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The emotional cost-of-carry: Chinese investor sentiment and equity index futures basis

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Abstract

Purpose – While the classic futures pricing tool works well for capital markets that are less affected by sentiment, it needs further modification in China's case as retail investors constitute a large portion of the Chinese stock market participants. Their expectations of the rate of return are prone to emotional swings. This paper, therefore, explores the role of investor sentiment in explaining futures basis changes via the channel of implied discount rates.

Design/methodology/approach – Using Chinese equity market data from 2010 to 2019, the authors augment the cost-of-carry model for pricing stock index futures by incorporating the investor sentiment factor. This design allows us to estimate the basis in a better way that reflects the relationship between the underlying index price and its futures price.

Findings – The authors find strong evidence that the measure of Chinese investor sentiment drives the abnormal fluctuations in the basis of China's stock index futures. Moreover, this driving force turns out to be much less prominent for large-cap stocks, liquid contracting frequencies, regulatory loosening periods and mature markets, further verifying the sentiment argument for basis mispricing.

Originality/value – This study contributes to the literature by relying on investor sentiment measures to explain the persistent discount anomaly of index futures basis in China. This finding is of great importance for Chinese investors with the intention to implement arbitrage, hedging and speculation strategies.

Keywords Investor sentiment, Equity index futures, Basis, Cost-of-carry model

Paper type Research paper

1. Introduction

Stock index futures have served as a main derivative instrument on stock exchanges. On the one hand, with the advantages of high liquidity and low transaction costs, index futures play an irreplaceable role for investors in hedging their positions against potential future losses. On the other hand, they also serve as a significant leading indicator of market trends for traders in betting on how the underlying index will move, promoting the prosperity of the equity market. Thus, since their first introduction to market use in the 1980s, stock index futures have always exhibited good risk management and speculation effects in mature financial markets. One can partly attribute this success to the satisfactory performance of the classic futures pricing model in mature markets, which mainly comprise hedgers and institutional investors who are less affected by sentiment.

For fast-growing markets, new products coexist with price deviations from intrinsic values. In April 2010, the China Financial Futures Exchange launched the country's first

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equity index futures, a.k.a. the China Securities Index (CSI) 300 Index Futures (IF). It contains a collection of futures contracts written on the spot CSI300 stock index and expiring on the third Friday of the current month, the next month and the first month of the next one- and two-quarters. Ever since, trading volume booms. However, in the wake of the stock market crash of 2015, a series of corrective trading restrictions and a heightened threshold of market access reduced transactions on the three futures contracts, that is, the IF contract, the Index Futures China (IC) contract and the Index Futures Shanghai (IH) contract. Long-term deep discounts in index futures prices emerge subsequently in China, weakening index futures' due role in spread trading construction and spot market prediction. What causes this persistent deviation? And what is the underlying mechanism? With these questions in mind, we focus on futures basis and investor sentiment, respectively, as the outcome and the most relevant influencing factor of such disequilibrium.

In the futures market, basis represents the difference between the cash price of a stock index and its associated futures price. Theoretically speaking, the basis is a negative number. Market participants who short futures pay a premium to the long speculators for the opportunity cost such as interest and dividend forgone during the holding period. The need to hedge the underlying equity exposure can also drive this premium, namely the famous hedging pressure hypothesis. At times of high market volatility, China's stock futures basis may fluctuate wildly and deviate from their normal levels, exhibiting a positive basis as shown in Figure 1. This pattern is in stark contrast to the US capital market, which presents a salient futures premium and a stable basis ratio (i.e. the ratio of index futures basis level over the price of the underlying stock index).

This study is consistent with the idea that sentiment affects equilibrium and results in deviations of futures prices from fundamentals. Sentiment constitutes our second focus point. While De Long *et al.* (1990) and Stein (1996) were among the first in defining sentiment when building their financial theories, Lee *et al.* (1991) took the lead in empirically attributing closed-end fund discount to investor emotions. The seminal work by Baker and Wurgler (2006) successfully quantified sentiment by a composite index, which had gained popularity and been widely used to explain and predict price deviations. Turning to the China case again, in addition to the country's unique and fast-changing market structure, there is also the issue of a disproportionate percentage of Chinese retail investors participating in the stock market. As shown in Table 1, the total number of accounts opened at the Shanghai stock exchange by the end of 2019 reached 21.48m, of which 85.37% are retail investor accounts [1] It is also worth

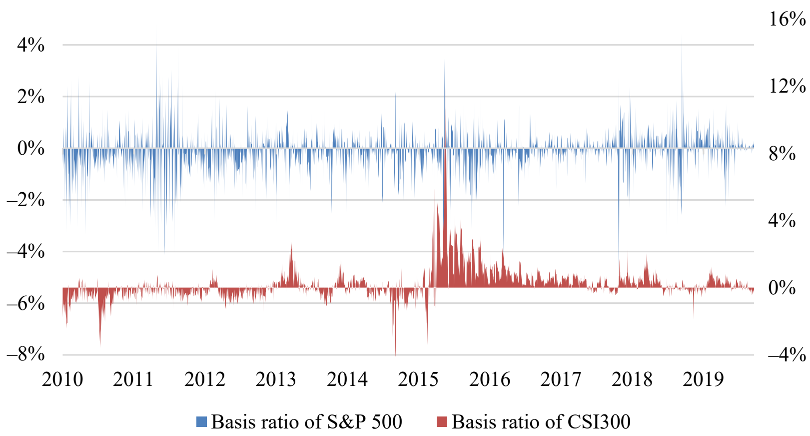

Figure 1.
Basis ratio of S&P 500 and CSI300

	Market value of shares (100 million)	Proportion (%)	Number of accounts (10 thousand)	Proportion (%)
Natural person	61,856	20.59	3856.96	99.76
Holdings				
0–10 million	3,280	1.09	2197.98	56.85
10–50 million	9,467	3.15	1102.65	28.52
50–100 million	6,893	2.29	288.24	7.46
100–300 million	10,202	3.40	193.00	4.99
300–1,000 million	8,824	2.94	57.70	1.49
>1,000 million	23,189	7.72	17.38	0.45
Nonfinancial firms	182,968	60.89	4.07	0.11
Shanghai stock connect	8,374	2.79	0.00	0.00
Professional institutions	47,283	15.74	5.28	0.14
Investment funds	12,328	4.10	0.37	0.01

Note(s): Data are sourced from the Statistical Yearbook of Shanghai Stock Exchange, volume 2020

Table 1.
Investor composition of the Shanghai Stock Exchange in 2019

noting that accounts registered to natural persons, whose investment shares display the highest turnover, have a market value of 20.59% of the Chinese stocks. Institutional investors only hold 15.74% of the market capitalization in China. As a result, pricing Chinese stocks indices (Wang *et al.*, 2018a) and marketable forwards instruments (Yu, 2013) from the sentiment perspective has always been a hot topic among scholars. Therefore, by combining the wisdom from these studies, we postulate that investor sentiment may have triggered the basis anomaly of stock index futures trading in China. We then aim to confirm whether explicitly incorporating the element of investor sentiment into the classical index futures pricing model could help restore the desirable functions of Chinese index futures contracts.

This paper considers the impact of investor sentiment on investors' expected return and basis. We first augment the classic holding cost model with an element of investor sentiment and then discuss the heterogeneity of model output under different scenarios in terms of contracts, market states, maturity and frequency. The finding is that investor sentiment affects the basis fluctuations through the implied discount rate, that is, the current expected rate of return of investors as a whole. We discuss the mechanism of investor sentiment on the implied discount rate according to market states. In stable market periods, investors are relatively rational. The risk-free interest rate drives investor sentiment in the medium and long term. Hence, the overall market trend dominates. When a bull or bear market starts, the risk-free interest rate will lose its stand as a determinant of sentiment, and the spread between its level and the current expected rate of return of investors will widen. At these market extremes, most investors are radical, and they can even expel rational institutional investors from the game or induce them to act irrationally accordingly. That is what happened in China's 2015 stock market crash, and the situation further deteriorated after promulgating restrictions on trading index futures contracts in a hurry. Most investors stopped hedging because of these restrictive rules. Hence, the index futures market freeze further exacerbated the abnormal fluctuations of the basis, and it, in turn, weakened the role of futures contracts. Based on the above reasons, we relax the rational investor assumption for the Chinese stock market and attempt to confirm the theoretical correctness of the cost-of-carry model in the presence of sentiment. The ultimate goal is to forecast basis trends better, improving the effectiveness of China's stock index futures contracts for hedging.

Our study contributes to the literature by relying on investor sentiment measures to explain the abnormal changes in the basis of China stock index futures. In terms of methodology, we first demonstrate that investor sentiment increases the goodness of fit by 2% when estimating the implied discount rate for the CSI300-IF pair. Then, we substitute the model-predicted discount rate into the cost-of-carry model, which more than doubles the predictive accuracy (from 0.04 to 0.11) of futures basis as measured by the adjusted *R*-squared. We also test the CSI500-IC pair that comprises small-cap stocks, and the results are robust. Finally, we demonstrate that the Shanghai Stock Exchange (SSE) 50 blue-chip stock index would be far less affected by investor sentiment [2].

Specifically, we find five regularities using our two-step empirical setup. First, the daily investor sentiment proxies obtained by mixing daily and monthly frequency data turn out to be effective and meaningful. Not only can it reflect the overall market trends, but it can also capture short-term fluctuations driven by emotions. Second, in the Chinese market, the cost-of-carry model with relaxed assumptions is theoretically correct and can be modified to better characterize index futures pricing by adding an element of investor sentiment. Third, while the medium and long-term influencing factors of futures basis relate to the macroeconomic conditions determined by the risk-free interest rate, we find investor sentiment to be the more significant and efficient influencing factor in the short term. The abnormal basis level is highly likely a result of extreme investor sentiment. Fourth, investor sentiment affects the stock spot prices by changing investors' consensus on the implied discount rate, namely the present expected rate of return. Lastly, the impact exerted by investor sentiment on the implied discount rate exhibits a nonlinear pattern. And the magnitude of this impact is significantly larger in extreme markets than during stable periods.

We also obtain three implications via robustness tests and logical reasoning. First, the influence of investor sentiment on the futures' basis had been in existence for a long time. It aggravates after the restrictive measures on transacting stock index futures contracts. Second, investors do not always remain rational or irrational. Their emotional state is affected by the risk-free interest rate in the medium to long term. For example, interest rate cuts under normal market conditions decrease the rate of return expected by equity investors. But rational investors may be forced by short-term extreme market conditions to exit the market. Third, the index futures basis and implied discount rate in China have no seasonal effect due to the specification of contract delivery time. We, however, cannot reject the null hypothesis of no weekend effect. Finally, the influencing mechanism of investor sentiment in the Chinese market is not tenable in relatively mature financial markets such as the US market represented by the S&P 500.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes data. Section 4 develops the hypotheses. Section 5 presents empirics. Section 6 reports robustness test results, followed by Section 7 that concludes.

2. Literature review

The present article is closely related to at least the following three branches of literature. First, we add to the research body that defines and prices the equity index futures. As an important indicator for hedging, the basis is defined as the difference between the price of the underlying asset and the price of its futures contract. One can also think of this difference as the cost of carrying the futures contract. Since there is no storage cost for the equity index, we argue in this article that, besides the time cost of money, there exist emotional costs that are overlooked by traditional pricing models. The seminal work on pricing equity index futures is by Cornell and French (1983, 1985), where they integrate multiple factors, such as the underlying index price, risk-free rate, dividend payout ratio and seasonal changes, maturity date and income tax, into a single cost-of-carry formula. Following them, Ramaswamy and Sundaresan (1985) add mean-reverting interest rates; Hemler and Longstaff (1991) solve for a similar cost-of-carry pricing equation under the Cox *et al.* (1985) general equilibrium;

Modest and Sundaresan (1983) derive an interval pricing model for stock index futures given no-arbitrage conditions, followed by Klemkosky and Lee (1991), who quantify the transaction costs to determine a reasonable lower and upper boundaries for the interval. Like them, we also attempt to bring the cost-of-carry model closer to reality. But, unlike them, our direction of modification is to explicitly incorporate the impact of investor sentiment.

Second, there exists a growing strand of literature that focuses on investor sentiment and how it is used in future pricing. Regarding investor sentiment, it is theoretically in existence since the stock market is too volatile to justify these changes only by fundamentals (Shiller, 1980; Giglio and Kelly, 2018), and investment decision-making does not conform to the neoclassical analysis framework (De Long *et al.*, 1990; Lee *et al.*, 1991). Empirically speaking, investor sentiment is unobservable and must be estimated. The sentiment proxy is increasingly linked to stock returns (Kumar and Lee, 2006) and risks (Verma and Verma, 2007; Verma and Soydemir, 2009), and there is a call for measuring it more precisely. To answer this call, Baker and Wurgler (2006) propose a composite index (BW index hereafter) based on series such as closed-end fund discount premium, trading volume, number of IPOs, first-day earnings, dividend income and share issuance ratio. Based on the BW index, Chinese researchers develop the CICSI (e.g. see Yi and Mao, 2009), that is, the monthly investor sentiment comprehensive indicator of China stock market index CSI300, which is widely recognized and used in behavior finance studies conducted in China. We follow this research line to construct sentiment measures in China's market to arrive at a better pricing model for equity index futures and the basis. What is more, this sentiment can be used as forward-looking factors in shaping futures since the stock market and the sentiment extracted from the market display inertia characteristics (Jegadeesh and Titman, 1993). Despite other sentiment measurement methodologies (Antweiler and Frank, 2004; Tetlock, 2007; Jiang *et al.*, 2019), the BW type of index is the most appropriate in our setup of adjusting the traditional model toward a realistic prediction of equity index futures basis.

In this second literature strand, concerning combining futures pricing models with investor sentiment, most contributions are traced back to behavioral finance. As for cognitive bias, Lien and Wang (2006) show that pessimism in futures and options markets causes a conservative hedging ratio; Mattos *et al.* (2008) find that profit and loss in the previous period can directly influence risk aversion in the current period. Turning to how investors behave in the futures market, Irwin and Yoshimaru (1999) suggest that the trading activities of managed futures funds magnify the volatility of futures prices. This magnification effect functions through fund size and trading system with positive feedback. Chen (1998) investigates whether major news would lead to a systemic overreaction among investors and finds that futures trading strategies are more likely to be affected by overreaction than equity investment strategies because of the low cost and high leverage of futures trading. Poteshman (2001) discovers that options investors have short-term underreaction and long-term overreaction in response to daily information arrivals. Our paper complements them in devising investor sentiment and sentiment-induced actions into futures pricing equations.

Third, our paper complements a growing body of literature that directly studies investor sentiment prevailing in the futures market. We discuss three papers that are related to ours, but none of them augment the futures and basis pricing models by considering the sentiment factor. Wang *et al.* (2018b) use the search volume index to measure investor sentiment in the Chinese stock index futures market. They find that the abnormal search volume index predicts return reversal in the short term, where the effect is mainly caused by the searches initiated with personal computers rather than mobile devices. They also find that restrictions on futures trading change the relationship between the abnormal search volume index and returns significantly. Overall, they provide a new set of results on the effects of investor sentiment on Chinese index futures markets. Singal and Tayal (2020) argue that theoretical predictions and empirical results are ambiguous regarding the effect of short-selling constraints on security prices. Since these constraints cannot be eliminated in equity markets, they use trades from futures markets where there is no distinction between short and long positions. They find that even with frictionless short selling, there is an upward bias in prices around weekends. The bias is stronger in periods of high volatility when short sellers are unwilling to accept higher levels of risk. On the other hand, the riskiness of long positions does not seem to have a similar impact on prices. Thus, evidence in their paper shows that security prices may be biased upward even without constraints on short selling due to asymmetric risk of short and long and positions. Kurov (2008) shows that traders in index futures markets are positive feedback traders – they buy when prices increase and sell when prices decline. Positive feedback trading becomes more active in periods of high investor sentiment. This finding is consistent with the notion that feedback trading is driven by expectations of noise traders. Consistent with the noise-trading hypothesis, order flow in index futures markets is less informative when investors are optimistic. Transitory volatility measured at high frequencies also seems to decline in periods of bullish sentiment, suggesting that sentiment-driven trading increases market liquidity.

There are two limitations in the existing literature on investor sentiment and futures pricing, that is, they only discussed the impact of investment activities on futures pricing or used complex econometric methods to measure the extent of the impact and lack the explanation of the impact path and the practicability and simplicity of the cost-of-carry model. Given the above being said, this paper augments the traditional modeling by filling in the missing aspects. Thus, our study adds to the existing literature on behavioral finance applied to the futures market.

3. Data and investor sentiment proxy

In this paper, we employ the closing prices of the CSI300 stock index and the IF futures contract to calculate the basis. To proxy for daily investor sentiment in the Chinese stock market, we adopt a principal component analysis framework of combining six indicators that can describe market trading activities in China from different perspectives. When we construct structural regression of futures basis on sentiment proxy, China's five-year government bond yield and the daily dividend yield of CSI300 are, respectively, used to represent the risk-free interest rate and dividend input involved in the cost-of-carry model. The range for our sample spans from April 16th, 2010 to December 31st, 2019 [3].

The extant research often adopts a monthly sentiment index to capture the trend of emotions prevailing on the market, but daily sentiment fluctuations are much more important for understanding the volatile equity index basis. As a result, we derive a daily Investor Sentiment Index (*ISI*) from taking the first principal component of a combination of monthly and daily indicators so that idiosyncratic noises in each indicator are removed [4]. At the monthly frequency, we have the level of consumer confidence index (CCI_{m-1}), the number of newly opened brokerage accounts (NIA_{m-1}), the number and the first-day returns of IPOs ($IPON_{m-1}$ and $IPOR_{m-1}$) over the last month if the *ISI* sampling day in consideration belongs to month m. These monthly measures are mainly affected by macroeconomic factors under normal market conditions. At the daily frequency, we record the Chinese A-share turnover ($TURN_{t-1}$) and the closed-end fund discount ($DCEF_{t-1}$) on day t, which are used for accounting for changes in *ISI* due to daily sentiment fluctuations. All data used to compute our investor sentiment are sourced from the CSMAR database.

After fitting data to a principal component analysis specification, we obtain Equation (1) below:

$$\begin{aligned} ISI_t = {} & 0.182 \times CCI_{m-1} + 0.459 \times NIA_{m-1} + 0.222 \times IPON_{m-1} + 0.225 \times IPOR_{m-1} \\ & + 0.381 \times TURN_{t-1} + 0.148 \times DCEF_{t-1}, \end{aligned} \tag{1}$$

where the estimated coefficients are factor loadings. Table 2 presents the summary statistics and the pairwise correlations among our six component factors. Admittedly, due to data limitations, previous research on how emotion affects financial market outcomes mainly adopts monthly indicators as basis to construct the investor sentiment proxy. However, as characterizing the changes in index futures basis needs a higher degree of accuracy, we substitute several monthly indicators that have daily data available with their corresponding daily-frequency statistics, so that the information contained in the potential sentiment determinants of basis fluctuations can be captured to the largest extent.

The pros and cons of using mixed-frequency sentiment indicators can be summarized as follows. First of all, the four monthly indicators mainly reflect the medium and long-term conditions of market macroenvironment. Therefore, even if it is possible to replace end-of-month values with daily observations, one might still reasonably assume that such replacements would not exert a significant impact on the fitted emotional proxy. Technically speaking, employing monthly indicators in a daily sentiment determination specification is equivalent to assume that they stay constant over the concerning month. Secondly, the two daily indicators are employed to reflect short-term market fluctuations driven by sentiment. Given that these two proxies vary from day to day in the Chinese market, if we use their monthly aggregates, then there will be serious lags and smoothing of the sentiment measure. At last, the daily sentiment index we have fitted using mixed-frequency inputs turns out to meet the requirements of a typical BW type of index in the sense that it can better reflect the anecdotal fluctuations of the historical stock index. The correlation coefficient between our daily sentiment index and the equity market index in China reaches 0.822, much higher than the proxy estimated with straight monthly-frequency indicators.

Moreover, many scholars have verified that the mixed-frequency approach is applicable in the field of sentiment research and other relevant fields using data samples drawn from Chinese financial markets. For example, Zhou *et al.* (2018) construct a general index of Chinese real-time financial conditions (sentiment being one of the component indices) based on mixed-frequency data. He has shown that using real-time mixed-frequency data can increase the accuracy and significance of estimation because they can reduce the information loss caused by converting high-frequency indicators to the same frequency as low-frequency ones. Moreover, Gao (2015) holds the same view as us when constructing his own sentiment index to price the sentiment-based stock futures, that is, if only monthly-frequency data are used as regressors, the high volatility of the daily stock index futures as the regressand will be smoothed out, hence weakening the influence of investor emotion. For another example, Wang (2011) studies the price influencing factors in the European Union emission quota

	ISI_t	CCI_{m-1}	NIA_{m-1}	$IPON_{m-1}$	$IPOR_{m-1}$	$TURN_{t-1}$	$DCEF_{t-1}$
Mean	<-0.001	108.88	275.86	17.33	4.46	1.27	0.05
Median	0.001	105.60	267.08	15.00	4.09	1.10	0.11
Std. dev.	1.00	8.49	268.54	13.35	5.06	0.66	1.10
Max	4.62	126.00	1439.72	54.00	39.16	4.62	7.56
Min	−1.53	97.00	28.53	0.00	−2.32	0.39	−6.03
Correlations							
CCI_{m-1}	0.36**	1					
NIA_{m-1}	0.89**	0.26**	1				
$IPON_{m-1}$	0.43**	0.1**	0.35**	1			
$IPOR_{m-1}$	0.44**	0.18**	0.17**	0.09**	1		
$TURN_{t-1}$	0.75**	−0.09**	0.61**	0.13**	0.19**	1	
$DCEF_{t-1}$	0.26**	0.18**	0.23**	−0.33**	0.01	0.16**	1

Note(s): **Denotes significance at the 5% level

Table 2. Descriptive statistics of sentiment measures

trading market. To characterize price fluctuations of this particular market, besides monthly and quarterly factors representing the macroeconomic environment, he also adopts potential daily-frequency drivers to support the high volatile component of the emission quota trading activities. His treatment is similar to the mixed-frequency approach used in our paper.

In addition to the mixed-frequency issue, as BW index is commonly considered to be an indirect index, which reflects the consistent and long-term sentiment of all investors in the market. Therefore, when choosing the method of constructing investor sentiment index, one may also have concerns about the following two drawbacks of using the CICSI type of index in our setup. One is that the innovative component of CICSI describes more of individual investor sentiment. The other is that its BW-alike component tends to reflect long-term emotional fluctuations.

For the first concern, investor sentiment by definition is closely aligned with retail (i.e. uninformed) investors. While institutions as major participants in the index futures market are supposed to have no sentiment, retail investor sentiment could play a role via affecting future basis and discount rates. Hence, we argue that institutional investors should pay attention to retail investor sentiment and seriously consider its impact on index futures in China when speculating with such contracts. In essence, the BW and CICSI index differ in the index construction method. According to Baker and Wurgler (2006), the BW index is defined using a "top-down" method, which treats investor sentiment as exogenous and pays attention to its empirical consequences instead of its theoretical origin. When constructing the CICSI, Yi and Mao (2009) concluded that whether investor sentiment can effectively explain the behavioral phenomena that occurred in stock markets is closely related to the accuracy of sentiment measurement in addition to different research methods and sample differences emphasized by Liu and Xiong (2004). Therefore, Yi and Mao (2009) added CCI and the number of newly-opened stock trading accounts to capture the irrationality of individual investors so that these micro-level proxies can complement the macro-level characteristics of Chinese market sentiment. In some sense, the CICSI index is one step closer to the "bottom-up" sentiment index construction method as described in Baker and Wurgler (2006), which relies more on individual psychological biases such as overconfidence, representativeness and conservatism to explain how retail investors underreact or overreact to past returns and firm fundamentals.

For the second concern, as we aim to augment the classical theoretical model by adding investor sentiment and use it to determine the fundamental value of index futures. If we can decompose sentiment into long-term trending part and short-term cyclical part, the cyclical short-term sentiment should only complicate the market prices of index futures. There are two reasons why the BW index and hence its adjusted CICSI version are more appropriate for long-term sentiment. On the one hand, the BW index is originally positioned to measure market sentiment on individual stocks, but individual stocks often fail to give timely feedback to investor sentiment, which has a certain lag. On the other hand, they subtract the moving average of discount of closed-end funds, use the current value and lag value of monthly data at the same time to construct investor sentiment, which is, in fact, also a smoothing from short-term data to long-term data, and consider to use the second principal component as the sentiment index to eliminate the short-term changes caused by factors such as trading rules, which makes the index no longer reflect the details of short-term fluctuations. And it is worth mentioning that, following Lee *et al.*'s (1991) research on the closed-end fund puzzle, Liu and Xiong (2004) found that Chinese investors care more about liquidity instead of long horizon. Hence, the classical theory focusing on fundamentals cannot explain the mystery of fund discounts in China, which also indirectly reflects the short-term significant role of Chinese investor sentiment. In this case, we state that although individual stocks differ with each other in emotion feedback lags, they are collectively quite responsive to sentiment as index constituents.

For data on equity market indices, index futures and basis, the CSI300 covers all 13 industries classified by the China Securities Regulatory Commission. Additionally, it is regarded as the most representative index for the Chinese stock market. The SSE50 captures the performance of the blue-chip mature market where listed companies have better operating performance and stronger risk-bearing ability, and the CSI500 represents the SME market containing shares of firms that need to improve their operations to realize their growth potential. We distinguish between different market sections since market sentiment is expected to exert different impacts on pricing according to the level of difficulty in firm valuation and arbitrage implementation. Besides, different market sections also accommodate investors with varying purposes and investment strategies. Such a difference in investor composition is also a key determinant of market sentiment. All company financial performance data are obtained from the WIND database.

4. Model and hypotheses

In this paper, we assume that the following classic cost-of-carry model is theoretically correct.

$$F_t = S_t e^{r_{r,t}(T-t)} \tag{2}$$

After reviewing the relevant assumptions and premises of the model, and after considering the unique situation of the Chinese market, we relax some general conditions inappropriate for China. Based on these adjustments, we then derive our hypotheses by adding an element of investor sentiment index to the traditional cost-of-carry pricing model for stock index futures.

4.1 Cost-of-carry model and its assumptions

According to the classic model developed by Cornell and French (1983), for the traditional cost-of-carry model to function for the pricing of stock index futures, the following four assumptions specified by them plus one implicit assumption must be satisfied: (1) Capital markets are complete with zero taxes and transaction costs; assets can be divided indefinitely and short sales are permitted. (2) The stock follows a regular dividend cycle, and the dividend amount is, however, fixed. (3) Funds for lending purpose is sufficient, and its rate is the risk-free rate. (4) The market is fully liquid, in which investors can buy and sell any stock or portfolio at their free will. (5) Investors are rational and capable, and they act with no influence of emotions.

These assumptions are more likely to be met in larger and more mature markets. In China, there exist strict shorting restrictions and unavoidable trading fees. But this violation of assumption (1) does not invalidate the cost-of-carry model because these barriers can all be summarized in the general carrying costs. As for assumption (2), although the three major Chinese stock indices exhibit no standard cycles in terms of paying constant dividends at regular intervals, we do observe a stable increasing trend and a relatively even distribution of dividend payments for each index as illustrated later in Figure 3A. Assumptions (3)–(4) can also be tested with our hierarchy of three tiers of market portfolios: SSE50 for a mature equity market, CSI500 for a growth one and CSI300 for a comprehensive stock market in fast development. We relax the last assumption (5) by proposing a new type of carrying cost, which is associated with investor sentiment when the nonphysical stock index serves as the underlying asset in futures contracts.

4.2 Hypothesis development

All of our four hypotheses relate to accounting for the cost-of-carry model's potential distortion in predicting changes in the equity index futures basis in China. They are developed by combining the stylized patterns observed in the time series of Chinese index futures prices and the insights derived from the following two strands of relevant literature. On the one hand, traditional models for derivatives pricing are often based on conditions that are difficult to be satisfied in reality. According to the seminal work of

Simon (1955) and the large body of follow-up studies, investors who have a stake in index futures (not necessarily confined to those index futures market participants) are not as rational as what has been assumed by the classical futures pricing theory due to cognitive and other psychological biases distorting the decision-making process. On the other hand, arbitrage plays an important role in the futures market. If many rational arbitragers are active, the basis representing the price differential between the spot and futures market should narrow down or even quickly disappear (Friedman, 1953; Sharpe and Alexander, 1990). However, implementing arbitraging strategies is limited and the basis of index futures is likely to stay at some level for a while. The reason is that, in reality, trading futures is not frictionless, and futures market participants will face large transaction costs and get exposed to various risks (Gao, 2015). Given the above being said, we can develop the following hypotheses.

The first hypothesis is that investor sentiment is an important factor that leads to the distortion of stock index futures basis in China, especially after strict trading rules were imposed on this market after the 2015 stock crash. This is a reasonable conjecture because sentiment is proved to explain returns on stocks that are difficult to value and costly to arbitrage, such as unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks (Zhou, 2010, 2018). As a result, we propose that Chinese investor sentiment can explain, correct and even predict the stock index futures basis to a great extent with varying explanatory power in different periods.

Secondly, we hypothesize that investor sentiment in China's index futures markets could reconcile the classical cost-of-carry model's prediction with the persistently deviated basis of equity index futures in China. As Baker and Wurgler (2006) have pointed out, sentiment represents investors' belief in future cash flow and investment risk, which has not yet been confirmed by the information and facts available. In this case, the question is no longer whether investor sentiment will affect stock prices, but how to measure investor sentiment and quantify its impact. They adopted a top-down method and established the BW index to explain which stocks can be easily affected by sentiment. But in terms of exploring the underlying mechanism of sentiment, we believe that incorporating the element of investor sentiment into classical models to account for distortions and deviations might act as a desirable bottom-up method. For this purpose, we have also deliberately adopted the CICSI index with contains micro-level factors rather than all macro-level-factor BW approach to reflect the psychological biases (such as overconfidence, representativeness and conservatism) of individual investors in the relatively immature Chinese market. We attempt to explain how individual investors' emotions can distort futures pricing not directly through participation but indirectly through the implied discount rate channel given their insufficient or excessive response to past returns and fundamentals. This attempt leads to our third hypothesis.

The second hypothesis also indicates that investor sentiment should have distinct effects on equity index futures basis for China's stock indices. Moreover, if we focus on a single index, this effect also turns out to be asymmetric following equity index futures premium and discount. Whether the equity index futures are trading higher (premium) or lower (discount) than the spot depends on the interactions between investor sentiment, short-sale constraints and arbitrage activities.

Theoretically speaking, the cost of carry for a stock index should be the excess of the risk-free rate over the index's dividend yield. We argue that there also exists an index- and time-specific emotional component in overall carrying cost. So, by incorporating sentiment into the traditional cost-of-carry model, we can better predict changes in equity index futures basis. How do premium or discount periods in the futures market emerge? When the basis equals the cost of carrying, there would be no room for speculators. That is to say, arbitrage is profitable across the futures and spot market only if the absolute value of the basis is always greater than the carrying cost. In equilibrium, the futures market is called positive in arbitrager's viewpoint if the basis is negative; whereas the market will be referred to as inverted if they observe a positive basis. This shift in the market state is bound to cause overpricing or underpricing. Since shorting is more accessible in the futures market, given a positively deviated market, speculators will exploit the market premium by longing the spot stock index and shorting the corresponding equity index futures simultaneously. If the premium vanishes after these speculation attempts, then the market at this point is unbiased and effective. However, given an inverted market with overvalued stocks, due to restrictions on short sales in the Chinese spot market, investors can only buy futures contracts. Thus, the intertemporal market for the equity index deviates from its equilibrium, and the futures market falls into the discount state.

The third hypothesis states that emotional factors affect futures basis through implied discount rate, which is used in the formula determination of futures contract prices. Since this rate is composed of the risk-free rate and the holding-period return, higher returns should be anticipated for equity index futures investment when these contracts are held over high sentiment periods. The continuous pursuit for quantifying the expectations on future returns can cause counterintuitive individual actions (Chang *et al.*, 2015). So, we hypothesize that the nonzero average return across different index futures contracts may reflect the unexplained part of basis fluctuations, which is most likely to be a consequence of investor sentiment movements.

As for the fourth hypothesis, the distorted fluctuations of equity index futures basis should be stronger following periods of high investor sentiment (i.e. radical investor behaviors irrespective of positive or negative emotions). According to Shleifer and Vishny (1997), when irrational investors prevail and dominate, rational arbitragers may be forced to liquidate their positions and eventually exit the market, further exacerbating market volatility. Therefore, our last hypothesis states that, in high emotional times, opinions on the stock market tend to be overly optimistic or pessimistic. This leads to mispricing for stocks and more so for futures products. In contrast, at times of low sentiment, investors' trading activities are stable, that is, when investors are relatively rational as a whole, and we would probably not observe irregularities of futures basis. To sum up, investor sentiment will be at least partially driving the unusual fluctuations in the spread between the price of the equity index and the price of the futures contracts written on this underlying index.

The last issue here is that this effect of sentiment on the basis (price difference between spot and futures) might be merely determined by only the spot market, as futures market participants are typically institutional investors. We argue that sentiment plays similar roles in both the equity index spot market and the corresponding futures market. This is because, although most participants in China's stock market are retail investors (i.e. investors with holdings less than 500,000), an analysis on the composition of stock holdings at the end of 2019 tells us that the shares transacted by these 85.37% retail investors only accounts for 4.24% of the total market capitalization. As a result, retail investors who are easily influenced by guts and emotions do have a large impact on public opinions and market-wide sentiment, but their activities will hardly alter market trends. In addition, when the activities of retail investors are strong enough to affect the whole market, for example, during China's stock market boom in early 2015, a large number of retail investors crowded into the stock market, and the maximum number of monthly new-open accounts reached 14.40m. Here, it is reasonable to question whether institutional investors can remain rational and not be driven by the market boom. The bottom line of investors is more difficult to correct than the wrong pricing in the real world. Given that institutional and professional individual investors control almost all funds in the spot and futures market, so the different roles of sentiment in these two markets should not be as significant as we suspect.

5. Empirical analysis: sentiment, implied discount rate and basis

According to the cost-of-carry model and the third hypothesis that *ISI* affects the fluctuation of basis through the implied discount rate, we can easily obtain a two-stage regression model specified as follows:

$$Basis = S_t - F_t = S_t\left(1 - e^{r_{r,t}(T-t)}\right), \quad \text{with } r_{r,t} = \mu(r_{r,t-1}, div_{t-1}, r_{f,t-1}, ISI_{t-1}) \tag{3}$$

where S_t is the current value of the stock index. This index pays dividends according to a distribution rule of $div_t = e^{D_t(T-t)}$. F_t is the price of the corresponding equity index futures with maturity T, r_r denotes the implied discount rate, D_t represents the dividend yield of the underlying index, div_t is the dividend of the CSI300 index, and r_f denotes the risk-free interest rate. Rearranging the above equation and assuming a $linea_r$ sentiment effect yields a testable empirical specification of the discount rate. In particular, the implied discount rate can be expressed as a function of investor sentiment, risk-free rate and equity index dividend yield:

$$\begin{aligned} r_{r,t} &= \frac{\ln F_t - \ln S_t}{(T-t)} = \frac{\ln\left(1 - \frac{Basis_t}{S_t}\right)}{(T-t)} = \mu(r_{r,t-1}, div_{t-1}, r_{f,t-1}, ISI_{t-1}) \\ &= \alpha_0 + \alpha_1 r_{r,t-1} + \alpha_2 div_{t-1} + \alpha_3 r_{f,t-1} + \alpha_4 ISI_{t-1} + \alpha_5 e^{ISI_{t-1}} + \varepsilon_t \end{aligned} \tag{4}$$

For our two-stage empirical modeling framework, the reason why we adopt an exponential nonlinear specification in the second stage of estimation is twofold. On the one hand, an alternative linear specification will produce results that are inconsistent with those produced by running quantile regressions on Equation (4). The coefficients of investor sentiment estimated at each quantile are all negative but display a wave pattern (see the blue and orange lines drawn in Figure R1-1 below), implying the existence of nonlinearity. Furthermore, under the linear relationship assumption, although we can still obtain a strong negative association between the implied discount rate and investor sentiment, both the magnitude and significance of the correlation between the fitted and actual value of the index futures basis fall below expectations for a practical futures pricing model. Combining the above two arguments made from, respectively, the validation and usefulness perspective, we apply a nonlinear model of investor sentiment.

On the other hand, nonlinear specifications other than the exponential form cannot correctly account for negative sentiment statistics. Since our investor sentiment after standardization is not always a positive number, if a quadratic form on sentiment is used, then periods of extremely low investor sentiment will be ignored, and a cubic form on sentiment may overamplify the effects of the emotional variable. The simplest nonlinear model that can inherit the monotonicity of our investor sentiment proxy and can incorporate negative sentiment figures simultaneously is hence the exponential function. Next, we carry out quantile regressions again under the assumption of an exponential relationship. The coefficients before the investor sentiment index estimated at each quantile constitute a monotonically increasing line, which reconciles the reality with our theoretical prediction, that is, the influence imposed by investor sentiment on the implied discount rate (i.e. index futures basis) in periods of stock market extremes should be much greater than the corresponding influence under normal market conditions.

Table 3 tells us that before the stock disaster, that is, from April 2010 to May 2015, the basis is in a state of premium, the sentiment index is low, and the implied discount rate is positive. For the postdisaster period, the basis is in a state of discount, and high sentiment is associated with a negative implied discount rate. Thus, a preliminary conclusion can be drawn that the implied discount rate is negatively correlated with *ISI*. But under the cost-of-carry model, the basis is positively correlated with *ISI*. When *ISI* is higher, the stock index increases, the implied discount

		$r_r \times 10^4$	r_f	*div*	*ISI*	*Basis*
Whole sample 2010.04–2019.12	Mean	−2.670	3.299	0.262	<−0.001	7.485
	Median	−0.621	3.256	0.000	0.001	2.420
	Std. dev.	19.050	0.454	0.738	1.000	34.217
	Max	217.230	4.529	9.330	4.620	400.030
	Min	−345.020	2.40	0.000	−1.526	−172.820
	Num. obs.	2,363	2,363	2,363	2,363	2,363
Pre-crash subsample 2010.04–2015.05	Mean	1.520	3.44	0.208	−0.506	−6.577
	Median	0.833	3.410	0.000	−0.800	−4.605
	Std. dev.	11.880	0.467	0.575	1.002	20.322
	Max	217.230	4.529	7.210	4.620	65.240
	Min	−78.540	2.402	0.000	−1.526	−172.820
	Num. obs.	1,246	1,246	1,246	1,246	1,246
Post-crash subsample 2015.06–2019.12	Mean	−7.340	3.137	0.321	0.564	23.171
	Median	−2.510	3.078	0.000	0.437	13.300
	Std. dev.	23.860	0.378	0.882	0.625	39.374
	Max	29.040	3.936	9.330	4.190	400.030
	Min	−345.020	2.406	0.000	−0.352	−70.720
	Num. obs.	1,117	1,117	1,117	1,117	1,117

Note(s): r_r is the implied discount rate backed out from the cost-of-carry model, in order to facilitate the calculation of basis, decimal form is adopted here; r_f is the annualized 5-year China treasury rate; *div* is the dividend of CSI300 index; *basis* is calculated as the difference between the CSI300 index and the closest-to-maturity IF index futures. *ISI* represents the investor sentiment index

Table 3. Descriptive statistics of main variables used in estimating Equation (4)

rate decreases and we observe positive basis, then there will be a discount. Such relation is consistent with our hypothesis, but a formal analysis is still in need.

5.1 Stage 1: Regression on CSI300 and IF contracts

Panel A of Table 4 presents the ordinary least square (OLS) estimates and the model fit evaluation statistics for Equation (4) with different set of controls. Since the effect of investor sentiment on the implied discount rate becomes increasingly more prominent as emotions accumulate, we add an exponential term of *ISI* to control for such nonlinearity.

In regression Equation (4-1), we only use indicators specified in the classical cost-of-carry model, that is, the risk-free interest rate, the dividend rate and the first-order lagged term of the implicit discount rate. The results show that the variables except the dividend rate are significant, and the fitting degree of the model is high, which indicates that the implied discount rate has a certain degree of autoregression. It is worth noting that the constant term is significant, which means that there is still an unexplained part in the dependent variable. After we add *ISI* to this model, we get regression Equation (4-2). It is clear that the significant levels of coefficients in front of the constant term and the risk-free interest rate decrease. In conjunction with the regression Equation (4-3) including the *ISI* exponential term, we conclude that the unexplained part of the error term can be captured by *ISI* to a large extent, and the risk-free interest rate becomes less important than the sentiment index.

When the annual and monthly dummy variables are excluded, we find that dividend yield seems to be a noncritical variable. The level and the exponential term of *ISI* are significant explanatory variables, and investor sentiment is negatively correlated with the implied discount rate. According to the cost-of-carry model, we can easily deduce that the basis increases with the rise of investor sentiment. After adding dummy variables, we get regression Equation (4-4), in which some dummy variables improve the goodness of fit because they can mark the period when the implied discount rate fluctuates a lot, but their presence would also reduce the significance of emotional indicators. According to the classic cost-of-carry model, the dividend

Table 4. Two-stage regression results of estimating Equations (3) and (4) for the CSI300-IF pair

Panel A: Stage 1

Equation (4) $r_{r,t} = \alpha_0 + \alpha_1 r_{r,t-1} + \alpha_2 div_{t-1} + \alpha_3 r_{f,t-1} + \alpha_4 ISI_{t-1} + \alpha_5 e^{ISI_{t-1}} + \varepsilon_t$

Specification	(4-1)	(4-2)	(4-3)	(4-4)
Constant	−0.0008*** (0.0008)	−0.0007* (0.079)	−0.0001** (0.0186)	−0.0002 (0.6809)
$r_{r,t-1}$	0.5223*** (<0.0001)	0.5193*** (<0.0001)	0.5156*** (<0.0001)	0.4667*** (<0.0001)
div_{t-1}	−0.0001 (0.2843)	−0.0001 (0.3177)	−0.0001 (0.2659)	0.0001 (0.9153)
$r_{f,t-1}$	0.0002*** (0.0035)	0.0002** (0.0258)	0.0001* (0.0785)	0.0001 (0.6384)
ISI_{t-1}		−0.0001** (0.0026)	−0.0002*** (0.0013)	−0.0003* (0.0753)
$e^{ISI_{t-1}}$			0.0001** (0.0188)	0.0001* (0.0751)
Months				Yes
Years				Yes
DW-test	2.0818	2.0793	2.0762	2.0430
Num. obs.	2,363	2,363	2,363	2,363
Adj-R^2	0.2830	0.28433	0.2847	0.3020

Panel B: Stage 2

Equation (3) $Basis_t = \alpha_0 + \alpha_1 \widehat{Basis}_t + \varepsilon_t = \alpha_0 + \alpha_1 S_t(1 - e^{\widehat{r_{r,t}}(T-t)}) + \varepsilon_t$

OLS regression

Specification	(3-1)	(3-2)	(3-3)	(3-4)
Constant	1.3300 (0.1497)	1.656* (0.0518)	−0.2191 (0.7864)	0.6105 (0.3245)
$\widehat{Basis}_t$	0.464622*** (<0.0001)	0.4044*** (<0.0001)	0.5272*** (<0.0001)	0.4758*** (<0.0001)
DW-test	0.3948	0.4007	0.4440	0.6122
Num. obs.	2,363	2,363	2,363	2,363
Adj-R^2	0.0405	0.0531	0.1063	0.3038

Quantile regression

Quantile	0.2	0.4	0.5	0.6	0.8
Constant	−9.8868*** (<0.0001)	−3.0902*** (<0.0001)	−0.3401 (0.2546)	2.3609*** (<0.0001)	10.1498*** (<0.0001)
$\widehat{Basis}_t$	0.2996*** (<0.0001)	0.3711*** (<0.0001)	0.4079*** (<0.0001)	0.4519*** (<0.0001)	0.5815*** (<0.0001)
Adj-R^2	0.1212	0.1722	0.1959	0.2155	0.2603

Note(s): r_r is the implied discount rate backed out from the cost-of-carry model; r_f is the 5-year Chinese treasury rate; *div* is the dividend of CSI300 index; *basis* is calculated as the difference between the index and the closest-to-maturity index futures. *ISI* represents the daily investor sentiment index. $\widehat{Basis}_t$ and $\widehat{r_{r,t}}$ are the predicted value fitted by Equations (3) and (4), respectively. ***, ** and * denote significance at the 1, 5 and 10% level, respectively point and risk-free interest rate, which should have a significant impact on the discount rate, perform poorly in these regressions. However, whether it is invalid or not still needs to be judged through the second-stage regression to observe the correction of our Chinese investor sentiment index to the concerned basis proxy.

5.2 Stage 2: Backtests

Panel B of Table 4 presents the estimates of OLS and quantile regressions and the model fitting statistics for Equation (3), using the forecasted implied discount rate, which we can obtain from Panel A of Table 4. As can be seen from the OLS regression results reported, we find that once we add the exponential term of *ISI* to get the regression model (4-3), the goodness of fit of the model itself is not greatly improved; however, the fitting degree of the regression Equation (3-3) for the basis in the second stage has been significantly improved. This means that the implied discount rate and investor sentiment are likely to have a nonlinear relationship of a high degree. What is more, the results of quantile regression demonstrate that, as the basis widens, the accuracy of the predicted basis values enhances. This implies that the influence of investor sentiment on index futures pricing increases with basis.

Finally, to get the big picture of the model fitting to real-world basis intuitively, Figure 2 plots the trend chart of the actual IF contract basis and the forecasted values of the basis calculated by the traditional cost-of-carry model and our modified model, respectively. These patterns well illustrate how our modification has brought the prediction of the traditional pricing model closer to actual changes in the futures basis.

6. Robustness tests

This paper examines the results in four robustness checks. First, we analyze the generality of our conclusion using heterogeneous index futures such as the Chinese IC and IH contract and the US E-mini S&P 500 futures (ES) contract. Then, we explore the mechanism of sentiment affecting the implied discount rate. Next, we deal with the potential endogeneity and multicolinearity. Finally, we validate the results with alternative data frequency, time dummies and regulatory tightening.

6.1 Heterogeneity analysis

Let us replace the CSI300-IF pair by either the CSI500-IC or SSE50-IH data pair. The corresponding results after repeating the five-step exercise are shown in Table 5. The

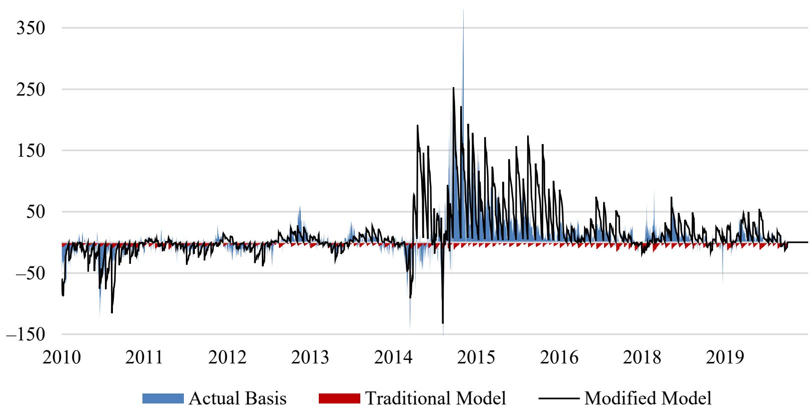

Figure 2.
Actual basis and the fitted value of basis computed by the traditional and modified cost-of-carry model (based on the CSI300-IF pair)

cost-of-carry model augmented by investor sentiment produces better-fitted values for CSI500 index futures. However, it slightly underperforms when predicting futures prices for the blue-chip SSE50 index. The implication is that the impact of sentiment on basis differs across stock indices – futures written on index containing less liquid and smaller-cap stocks are affected more prominently. This is because retail investors tend to hold these stocks and act emotionally, leading to sentiment-induced basis discounts in the corresponding index futures market.

We move on to the relatively mature US index futures market and find that our setup does not hold any more. In the USA, the key factor driving the implicit discount rate is the dividend rate, rather than sentiment in China. This is exactly what one will expect for a relatively mature market – sentiment should exert a much smaller impact when information can be efficiently impounded into price. We also believe that the success of sentiment cost-of-carry model in China has a lot to do with the series of futures trading restrictions implemented after China's 2015 stock disaster. These restrictions have greatly reduced the trading volume of stock index futures contracts, making it illiquid and its pricing vulnerable under the influences of sentiment.

The S&P500-ES futures contract differs from its CSI300-IF counterpart in at least three distinct ways. First, according to Figure 1, the ES basis is less volatile and can quickly attain future premium; whereas the IF basis experiences a deeper discount for a longer time and has reached extreme values. Therefore, given that the basis fluctuation is in large part caused by emotional changes, investor sentiment should play a major role in pricing Chinese equity stock index futures. Second, as can be seen in Figure 3A, due to its strong seasonality and high

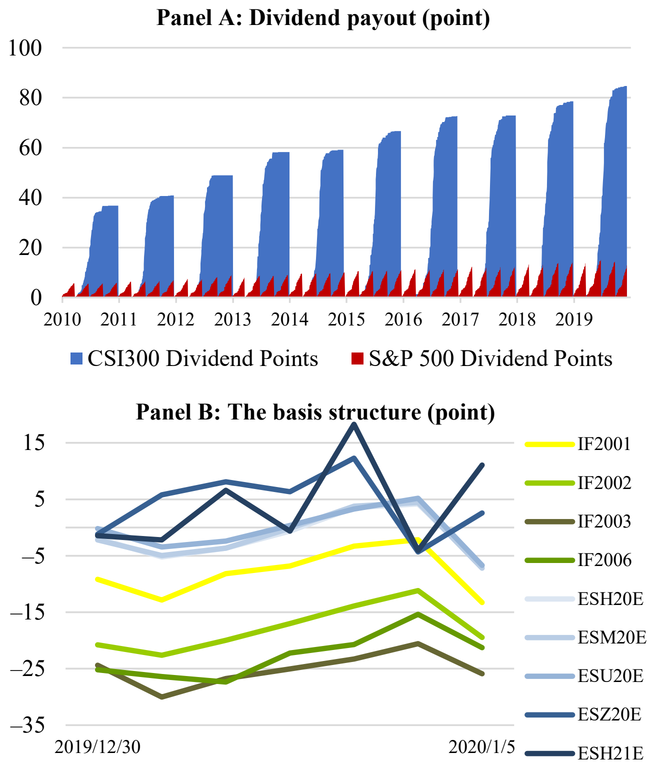

Figure 3.
Dividend distribution and basis term structure in China vs in the USA

Table 5. Two-stage regression results of estimating Equation (3) for the CSI500-IC and SSE50-IH pair

	Panel A: CSI500-IC			Panel B: SSE50-IH		
Stage 1						
Equation (4) $r_{r,t} = \alpha_0 + \alpha_1 r_{r,t-1} + \alpha_2 div_{t-1} + \alpha_3 r_{f,t-1} + \alpha_4 ISI_{t-1} + \alpha_5 e^{ISI_{t-1}} + \varepsilon_t$						
Specification	(4-1)	(4-2)	(4-3)	(4-1)	(4-2)	(4-3)
Constant	−0.0027*** (<0.0001)	−0.0022*** (−0.0030)	−0.0017** (−0.0325)	−0.0016*** (<0.0001)	−0.0014*** (−0.0008)	−0.0008** (−0.0452)
$r_{r,t-1}$	0.4830*** (<0.0001)	0.4754*** (<0.0001)	0.4680*** (<0.0001)	0.4000*** (<0.0001)	0.4005*** (<0.0001)	0.3813*** (<0.0001)
div_{t-1}	<0.0001 (0.6622)	<0.0001 (0.5831)	<−0.0001 (0.6588)	<−0.0001 (0.7399)	<−0.0001 (0.8048)	<−0.0001 (0.6170)
$r_{f,t-1}$	0.0007*** (0.0032)	0.0005** (0.0325)	0.0003 (0.2547)	0.0004*** (0.0005)	0.0004*** (0.0056)	0.0001 (0.3149)
ISI_{t-1}		−0.0002** (0.0286)	−0.0005*** (0.0018)		−0.0001* (0.0933)	−0.0003*** (<0.0001)
$e^{ISI_{t-1}}$			0.0001** (0.0221)			0.0001*** (<0.0001)
DW-test	1.9862	1.9784	1.9752	1.7480	1.7539	1.7473
Num. obs.	1,152	1,152	1,152	1,152	1,152	1,152
Adj-R^2	0.2591	0.2616	0.2643	0.2256	0.2268	0.2400
Stage 2						
Equation (3) $Basis_t = \alpha_0 + \alpha_1 \widehat{Basis}_t + \varepsilon_t = \alpha_0 + \alpha_1 S_t(1 - e^{\widehat{r_{r,t}}(T-t)}) + \varepsilon_t$						
Specification	(3-1)	(3-2)	(3–3)	(3-1)	(3-2)	(3-3)
Constant	41.4669*** (<0.0001)	37.6887*** (<0.0001)	31.9887*** (<0.0001)	6.7830*** (<0.0001)	6.7537*** (<0.0001)	6.2296*** (<0.0001)
$\widehat{Basis}_t$	0.1993*** (<0.0001)	0.2218*** (<0.0001)	0.2703 (<0.0001)	0.0235** (0.0264)	0.0253** (0.0194)	0.0657*** (<0.0001)
DW-test	0.5100	0.5507	0.6276	0.5890	0.5910	0.6595
Num. obs.	1,152	1,152	1,152	1,152	1,152	1,152
Adj-R^2	0.0577	0.0956	0.1422	0.0049	0.0038	0.0306

Note(s): ***, ** and * denote significance at the 1, 5 and 10% level, respectively dividend intensity, Chinese companies' volatile dividend payout patterns can cause much larger fluctuations in both sentiment and the underlying index. Yet, there exists no coordinated dividend payout for US publicly listed companies. Third, the term structure of IF is different from that of ES. Figure 3B tells us that the ES basis is structured in a simple and ordered way, but there exists a large degree of heterogeneity in short- and medium-term IF contracts.

In sum, this article attributes the distinct performance of stock index futures in the two countries to a limited pool of short-selling tools, a large number of retail investors and government interventions in China's stock markets. Combined with China's unique retail and institutional investor composition, all these reasons exaggerate the adverse effects of sentiment on equity index basis either directly through the implied discount rate or indirectly via the abovementioned three differences, that is, basis convergence pattern, dividend payout rules and contract maturity structure.

6.2 Mechanism exploration

This subsection does not aim to specify the exact channels via which changes in sentiment could affect the implied discount rate. Table 6 is organized according to the logic flow of empirically discovering the comovements between the investor sentiment proxy and the implied discount rate proxy step by step. In Panel A, we conduct regressions using either the investor sentiment proxy or the implied discount factor as the dependent variable with the index dividend yield (measuring the attractiveness of the overall equity market) and the risk-free interest rate (acting as an intuitive ideal return on investment) being independent variables. The finding is that both the sentiment and discount factor are significantly affected by the risk-free interest rate in opposite directions. In other words, a low required rate is related to new funds flowing into the stock market due to the declined risk-free interest rate. This is because there exists a significant negative correlation between the sentiment variable and risk-free rate over the long run.

Regarding the quantile regression coefficients presented in Panel B, the effect of risk-free rate on sentiment has the largest magnitude when sentiment locates near its median. Such impact becomes small at the tails of sentiment distribution, especially during sample periods of low sentiment. The strong negative correlation between the risk-free rate and sentiment is a direct result of the fact that large-scale interest rate cuts will stimulate investors' enthusiasm for equity market participation. If the expected rate of return from stocks is also very low, that is, the implied discount rate has been positively associated with the risk-free rate for a long time, then a higher discount rate indicates that investor sentiment will be less affected by the risk-free interest rate.

Panel C runs regressions under three different market scenarios. We also include investor sentiment as a potential explanatory variable of the implied discount rate. The results corroborate our previous assertion of a nonlinear relationship between investor sentiment and implied discount rate. In terms of economic implications, the result from the previous paragraph is to some extent contrary to common sense. But it reflects one aspect of rationality – when the risk-free interest rate is lowered, investors' expected rate of return on all financial markets will reduce accordingly. By digging deeper into the time dimension of our data, we find this rational reaction to be a temporary phenomenon among Chinese retail investors. Although the risk-free interest rate acts as a relatively stable driving force of investor sentiment in the long term, fluctuations in the stock market have a stronger short-term impact on investor sentiment. For example, in the short run, investors facing bull markets are optimistic with surging positive sentiment, and they would be unsatisfied with interest rate instruments that may produce a negative return in real terms but are keen on speculating equities. When a bear market starts, the sudden decline of investor sentiment makes investors to stop speculation or even withdraw from the stock market and turn to financial products with relatively low risk and return. In terms of economic implications, this finding rings an alarm for policymakers. With imperfect and

Table 6. Regressing investor sentiment index and implied discount rate separately on the risk-free interest rate with OLS and quantile model in different market states

Specification	Panel A: OLS regression (full sample as long term) (1) $ISI_t = \alpha_0 + \alpha_1 r_{f,t} + \alpha_2 div_t$	(2) $r_{r,t} = \alpha_0 + \alpha_1 r_{f,t} + \alpha_2 div_t$	Panel B: Quantile regression	Coefficient of r_f in (1)	(2)	Coefficient of dt in (1)	(2)
Constant	2.0353*** (<0.0001)	−0.6591*** (<0.0001)	0.1	−0.2352	0.2601	−0.0338	−0.0639
			0.2	−0.3845	0.1278	0.0486	−0.0446
$r_{f,t}$	−0.6197*** (<0.0001)	0.1735*** (<0.0001)	0.3	−0.6742	0.0796	0.0410	−0.0390
			0.4	−0.7590	0.0621	0.0496	−0.0399
Div_t	0.0441 (0.1020)	−0.4124*** (<0.0001)	0.5	−0.7724	0.0526	0.0223	−0.0337
			0.6	−0.6811	0.0442	0.0064	−0.0346
DW-test	0.0464	0.9607	0.7	−0.5961	0.0264	−0.0108	−0.0288
Num. obs.	2,363	2,363	0.8	−0.5439	0.0157	−0.0053	−0.0182
Adj-R^2	0.0801	0.0152	0.9	−0.5181	0.0125	0.1073	−0.0113

Panel C: OLS regression in different market states (subsample as short term)

Period	(1) $ISI_t = \alpha_0 + \alpha_1 r_{f,t} + \alpha_2 div_t$ Stable	Bull	Bear	(2) $r_{r,t} = \alpha_0 + \alpha_1 r_{f,t} + \alpha_2 div_t$ Stable	Bull	Bear	Period	(3) $r_{r,t} = \alpha_0 + \alpha_1 r_{f,t} + \alpha_2 div_t + \alpha_3 ISI_t$ Stable	Bull	Bear
Constant	1.8453*** (<0.0001)	2.0171*** (<0.0001)	−0.5838 (0.1067)	0.2394** (0.0199)	−1.1814*** (<0.0001)	−1.3939*** (<0.0001)	*Constant*	0.1842 (0.1005)	−1.3362*** (<0.0001)	−1.5423*** (<0.0001)
$r_{f,t}$	−0.6817*** (<0.0001)	−0.4074*** (<0.0001)	0.0689 (0.5298)	−0.0609** (0.0395)	0.3141*** (<0.0001)	0.3908*** (<0.0001)	$r_{f,t}$	−0.0405 (0.2322)	0.3454*** (<0.0001)	0.4083*** (<0.0001)
div_t	−0.0091 (0.7881)	−0.0401 (0.3423)	0.2152*** (<0.0001)	−0.1093*** (<0.0001)	−0.0422 (0.2675)	−0.0106 (0.7542)	div_t	−0.1090*** (<0.0001)	−0.0391 (0.3027)	0.0441 (0.1786)
DW-test	0.1150	0.0695	0.1281	1.1634	0.9706	0.9467	ISI_t	0.0299 (0.2207)	0.0767*** (0.0128)	−0.2543*** (<0.0001)
Num. obs.	808	855	700	808	855	700				
Adj-R^2	0.2443	0.0417	0.0378	0.0285	0.0309	0.0267	DW-test	1.162994	0.978291	1.035226
							Num. obs.	808	855	700
							Adj-R^2	0.0303	0.0380	0.1207

Note(s): *** and ** denote significance at the 1 and 5% level, respectively. In order to make the results more readable, the implied discount rate here is annualized. This paper roughly follows Adrian R. pagan (2003), taking the window of rising or falling trend of more than 25% for three consecutive months as the bear market or bull market samples, and the rest as the stable market samples incomplete market access, interest rate cuts on a large scale may lead to recession after the short-term prosperity of the financial market. Therefore, the monetary authority should cut interest rates with caution and carefully guard the bubble economy brought up by overheated investing behaviors against sudden bursts.

6.3 Endogeneity and multicolinearity

To soothe concern about the endogeneity problem, we first investigate the correlations between *ISI*, various stock indices and the associated basis. When employing the OLS model for regression analysis, we find the Pearson coefficients of *ISI* with CSI300, CSI500 and SSE50 to be 0.822, 0.879 and 0.752 respectively, which means that our *ISI* is highly correlated with the prices of the IF, IH and IC contracts or equity index futures written on the CSI300, SSE50 and CSI500 index, respectively. When it came to testing the correlation between *ISI* and the basis of three contracts, a crude inspection of the association between the *ISI* and the three equity index futures basis (i.e. IF-B, IH-B, IC-B) via assessing the Pearson coefficients generates divergent outcomes. We discover that the Pearson coefficients of *ISI* with CSI300, CSI500 and SSE50's basis are 0.027, 0.227 and −0.102, respectively. This implies that *ISI* is positively correlated with both IF and IC contract futures basis with the *ISI*-IC combination showing a much more prominent relationship, whereas the correlation between *ISI* and IH contract basis turns out to be negative, so we assume that investor sentiment does not directly affect the basis. Nevertheless, combining the different representativeness of the three stock indices, the sentiment demonstrates a negative association with large-cap stock index basis but displays a positive association with small- and medium-cap stock index basis.

Given that this paper utilizes a two-stage model, there should be no new endogeneity problem introduced in the second stage. The reason is that the second-stage independent variables include only a constant and a fitted value computed in the first stage. As a result, the problem of endogeneity can only emerge from the first stage. In view of the research content and the data used in this paper, the problem of endogeneity caused by measurement errors should be minimal. We continue to investigate whether there could be endogeneity due to model errors or variable omission. In the first-stage regression, besides the main independent variable of investor sentiment, this paper also includes its exponential term to account for the nonlinearity in the basic linear equation. We may, therefore, suffer from model misspecification. However, the LR test statistic of our estimation results equals 17.51, indicating that all independent variables affect the implied discount rate significantly, that is, the construction of this model is meaningful. Moreover, our proposed model has incorporated all independent variables suggested by the theoretical model. So, we believe that there is no omission of key variables. Both the implicit discount rate and the sentiment are closely related to individual investors' expectations of the financial market. Indeed, there may be endogeneity problems caused by reverse causality. To check the severity of two-way causality, after performing the ADF test for confirming the stability of the sequences under concern, we continue to conduct a Granger causality test on the investor sentiment index and the implicit discount rate. The results are summarized in Table 7 below. As can be seen, Chinese retail investor sentiment Granger causes the changes in the

Table 7.
Granger causality tests for investor sentiment index, implied discount rate and risk-free interest rate

Null hypothesis	Num. obs.	*F*-statistic	Prob.
r_r does not Granger cause *ISI*	2,361	2.7540	0.0639
ISI does not Granger cause r_r		6.7659	0.0012
r_f does not Granger cause r_r	2,361	4.0814	0.0170
r_r does not Granger cause r_f		2.5391	0.0792

implicit discount rate. The implicit discount rate is not a driver of our investor sentiment index. It merits a note that reverse causality is not an issue in our robustness tests as well.

For the multicolinearity problem, our investor sentiment proxy is to some extent correlated with each of the dependent variables in the model. Although the correlation coefficients are small, we still need to gauge the severity of potential multicollinearity problems. To begin with, we inspect roughly the correlation coefficient matrix and find that the pairwise correlation coefficients fall far below the alerting threshold. Then, we move on to test the variance expansion factor of each model and find that the variance inflation factor (VIF) test statistics are far less than 10. Therefore, it can be determined that there should be no worries about biases caused by multicollinearity in each regression stage of our proposed two-stage index futures pricing model (see Table 8).

6.4 Data frequency and subsamples

We use monthly-frequency data to fit the concerned sentiment–basis relationship. The results stay unchanged. To further observe possible seasonal effects in the medium and long run, we have reviewed the monthly trend chart of index futures basis and implied discount rate and found that it is of waveform fluctuating around the horizontal axis (See Figure 4). This means that both times series follow the theoretically predicted patterns and there is no seasonality. In other words, they are not driven by medium-term time factors. Otherwise, we should observe floating above or below zero from time to time. Furthermore, to test the robustness of our results in the presence of seasonal effects, we have added time dummies at the monthly frequency and investigated whether these month variables are significant or not. The corresponding results show that none of the 12-month dummies produce statistically significant coefficients. Moreover, the goodness of fit of Equations (3) and (4) stays unchanged, which confirmed our conjecture of no seasonality.

Given the above being analyzed, we claim that current market status and weekend effects are potentially important influencing factors. To test whether weekend effects are a strong driving force, we have smoothed daily transaction data into the weekly frequency to filter out possible weekend effects. What we find is that, although the significance of the main explanatory variables in Equation (4) has decreased at the weekly frequency, our interested

Equation (1) $ISI_t = 0.182 \times CCI_{m-1} + 0.459 \times NIA_{m-1} + 0.222 \times IPON_{m-1} + 0.225 \times IPOR_{m-1} + 0.381 \times TURN_{t-1} + 0.148 \times DCEF_{t-1}$

	Coefficient variance	Uncentered VIF	Centered VIF
Constant	0.0000	1.0057	NA
CCI	0.0000	1.2793	1.2773
NIA	0.0000	2.3798	2.3796
IPON	0.0000	1.4849	1.4831
IPOR	0.0000	1.1016	1.1016
TURN	0.0000	1.9106	1.9105
DCEF	0.0000	1.3381	1.3366

Equation (4) $r_{r,t} = \alpha_0 + \alpha_1 r_{r,t-1} + \alpha_2 div_{t-1} + \alpha_3 r_{f,t-1} + \alpha_4 ISI_{t-1} + \alpha_5 e^{ISI_{t-1}} + \varepsilon_t$

	Coefficient variance	Uncentered VIF	Centered VIF
Constant	0.0000	78.2298	NA
$r_{r,t-1}$	0.0003	1.0752	1.0544
div_{t-1}	0.0000	1.1342	1.0075
$r_{f,t-1}$	0.0000	66.3715	1.2307
ISI_{t-1}	0.0000	5.4284	2.6419
$e^{ISI_{t-1}}$	0.0000	2.4477	2.3457

Table 8. Variance inflation factors of Equations (1) and (4)

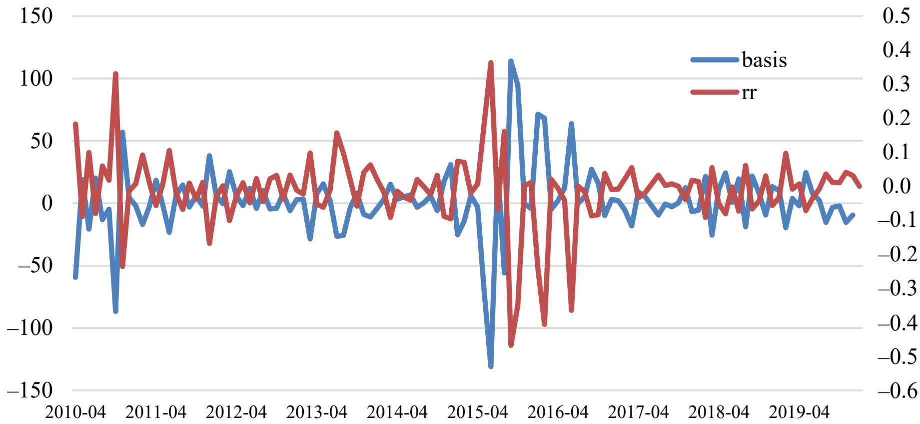

Figure 4.
Trends of basis and implied interest rate

effect still exists. And it merits a note that the correlation between the smoothed implicit discount rate and its first-order lag term has increased sharply, which explains the fluctuations of most of our dependent variables. Recall that only the 2015 year dummy is significant when we incorporate the dummy variables of years in Equation (4-3). Adding time dummies has improved the goodness of fit though. This is probably because the time dummies mark the change of futures market trading rules in 2015 or other time-related factors that may lead to market failures.

In light of such policy influences, we have segmented the entire sample into two subperiods before and after the introduction of trade restrictions in June 2015 [5]. The finding is that the explanatory power of sentiment in the whole sample regression is weaker than that in the subsample starting from the 2015 policy adjustment. Table 9 below reports the

Stage 1
Equation (4) $r_{r,t} = \alpha_0 + \alpha_1 r_{r,t-1} + \alpha_2 div_{t-1} + \alpha_3 r_{f,t-1} + \alpha_4 ISI_{t-1} + \alpha_5 e^{ISI_{t-1}} + \varepsilon_t$

Specification	2010.04–2015.06	2015.06–2019.12	Whole sample
Constant	0.0007* (0.0056)	−0.0006 (0.3303)	−0.0001** (0.0186)
$r_{r,t-1}$	0.3453*** (<0.0001)	0.5053*** (<0.0001)	0.5156*** (<0.0001)
div_{t-1}	−0.0001* (0.0561)	−0.0001 (0.8051)	−0.0001 (0.2659)
$r_{f,t-1}$	−0.0002** (0.0234)	0.0001 (0.8033)	0.0001* (0.0785)
ISI_{t-1}	0.0001** (0.0338)	−0.0001*** (<0.0001)	−0.0002*** (0.0013)
$e^{ISI_{t-1}}$	−0.0001 (0.6647)	0.0001** (0.0438)	0.0001** (0.0188)
DW-test	2.0722	2.0223	2.0762
Num. obs.	1,246	1,117	2,363
Adj-R^2	0.1439	0.3045	0.2847

Stage 2
Equation (3) $Basis_t = \alpha_0 + \alpha_1 \widehat{Basis_t} + \varepsilon_t = \alpha_0 + \alpha_1 S_t(1 - e^{\widehat{r_{r,t}}(T-t)}) + \varepsilon_t$

Specification	2010.04–2015.06	2015.06–2019.12	Whole sample
Constant	−1.0094* (0.0665)	2.7944 (0.0268)	−0.2191 (0.7864)
$\widehat{Basis_t}$	0.4884*** (<0.0001)	0.4388*** (<0.0001)	0.5272*** (<0.0001)
DW-test	0.7881	0.6463	0.4440
Num. obs.	1,246	1,117	2,363
Adj-R^2	0.1433	0.2934	0.1063

Note(s): ***, ** and * denote significance at the 1, 5 and 10% level, respectively

Table 9.
Two-stage regression results of estimating Equations (3) and (4) with subsamples divided by the policy change time point

corresponding comparison results. Therefore, we believe that the implementation of a harsher "circuit breaker" or trading curb mechanism and the establishment of a higher threshold of transaction prohibit retail investors from hedging activities in the futures market. However, this does not mean that these individuals will also stop trading in the spot market. Without hedging venue, the impact of investor sentiment on financial markets as a whole has escalated. Since our original intention is to study basis anomaly in China, that is, long-standing biases or asymmetries between the spot and futures trading on index futures, this tremendous policy change in China's stock index futures trading rules provides us with data to discuss the deviation of index market from the theoretical prediction of futures basis in the absence of derivatives tools.

7. Concluding remarks

Based on the above argument, we find evidence supporting our hypotheses. The cost-of-carry model has been proven to be theoretically correct and to possess practical value for Chinese stock index futures. By applying the model, one can easily derive the spot and futures price, and their basis is determined by a key factor, that is, the implied discount rate. The conventional wisdom tells us that this discount rate is determined only by the dividend yield and risk-free interest rate. However, this is not true for markets or periods affected by emotional factors. We show that investor sentiment also serves as a potential strong determinant of the implied discount rate. Moreover, its importance could outweigh the key variables identified under rationality. By incorporating investor sentiment into the implied discount rate, we significantly improve the pricing effectiveness of the cost-of-carry model whenever investor sentiment plays a role. We also document how the distorted basis of the Chinese stock index futures market has emerged and changed over time under the influence of retail sentiment. This finding is of great importance for Chinese investors with the intention to implement arbitrage, hedging and speculation strategies.

Consider the 2015 bursting of the Chinese stock market bubble, during which security prices slumped and retail investors rushed to liquidate their stock holdings. At the beginning of this crash, futures contracts were mainly held by institutional investors, and their prices stayed at high levels compared to spot prices, leading to futures premium. Typically, participants in the futures market with premium will construct strategies of long spot and short futures. Stock index futures and spot prices will return to equilibrium given such arbitrage activities. However, these high prices are not supported by growth in company value but are related to investors' fanatical pursuit and short-selling restrictions. Putting government rescue actions aside, it is then difficult for market participants themselves to take the initiative in restoring the order of the stock market in failure and distress. The long-term deep discount of futures basis in China after 2015 reflects the irrational investment behavior of market players.

As sentiment is bad for market self-correction, experiences from mature financial markets suggest the replacement of retail investors by institutions to stabilize the stock market and minimize the effect of investor sentiment on the futures basis. While a large proportion of institutional investors provide stability during normal market conditions, it is not always the case since speculative institutions like hedge funds tend to chase rather than fix bubbles (Brunnermeier and Nagel, 2004). Therefore, in a stock market boom or turmoil, over-the-counter transaction parties will march into the market with a high mood or exit the market with poor expectations and low sentiment. The entire market's attention would also be affected by their activities. In addition, most institutional investors often act solely from the perspective of making a short-term profit. So, the presence of institutional investors cannot guarantee a smooth and healthy operation of the stock market. The bottom line is to what extent sentiment affects mispricing in reality. Our paper provides a benchmark analysis.

All in all, the role of investor sentiment is not to be ignored concerning basis pricing. Hence, incorporating sentiment into the cost-of-carry model serves as a potential solution to imperfections reflected by the difference between the rational and actual basis in the Chinese equity index futures markets. These imperfections are rooted in at least two aspects. First, the transaction costs in China's spot and futures markets are too high, so that arbitrage and hedging are difficult to accomplish original expectations. This makes the basis more affected by investor sentiment, much harder to return to a reasonable level following deviations. Second, long and short positions in the Chinese stock market are highly unbalanced. Because implementing stock short sales faces many obstacles in China and only a limited amount of stocks can be collateralized to borrow cash, the no-arbitrage pricing principle fails here as investors have no way to take advantage of overpricings even though there are many investors and abundant information. Risk management tools are insufficient to support a developed hedging universe in China.

Notes

1. By contrast, institutional investors accounted for more than 70% of the US equity market participation.
2. We denote the CSI300 index futures by the IF contract. And let IC and IH be the futures contracts corresponding to the CSI500 and SSE50 index, respectively. Both IC and IH got listed on April 16th, 2015.
3. Since the futures of CSI300 were listed on April 16th, 2010, we choose this day as the starting point of our sample.
4. This paper follows the method proposed by Yi and Mao (2009) in constructing their CICSI measure. We differ from them in the choice of indicators used to obtain the sentiment proxy. Yi and Mao (2009) select component indicators of the Chinese market that can correspond exactly to those defined in the BW method for the US market.
5. Regarding the choice of June 2015 as the sample division time point, we have three considerations. First, the occurrence of the Chinese stock market crash and the promulgation of new regulations on stock index futures trading are the cause and outcome of the same event. Second, restrictions on trading come into operation as early as July 2015, and there are multiple rounds of tightening adjustments. As a result, it is better to set the boundary before the beginning of a series of policies. Third, given our focus is the relationship between sentiment and index futures basis, we have observed significant changes in this relationship precrash from premium to discount.

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