the 'gradual roll' approach in this study. The difference between gradual roll and conventional roll is that the rollover takes five days to complete, with 20% of positions being rolled to the target contracts each day. This rolling method is most suitable for industry practitioners, as positions are not transacted on a single day which results in significant trading and liquidity issues when investment capital is large.

Second, constructing long-short portfolios have been widely exploited in the commodity risk premia literature. The construction of portfolios come with several weighting schemes in the literature, namely equal weight (Miffre & Rallis, 2007; Szymanowska et al., 2014), rank weight (Koijen et al., 2018), strength weight (Fan et al., 2019) and volatility weight (Moskowitz et al., 2012). However, there is no study which compares risk premia across different portfolio weighting methods. The only study that approaches this issue is Asness et al. (2013) who test value and momentum premium using rank and equal weights.

3 Data

3.1 Commodity futures

As of the end of June 2018, 48 commodity futures are traded in China, of which 44 are archived in Datastream International. We obtain the entire history of the 44 products including settlement price, trading volume, open interest and contract size. This results in more than 4,400 contracts from 1993. The 15 commodities traded in Zhengzhou Commodity Exchange (ZCE) are *Sugar, Cotton, Rapeseed Oil, PTA, Strong Wheat, Common Wheat, Methanol, Flat Glass, Rapeseed meal, Rapeseed, Early Rice, Thermal Coal, Japonica Rice, Ferrosilicon and Silicon Manganese.* The Dalian Commodity Exchange (DCE) manages 16 products, namely *No.1 Soybean, No.2 Soybean, Corn, LLDPE, Soybean Meal, Palm Olein, PVC, Soybean Oil, Metallurgical Coke, Coking Coal, Plywood, Fiberboard, Egg, Iron Ore, PP and Corn Starch.* The remaining 13 commodities traded in Shanghai Futures Exchange (SHFE) are

Aluminium, Gold, Copper, Fuel Oil, Lead, Steel Rebar, Natural Rubber, Steel Wire Rod, Zinc, Silver, Bitumen, Hot-rolled Coil and Tin.

To construct long-short portfolios, we require a minimum of eight assets in the cross-section. As a result, our final sample begins from February 2004. Furthermore, several commodities were thinly traded through different periods of time. These products have been widely recognised as the "Zombie 9" by Chinese media. These commodities include *Common Wheat, No.2 Soybean, Plywood, Fiberboard, Fuel oil, Steel Wire Rod, Rapeseed, Early Rice and Japonica Rice*. There are three major reasons which have caused the zombie phenomenon. First, there are other similar securities being traded in the market, such as *Common Wheat* versus *Strong Wheat*. Second, fundamental changes in the spot market make the futures contracts less ideal to facilitate hedging activity, such as lower production caused by lower demand. Third, difficulty in delivery fueled the reduction in hedging and speculative activity. The inactive *Fuel Oil* futures contract can be attributed to this category. Assuming the role of an institutional investor, we exclude a commodity in the portfolio construction when the monthly total trading volume of its most liquid contract is below 10,000 lots.[1]

Table 1 reports the summary statistics of the m^{th} ($m=1, 2, 3, 4$) nearest contract of the individual commodity. It is clear that the majority of the commodities exhibit monthly returns that are insignificantly different from zero. The even worse cases are the *Strong Wheat*, *Common Wheat*, *Egg* and *Bitumen* futures, which have seen statistically significant losses during the sample period. However, there are some commodities reporting significant profits, including *Flat Glass, Thermal Coal, Silicon Manganese, Soybean Meal, Fiberboard, Iron Ore* and *Copper*, though these profits do not persist along the futures curve. Moreover, the estimated standard deviations suggest that the Samuelson (1965) hypothesis does not hold well in the Chinese markets, as 15 out of 44 commodities appear to be more volatile on the distant contracts rather than the front contracts. Furthermore, the open interest data confirm the above-mentioned "zombie contracts" phenomenon in China, such as the *Japonica Rice* futures whose monthly aggregate open interest only averages at 380 over the sample period.

[1] After studying the liquidity pattern of all commodities traded in China, we find the zombie contracts are essentially those with a monthly trading volume below 10,000 lots. Therefore, we use '10,000 lots' as the threshold to clean the sample.

3.2 Explanatory variables

To identify the potential drivers of systematic risk premia, we obtain several macroeconomic and financial variables.

Unexpected inflation: the inflation shock is estimated as the difference between actual and consensus inflation, are obtained from Bloomberg. *OECD Recession indicator (*RI*):* RI provide insights on the future economic activities in China, is used as a general proxy for turning points of an economy. RI data is downloaded from the OECD database.

As for the financial variables, the stock and bond market performance are measured using CSI 300 and Barclays China Aggregate index, respectively. To construct the Chinese TED spread, we follow the US methodology to employ the 3-month SHIBOR (Shanghai Interbank Offered Rate) and 3-month Chinese T-bill interest rate. All financial data are acquired through Bloomberg.

4 Methodology

4.1 Continuous returns

One of the major challenges in commodity futures studies is the construction of continuous time-series returns. Unlike other asset classes such as stocks, multiple contracts with varying maturities are traded at the same time and each of these contracts only exists for a certain period in time. Therefore, it is inevitable to roll investor's positions from the expiring contract to the target contract. The fundamental rule is that return must be calculated using two prices derived from the same contract, therefore the return for a given commodity contract *i* at time *t* can be standardised as:

$$r_{i,t} = \frac{F_{i,t}}{F_{i,t-1}} - 1 \tag{1}$$

where $F_{i,t}$ denotes the futures price of contract *i* at time *t.*

It is also important to acknowledge the fact that any conclusions drawn from a comparison analysis between different studies can be misleading unless they employ the identical rolling approach on the identical contract universe. To unravel the potential impacts caused by different rolling designs, this study proposes *four* different rolling structures. Considering the illiquid nature of futures contracts in the delivery month along with the unique 'force liquidation' rule in Chinese markets, we exclude the price information during the delivery month (*month T*).

Conventional roll: Following Miffre and Rallis (2007), we hold the m^{th} *(m=1, 2, ..., 12)* nearest contract until the last trading day when its m^{th} status is still true, then the position will be rolled to the next m^{th} nearest contract. This study compiles up to the 12th nearest series and focuses on the first four maturities since they jointly represent 67% (62%) of market total trading volume (open interest). In addition, the 3rd nearest contracts are set as the main contracts cross-sectionally. This is due to the fact that they exhibit the highest volume and open interest on average. This is particularly important for Chinese studies, although only a select few studies pointed out this uniqueness (Jiang et al., 2017; Yang et al., 2018).

Max-volume (MaxVm) roll: We design the MaxVm roll to reflect investor's trading preference on specific maturity in the Chinese market. In the MaxVm roll, the contract with the highest volume will be held until the last trading day of the preceding month (T-1), then the position will be rolled to the next contract that has the highest trading volume on that day. The advantage of MaxVm roll is to always stay in the most actively traded contract. For example, although gold futures are available in all calendar months, it is only the June and December contracts that manifest the highest trading volume. Therefore, only June and December contracts are included under the MaxVm roll, while the 'conventional roll' approach covering all maturities can include these relatively inactive maturities. Previous studies that have adopted similar rolling methods include Yang et al. (2018) and Liu et al. (2018).

Dynamic max-volume (Dynamic) roll: Building on MaxVm roll, we propose a Dynamic roll approach. Inspired by Asness et al. (2013), the Dynamic roll relies on the market to decide the rollover dates for each commodity and each contract, instead of mechanically rolling all the positions on the last trading day of month T-1. The difference between Dynamic and MaxVm roll is that the Dynamic roll approach does not necessarily hold the contract with the highest volume until the last trading day of month T-1. The rollover occurs when the trading volume of contracts being held is outpaced by the target contract for three consecutive days. For instance, instead of holding June 2008 gold futures until the end of May 2008 as proposed by MaxVm roll, the position will be rolled to the December 2008 contract on 29th April 2008 in the Dynamic roll, as the December contract's trading volume has had exceeded the June contract three days in a row. This rolling method has been applied by some well-established commercial commodity indices in China, such as the NanHua index.[2]

Gradual roll: Inspired by the S&P GSCI index and de Groot et al. (2014), we construct the gradual roll based on the conventional roll. The fundamental difference is that the rollover process will be facilitated across the last five trading days of month T-1, and only 20% of total positions will be rolled to the next contract. Consequently, the last four trading days' returns will be a weighted average of the holding contract and the targeting contract, which can be written as

$$r_t = \begin{cases} 0.8 \times r_{t,holding} + 0.2 \times r_{t,targeting} & t = 4^{th}\ last\ trading\ day \\ 0.6 \times r_{t,holding} + 0.4 \times r_{t,targeting} & t = 3^{rd}\ last\ trading\ day \\ 0.4 \times r_{t,holding} + 0.6 \times r_{t,targeting} & t = 2^{nd}\ last\ trading\ day \\ 0.2 \times r_{t,holding} + 0.8 \times r_{t,targeting} & t = 1^{st}\ last\ trading\ day \end{cases} \quad (2)$$

After the continuous return is composed, the next section will elaborate on the sorting signals for a basket of long-short strategies.

4.2 Long-short strategies

This study aims to investigate six long-short strategies that can be categorised into two groups, namely, 'conventional' and 'dynamic selection'. The conventional set includes cross-sectional momentum (*MOM*), carry (*CARRY*) and basis-momentum (*BMOM*), while the dynamic selection strategies are high roll-yield (*HRMOM*), high momentum (*HMMOM*) and all contracts (*ALLMOM*).

4.2.1 Conventional strategy

MOM: Cross-sectional momentum strategy essentially takes long positions on past winners and simultaneous short positions on past losers. The two rationales for the presence of momentum are (i) behavioural biases and (ii) proxy for macroeconomic risks. The behavioural explanation argues the momentum effect is partially due to investor's anchoring bias (Bianchi, Drew, & Fan, 2016) and overaction bias (Shen, Szakmary, & Sharma, 2007), while macroeconomic risks, such as global funding liquidity, are also found to be related to momentum returns (Asness et al., 2013).

[2] Details see https://www.nanhua.net/subpageNew/research/nawaaindex/index-download.html

Following Boons and Prado (2018), we define the momentum signal on mth maturity as the past-12 month compounding return (M_t).

$$M_t = \prod_{s=t-11}^{t} \left(1 + r_{c,s}^{m}\right) - 1 \tag{3}$$

where $r_{c,s}^{m}$ represents the *mth* nearest return of commodity *c* at time *s*.

CARRY: Carry is a concept originated from currency futures trading, which effectively refers to the term structure in the context of commodity futures. The economic intuition for carry is that the holding backwardated commodities, whose futures price is below the spot price, are expected to earn a premium due to price rises, as the futures price should converge to the spot price at maturity. Exploiting roll-yield (RY), the carry strategy buys the backwardated and sells the contangoed commodity contracts. Following de Groot et al. (2014), the sorting signal for the carry strategy on the mth nearest exposure for a given commodity can be expressed as

$$RY_t = F_t^{m-1}/F_t^{m} - 1 \tag{4}$$

where F_t^{m} is the price of the mth nearest contract at time *t.* It is worth noting that F_t^{0} is the spot the price at time *t*, which is extrapolated using a piecewise cubic interpolation method introduced by Fritsch and Carlson (1980). The advantage of this method is twofold. First, the spot price is estimated in a way that preserves the shape of the term structure. Second, the front contracts are investable by using the corresponding signal.

BMOM: Basis-momentum is a relatively new return predictor proposed by Boons and Prado (2018). The economic rationale for basis-momentum is less related to the conventional commodity theories, but more based on the market-clearing ability of speculators and financial intermediaries. It is found that basis-momentum indicates stronger predictability when speculators have more spreading positions (Boons & Prado, 2018). It incorporates both the slope and curvature of the futures term structure and has been proven to be a priced factor at the individual market and portfolio level in the commodity futures literature. The sorting signal for basis-momentum on the mth nearest maturity is defined as

$$BM_t = \prod_{s=t-11}^{t} \left(1 + r_{c,s}^{m}\right) - \prod_{s=t-11}^{t} \left(1 + r_{c,s}^{m+1}\right) \tag{5}$$

4.2.2 Dynamic contract selection strategy

HRMOM: High roll-yield strategy is also known as "optimal roll" in de Groot et al. (2014). It first sorts commodities using the momentum signal as per equation (3) based on the 3rd nearest contracts, then selects the contract with the highest (lowest) roll-yield across the futures curve within each winner (loser) commodity to construct the long-short portfolio. The motivation for estimating HRMOM is twofold. First, in light of the outstanding performance of momentum and term structure strategy documented in Fan and Zhang (2018), it is intuitive to explore the joint dynamics of the two risk premia, and HRMOM is an approach proposed in the US market but has not been tested in the Chinese market. Second, given that this study focuses on the impact of the contract rolling method, HRMOM provides an alternative perspective to understand the research question, as strategically selecting contracts along the futures curve is effectively rolling positions.

HMMOM: High momentum strategy is the opposite of high roll-yield. We first sort commodities by the carry signal as per equation (4) estimated on the 3rd nearest series, to separate backwardated from contangoed markets. Then, we take long (short) positions on the contract with the highest (lowest) momentum across the futures curve for each of the backwardated (contangoed) commodities. The motivation of proposing this strategy is the same as that of HRMOM. However, the underlying assumptions of HRMOM and HMMOM are slightly different. The HRMOM conjectures the momentum effect observed on one maturity persists across the futures curve, while the HMMOM expects the carry attribute estimated on one maturity applies to the entire futures curve for a given commodity.

ALLMOM: Following de Groot et al. (2014), we first calculate the momentum signals up to the 12th nearest series per equation (3) for each commodity and only keep the highest and lowest momentum contracts within each commodity, which will be labelled as "candidates" for winners and losers, respectively. Secondly, the long (short) portfolio is comprised of the top (bottom) x% ($x = 25$) candidates from the winners (losers) pool. The distinguishing feature of the *ALLMOM* strategy is that one commodity (with different maturities) could end up in both long and short portfolios. Therefore, the economic motivation for ALLMOM is that the relative momentum strength measured in the vertical cross-section may be under-/over-stated in a two-dimension (vertical-horizontal) universe.

After the sorting signals being determined, the next intuitive question would be how to weigh these constituents in each portfolio. We now proceed to the details about portfolio weighting.

4.3 Portfolio weighting

This study implements three different weighting schemes, namely, equal weight (*EW*), rank weight (*RW*), volatility weight (*VW*) and strength weight (SW).

EW: Equally-weighted portfolio simply averages the returns of all constituents to derive the portfolio performance. Numerous studies have employed the equally-weighted portfolio, such as Miffre and Rallis (2007) and Szymanowska et al. (2014). Returns of an equally-weighted portfolio can be evaluated as

$$R_t^{L/S} = \frac{1}{N}\sum_{c}^{N} r_{c,t}^{L/S} \tag{6}$$

where $R_t^{L/S}$ denotes the long (short) portfolio return at time *t,* $r_{c,t}^{L/S}$ represents the return of constituent *c* for the long (short) portfolio at time *t,* and $\frac{1}{N}$ is the weight of commodity *c* in the long or short portfolio at time *t.* Therefore, the performance of the equally-weighted long-short portfolio is expressed as $R_t^L - R_t^S$.

RW: A rank-based portfolio construction does not need a defined breakpoint to sort commodities cross-sectionally. The asset weight is determined by the rank of its signal. Following Koijen et al. (2018) and Asness et al. (2013), we define the weight for commodity *c* at time *t* as

$$w_t^c = z_t\left(rank(S_t^c) - \frac{N_t + 1}{2}\right) \tag{7}$$

where S_t^c is the sorting signal of commodity *c* at time *t,* N_t is the total number of available commodities at time *t,* and z_t is the scalar to ensure the sum of long (short) portfolio has a total weight of 100%. Notably, commodities with lower-rankings will be inherently allocated to the short side, and only the commodity in the middle will be excluded from portfolio construction when N_t is an odd number. Consequently, a rank-weighted portfolio return will be the weighted sum of returns of the individual commodities.

$$R_t^{L/S} = \sum_{c}^{N} r_{c,t}^{L/S} \times w_t^c \tag{8}$$

VW: The volatility-weighted portfolio is underpinned by the idea that it decreases risk exposure when the recent volatility is high and vice versa (Moreira & Muir, 2017). Following Moskowitz et al. (2012), we define the weight for commodity *c* at time *t+1*

$$w_{t+1}^c = \begin{cases} z_{t+1}(1/\sigma_t) & if\ commodity\ c\ in\ the\ long\ portfolio \\ z_{t+1}\sigma_t & if\ commodity\ c\ in\ the\ short\ portfolio \end{cases} \tag{9}$$

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2 \tag{10}$$

z is the scalar to ensure the sum weight of the long (short) portfolio equals to 100%, σ_t is the commodity's ex ante volatility estimated using exponentially weighted lagged squared returns. The scalar 261 is employed to annualise the variance, and δ is the decay factor chosen to make the sum of $(1-\delta)\delta^i$ equal to one. The evaluation of the volatility-weighted long (short) portfolio is the same as equation (8).

SW: Following Fan et al. (2019), we adopt a strength-weight method, which can be expressed as follows:

$$w_t^c = SS_{c,t} / \sum_{c=1}^{N} |SS_{c,t}| \tag{11}$$

$$SS_{c,t} = (S_t^c - \bar{S}_t)/\sigma_{S,t} \tag{12}$$

where S_t^c is the sorting signal of commodity *c* at time *t;* $\bar{S}_t$ denotes the average value of sorting signal for all commodities in the cross-section with a standard deviation of $\sigma_{S,t}$. The evaluation of the strength-weighted long (short) portfolio is the same as equation (8).

5 Result and discussion

5.1 Strategy baseline performance

Table 2 reports the baseline performance of momentum, carry and basis-momentum under the conventional roll and equal weight scheme. There are several interesting findings from Table 2. First, consistent with Fan and Zhang (2018) and He et al. (2018), momentum and carry strategies constantly generate statistically significant economic profits across the futures curve. The success of carry and momentum in China implies that the Chinese commodity futures market is also in line with the prediction of the *Theory of Storage*. Second, Basis-momentum appears to be successful only on the front and 3rd nearest contracts. This could be due to the maturity-specific component in basis-momentum, which varies across the futures curve (Boons & Prado, 2018). However, inconsistent with Boons and Prado (2018) who demonstrate that the illiquid commodities measured by Amihud illiquidity enjoy a stronger basis-momentum effect, our results on the 3rd nearest contracts, which are more liquid than the front contracts, outperform that of nearby contracts statistically and economically (14.23% $t=4.01$ versus 12.54% $t=3.50$). This finding reveals the uniqueness of the Chinese markets and its puzzling liquidity issue documented in Fan and Zhang (2018). They find there is no premium for holding illiquid assets in the Chinese commodity futures market. This also rules out the possibility of a liquidity explanation for basis-momentum in China.

Third, a monotonic pattern along the futures curve is only observed for the momentum strategy, as the profitability deteriorates when moving to the distant contracts. However, this does not change the fact that the momentum strategy outperforms the other two in terms of absolute (ranging from 16.40% to 24.51% per annum) and risk-adjusted returns, with one exception where basis-momentum on the third nearest contracts reveals a higher Sharpe ratio than momentum (1.0286 versus 0.9156). In terms of attractiveness relative to a risk-free investment, the momentum strategy still prevails per certainty equivalent return (CER). Similarly, the omega ratio also favours the momentum strategy from a probability-weighted ratio of gains-versus-losses perspective. The profitability erosion observed on the futures curve for the momentum strategy might be due to policy-induced limits-to-arbitrage (Fan & Zhang, 2018), as the majority of market participants cannot trade sufficiently on the nearby contracts, hence there exists a larger premium. Nevertheless, the stronger basis-momentum on the 3rd nearest contracts seems to contradict this conjecture. A possible explanation for the contradiction could be the "opposing effects" caused by the herding behaviour of individual investors who dominate the market as suggested by Li et al. (2017). On one hand, the herding behaviour can enhance the trend during the inception stage; on the other hand, the profitability of the trend will likely deteriorate subsequently following an overwhelming crowd. The yet-weakened basis-momentum on the most liquid markets in China could reflect the relatively new nature of basis-momentum premia and less sophisticated individual investors. As for the non-monotonic return pattern in the carry strategy, it may be attributable to a shape variation in the term structure driven by the maturity preference revealed by investors as mentioned above.

Overall, Table 2 confirms the predictability of past returns, roll yield and basis-momentum in the Chinese commodity futures markets. Consistent with previous literature, the momentum strategy delivers the highest return. Findings on basis-momentum in China challenge one of the explanations based on the US market. Results on carry indicate a more sophisticated term structure caused by unique trading behaviour. After the baseline performance, we now proceed to answer the first part of the research question regarding the impact of portfolio weights.

5.2 Impact of portfolio weights

Table 3 reports the strategy performance based on the 3rd nearest contracts when the portfolios are rank weighted (RW) and strength weighted (SW). Since both RW and SW methods incorporate the entire cross-section into the long-short portfolio, we have added the equal weight (EW) performance as the benchmark, with a breakpoint of two in the sorting step. There are several findings from this table. First, the three risk premiums are not subsumed by portfolio weighting schemes, with statistically significant profits ranging from 8.71% per annum to 17.72%. The portfolio weights test reaffirms the superiority of the momentum strategy in the Chinese markets, with three weighting methods averaging at an annual return of 13.80% (versus 8.54% for carry and 12.50% for basis-momentum). Second, RW portfolio outperforms the other two approaches in momentum strategy in terms of risk-adjusted returns, whereas carry (basis momentum) strategy favours the EW (SW) method. The overall outperformance by RW method relative to EW can also be seen from Figure 1 where RW portfolios deliver relatively stable returns in cumulative terms. Third, when it comes to absolute return, SW portfolios overwhelm the RW and EW portfolios across all strategies. In particular, compared RW and EW, the SW approach improves the basis-momentum profitability by 86% and delivers the highest Sharpe, omega, CER and the lowest maximum drawdown. Third, it is also true that alternative portfolio weights cannot improve the portfolio capacity expressed as the maximum value in thousand RMB can be invested.

To sum up, findings from Table 3 suggest that the performance of carry, momentum and basis-momentum are not due to equally weighting the portfolio, i.e. alternative portfolio weights do not fundamentally affect the results in the Chinese market. While each weighting scheme shows strengths and weaknesses, the SW approach is relatively more preferable given the overall outperformance. By far, the first part of the research question has been discussed, the next section will proceed to the second part.

5.3 Impact of the rolling of futures contracts

Table 4 exhibits the three strategies' performance employing three alternative rolling structures including *Gradual, MaxVm* and *Dynamic.* The performance on *Gradual* roll is based on the 3rd nearest contracts, while the performance on *MaxVm* and *Dynamic* roll exploits the corresponding return series. We re-emphasise the essence of focusing on the 3rd nearest contracts in the Chinese market, as the majority of trading activities occur on the 3rd nearest contracts which, therefore, are more representative of the market. The most recognizable finding in Table 4 is that momentum, carry and basis-momentum are not sensitive to contract rolling, given all the profits are statistically and economically significant. Momentum is still the most profitable strategy regardless of the rolling procedures. The *Gradual* and *MaxVm* rolls report consistent results with the *Conventional* roll for all three strategies, despite minor differences on all metrics. However, a noticeable underperformance is documented across three strategies when *Dynamic* roll is utilised, in terms of profitability, risk-reward ratio, omega ratio and CER, with momentum dropped the most (an average of 32.56% decrease compared to all other rolling methods). Considering *Dynamic* roll constructs the most liquid sample compared to the other rolling methods, this implies that liquidity might, more or less, impact the risk premium, which casts more shadows on the liquidity puzzle in the Chinese market. Although previous discussion states liquidity does not predict returns in the cross-section in China, this seemingly liquidity-driven profit decline suggests the liquidity proxy examined in previous literature maybe not the best estimator for the Chinese market. Moreover, the fact that momentum premia sees the worst deterioration in the most liquid sample supports the argument of most individual investors being trend followers and the aforementioned “opposing effect” of herding behaviour. Furthermore, an “almost” identical profitability delivered by the *Gradual* roll relative to *Conventional* roll implies that a five-day rolling window does not impose a significant time cost. Inspired by Mou (2010), we conjecture the indifference between *Gradual* and *Conventional* roll is due to the absence of investable indices and index funds in the Chinese commodity futures markets. In addition, it is interesting that the three strategies react differently to alternative rolling methods. It appears that momentum and carry perform the best under *MaxVm* roll in terms of absolute and risk-adjusted returns, while basis-momentum excels with *Gradual* roll which, however, still underperforms the *Conventional* roll. Also, basis-momentum is the least sensitive to rolling methods, as it shows the lowest return variation across different rolling techniques. Given that basis-momentum captures both the slope and curvature of the term structure, we posit a strategy incorporating more information of term structure may be less likely affected by rolling methods.

Overall, Table 4 demonstrates the success of three risk premiums is not eliminated after switching to alternative contract rolling methods. The lowest return in the most liquid sample implies a connection between liquidity and risk premia. The absence of a significant arbitrage opportunity arising from timing the rolling may be due to lack of in-depth institutional engagement. To scrutinise the feasibility of the three strategies, the next section re-evaluates the performance under a more practical framework.

5.4 Implementation analysis

Table 5 presents the performance of the three strategies under three practical conditions, namely LAG, VW and TargetV. LAG is the scenario when a 3-day gap is applied between sorting and execution date. VW represents volatility weight, in which each constituent of the long/short portfolio is weighted by its ex ante volatility. TargetV is the situation when both long and short portfolios are weighted by a proportion of their last month standard deviation. Compared to the benchmark performance on the 3rd nearest contracts in Table 2, there are two interesting findings.

First, it is certain that a 3-day delayed execution incurs a cost. On average, the three strategies lose 2% profits per annum under the LAG scenario, with the carry premium declined the most. However, the cost of delayed execution does not change the significance of the risk premia, as all the strategies remain statistically profitable. Second, it appears that the risk-managed portfolios do not necessarily improve the risk-return trade-off. The momentum strategy is only enhanced when the risk is managed at the portfolio level; while carry premium sees improvements when the risk is managed at both individual and portfolio level. However, the basis-momentum performs the best when there is no active risk control.

Overall, this table highlights the deviation between the theoretical return and practical/risk-managed profits. To further investigate the impact of contract rolling and portfolio construction methods on risk premia, the next section will discuss three rolling-driven momentum strategies performance.

5.5 Dynamic contract selection strategy performance

Inspired by de Groot et al. (2014), this study proposes three dynamic contract selection (DCS) strategies to add a new dimension to the examination of contract rolling and portfolio weighting. Table 6 presents the performance statistics of the three DCS "momentum" strategies, namely, high roll-yield momentum (HRMOM), high momentum (HMMOM) and all contracts momentum (ALLMOM). Given the solid results on momentum premia discussed above, it is not of surprise that all the DCS profits in Table 6 are statistically and economically significant. Among the three DCS strategies, HRMOM not only outperforms the other two, but also defeats the conventional momentum on the 3rd nearest contracts in terms of risk-adjusted return, as can be seen from Figure 1. Moreover, consistent with de Groot et al. (2014), HRMOM and ALLMOM significantly improves the Sharpe ratios comparing to conventional momentum, with an average 16.87%% increase in the risk-adjusted return by HRMOM and 11.41% by ALLMOM across the three weighting approaches. Another consistency is the noticeable reduction on maximum drawdown by HRMOM and ALLMOM. Slightly different from their findings, it appears that the improvement in the Sharpe ratio is primarily driven by lower volatilities for HRMOM and ALLMOM.

Further, between HRMOM and HMMOM strategies, the findings suggest that the momentum effect can be amplified by strategically being long (short) the most backwardated (contangoed) contract within each winner (loser) commodity. In contrast, the carry effect would likely remain unchanged regardless of whether the winner (loser) contract is chosen for each backwardated (contangoed) commodity. This could be due to that most of the backwardated (contangoed) contracts happen to be the one with highest (lowest) momentum, but not vice versa. Therefore, HRMOM rolls to an advantageous contract after the first sort, while HMMOM already sits in the most beneficial positions with or without the second selection. Finally, when it comes to the impact of portfolio weighting methods, the DCS strategies show different preferences, with HRMOM and ALLMOM favouring the RW approach, HMMOM leaning towards on the EW.

Overall, results from Table 6 confirm the pervasive performance of momentum, carry and basis-momentum in the Chinese market despite how contracts are rolled, selected or weighted. The momentum profits can be enhanced through incorporating carry signals, whereas the carry profits cannot be improved by combing the information from past returns. Next, we will proceed to explore how these strategies interact with each other and traditional asset classes.

5.6 Strategy correlation and diversification

Table 7 reports the Pearson pairwise correlation across all tested strategies. Panel A focuses on the correlation between the three conventional and three DCS strategies, while Panel B reports the correlation between conventional and alternative roll performance of the three conventional strategies. The correlation analysis provides insights on how momentum interacts with carry and the dynamics among different rolling methods. There are several interesting findings. First, results in Panel A suggest that all the six strategies are significantly and positively correlated with each other, with the highest correlation of 0.9362 being observed on the HRMOM and momentum, and the lowest correlation of 0.2762 between basis-momentum and HMMOM strategy. It is also clear that the correlations among momentum, HRMOM and ALLMOM, and between carry and HMMOM are considerably higher than any other pairs. The high correlation implies a strong connection between these strategies, which is consistent with performance statistics. Second, a correlation of 0.4230 between momentum and carry strategy is consistent with Fan and Zhang (2018), and also reaffirms the statement of Fernandez-Perez et al. (2018a) arguing backwardation (contango) likely leads to a future rise (fall) on futures prices. Moreover, the relatively lower correlations of basis-momentum and momentum/carry pairs suggest that basis-momentum is largely different from the other two strategies, which reflects the findings from Boons and Prado (2018) who argue basis-momentum is less likely linked with the *Theory of Normal Backwardation* and the *Theory of Storage*.

As for Panel B, gradual roll reveals the highest correlation with conventional roll for momentum and carry strategies, while dynamic roll appears to intertwine with conventional roll in the basis-momentum strategy. This is consistent with our previous hypothesis arguing the five-day rollover window has not become an influential factor to cause significant changes in China yet. Further, across the three strategies, the correlation between the conventional roll and dynamic roll is always higher than that of conventional and MaxVm roll. This is surprising, as conventional roll should overlap more with MaxVm roll given that they all hold contracts until the last trading day of the preceding month. However, unsurprisingly, the interaction between dynamic and MaxVm roll is stronger than that of MaxVm and conventional roll, as both dynamic and MaxVm roll centre on the most-actively traded contract and neglect less actively traded contracts.

We now proceed to examine the potential diversification benefits of Chinese commodity futures. Figure 2 illustrates the correlations between six strategies and the Chinese stock and bond market returns, as well as inflation shocks. Firstly, it is undeniable that all the six long-short commodity portfolios can be used to hedge traditional assets in China, as the correlations with stocks and bonds are relatively low (<0.17). In particular, the ALLMOM strategy exhibits a negative correlation with the stock market, which makes it the best candidate for diversifying Chinese equity risk. Secondly, the DCS strategies, on average, outperform the conventional strategies in providing diversification benefits for stock assets, but underperform for hedging bond exposures and unexpected inflation. Overall, the six long-short commodity strategies all exhibit potential for inflation hedging and portfolio diversification.

5.7 Factor and robustness analysis

5.7.1 Downside risk exposure

A large body of literature on downside risk argues financial assets' returns should contain a downside risk premium. To test whether downside risk matters in the Chinese commodity futures markets, following Koijen et al. (2018), we employ two models proposed by Henriksson and Merton (1981) and Lettau, Maggiori, and Weber (2014). As shown in Table 8, Panel A reports the results based on the Henriksson and Merton (1981) regression:

$$R_t = \alpha + \beta_{MKT} R_{MKT,t} + \beta_{down} max\{0, -R_{MKT,t}\} + \epsilon_t \tag{13}$$

where R_t is the strategy return at time *t,* $R_{MKT,t}$ denotes the long-only market portfolio return estimated as the average of sample constituents at time *t.* β_{down} is the downside risk exposure estimator which, according to our results, suggests that none of the risk premia is related to downside risk given all the coefficients are insignificant. Panel B exhibits the downside risk exposures using Lettau et al. (2014) regressions. There are two time-series regressions involved per equation (12) and (13), one for the entire sample and one for the subsample where the market return in the downstate is defined as one standard deviation below zero:

$$R_t = \alpha + \beta_{MKT} R_{MKT,t} + \epsilon_t \tag{14}$$

$$R_t = \alpha + \beta_{down} R_{MKT,t} + \epsilon_t \quad \text{where } R_{MKT,t} < \mu - \sigma \tag{15}$$

It appears that carry, basis-momentum and HMMOM are exposed to downside risk, with statistically significant coefficients. This is consistent with Koijen et al. (2018) who also confirm a positive loading on downside risk.

5.7.2 Macroeconomic risk and market conditions

Table 9 demonstrates the strategy performance between up- and down-states in four indicators which are inflation (Panel A), OECD recession indicator (Panel B), market volatility measured by the CSI 300 index (Panel C) and TED spread (Panel D). There are several interesting findings. First, all the six premia appear to be indifferent between high and low inflation periods given the low *t*-statistics from the difference in mean test, though they maintain the statistically and economically significant profitability. This is inconsistent with Levine et al. (2018) who document an overwhelming performance of an equally-weighted commodity portfolio during inflation-up states (10.1% versus -1.0%). Second, similar to the inflation states analysis, the business cycle, measured by the OECD recession indicator, does not cause statistically significant changes in risk premia, either. However, in terms of absolute returns, four out of six strategies indicate large differences, with momentum, carry, HRMOM and ALLMOM returns being halved during recessionary periods. Moreover, it is interesting that all strategies perform better during up states in terms of the business cycle. This implies that commodity prices are pushed up when investors are optimistic on the future economy.

Third, when market states are measured by volatility, the mean-comparison *t*-statistics shows that carry, HMMOM and ALLMOM strategies clearly outperform during low-volatility periods (low volatility periods are defined as market up-states), with an 18.64% per annum differential. This suggests that commodity assets neither perform well when the stock market is turbulent in China. Figure 5 also demonstrates that MOM, CARRY and BMOM are highly volatile during market downturns in terms of Sharpe ratios. Fourth, although results in Panel D illustrate that the Chinese commodity risk premia are not sensitive to the credit environment in terms of comparison *t*-statistics, the overall significance of profits has reduced considerably. Finally, if each month is considered as a unique market state, the seasonality test shown in Figure 3 implies that both conventional and DCS strategies' profitability cannot be subsumed to any months.

5.7.3 Transaction cost

Transaction cost is considered neglectable in commodity futures investments, according to the literature in the US market. Transaction cost consists of several components, such as bid-ask spread, commission and other fees. However, there is no comprehensive research specialising in the market microstructure to unveil the real transaction cost in the Chinese markets. Given the limitation of our data and monthly-rebalance portfolio design, this paper primarily focuses on the commission fee.

In the context of trading strategy, the transaction (commission) fee will be incurred whenever a contract is bought or sold, which normally happens if (i) the composition of long/short portfolio changes, or (ii) a contract rollover process occurs when the holding position expires. The transaction cost is expressed as the percentage of commission fee charged on buying/selling one contract to the contract value, assuming a position is fully collateralised. To derive an aggressive transaction cost estimation and remain conservative in strategy evaluation, this paper exploits the median monthly transaction cost rate as the proxy for a commodity during the sample period. Moreover, given most of the commodities in our sample have monthly maturities, we assume the turnover for the long/short portfolio will be 100%, meaning a transaction fee will be charged on each commodity in every month during the sample period. Figure 4 illustrates the transaction cost estimation for each commodity. It is clear that transaction cost is too small to be a concern for the strategy profitability, as several commodities reveal nearly zero cost and the highest cost is merely 0.016%.

6 Conclusion

In this paper, we investigated two matters that are important to the commodity futures literature but have not gained enough research attention, namely, the rolling of futures contracts and portfolio weights. The Chinese commodity futures markets are the fastest-growing ones in the world. Although they have provoked much interest in academia lately, the relevant literature is relatively underdeveloped and has not thoroughly incorporated the unique market conditions into empirical analysis. The unique market conditions also make these markets an ideal and challenging place to examine our research question. This paper contributes to the literature in four areas. First, for the first time, we confirm, the well-established carry and momentum premia are not subject to contract rolling and portfolio weighting methods, after employing four different rolling and three portfolio construction approaches. However, the benefits of alternative portfolio weights are inconclusive. Second, this paper is the first study to examine basis-momentum in the Chinese markets. Consistent with the literature, we found basis-momentum can deliver alpha and appears to be maturity-sensitive. Third, we confirm a significant improvement in momentum by strategically selecting the most favourable contracts along the futures curve. Lastly, we found some risk premia in

China have a downside risk exposure, are statistically higher when the investors hold higher future expectations on the economy and when the stock market is less volatile.

Table 1 Summary statistics

This table presents the summary statistics of the m^{th} nearest exposure ($m=1, 2, 3, 4$) of the individual commodity traded on Zhengzhou (ZCE), Dalian (DCE) and Shanghai (SHFE) commodity/futures exchange. Mean and SD denotes the monthly average return and standard deviation, respectively. *t*-statistics is reported in parentheses. The last column reports the aggregate monthly average open interest along the futures curve of each commodity. The sample covers the period of February 2004-June 2018.

Exchange	Commodity	Mean (t-statistics)								SD				Open Interest
		m=1		*m=2*		*m=3*		*m=4*		*m=1*	*m=2*	*m=3*	*m=4*	
	Sugar	0.01%	(0.02)	-0.07%	(-0.14)	-0.11%	(-0.22)	-0.08%	(-0.17)	6.14%	5.99%	5.94%	5.58%	789145
	Cotton	-0.10%	(-0.22)	-0.14%	(-0.34)	-0.10%	(-0.23)	-0.09%	(-0.20)	5.64%	5.42%	5.52%	5.53%	284943
	Rapeseed Oil	-0.38%	(-0.86)	-0.33%	(-0.69)	-0.20%	(-0.38)	-0.36%	(-0.68)	5.11%	5.54%	6.00%	6.15%	204788
	PTA	-0.13%	(-0.22)	-0.35%	(-0.61)	-0.36%	(-0.65)	-0.23%	(-0.43)	7.06%	6.71%	6.59%	6.38%	760088
	Strong Gluten Wheat	-0.78%	(-3.02)	-0.56%	(-2.47)	-0.56%	(-2.63)	-0.39%	(-1.82)	3.40%	2.97%	2.81%	2.83%	155158
	Wheat	-1.24%	(-4.44)	-0.76%	(-3.40)	-0.45%	(-2.15)	-0.34%	(-1.60)	3.66%	2.95%	2.74%	2.76%	11148
	Methanol	-0.24%	(-0.28)	-0.07%	(-0.09)	-0.25%	(-0.36)	-0.10%	(-0.14)	7.61%	6.57%	6.26%	6.43%	354176
ZCE	Flat Glass	1.67%	(1.83)	1.12%	(1.93)	0.65%	(1.07)	0.24%	(0.43)	7.51%	4.73%	4.99%	4.63%	433271
	Rapeseed Meal	0.94%	(1.03)	0.96%	(1.31)	0.99%	(1.37)	0.88%	(1.34)	7.47%	6.00%	5.90%	5.36%	1085157
	Rapeseed	0.40%	(0.85)	-0.21%	(-0.51)	-0.13%	(-0.28)	-0.29%	(-0.59)	3.82%	3.39%	3.76%	4.03%	2264
	Non-Glutinous Rice	-0.69%	(-1.39)	-0.69%	(-1.46)	-0.25%	(-0.76)	-0.31%	(-1.07)	5.19%	5.01%	3.50%	3.09%	46208
	Thermal Coal	2.02%	(2.11)	1.08%	(1.40)	0.47%	(0.61)	0.79%	(1.10)	7.32%	5.91%	5.87%	5.46%	213387
	Japonica Rice	0.45%	(0.94)	0.37%	(0.73)	-0.19%	(-0.31)	0.36%	(0.59)	3.56%	3.79%	4.44%	4.56%	380
	Ferrosilicon	1.88%	(1.39)	2.11%	(1.54)	0.08%	(0.06)	1.21%	(0.93)	9.25%	9.40%	9.62%	8.91%	47465
	Silicon Manganese	1.71%	(1.65)	3.41%	(2.85)	1.77%	(1.23)	2.12%	(1.65)	7.12%	8.20%	9.86%	8.80%	48563
	No.1 Soybean	-0.37%	(-1.06)	-0.10%	(-0.30)	0.26%	(0.74)	0.20%	(0.57)	4.60%	4.30%	4.57%	4.65%	400153
	No.2 Soybean	0.62%	(1.36)	0.30%	(0.83)	0.45%	(1.24)	0.24%	(0.60)	5.87%	4.55%	4.61%	5.09%	5980
	Corn	-0.31%	(-1.06)	-0.08%	(-0.33)	0.02%	(0.10)	-0.06%	(-0.23)	3.75%	3.11%	2.87%	3.10%	890909
	LLDPE	0.49%	(0.77)	0.25%	(0.40)	0.16%	(0.25)	-0.01%	(-0.01)	7.26%	7.27%	7.18%	7.75%	349092
	Soybean Meal	1.20%	(2.27)	1.03%	(2.22)	0.85%	(1.82)	0.73%	(1.59)	6.97%	6.11%	6.13%	5.98%	1666478
	Palm Oil	-0.75%	(-1.36)	-0.99%	(-1.64)	-0.55%	(-0.91)	-0.27%	(-0.47)	6.31%	6.88%	6.92%	6.56%	485099
	PVC	-0.16%	(-0.30)	0.08%	(0.16)	0.10%	(0.20)	-0.24%	(-0.49)	5.67%	5.28%	5.49%	5.09%	108639
DCE	Soybean Oil	-0.07%	(-0.13)	-0.12%	(-0.25)	0.03%	(0.06)	-0.04%	(-0.08)	6.56%	6.21%	6.14%	6.03%	658389
	Coke	-0.03%	(-0.02)	-0.10%	(-0.09)	-0.08%	(-0.07)	0.51%	(0.45)	11.43%	10.41%	10.40%	10.61%	191846
	Coking Coal	0.99%	(0.81)	-0.11%	(-0.11)	0.57%	(0.48)	0.55%	(0.47)	9.74%	8.45%	9.51%	9.20%	258882
	Plywood	0.27%	(0.18)	-0.54%	(-0.53)	-0.04%	(-0.04)	-0.56%	(-0.62)	10.77%	7.53%	7.21%	6.74%	15608
	Fiberboard	2.85%	(1.78)	1.06%	(0.84)	1.67%	(1.28)	1.08%	(0.95)	11.88%	9.33%	9.69%	8.42%	18135
	Egg	-2.41%	(-1.94)	-1.57%	(-1.58)	-1.01%	(-1.26)	-0.32%	(-0.49)	9.29%	7.46%	5.98%	4.84%	237737
	Iron Ore	2.99%	(1.96)	0.70%	(0.51)	0.83%	(0.63)	0.09%	(0.06)	11.49%	10.34%	9.95%	10.40%	1508383
	Polypropylene	1.32%	(1.40)	0.91%	(1.19)	0.75%	(0.98)	0.63%	(0.87)	7.55%	6.15%	6.09%	5.78%	447848
	Corn Starch	-0.12%	(-0.13)	0.05%	(0.07)	-0.22%	(-0.27)	-0.15%	(-0.19)	6.04%	5.00%	5.22%	5.14%	532012
	Aluminium	-0.09%	(-0.26)	-0.16%	(-0.47)	-0.18%	(-0.54)	-0.14%	(-0.41)	4.60%	4.43%	4.41%	4.43%	309270
	Gold	0.18%	(0.38)	0.10%	(0.22)	-0.02%	(-0.06)	0.34%	(0.52)	5.33%	5.17%	4.94%	5.69%	164124
	Copper	1.16%	(1.98)	1.22%	(2.05)	1.05%	(1.73)	0.99%	(1.62)	7.70%	7.85%	7.97%	8.05%	413921
	Fuel Oil	-0.46%	(-0.69)	-0.13%	(-0.22)	0.30%	(0.52)	-0.24%	(-0.43)	8.72%	7.76%	7.40%	7.22%	44408
	Lead	0.31%	(0.47)	0.28%	(0.45)	0.23%	(0.37)	0.10%	(0.17)	6.18%	5.92%	5.79%	5.70%	34840
	Steel Rebar	0.17%	(0.22)	0.21%	(0.30)	0.23%	(0.36)	0.17%	(0.27)	8.26%	7.30%	6.92%	6.83%	2184398
SHFE	Natural Rubber	-0.52%	(-0.78)	-0.31%	(-0.45)	-0.34%	(-0.48)	-0.47%	(-0.68)	8.67%	8.97%	9.22%	9.21%	230944
	Steel Wire	-0.28%	(-0.50)	0.20%	(0.35)	0.39%	(0.68)	-0.05%	(-0.10)	5.88%	6.16%	6.06%	5.45%	3453
	Zinc	-0.01%	(-0.02)	-0.08%	(-0.13)	-0.10%	(-0.17)	-0.08%	(-0.13)	7.05%	7.10%	7.21%	7.25%	308827
	Silver	-0.99%	(-1.34)	-0.95%	(-1.28)	-0.84%	(-1.12)	-0.64%	(-0.85)	6.25%	6.27%	6.35%	6.39%	531410
	Bitumen	-1.66%	(-1.65)	-1.52%	(-1.44)	-1.37%	(-1.47)	-1.17%	(-1.22)	7.57%	7.95%	7.04%	7.23%	403838
	Hot-Rolled Coil	1.60%	(1.31)	1.63%	(1.50)	1.17%	(1.04)	0.92%	(0.81)	8.82%	7.82%	8.15%	8.15%	341629
	Tin	-0.10%	(-0.13)	0.24%	(0.33)	0.53%	(0.71)	0.22%	(0.33)	4.79%	4.65%	4.73%	4.18%	16318

Table 2 Baseline performance

This table reports the performance statistics of *Momentum, Carry and Basis-Momentum* strategy on m^{th} (*m=1,2,3,4*) nearest contracts. Momentum strategy sorts commodities based on the m^{th}-nearest past 12-month compounding return, carry signal on m^{th} exposure is defined as the $F_t^{m-1}/F_t^m - 1$ where F_t^m denotes the price of m^{th} nearest contract at time *t* (F_t^0 represents the spot price at time *t*) (de Groot et al., 2014). Following Boons and Prado (2018), basis-momentum exploits the difference in momentum signals on m^{th} and $m+1^{\text{th}}$ nearest contracts. Based on these signals, the sample is sorted into quartiles, and strategy return is evaluated as the spread between the top and bottom quartile portfolio. All portfolios are rebalanced monthly, and the sample covers the period of February 2004-June 2018. Annualised mean is the geometric annual return.

	Momentum				Carry				Basis-Momentum			
	m=1	*m=2*	*m=3*	*m=4*	*m=1*	*m=2*	*m=3*	*m=4*	*m=1*	*m=2*	*m=3*	*m=4*
Annualised Mean	0.2451	0.1945	0.1739	0.1640	0.1097	0.1568	0.1033	0.1144	0.1254	0.0381	0.1423	0.0122
t-statistics	5.20	4.38	3.68	3.48	2.97	3.94	2.75	2.78	3.50	1.30	4.01	0.58
Annualised Volatility	0.1834	0.1741	0.1900	0.1905	0.1556	0.1637	0.1593	0.1799	0.1410	0.1317	0.1383	0.1273
Annualised Downside Volatility	0.0985	0.0990	0.0994	0.1104	0.1282	0.1414	0.1043	0.1672	0.0998	0.1045	0.0921	0.0795
Sharpe Ratio	1.3365	1.1168	0.9156	0.8613	0.7049	0.9577	0.6482	0.6359	0.8891	0.2896	1.0286	0.0961
Sortino Ratio	2.9934	2.3272	2.1030	1.7890	1.0077	1.3044	1.1715	0.8392	1.4422	0.4587	1.7678	0.2575
Omega Ratio	2.9530	2.6531	2.4734	2.0226	2.1392	2.2702	1.6876	1.7109	1.9848	1.3702	2.2232	1.0942
Skewness	0.4471	0.5799	0.6085	0.4689	-1.0459	-0.8635	-0.1027	-1.9570	-0.3782	-0.8822	-0.0840	0.0568
Excess Kurtosis	1.9217	2.3083	2.0255	1.6066	5.1041	7.1501	1.4500	17.9406	2.2126	2.5314	0.6600	1.3023
99%VaR(Cornish-Fisher)	0.1900	0.1863	0.1975	0.1867	0.1366	0.1728	0.1274	0.3160	0.1128	0.0901	0.1082	0.1006
% of Positive Months	0.6750	0.6563	0.6375	0.6250	0.6395	0.6919	0.5930	0.6105	0.6438	0.5500	0.6687	0.5250
Maximum Drawdown	-0.4276	-0.3032	-0.3506	-0.2736	-0.3469	-0.3107	-0.3325	-0.5339	-0.2574	-0.4162	-0.2569	-0.4366
CER	0.1745	0.1335	0.1041	0.0932	0.0527	0.0913	0.0508	0.0064	0.0824	0.0002	0.1018	-0.0203

Table 3 Performance on alternative weight

This table exhibits the performance statistics of *Momentum, Carry and Basis-Momentum* strategy with alternative weighting methods. The equal weight (EW) is the same as those in Table 2 except that the sample is sorted into two portfolios instead of four. Following Asness et al. (2013) and Koijen et al. (2018), rank weight (RW) method assigns a weight w_t^c to commodity c at time *t,* which equals to $z_t\left(rank(S_t^c)-\frac{N_t+1}{2}\right)$ where S_t^c is the signal of commodity c at time t and N_t is the total number of available commodities cross sectionally at time *t.* z_t is the scalar that makes the sum of long (short) positions equal to 1 (-1). Inspired by Fan et al. (2019), we also adopt a strength weight (SW) method that defines the weight of each commodity c at time t as $SS_{c,t}/\sum_{c=1}^{N}\left|SS_{c,t}\right|$, where $SS_{c,t}$ represents the standardised signal of commodity c at time t and equals to $(S_t^c-\overline{S_t})/\sigma_{S,t}$ The sorting signals are the same as those in Table 2, and all performances are evaluated on the 3rd nearest contracts. For RW and SW, all the constituents in long (short) portfolio have a total weight of 1 (-1), so to make the three weighting methods comparable. All portfolios are rebalanced monthly, and the sample covers the period of February 2004-June 2018. Annualised mean is the geometric annual return.

	Momentum			Carry			Basis-Momentum		
	EW	RW	SW	EW	RW	SW	EW	RW	SW
Annualized Mean	0.0957	0.1479	0.1705	0.0798	0.0871	0.0894	0.0797	0.1180	0.1772
t-statistics	3.14	3.69	3.59	3.21	2.90	2.66	3.05	3.89	4.63
Annualized Volatility	0.1194	0.1583	0.1913	0.1001	0.1238	0.1408	0.1015	0.1171	0.1482
Annualized Downside Volatility	0.0615	0.0827	0.0969	0.0704	0.0863	0.0757	0.0634	0.0768	0.0844
Sharpe Ratio	0.8013	0.9340	0.8910	0.7971	0.7037	0.6346	0.7855	1.0081	1.1958
Sortino Ratio	1.7507	2.0834	2.1180	1.2511	1.1463	1.3709	1.3904	1.7206	2.4277
Omega Ratio	2.0182	2.2762	2.0416	1.8261	1.8724	1.7540	1.9272	2.2789	2.5739
Skewness	0.3923	0.4487	0.4418	-0.2453	-0.4562	0.3423	0.3006	0.0236	0.2432
Excess Kurtosis	0.4945	0.9992	0.8220	1.7564	1.7028	0.9167	1.7450	0.9769	0.7154
99%VaR(Cornish-Fisher)	0.1052	0.1488	0.1768	0.0792	0.0906	0.1246	0.0956	0.0976	0.1325
% of Positive Months	0.5687	0.6062	0.6312	0.6047	0.6279	0.5756	0.6125	0.6375	0.6687
Maximum Drawdown	-0.3093	-0.3623	-0.3629	-0.2363	-0.2768	-0.2167	-0.2391	-0.2320	-0.1560
CER	0.0673	0.0982	0.0992	0.0587	0.0546	0.0505	0.0589	0.0891	0.1310
Capacity (in thousand RMB)	221.30	110.65	174.49	265.56	154.88	112.24	205.52	147.53	140.55

Table 4 Performance on alternative rolling

This table presents the performance statistics of the *Momentum, Carry and Basis-Momentum* strategy under different rolling schemes. *Gradual* refers to the rolling scheme that assumes to hold the m^{th} nearest contracts until the 5^{th} last trading day of the preceding month, at the end of which a 20% position will be rolled to the next m^{th} nearest contracts. The remaining 80% position will be gradually and evenly rolled over the remaining 4 trading days. *MaxVm* rolling scheme always holds the contract with the highest trading volume until the last trading day of the prior month, then rolls the next highest-volume-contract. *Dynamic* roll also starts with the highest-volume-contract but will change position to the target contract whose trading volume exceeds the current contract for three consecutive days. Momentum strategy sorts commodities based on the past 12-month compounding return derived from the three rolling schemes' return series, while carry and basis-momentum employ signals estimated on the 3^{rd} nearest contracts as described in Table 2. All portfolios are rebalanced monthly, and the sample covers the period of February 2004-June 2018. Annualised mean is the geometric annual return.

	Momentum			Carry			Basis-Momentum		
	Gradual	MaxVm	Dynamic	Gradual	MaxVm	Dynamic	Gradual	MaxVm	Dynamic
Annualised Mean	0.1796	0.1851	0.1210	0.1082	0.1166	0.0873	0.1406	0.1346	0.1100
t-statistics	3.80	4.05	2.76	2.89	3.05	2.41	3.91	3.87	3.21
Annualised Volatility	0.1889	0.1810	0.1817	0.1580	0.1603	0.1562	0.1406	0.1354	0.1357
Annualised Downside Volatility	0.1032	0.0883	0.1022	0.1036	0.1073	0.1059	0.1037	0.0828	0.0883
Sharpe Ratio	0.9509	1.0229	0.6659	0.6848	0.7271	0.5591	0.9999	0.9946	0.8113
Sortino Ratio	2.0877	2.4959	1.4295	1.2296	1.2792	0.9827	1.5560	1.8530	1.4250
Omega Ratio	2.3169	2.2692	1.7300	1.7221	1.8247	1.6353	2.2059	2.1808	1.9553
Skewness	0.5807	0.8358	0.3603	-0.0823	0.0074	-0.0931	-0.5100	0.0614	0.0021
Excess Kurtosis	2.0205	3.0509	1.2781	1.4873	1.1055	1.6402	1.8860	0.2943	0.7456
99%VaR(Cornish-Fisher)	0.1959	0.2084	0.1667	0.1281	0.1308	0.1261	0.1067	0.1081	0.1079
% of Positive Months	0.6500	0.6250	0.6000	0.5988	0.6279	0.6047	0.6563	0.6250	0.6250
Maximum Drawdown	-0.3748	-0.3812	-0.3905	-0.3095	-0.2716	-0.3123	-0.2763	-0.2513	-0.2646
CER	0.1100	0.1219	0.0567	0.0566	0.0641	0.0372	0.0970	0.0965	0.0723

Table 5 Implementation

This table illustrates the performance statistics of *Momentum, Carry and Basis-Momentum* under three circumstances. LAG is the situation where the strategies are evaluated when a 3-day gap is applied between sort and execution date. VW stands for volatility weight. Inspired by Moskowitz et al. (2012), VW gives each commodity c in the long portfolio a weight of $z_t(1/\sigma_{t-1})$ where $\sigma_t^2 = 261\sum_{i=0}^{\infty}(1-\delta)\delta^i(r_{t-1-i}-\bar{r}_t)^2$ is the exponentially weighted volatility and z_t is the scalar that makes the sum of long (short) positions equal to 1 (-1), whereas each commodity c in the short portfolio is assigned a weight of $z_t\sigma_{t-1}$. Following Moreira and Muir (2017), we evaluate the three strategies by applying a target volatility (TargetV). The long and short portfolio returns are defined as $R_{t+1} = \frac{c}{\sigma_{R,t}}R_{t+1}$, where $\sigma_{R,t}$ is the portfolio's previous month standard deviation and c is the target level. All portfolios are rebalanced monthly, and the sample covers the period of February 2004-June 2018. Annualised mean is the geometric annual return.

	Momentum			Carry			Basis-Momentum		
	LAG	VW	TargetV	LAG	VW	TargetV	LAG	VW	TargetV
Annualized Mean	0.1555	0.1547	0.1582	0.0757	0.0888	0.0890	0.1257	0.1219	0.0897
t-statistics	3.55	3.29	4.28	2.30	2.37	2.47	3.72	3.47	2.78
Annualized Volatility	0.1753	0.1909	0.1434	0.1412	0.1620	0.1539	0.1319	0.1380	0.1292
Annualized Downside Volatility	0.1018	0.1028	0.0658	0.0947	0.0890	0.0943	0.0897	0.0909	0.1150
Sharpe Ratio	0.8871	0.8103	1.1033	0.5360	0.5486	0.5782	0.9528	0.8832	0.6944
Sortino Ratio	1.8125	1.8139	2.7601	0.9412	1.1961	1.1133	1.5933	1.5347	0.8941
Omega Ratio	1.9914	2.0885	2.7211	1.5103	1.6154	1.6297	2.1206	1.9631	1.7992
Skewness	0.2772	0.6415	1.4235	-0.2530	0.6003	1.4089	-0.0843	-0.1167	-0.9717
Excess Kurtosis	1.0601	2.3576	5.5698	1.5978	1.4265	10.0377	0.6756	0.9731	11.0526
99%VaR(Cornish-Fisher)	0.1580	0.2022	0.1956	0.1072	0.1565	0.2496	0.1025	0.1080	0.1659
% of Positive Months	0.6125	0.6375	0.6188	0.5930	0.5640	0.5872	0.6625	0.6687	0.6625
Maximum Drawdown	-0.2526	-0.3544	-0.1874	-0.3457	-0.3765	-0.2533	-0.2409	-0.1792	-0.2319
CER	0.0940	0.0849	0.1188	0.0342	0.0391	0.0454	0.0892	0.0821	0.0502

Table 6 Dynamic contract selection

This table reports the performance statistics of three dynamic contract selection strategies, namely *High Roll-Yield*, *High Momentum* and *All Contracts,* with equal weight (EW), rank weight (RW) and strength weight (SW). *High Roll-Yield* firstly sorts commodities based on the momentum signal estimated on the 3rd nearest contracts, then chooses the contracts with highest roll yields for winners and contracts with lowest roll-yields for losers. Conversely, *High Momentum's* first sort is based on the carry signal on the 3rd nearest contracts, and then selects the highest-momentum contracts for backwardated commodities and lowest-momentum contracts for contangoed commodities. *All Contracts* strategy first selects the highest and lowest-momentum contracts across the futures curve within each commodity as momentum winner and loser candidates, then cross-sectionally long (short) the higher (lower) winner (loser) candidates. Signals and weight methods are the same as those in previous tables. All portfolios are rebalanced monthly, and the sample covers the period of February 2004-June 2018. Annualised mean is the geometric annual return.

	High Roll-Yield			High Momentum			All Contracts		
	EW	RW	SW	EW	RW	SW	EW	RW	SW
Annualised Mean	0.1211	0.1751	0.2011	0.0986	0.0800	0.0728	0.1101	0.1616	0.1782
t-statistics	3.91	4.43	4.21	3.63	2.74	2.14	3.52	4.23	4.20
Annualised Volatility	0.1197	0.1538	0.1898	0.1045	0.1154	0.1408	0.1218	0.1486	0.1668
Annualised Downside Volatility	0.0658	0.0875	0.1093	0.0592	0.0733	0.0934	0.0683	0.0743	0.0832
Sharpe Ratio	1.0117	1.1387	1.0597	0.9432	0.6936	0.5170	0.9038	1.0877	1.0686
Sortino Ratio	2.0635	2.3240	2.2125	1.8425	1.2305	0.9192	1.8129	2.5092	2.5156
Omega Ratio	2.1899	2.6770	2.3493	2.1938	1.7154	1.4819	1.9960	2.4538	2.4137
Skewness	0.3187	0.3271	0.2794	0.3781	-0.1410	-0.1802	0.3001	0.5556	0.6273
Excess Kurtosis	0.4879	1.0692	1.0102	1.0169	0.1228	1.8742	1.7641	1.5237	1.5714
99%VaR(Cornish-Fisher)	0.1054	0.1436	0.1733	0.0966	0.0809	0.1119	0.1161	0.1499	0.1708
% of Positive Months	0.6188	0.6438	0.6375	0.6125	0.5875	0.5625	0.5938	0.6188	0.5875
Maximum Drawdown	-0.2268	-0.2192	-0.2609	-0.2331	-0.2221	-0.3142	-0.3129	-0.3000	-0.2609
CER	0.0916	0.1262	0.1281	0.0762	0.0527	0.0319	0.0798	0.1170	0.1231

Table 7 Correlation

This table reports two sets of correlations. Panel A reveals the correlation conventional strategies, namely, *Carry* (CARRY), *Momentum* (MOM), *Basis-Momentum* (BMOM), and dynamic selection strategies including *High Roll-yield Momentum* (HRMOM), *High Momentum* (HMMOM) and *All-contracts Momentum* (ALLMOM). Panel B exhibits the correlation across strategies under the conventional roll and alternative roll methods. Letter G, M and D refer to *Gradual* roll, *MaxVm* roll, *Dynamic* roll, respectively. * indicates significance at the 5% level.

Panel A: Correlation between conventional and dynamic selection strategies

	MOM	CARRY	BMOM	HRMOM	HMMOM
CARRY	0.4230*				
BMOM	0.3291*	0.2962*			
HRMOM	0.9362*	0.4244*	0.3291*		
HMMOM	0.4902*	0.8660*	0.2762*	0.4797*	
ALLMOM	0.8565*	0.3646*	0.3152*	0.8547*	0.5123*

Panel B: Correlation between conventional and alternative-rolling performance

B (i)

	MOM	GMOM	MMOM
GMOM	0.9853*		
MMOM	0.8609*	0.8539*	
DMOM	0.9255*	0.9298*	0.8898*

B (ii)

	CARRY	GCARRY	MCARRY
GCARRY	0.9950*		
MCARRY	0.9149*	0.9142*	
DCARRY	0.9553*	0.9569*	0.9487*

B (iii)

	BMOM	GBMOM	MBMOM
GBMOM	0.8468*		
MBMOM	0.9126*	0.7549*	
DBMOM	0.9596*	0.8131*	0.9264*

Table 8 Downside risk exposures

This table exhibits the exposures of six long-short strategies on downside market risk. Panel A exploits the Henriksson and Merton (1981) model, where downside beta is derived from a regression of strategy returns on the market (MKT) and the maximum of zero or minus market returns (Downside beta). Panel B employs the Lettau et al. (2014) model which consists of two time-series regressions. The MKT in Panel B is the regression beta of strategy returns on market returns, whereas the Downside corresponds to coefficients of strategy returns on the market returns conditioned on where the market is below the mean minus one standard deviation.

	MOM	CARRY	BMOM	HRMOM	HMMOM	ALLMOM
Panel A: Henriksson and Merton (1981) downside risk						
MKT	0.340	0.268*	0.413**	0.305	0.391**	0.220
	-1.24	-1.96	-2.59	-1.15	-2.34	-0.79
Downside	-0.167	-0.381	0.092	-0.253	-0.085	-0.153
	(-0.54)	(-1.59)	-0.41	(-0.80)	(-0.40)	(-0.45)
Constant	0.018***	0.015***	0.011***	0.022***	0.010**	0.018***
	-3.24	-3.15	-2.96	-3.50	-2.10	-3.39
Panel B:Lettau et al. (2014) downside risk						
MKT	0.430***	0.477***	0.363***	0.442***	0.437***	0.303**
	(2.87)	(3.81)	(3.39)	(2.88)	(4.38)	(1.98)
Downside	0.288	0.870***	0.667***	0.274	0.633***	-0.032
	(1.69)	(3.82)	(10.05)	(1.39)	(5.77)	(-0.25)

Table 9 Market states analysis

This table reports the strategy performance during up- and down-market states proxied by four indicators. Panel A defines market up-state as those periods when the inflation rate is above the sample median. Panel B divides the market into up- and down-states using the OECD recession indicator, where an expansionary (recessionary) period is considered as upturn. Panel C separates market by the volatility measured by the Chinese stock index (CSI300). Panel D categorises market condition by the Chinese credit risk measured as the difference between the interbank lending rate and the 3-month Chinese government bond yield. The last row of each panel is the difference-in-means *t*-statistics for the up- and down-sample.

	MOM		Carry		BMOM		HRMOM		HMMOM		ALLMOM	
	Up	Down	Up	Down	Up	Down	Up	Down	Up	Down	Up	Down
Panel A: Market states by inflation												
#months	75	85	86	86	75	85	75	85	75	84	75	85
Annualized Mean	0.1933	0.1569	0.1114	0.0951	0.1449	0.1400	0.1991	0.2118	0.1607	0.0410	0.2204	0.1366
t-statistics	3.20	2.23	2.00	1.89	2.52	3.21	3.30	2.87	2.65	0.85	3.95	2.02
Annualized Volatility	0.1607	0.2134	0.1683	0.1507	0.1553	0.1223	0.1603	0.2171	0.1640	0.1723	0.1459	0.2069
difference *t*-stat	0.26		0.23		0.12		-0.22		1.28		0.76	
Panel B: Market states by business cycle												
#months	91	69	103	69	91	69	91	69	90	69	91	69
Annualized Mean	0.2162	0.1184	0.1405	0.0479	0.1725	0.1025	0.2647	0.1286	0.1055	0.0866	0.2227	0.1141
t-statistics	3.12	1.95	2.89	0.89	3.81	1.84	3.63	2.24	1.91	1.44	3.30	2.03
Annualized Volatility	0.2093	0.1608	0.1544	0.1662	0.131	0.1477	0.2182	0.1489	0.1712	0.1667	0.2018	0.1475
difference *t*-stat	1.05		1.04		0.87		1.47		0.21		1.23	
Panel C: Market states by volatility												
#months	76	75	76	75	76	75	76	75	76	75	76	75
Annualized Mean	0.2129	0.1064	0.1772	-0.0065	0.1392	0.1240	0.2374	0.1268	0.1777	-0.0141	0.2541	0.0705
t-statistics	2.92	1.73	3.79	0.13	3.45	2.13	3.23	2.00	3.33	0.03	3.65	1.23
Annualized Volatility	0.1997	0.1747	0.1224	0.1753	0.1056	0.1602	0.1995	0.1776	0.1415	0.1837	0.1861	0.1724
difference *t*-stat	1.04		2.06		0.11		1.07		1.99		1.83	
Panel D: Market states by credit risk												
#months	45	44	45	44	45	44	45	44	45	44	45	44
Annualized Mean	0.1294	0.1017	0.0628	0.0763	0.0923	0.1441	0.1333	0.1495	0.0014	0.0742	0.1161	0.1656
t-statistics	1.76	1.51	1.10	1.54	1.85	3.09	2.00	2.17	0.14	1.35	1.68	2.38
Annualized Volatility	0.1558	0.1414	0.1243	0.1014	0.1016	0.0917	0.1384	0.1402	0.1267	0.1138	0.1459	0.1411
difference *t*-stat	0.27		-0.13		-0.72		-0.16		-0.81		-0.46	

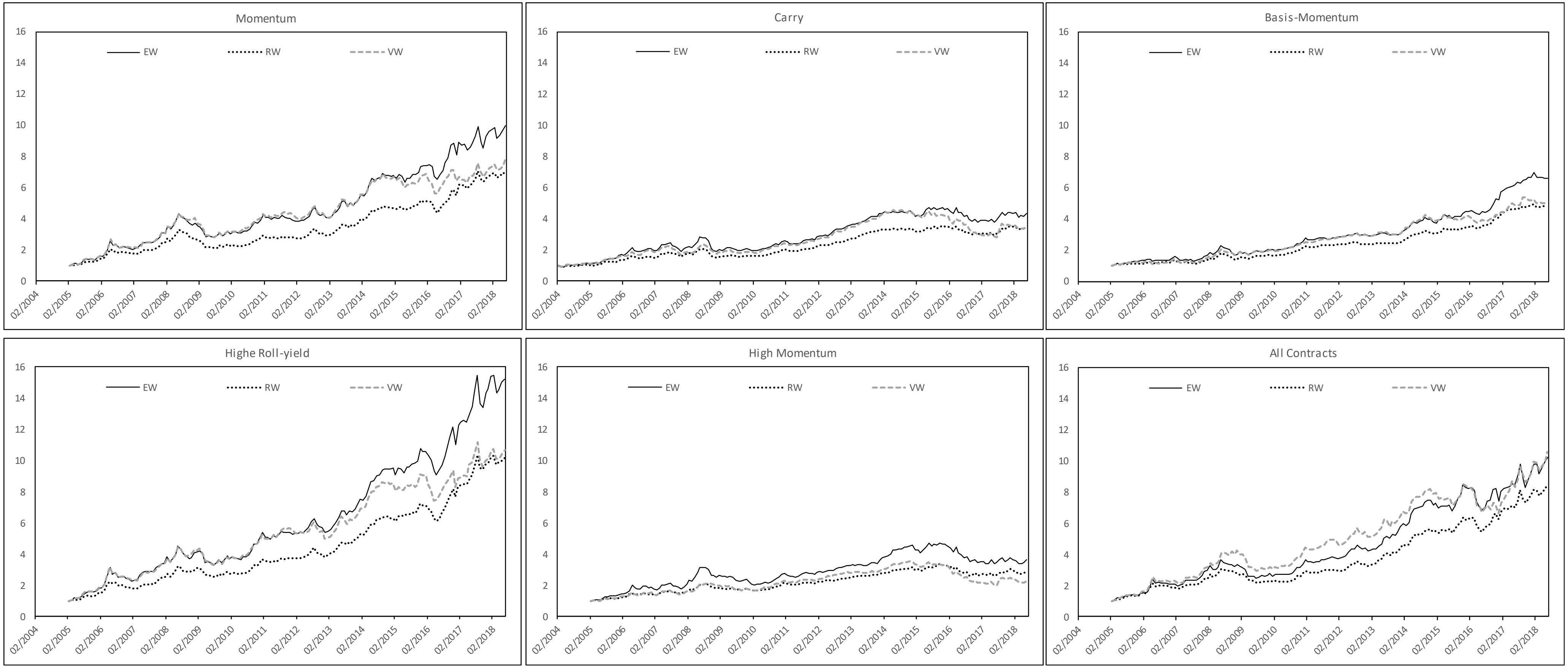

Figure 1 Strategy Performance

This figure demonstrates the cumulative performance of the six strategies under three different portfolio weighting schemes. At each time t, the performance index value $I_t = I_{t-1} \times (1 + r_t)$, where r_t represents the strategy return at time t. All strategies are rebalanced monthly.

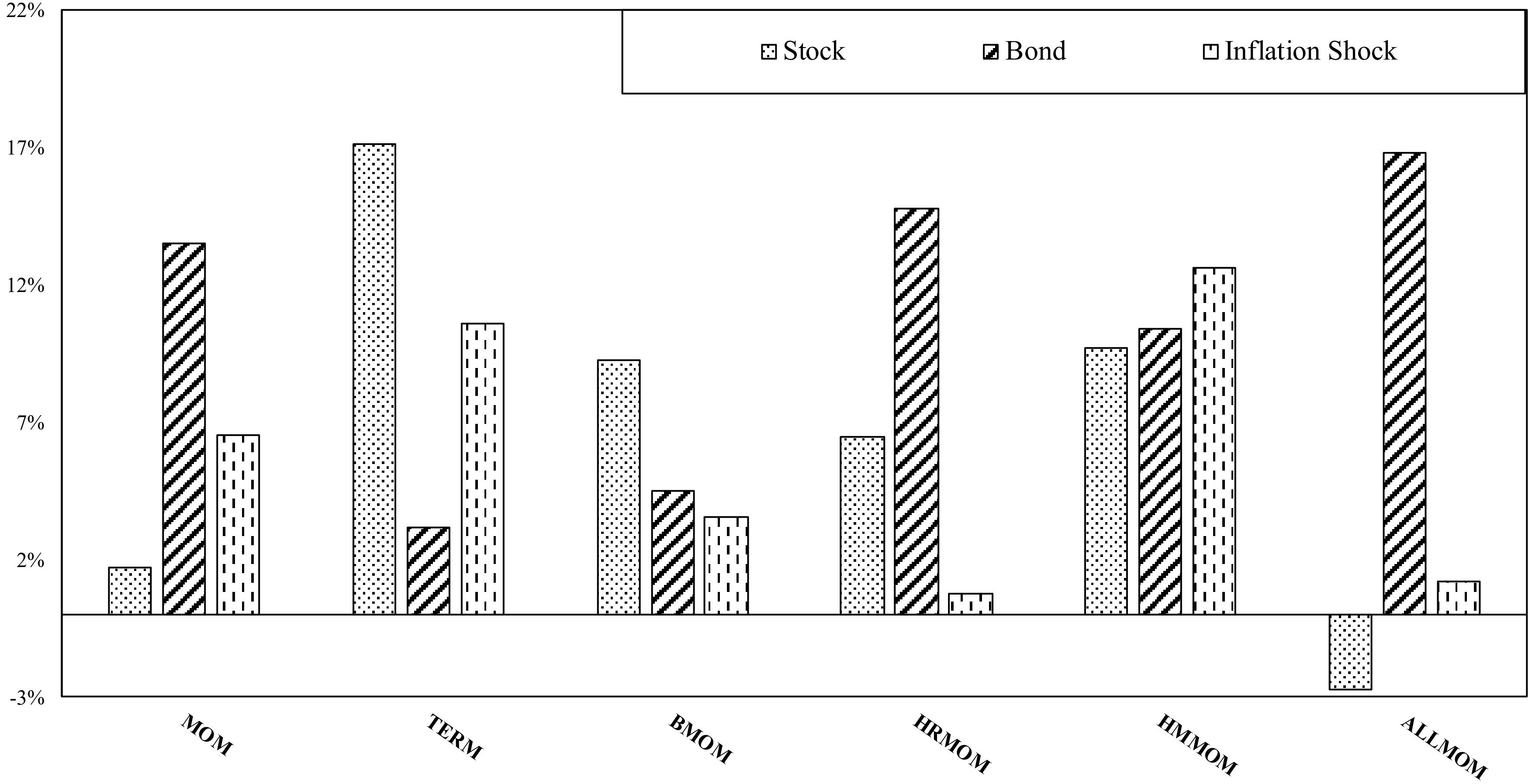

Figure 2 Strategy diversification potential

This chart demonstrates the correlation between strategies and Chinese stocks, bonds and unexpected inflation.

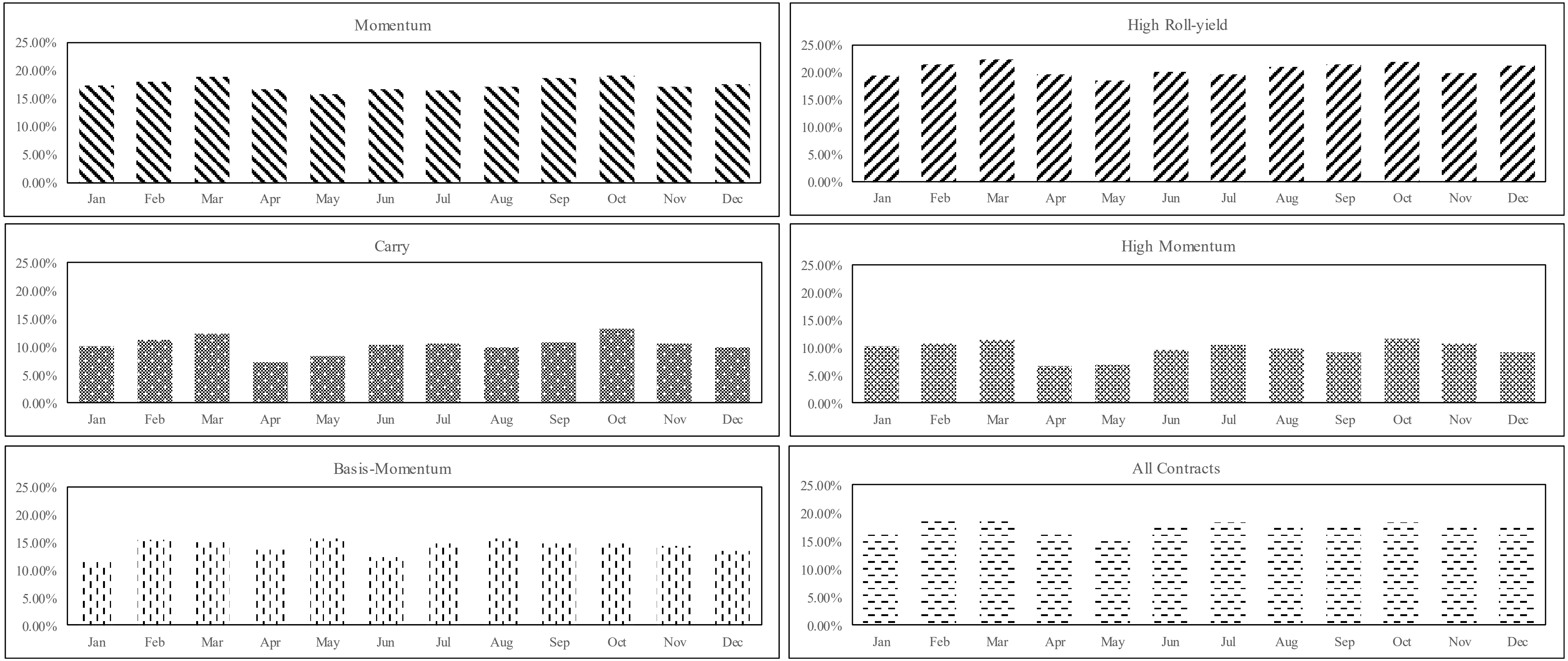

Figure 3 Seasonality

This chart illustrates the seasonal performance of the six strategies. Each bar presents the annualised geometric mean return when excluding the underlying month from the sample.

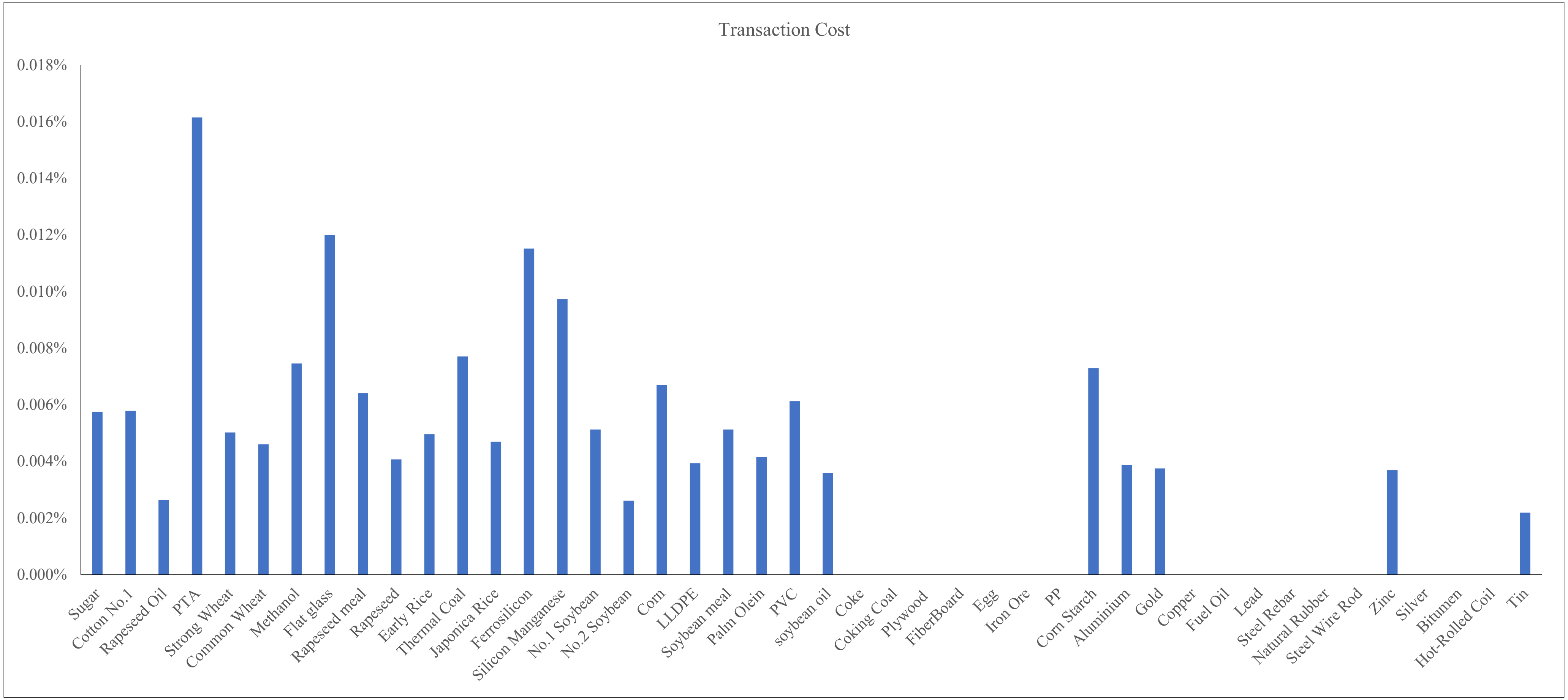

Figure 4 Transaction cost

This graph reveals the transaction cost estimates for all commodities in the sample. Each bar represents the median of monthly transaction cost of the corresponding commodity.

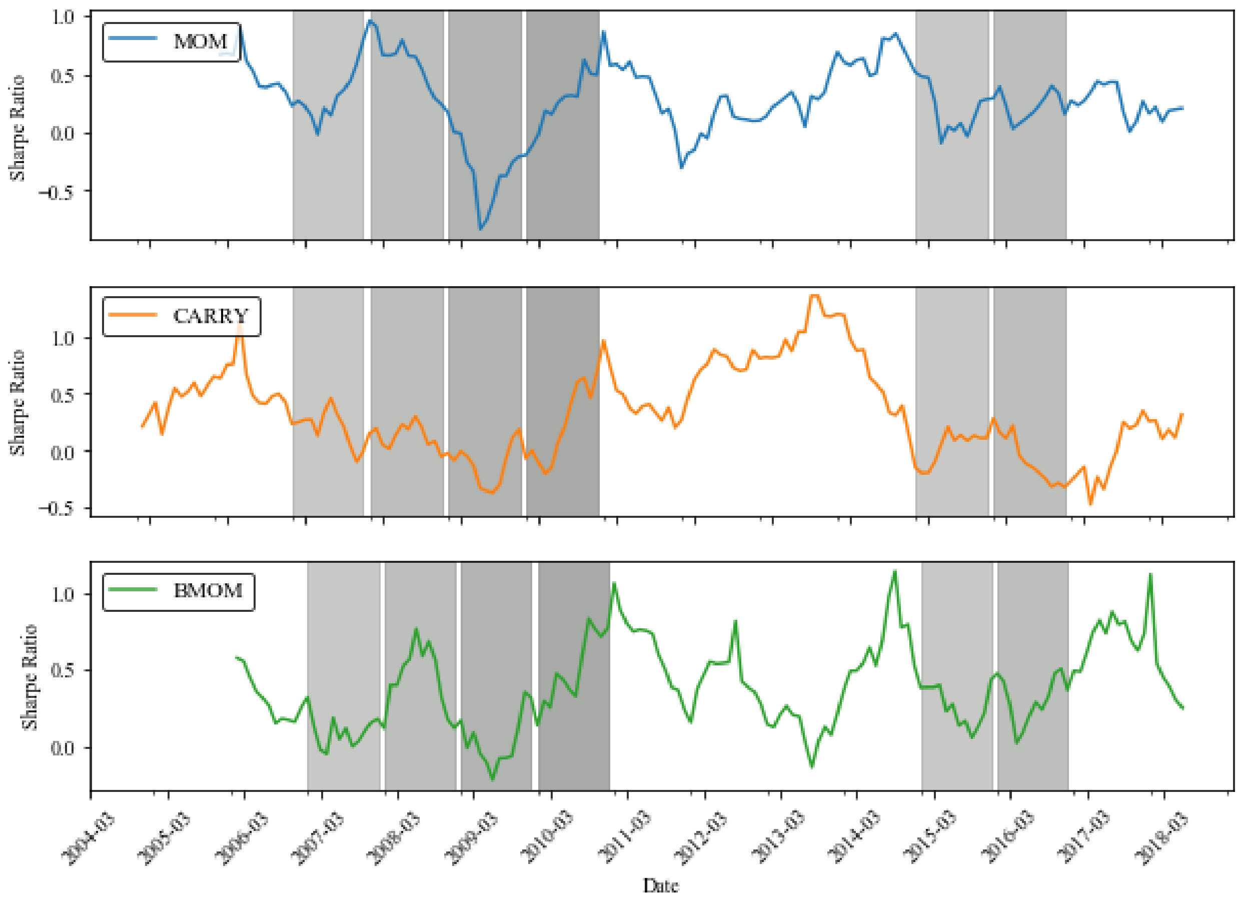

Figure 5 Rolling Sharpe ratio

This figure exhibits the 12-month rolling Sharpe ratios of the three strategies. The grey areas are the market down-states proxied by the Chinese stock market.

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