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Abstract

We document that hedge funds nurture mispricing in the Chinese financial market. We exploit the relationship between hedge fund holdings and the degree of mispricing in case that hedge fund holdings of stocks are mainly for arbitrage purpose but not for hedging, and that with and without short-selling restrictions. Hedge funds intentionally hold overvalued stocks. Their trades, which generate an abnormal return to 1.78% per month, also impede the dissipation of stock mispricing. Further, we find trend chasing may be the reason why hedge funds prefer to hold overvalued stocks. This research sheds new lights on the information content and potential investment value of hedge funds holdings in emerging markets.

Keywords: Hedge funds, stock mispricing, asset pricing, arbitrage

1. Introduction

There is controversy regarding whether arbitrageurs are a stabilizing force that keeps stock prices close to fundamental values. Many studies focus on hedge funds to study value arbitrage behavior (Ben-David et al. 2013), because they are less regulated, and compared with mutual funds, they have a better principal-agent relationship and better stock selection and market timing abilities. Hedge funds are expected as the representative arbitrageur to engage in trading securities based on their price deviation from fundamental values (Cao, Chen, et al. 2018).

However, whether hedge funds' trading corrects asset pricing errors is still in controversy. Some studies show that hedge funds have the ability to exploit and correct price inefficiency (Stulz 2007). Subsequent research supports this view, presenting evidence that hedge funds reduce the degree of mispricing at both the stock (Cao, Chen, et al. 2018) and the market levels (Kokkonen and Suominen 2015). On the contrary, other studies find that rational speculators may also ride a trend and drive a bubble. Speculators may initiate or contribute to price movements based on the expectation that positive-feedback traders will purchase the securities later at even higher prices (De Long et al. 1990a; Schauten, Willemstein, and Zwinkels 2015). Arbitrageurs, knowing that the market is overvalued, maximize profits by riding the bubble (Abreu and Brunnermeier 2003). Due to capital constraints, the bubble only bursts when there is a coordinated selling effort in arbitrageurs. Brunnermeier and Nagel (2004) and Griffin et al. (2011) document that hedge funds prefer to ride bubbles, suggesting that they sometimes nurture mispricing in financial markets.

This paper contributes to the debate by investigating hedge fund holdings and trades in China. Specifically, we examine whether hedge funds hold undervalued or overvalued stocks. Further, we shed light on the source of hedge funds' performance for a better understanding of their holdings and trades. We also examine the effect of alleviation of market friction on hedge fund holdings and trades.

The Chinese hedge fund data we used in this paper has its advantages. Market conditions in China make the Chinese hedge funds better candidates for representative arbitrageurs to engage in trading securities based on their price deviation from fundamental values than the U.S. ones studied in Cao, Chen, et al. (2018), because there are limited number of derivative instruments in the Chinese stock market and this limits means of hedging. As an emerging market, the Chinese stock market is gradually perfecting hedging instruments. CFFEX CSI 300 index futures only began trading on the China Financial Futures Exchange (CFFEX) in April 2010[1] and the vast majority of stocks have no corresponding futures in China. Compared with developed stock markets which has abundant index futures and individual stocks futures, excluding index constituents has relatively little impact on sophisticated investors' trading behavior in the Chinese stock market. In addition, the Chinese stock market lifted the short-selling ban in 2010, which allows us to compare hedge fund behavior before and after the alleviation of that market friction. Moreover, the existing contrary empirical results on hedge fund behavior may be due to the fact that hedge funds hold and trade stocks for both value arbitrage and hedge purposes, and they may also have to hold overpriced stocks due to friction in the stock market, such as short-selling restrictions (Miller 1977; Scheinkman and Xiong 2003; Y. Chen, Da, and Huang 2019). It is usually difficult to disentangle the arbitrage effects from hedge effects in empirical studies. Study of Chinese hedge funds would provide new evidence on the behavior of arbitrageur and contribute to the debate of whether hedge funds drive stocks prices to converge on their fundamental values.

In this paper, we focus on hedge funds in China to investigate the role of sophisticated investors in the security price formation process. Noting that there are no funds is explicitly named as "hedge funds" in China, following Huang, Yao, and Zhu (2018), the privately offered funds in China are defined as hedge funds in our study.[2] The privately offered funds share similar characteristics (e.g. establishment conditions, qualified investors, operation modes, management and performance fees, and etc.) with hedge funds in the U.S. market, except lack of instruments to adopt hedging strategies. For facility, we called the "privately offered fund" as the "hedge fund" in the rest part of this paper. Hedge funds have developed considerably over the past decade in China. According to a report by the Asset Management Association of China (AMAC), there are 11,332 registered hedge fund managers and 16,813 registered hedge funds that invest in the stock market, and the asset management scale had reached 1,960.5 billion CNY (284.29 billion USD) by the end of March 2016. Panel A of Figure 1 shows the development of all hedge funds including the number of hedge funds, the total net assets under management (TNA), and the TNA of hedge funds that invested in the stock market. We see that hedge funds in China have grown rapidly since 2014. The Chinese State Council issued official documents to foster hedge fund industry in May 2014. The Asset Management Association of China (AMAC) promptly responded to the government demand and implemented a series of policy to register and manage hedge funds. Consequently, we observe a boom in hedge fund industry, and even some outstanding mutual fund managers moved to the industry, such as Lu Guoqiu and Wang Xiaoming. Since 2015, the AMAC has reported in detail the number and assets under management (AUM) of hedge funds that only invest in the stock market. Panel B suggests that hedge funds have become an increasing proportion of the Chinese stock market since 2015.

We obtain hedge fund data from the AMAC. All hedge funds in China must be registered in the AMAC. Our final sample of hedge funds includes 10,096 funds and spans January 2007 through March 2016, covering all major hedge funds trading in Chinese stock market. We match hedge funds with the top 10 outstanding shareholders reported by listed companies each quarter. It is worth noting that the Chinese government allowed the trading of futures contracts in the CSI 300 Index beginning in 2010. Thus, we delete CSI 300 membership stocks from the sample to ensure that our sample includes only stocks without hedging instruments. Last, we assemble a database of quarterly shareholdings of hedge funds in the Chinese stock market. Our empirical analysis produces three sets of main findings.

First, we explore the relationship between hedge fund holdings and stock mispricing measured by relative and absolute valuation models. We find strong evidence that hedge funds tend to hold overvalued stocks with lower idiosyncratic volatility (Hou and Loh 2016). We also propose a simple return-based fund-position estimation to visualize a fund's entire position, especially funds that are not included in the top 10 outstanding shareholders data. The result of the return-based fund-position estimation suggests that hedge funds tend to hold overvalued stocks at the fund level. We suggest that hedge fund holdings nurture mispricing in the emerging financial market.

Moreover, we find that hedge fund holdings and trades impede stocks convergence on the security market line in the following quarter.

Next, we investigate whether hedge funds profit from holding overvalued stocks. We separately track price movements for stocks with previous high versus low hedge fund holdings. The results show that stocks with high hedge fund holdings generate an abnormal return to 1.78% per month, resulting in a return spread of approximately 4.8% per year compared with low hedge fund holdings. We also document that hedge fund performance comes mainly from the momentum factor. This implies that the key reason why hedge funds prefer to hold overvalued stocks is their trend-chasing behavior.

Third, we investigate changes in hedge fund holdings around market bubbles and short-selling ban lifts, respectively. We find that hedge funds reduce their holdings before prices collapse, but there are no significant changes before or after a short-selling ban lift. This suggests that hedge funds deliberately hold overvalued stocks. Their riding on bubble behavior is not caused by market friction, which is consistent with Griffin et al. (2011) and Brunnermeier and Nagel (2004).

Our paper makes two contributions to the literature. First, we contribute to the debate on whether hedge funds drive stocks prices to converge on their fundamental values. By using unique Chinese hedge funds data, where the hedge fund holdings are mainly come from arbitrage but not hedge, our research provides better understanding for the behavior of arbitrageurs and new evidence on the role of hedge funds in the security price formation process. Further, the short-selling ban lift in China also allows us to study the behavior of hedge funds before and after market friction has been alleviated, which is different from Huang, Yao, and Zhu (2018) who focus on hedge fund performance and growth under short-selling restrictions in China. Our results support the view that hedge fund trading nurtures mispricing in China. Second, our study reveals the role of arbitrageurs in asset pricing, and the information content and potential investment value of hedge funds holdings in emerging markets.

The remainder of this paper is organized as follows. In Section 2, we review related literature and develop testable hypotheses. Section 3 describes the data collection and provides the summary statistics of the sample. It also introduces measures of stock mispricing. Section 4 reports the main empirical results. The final section presents our conclusions.

2. Related Literatures and Hypotheses Development

Regarding the debate on the role of hedge funds in asset pricing, we first study the relationship between hedge fund holdings and stock mispricing.

The conventional wisdom is that arbitrageurs trade against mispricing and bring stock prices back to fundamentals. Friedman (1953) argues that when irrational and sophisticated investors coexist in securities markets, sophisticated investors will trade against irrational investors and quickly eliminate mispricing. Representing sophisticated investors, hedge funds look for mispriced securities, and their trading can bring prices closer to fundamental values (Akbas et al. 2015; Stulz 2007), improve stocks' price efficiency (Cao, Liang, et al. 2018), and reduce market-level misvaluation (Kokkonen and Suominen, 2015).

However, other research challenges this view and finds that sophisticated investors nurture mispricing in financial markets. Abreu and Brunnermeier (2003) present a model and document that it can be optimal for rational investors to invest in overpriced securities if they believe that other rational investors will not yet trade against the bubble. Empirical researches also provide evidence that institutions have a strong tendency to buy overvalued stocks (Edelen, Ince, and Kadlec 2016) and the increase in the number of sophisticated investors does not necessarily lead to greater market efficiency (Stein 2009). During the tech bubble period, Brunnermeier and Nagel (2004) and Griffin et al. (2011) show that hedge funds rode with the bubble and destabilized the market.

These contrary findings may be attributable to the ambiguous purpose of hedge fund holdings and trades (Cao, Chen, et al. 2018). In this research, we study hedge funds in China, where the hedge fund holdings of stocks are mainly for arbitrage purpose and with limited or no hedging effect.

In China, two potential reasons make it more difficult to pick up undervalued stocks than that in developed markets. First, the Chinese stock market is highly speculative, stock prices have weak links to their fundamentals and the macro economy, and both the market and regulators are immature and imperfect, the well-known Chinese economist Wu Jinglian dubbed it “casino” in 2001[3]. There are major incidents that spectacular price rallies followed by severe market crashes occurring in the 1990s, 2000s and 2010s, which are difficult to explain by market fundamentals. Reported by Bloomberg in April 2015, the average price earnings ratio of Chinese tech stocks is 41% higher than that of their U.S. counterparts at a price peak in March 2000. Compared with a much developed market of Hong Kong, the mainland Chinese stock market has significantly speculative bubbles (Pavlidis and Vasilopoulos 2020).

Second, the Chinese stock market is dominated by noise traders whose trading create a risk of the price that deters rational arbitrageurs from aggressively betting against them (De Long et al. 1990b). In the Shanghai Stock Exchange of China, retail investors held 25.18% of the market value, while investment funds held only 2.93% by 2016. Of those retail investors, 74.7% do not have a college education which means it's hard for them to calculate fundamental value[4]. However, the U.S. institutional investors own 80% of the market value far more than retail investors own[5].

Therefore, prices may deviate from fundamental values for a long time in the Chinese stock market, which limits professional investors' risk-bearing capacity (Shleifer and Vishny 1997). Kang, Kondor, and Sadka (2014) document that hedge funds might reduce their positions after a series of adverse shocks, which leads to the increased idiosyncratic volatility of high-idiosyncratic-volatility stocks and the decreased idiosyncratic volatility of low-idiosyncratic-volatility stocks. Jiang, Xu, and Yao (2009) show that the higher institutional ownership, the lower idiosyncratic volatility of stocks.

To summarize, rather than competing with retail investors to buy the sought-after undervalued stocks, overvalues stocks are more difficult to explore by retail investors because short selling is costly, it is not allowed or is very limited in China, hedge funds can explore overvalued stocks and use their skills to time the market and hold low idiosyncratic risk stocks to ride the trend, and quickly pull capital out of the market before a crash while retail investors continue to buy and hold them. We have

Hypothesis 1: Hedge funds prefer to hold overpriced stocks with low idiosyncratic risk.

We expect to find that hedge fund holdings are positively related to the degree of stock mispricing, in particular for overpriced stocks, and negatively related to idiosyncratic volatility.

If hedge funds hold overpriced stocks and ride on the price trend of stocks, this is to drive stocks prices further away from their fundamental values. We have

Hypothesis 2: Hedge fund holdings and trades impede the dissipation of mispricing.

If the market is efficient, mispricing will be quickly corrected, stocks with abnormal performance will not maintain the performance subsequently. However, when market is inefficient and mispricing persistence, holding stocks with abnormal past performance might be profitable (Y. Chen, Da, and Huang 2019). In the case of Chinese hedge funds, we have

Hypothesis 3: Hedge fund trades predict stock returns.

We now turn to investigate the sources of hedge fund performance. The literature usually measures hedge fund performance under a factor model framework (Agarwal and Naik 2004; Capocci and Hübner 2004; Eling and Faust 2010; Hong, Huang, and Zhao 2019; Sancetta and Satchell 2005). Griffin and Xu (2009) document that hedge funds exhibit a strong preference for high-momentum stocks compared with other firm characteristics. Huang, Yao, and Zhu (2018) show that Chinese hedge funds outperformed the stock market despite regulatory disruptions, and the performance is significantly positively associated with the momentum factor.

The Chinese stock market is generally regarded as having a speculative nature with a large number of young and inexperienced retail investors. The demand shocks of retail investors are easy to correlate with the rise of strong and persistent mispricing over time (Baker and Wurgler 2006; Han and Li 2017), which provides opportunities for hedge funds to profit from trend-chasing strategies. If hedge funds prefer to hold overpriced stocks, they will make profit by riding the trend, hedge funds returns should be positively associated with momentum factor. It would be intersecting to test

Hypothesis 4: Hedge fund returns come from the momentum factor.

Last but not least, we analyze whether hedge funds intentionally hold overvalued stocks. Previous studies suggest that market friction, particularly short-selling restrictions, forces sophisticated traders to hold overvalued stocks. With short-selling constraints, stock prices which mainly reflect investors' heterogeneous expectations are higher than their real value (Miller 1977) , investors are willing to pay a higher price for the right to resell shares to other agents who have more optimistic beliefs rather than hold them forever (Harrison and Kreps 1978; Scheinkman and Xiong 2003).

There are studies suggest that fund managers have skills to accurately identify mispriced stocks and get superior fund performance (Dong and Doukas 2020; R. Huang, Asteriou, and Pouliot 2020; Barras, Scaillet, and Wermers 2019). Moreover, hedge funds ride a bubble deliberately (Brunnermeier and Nagel 2004; Griffin et al. 2011) and manipulate stock prices (Ben-David et al. 2013) rather than simply failing to understand that stocks are overvalued. In summary, if hedge funds deliberately hold overpriced stocks, we would expect

Hypothesis 5: Hedge fund holdings of overvalued stocks decrease before a price peak, but they do not decrease after the short-selling ban is lifted.

3. Data and Measures of Mispricing

We compile a dataset of hedge fund equity holdings. Our sample includes 6,849 hedge fund management companies, which together manage more than 10,096 funds spanning January 2007 through March 2016. This dataset covers all major hedge funds trading in Chinese equity markets.

3.1. Hedge Fund Data

We collect a master list of hedge funds and their management companies from the AMAC. The list contains all hedge fund management companies and all hedge funds that only invest in the secondary stock market.

To obtain hedge fund holdings data, following Li, Brockman, and Zurbruegg (2015), we collect the top 10 shareholders' quarterly holdings of Chinese A-share stocks from the RESSET database and match stock holdings to hedge funds[6]. To compare with other funds' holding behaviors, we also collect other funds' quarterly holdings of Chinese A-share stocks from the RESSET database.

For funds included in our hedge fund list, we collect daily and monthly net asset value (NAV) data from the WIND database. Hedge fund returns are calculated based on funds' NAV adjusted for dividend payout. We also collect data on funds' issuance scale.

3.2. Stock Market Data

We collect Chinese A-share stock market data from the CSMAR databases. Our sample covers all publicly listed stocks on the Shanghai and Shenzhen Stock Exchanges except CSI 300[7] stocks, and comprises 2,591 stocks as of March 2016. This is to ensure that our sample only includes stocks that are less likely to be used as hedging instruments. Our stock dataset includes but is not limited to the daily data of stock returns, risk-free return rate, trading status, quarterly data of market capitalization, market capitalization, book value, dividends, firm age, net income, and leverage ratio. We perform the same tests with the sample including CSI 300 stocks and find consistent results.[8]

We manually merge the fund holding and quarterly stock characteristics data. In each quarter, stocks are selected if their trades are not suspended at the previous quarter. Our merged panel data contain 19,681 firm-quarter observations over the January 2007 through March 2016 period.

Based on the comprehensive dataset, Panel A of Table 1 reports stock characteristics at the firm-quarter level for all stocks held by hedge funds (top 10 outstanding shareholders). Panel B and Panel C respectively report the corresponding results for the subsample of stocks within the top decile of hedge fund holdings and non-hedge fund holdings each quarter. The characteristics include book-to-market ratio, market capitalization, dividend yield, firm age, and price.

[Insert Table 1 Here]

The average book-to-market ratio is 0.80 with a median of 0.58 for the full sample, which is slightly higher than the average (median) book-to-market ratio of 0.71 (0.40) for stocks with high hedge fund holdings. Stocks with high hedge fund holdings have younger ages (176.83 months vs. 179.64 months) and higher share prices (15.31 CNY vs. 14.38 CNY) than the full sample of stocks in the merged dataset. Conversely, stocks that belong to the top decile of non-hedge fund holdings have lower book-to-market ratio (0.53 vs 0.80), larger market capitalization (6.36 billion CNY vs billion 4.97 CNY) than the full sample of stocks.

3.3. Measures of Mispricing

We use three proxies to measure stock mispricing. Specifically, relative mispricing is the degree of deviation between the stock price and the security market line, absolute mispricing refers to the degree of deviation between the stock price and the fundamental value of the stock, and anomaly mispricing points to the degree of mispricing measured by cross-sectional return anomalies shown in the finance studies that cannot be fully explained by standard risk models. Brennan and Xia (2001) define mispricing as the difference between the realized average return on a security and the return predicted by an asset pricing model. Therefore, we construct factors in the Chinese stock market (Guo et al. 2017) and use the intercept of the Fama-French three-factor (FF3) and five-factor (FF5) models to measure relative mispricing. Using daily stock returns for each quarter, we estimate the FF3 model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}MKT_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it}, \tag{1}$$

and the FF5 model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}MKT_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \varepsilon_{it} \tag{2}$$

in which R_{it} is the return on stock i on day t, R_{ft} is the free-risk return on day t, MKT_t is the value-weighted market excess return, SMB_t is the return of the zero-net-investment portfolio for size, HML_t is book-to-market equity, RMW_t is profitability, and CMA_t is investment factors. α_i is the measure of relative mispricing for stock i. The security market line is calculated by beta and factors in the right-hand sides and displays the expected returns of a stock. If a stock's expected return versus its systematic risk (beta) is plotted above the security market line, it is considered undervalued. Conversely, if a stock's expected return versus its systematic risk (beta) is plotted below the security market line, it is overvalued because the investor would accept a smaller return for the amount of systematic risk associated. The daily data are from CSMAR databases and calculated by weighting all A-share market shares by outstanding market value.

We measure absolute mispricing as the difference between the market value of a stock and its fundamental value as estimated by Rhodes–Kropf, Robinson, and Viswanathan (2005). We run a cross-sectional regression to estimate absolute mispricing.

$$ln(M)_{ijt} = \alpha_{jt} + \beta_{1jt} ln\,(B)_{it} + \beta_{2jt} ln\,(NI)^{+}_{it} + \beta_{3jt} I_{(<0)} ln\,(NI)^{+}_{it} + \beta_{4jt} Lev_{it} + \varepsilon_{it} \qquad (3)$$

in which $\ln(\mathrm{M})_{ijt}$ is the quarterly market value of stock i in quarter t and sector j, $ln\,(B)_{it}$ is book value, $\ln\,(NI)^{+}_{it}$ is the absolute value of net income, $I_{(<0)}\ln\,(NI)^{+}_{it}$ is an indicator function for negative net income, and Lev_{it} is the leverage ratio. This cross-sectional regression contains time-varying market expectations for the industry average growth and discount rates; a firm-specific error can be interpreted as a firm-specific deviation from the contemporaneous industry-average growth and discount rates. Therefore, we use the firm-specific error to measure mispricing, namely.

$$Firm\_value_{ijt} = \widehat{\alpha_0} + \widehat{\beta_{1Jt}} ln\ (B)_{it} + \widehat{\beta_{2Jt}} ln\ (NI)^{+}_{it} + \widehat{\beta_{3Jt}} I_{(<0)} ln\ (NI)^{+}_{it} + \widehat{\beta_{4Jt}} Lev_{it} \quad (4)$$

$$misp\_Firm_{ijt} = ln(M)_{ijt} - Firm\_value_{ijt} \quad (5)$$

For each sector, we use fitted values as the proxy of $Firm\_value_{ijt}$, and use the difference between market value and fitted value to measure absolute mispricing. Specifically, we classify industries into seven groups according to the Chinese A-share stock classifications: mining, manufacturing, energy, wholesale, transportation and warehousing and postal services, real estate, and other industries.

Finally, we follow Stambaugh, Yu, and Yuan (2015) and measure the degree of mispricing based on 10 cross-sectional return anomalies except for the net operating assets anomaly (Hirshleifer et al. 2004) because of lacking of corresponding accounting data in China. The 10 return anomalies include financial distress (Campbell, Hilscher, and Szilagyi 2008), O-Score bankruptcy probability (Ohlson 1980), Net stock issues (Ritter 1991), Composite equity issues (Daniel and Titman 2006), Total accruals (Sloan 1996), Momentum (Jegadeesh and Titman 1993), Gross profitability (Novy-Marx 2013), Asset growth (Cooper, Gulen, and Schill 2008), Return on assets (Fama and French 2006) and Investment-to-assets (Titman, Wei, and Xie 2004).

Based on the above 10 return anomalies, we first score all stocks in our sample each quarter according to their future returns predicted by each of these anomalies. This score ranges from 0 to 100 and increases as overpricing increases. Specially, the high value of momentum, gross profitability premium or return on assets is followed by high future return which means low degree of overpricing and is assigned to low score. The high value of O-Score or the five remaining anomalies is followed by low future return which means high degree of overpricing and is assigned to high score. A stock's aggregate score is the equal-weight average of the ranking percentile previously quarterly computed.

4. Empirical Results

4.1. Hedge Fund Holdings and Mispricing

In this section, we test Hypothesis 1. First, we test whether hedge funds hold overvalued stocks and the relationship between hedge fund holdings and the magnitude of relative mispricing, absolute mispricing or anomaly mispricing. Furthermore, we test the relationship between hedge fund holdings and value arbitrage costs proxied by idiosyncratic volatility.

4.1.1 Relative Mispricing

To test Hypothesis 1, we first investigate whether hedge funds tend to hold overvalued stocks that have significant negative alpha. We run the Fama-MacBeth regression:

$$SH_{i,t} = \alpha_t + \beta_{1t} D(PositiveAlpha)_{i,t-1} + \beta_{2t} D(NegativeAlpha)_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

in which $SH_{i,t}$ is hedge fund holdings (or non-hedge fund holdings) as the fraction of shares held by all hedge funds (or non-hedge funds) in stock i by the end of quarter t. $D(PositiveAlpha)_{i,t-1}$ is a dummy variable equaling one if the stock i had a significant positive alpha in quarter $t-1$ and equals zero otherwise, $D(NegativeAlpha)_{i,t-1}$ is a dummy variable equaling one if the stock i had a significant negative alpha in quarter $t-1$ and equals zero otherwise. $X_{i,t-1}$ is a vector of control variables of stock characteristics including one-quarter lagged values of book-to-market ratio, market capitalization, dividend yield, firm age, and share price. Following the literature, the dependent and independent variables (except dummy variables) are standardized at each quarter so that the regression coefficients can be compared across years (e.g., Gompers and Metrick 2001). Because stock holdings are measured as a percentage, we take the natural log for all stock characteristics (except dummy variables) so that the variables have similar interpretations. For dividend yield, the logarithmic transformation is $Ln(1 + D/P)$ because not all stocks pay dividends each quarter.

Hypothesis 1 expects that hedge fund holdings increase with significant overvalued stocks and β_{2t} is significantly positive.

[Insert Table 2 Here]

Table 2 reports the results of the relationship between fund holdings and two one-quarter lagged dummy variables, one for significant overpricing and another for significant underpricing. For hedge fund holdings, the average coefficient on $D(NegativeAlpha)_{i,t-1}$ is positive and significant in column (1) and column (3), but the average coefficient on $D(PostiveAlpha)_{i,t-1}$ is insignificant. This suggests that stocks with a significantly negative alpha in the previous quarter are associated with significantly higher hedge fund holdings in the present quarter, which supports Hypothesis 1. However, there is no significant relation between non-hedge fund holdings and the lagged dummy variables of significant alpha estimated by FF5 in column (4).

In terms of the relationship between stock characteristics and equity holdings by hedge funds, we find that hedge funds tend to hold smaller stocks compared with non-hedge funds, i.e., the coefficient on market capitalization is –0.058 $(t - statistic = -3.44)$ for hedge fund holdings in column (3) but 0.191 $(t - statistic = 8.02)$ for non-hedge fund holdings in column (4). Further, hedge funds prefer to hold growth stocks $(\beta = -0.032, t - statistic = -2.39)$ and stocks with higher lagged prices $(\beta = 0.077, t - statistic = 3.81)$.

Next, we exploit the relationship between hedge fund holdings and the degree of mispriced stocks with significant alpha:

$$SH_{i,t} = \alpha_t + \beta_t |Alpha_{i,t-1}| + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

in which $|Alpha_{i,t-1}|$ is the absolute value of significant intercept of FF3 or FF5 measuring the deviation from the security market line for stock *i* at the end of quarter $t-1$, which is estimated by using each stock's daily returns in quarter $t-1$. Thus, Hypothesis 1 expects that hedge fund holdings increase with the increase of $|Alpha_{i,t-1}|$ when stocks are overpriced; specifically, b_t is significantly positive when $Alpha_{i,t-1}$ is significant and negative in the previous quarter.

[Insert Table 3 Here]

Table 3 shows the results of the Fama-MacBeth cross-sectional regressions of hedge fund and non-hedge fund holdings on a one-quarter lagged significant alpha. For hedge fund holdings, the average coefficient on the absolute value of lagged significantly negative alpha is positive and significant $(i.e.\ \beta = 0.346\ , t - statistic\ = 3.43\ in\ Panel\ A; \beta = 0.477\ , t - statistic\ = 3.09\ in\ Panel\ B)$, which indicates that stocks with overvalued alpha in the previous quarter are associated with significantly higher hedge fund holdings in the present quarter, which supports Hypothesis 1 again. Our results are in line with Abreu and Brunnermeier (2003), indicating that rational investors invest in overpriced securities and support Hypothesis 1.

4.1.2 Absolute Mispricing

To further test Hypothesis 1, we use the valuation model proposed by Rhodes–Kropf, Robinson, and Viswanathan (2005) to estimate the degree of mispricing based on stock fundamental value. We test whether hedge fund stock holdings are once again cross-sectionally related to the magnitude of mispricing. We run the Fama-MacBeth regression:

$$SH_{i,t} = \alpha_t + \beta_t misp\_firm_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

in which $misp\_firm_{i,t-1}$ is the measure of deviation from the fundamental value of stock i at the end of quarter $t - 1$. Because $misp\_firm_{i,t-1}$ increases with the degree of overpricing, b_t should be positive in support of Hypothesis 1.

[Insert Table 4 Here]

Table 3 shows the results from regressions of fund holdings and one-quarter lagged mispricing. For hedge fund holdings, the average coefficient on lagged firm mispricing $(\beta = 0.072, t - statistic = 3.52)$ is positive and significant in column (1), suggesting that the more stocks are overvalued in the previous quarter, the higher the hedge fund holdings in the present quarter. However, there is no significant relationship between non-hedge fund holdings and firm mispricing ($\beta = -0.002, t - statistic = -0.18$) in column (2). Therefore, we find that hedge funds do not trade against mispricing but hold overvalued stocks, which is in line with the finding that hedge funds hold overvalued stocks as documented in Griffin et al. (2011) and again supports Hypothesis 1.

4.1.3 Anomaly mispricing

We finally employ the Stambaugh, Yu, and Yuan (2015) mispricing measure to further test Hypothesis 1. Based on the above 10 return anomalies, we compute the equal-weight average of the ranking percentile for each stock, each quarter. We examine whether hedge fund holdings are once again positively related to the degree of mispricing. We run the Fama-MacBeth regression:

$$SH_{i,t} = \alpha_t + \beta_t misp\_score_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

in which $misp\_score_{i,t-1}$ is the overpricing score for stock i at the end of quarter $t-1$. Because $misp\_score_{i,t-1}$ increases with the degree of overpricing, b_t should be positive in support of Hypothesis 1.

[Insert Table 5 Here]

Table 5 shows the results from the Fama-MacBeth cross-sectional regressions of fund holdings on one-quarter lagged overvalued score[9]. In column (1), the more the stocks are overvalued in the previous quarter, the higher the hedge fund holdings in the present quarter $(\beta = 0.041, t - statistic = 3.61)$. Meanwhile, there is a significant and negative relationship between non-hedge fund holdings and mispricing score $(\beta = -0.057, t - statistic = -2.89)$ in column (2). Thus, we find that hedge fund holdings increase with the degree of overvaluation, which is in line with the finding that institutions have a strong tendency to buy overvalued stocks (Edelen, Ince, and Kadlec 2016) and again supports Hypothesis 1.

Regarding the relationship between stock characteristics observed in the previous quarter and hedge fund and non-hedge fund equity holdings in the current quarter, the evidence is similar to that presented in Table 3.

4.1.4 Idiosyncratic Volatility

We find that hedge funds do not trade against mispricing. Intuitively, hedge funds then should not bear the cost of arbitrage. We now examine the relationship between hedge fund holdings and value arbitrage costs measured by idiosyncratic volatility.

Run the following Fama-MacBeth regression:

$$SH_{i,t} = \alpha_t + \beta_t IdioV_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t} \quad (10)$$

in which $SH_{i,t}$ is the hedge fund shareholding ratio (or non-hedge fund shareholding ratio) of stock i by the end of quarter t, $IdioV_{i,t}$ is idiosyncratic volatility for stock i and measured by the standard deviation of daily return residuals from the FF3 or FF5 over quarter $t-1$, and $X_{i,t}$ is a vector of stock characteristics.

[Insert Table 6 Here]

Table 6 presents the results. The estimation results in column (1) and (3) show that the average coefficient on the lagged idiosyncratic volatility is negative and significant $(i.e. \beta = -0.034, t-statistic = -3.26)$. A one-standard-deviation increase in idiosyncratic volatility leads to a 0.045 (0.034) decrease in hedge fund holdings in the next quarter, while there is a 0.043 (0.037) decrease in non-hedge fund holdings in the next quarter. The estimated coefficients on the other stock characteristics are similar to those in Table 3. Moreover, alpha is the intercept from FF3 or FF5 estimated using each stock's daily returns in last quarter.

In sum, hedge fund holdings are significantly negatively related to lagged idiosyncratic volatility, consistent with Hypothesis 1. This finding suggests that hedge funds are less willing to bear value arbitrage costs when they hold stocks, which is consistent with the notion that sophisticated investors may avoid holding stocks with high arbitrage risk (Shleifer and Vishny 1997). Meanwhile, the result is inconsistent with the evidence presented by Cao, Chen, et al. (2018), because the Chinese stock market is dominated by noise traders whose beliefs create a risk in the price of the asset (De Long et al. 1990b) and prices may deviate from fundamental values for a long time, which discourages rational hedge funds to bear the cost associated with arbitrage.

4.2. Hedge Fund Holdings and the Dissipation of Alpha

We now focus on how hedge fund holdings and trades are related to the degree of mispricing and test the Hypothesis 2. Following Cao, Chen, et al. (2018), we use the following logit regressions to see whether hedge fund holdings and trades are associated with the dissipation of negative alpha and positive alpha, respectively.

$$D(Negative\ Alpha\ dissipation)_t = \alpha + SH_{i,t-1} + \Delta SH_{i,t-1} + \gamma' X_{i,t-1} + \varphi_t + \varepsilon_{i,t}$$

$$D(Positive\ Alpha\ dissipation)_t = \alpha + SH_{i,t-1} + \Delta SH_{i,t-1} + \gamma' X_{i,t-1} + \varphi_t + \varepsilon_{i,t} \quad (11)$$

in which $D(Negative\ Alpha\ dissipation)_t$ ($D(Positive\ Alpha\ dissipation)_t$) is a dummy variable equaling 1 if the stock had a significantly negative (positive) alpha in quarter $t-1$ that is no longer significant in quarter *t* and equals 0 otherwise. alpha_t is the intercept from the FF3 or FF5 and is estimated using each stock's daily returns in quarter $t-1$. $\Delta SH_{i,t-1}$ is fund trades, and φ_t is a quarter fixed effect to control for changes in alpha over time.

[Insert Table 7 Here]

Table 7 reports results of the logit regression with standard errors clustered across stocks. The results in Panel A indicate that hedge fund trades in a quarter are significantly negatively related to the likelihood that negative alpha dissipates in the next quarter (β =– 0.067， $Z-score$ = – 2.02). Non-hedge fund holdings in a quarter are also significantly negatively related to the likelihood that negative alpha dissipates in the next quarter (β = – 0.115, $Z-score$ = – 2.58).

Panel B of Table 7 shows that both hedge fund holdings and trades in a quarter are significantly negatively related to the likelihood that a positive alpha dissipates in the next quarter. In particular, the coefficient on hedge fund holdings is $-0.163\ (Z-score=-2.31)$, and the coefficient associated with hedge fund trades is $-0.121(Z-score=-1.72)$ in column (2), suggesting that their holdings and trades actually impede stock price reversion to the security market line in the next quarter. However, non-hedge fund holdings and trades in a quarter are not significantly related to the likelihood that positive alpha dissipates in the next quarter.

Consistent with Hypothesis 2, hedge fund holdings and trades exacerbate mispricing, and the effect is more obvious on underpriced stocks. This finding is consistent with Brunnermeier and Nagel (2004), who find that rational arbitrageurs do not exert a correcting force on stock prices. Meanwhile, non-hedge fund holdings also exacerbate mispricing, and the effect is more obvious on overpriced stocks, which support Akbas et al. (2015) who find that aggregate flows to mutual funds appear to exacerbate cross-sectional mispricing.

4.3. Hedge Fund Performance

4.3.1 Does Hedge Fund Trade Predict Stock Returns?

In this section, we discuss if hedge funds trade exploit market inefficiency by examining if hedge fund trades predict future stock returns, the Hypothesis 3. We estimate the return predictability of hedge fund trades by comparing the investment returns of two portfolios. The stocks are sorted into two equally weighted portfolios based on hedge fund trades (changes in holdings) over quarter t; we use stocks with top 30% changes in holdings to build a high portfolio and use stocks with bottom 30% changes in holdings to build a low portfolio. Next, both portfolios are held for three months (quarter $t+1$) before rebalancing. Following Liu and Strong (2008), we obtain a monthly return time-series for each portfolio over the sample period and adjust according to market return, specifically, minus CSI 300 monthly return.

[Insert Table 8 Here]

Table 8 reports the portfolios' performance based on hedge fund trades. Those having larger hedge fund holdings outperform their counterparts with smaller hedge fund holdings. For example, the high hedge-fund-holding portfolio has an average return to 1.78% per month, significantly higher than the 1.38% monthly return for the low hedge-fund-holding portfolio. The return spread between the portfolios is 0.4% per month ($t-statistic$ = 1.99) and approximately 4.8% per year, which is both economically and statistically significant. Adjusted by FF3 (FF5) factors, the average return for high hedge-fund-holding portfolio still higher than for low hedge-fund-holding portfolio (0.36% vs -0.10% adjusted by FF3 and 0.09% vs -0.27% adjusted by FF5). Additionally, the high hedge-fund-holding portfolio exhibits higher Sharpe and information ratios (i.e., average excess return of the portfolio over its idiosyncratic volatility), suggesting that stocks more intensively held by hedge funds have more attractive risk-return trade-offs.

Therefore, the results are in line with Hypothesis 3, that hedge fund trades predict stock returns. Specifically, stocks with heavy hedge fund trades tend to have large abnormal returns subsequently. This finding is also consistent with the negative relation between idiosyncratic volatility and subsequent stock returns (Hou and Loh 2016), and in testing Hypothesis 1 we find that hedge fund holdings are significantly negatively related to lagged idiosyncratic volatility. Therefore, our finding implies that hedge funds buy overvalued stocks with low idiosyncratic volatility, not only for lower loss risk but also for higher future returns.

4.3.2 Measurement of Hedge Fund Performance

We have shown that hedge funds prefer to hold overvalued stocks and impede the dissipation of mispricing. Now we turn to identify the sources of hedge funds returns, the Hypothesis 4.

We measure the monthly performance of equally weighted (EW) and scale-weighted (SW) hedge fund portfolios using FF3 and FF5 with and without the momentum factor (MOM):

$$R_{HF,t} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t$$

$$R_{HF,t} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 MOM_t + \varepsilon_t \tag{12}$$

in which $R_{HF,t}$ is the return of EW and SW hedge fund portfolios in month t. The momentum factor (MOM_t) accounts for trend-chasing strategies in stock markets, i.e., buying stocks that were past winners and selling past losers (Carhart 1997). Other related variables are defined the same as in those in models (1) and (2).

[Insert Table 9 Here]

Table 9 reports the regression results. We find that both the EW and SW portfolios are significantly positive on the MOM and market factors. For example, the SW portfolio loads 0.074 (t-statistic = 2.07) on MOM and 0.038 (t-statistic = 12.82) on the market factor in column (8). The EW fund portfolio loads 0.089 (t-statistic = 2.46) on MOM and 0.279 (t-statistic = 11.61) on the market factor in column (4). In addition, the FF5 + MOM model generally performed well in explaining fund returns, with R^2 values of 0.655 in the EW portfolio and 0.675 in the SW portfolio. The results support Hypothesis 4 and show that both the EW and SW portfolios load significantly positive on MOM, suggesting that hedge funds tend to chase past winners. These results are similar to those of Griffin and Xu (2009), who show that hedge funds exhibit a strong preference for high-momentum stocks compared to other firm characteristics.

In the aggregate, our results show that hedge fund returns mainly come from the market and MOM factors and that trend-chasing behavior may be why funds prefer to hold overvalued stocks.

4.4. Do Hedge Funds Deliberately Hold Overpriced Stocks?

Having found that hedge funds are more likely to hold overpriced stocks at the stock and fund levels, we now turn to the question about whether hedge funds do so deliberately or whether they simply fail to eliminate a bubble caused by frictions such as short-selling restrictions. This is to test the Hypothesis 5.

4.4.1 Hedge Fund Holdings Around Stock Price Peaks

As a first approach to test Hypothesis 5, we look at hedge fund holdings around the price peaks of individual stocks. We choose the longest and most complete bull market in our sample time period, July 2014 to June 2015; at the time, the Shanghai Stock Index rose from 2,054 to 2,178.

Following Brunnermeier and Nagel (2004), we construct a quarterly return index from 2013 to 2015 for each stock. We define the price peak as the quarter-end at which the stock reached its maximum value. To ensure that we can observe holdings several quarters before a peak, we focus on stocks that peaked in 2014 or 2015. For each stock, we calculate the proportion of outstanding shares held by hedge funds. Using event study method, we align these quarterly series of hedge fund holdings with the event time. Event-time quarter 0 is the quarter of the price peak. We then take a value-weighted average across stocks and divide them into three samples based on the degree of mispricing.

Figure 2 reports the results. For highly overvalued stocks, i.e., stocks with a bottom 30% alpha estimated by the Fama-French five-factor (Panel A) or three-factor (Panel B) models or stocks with top 30% mispricing calculated by Rhodes-Kropf et al. (2005; Panel C), hedge funds owned a greater proportion of outstanding equity before than after the (quarterly) price peak.

[Insert Figure 2 Here]

In Panel A of Figure 2, hedge funds held a larger share, 3.6%, one quarter before a price peak, which decreased to 3.25% at the end of the peak-quarter and further declined in later quarters. Consistent with Brunnermeier and Nagel (2004), hedge funds seem to be more successful in timing their investments within overvalued stocks than within undervalued and other stocks. These stock-by-stock results suggest that hedge funds are successful in exiting before price collapses, which supports Hypothesis 5. Hedge fund managers stop increasing their share of overvalued stocks when stock prices near their peak, which intentionally causes other investors to suffer most of the losses from a price collapse.

4.4.2 Hedge Fund Holdings Around the Short-selling Ban Lifts

To further test Hypothesis 5, we examine whether hedge fund behaviors are caused by market friction. We use a difference-in-differences (DID) analysis that compares the difference in hedge fund holdings before and after a short-selling ban lift with those of a control group around the same ban lift to over- and undervalued stocks.

From 2010 onward, restrictions on short selling have been progressively lifted in the Chinese stock market. Specifically, 90 stocks could be sold short on February 12, 2010, and another 190 stocks were added to the list on November 25, 2011. The five main ban lifts occurred on February 12, 2010; November 25, 2011; January 25, 2013; September 6, 2013; and September 12, 2014. Until March 2016, 982 Chinese A-share stocks could be shorted after the five ban lifts. In our study, each of the short-selling ban lifts can be considered as a treatment, and the differences in changes in hedge fund holdings between stocks that can and cannot be shorted are the outcomes. The experimental groups are stocks that can be shorted. By comparing the changes in hedge fund holdings before and after each ban lift, the effect of market friction, i.e., short-selling policy, is tested. We estimate the following DID model:

$$SH_{i,t} = \alpha + \beta_1 Short_{i,t} + \beta_2 Time_{i,t} + \beta_3 Short_{i,t} * Time_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \qquad (13)$$

in which $Short_{i,t}$ is a dummy variable for which 1 represents stock i added to the shorting list and 0 represents stock i not added to the list. $Time_{i,t}$ is a dummy variable of time for which 1 indicates that stocks can be shorted during this period and 0 indicates that stocks cannot be shorted. $\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$ is an interaction term whose coefficient (i.e., β_3) measures the net effect of short-selling policy on hedge fund holdings. We estimate β_3 for each ban lift.

We further divide the sample into positive and negative alpha stocks to further investigate whether hedge funds are forced to hold overvalued stocks because of short-selling restrictions. If hedge funds are thus forced to hold overvalued stocks, hedge fund holdings should decrease in the negative alpha (overvalued stocks) subsample after short-selling restrictions relax and β_3 should be significantly negative. Meanwhile, in the positive alpha (undervalued stocks) subsample, hedge fund shareholding should increase after short-selling restrictions ease and β_3 should be significantly positive.

To select stocks for the control group, after separating the samples according to negative or positive alpha, we calculate the mean (μ) and standard deviation (δ) of the variables in the experimental group one year before the short-selling ban lift. Specifically, the variables include hedge fund holdings, alpha value, and five control variables (lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price). Next, we select the stocks from Chinese A-share listed stocks in the range (μ-3δ, μ+3δ) of these variables one year before the short-selling ban lift. If a stock has a value for either of these variables outside the selection range, the stock is not included in the control group.

[Insert Table 10 Here]

Table 10 reports the results of the DID analysis with alpha estimated by FF3 or FF5. In the negative alpha subsample, the coefficient on $\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$ is not significant and there is no significant change in hedge fund holdings before or after a short-selling ban lift for the alpha estimated by FF3 $(\beta = 0.326, t - statistic = 0.76)$ or FF5 $(\beta = 0.169, t - statistic = 0.41)$. This result implies that hedge funds are not forced to hold overpriced stocks. Further, in the positive alpha subsample, the coefficient on $\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$ is significant and positive in column (2) $(\beta = -2.562, t - statistic = -4.562)$ and column (4) $(\beta = -2.188, t - statistic = -3.69)$, which means that hedge funds decrease their holdings of undervalued stocks after short-selling restrictions are lifted.

Taken together, our results support Hypothesis 5 and suggest that hedge funds hold overpriced stocks on purpose but not because of market friction, which is consistent with the results of Abreu and Brunnermeier (2003).

5. Robustness

5.1 Hedge Fund Position and Degree of Mispricing

In above sections, hedge fund holdings are computed based on the top 10 shareholder's quarterly holdings, which may result in biased results. For example, hedge funds may separate risk and diversify their investments by having small holdings among various undervalued stocks. Now, we use an optimization method to investigate whether hedge funds mainly hold low-alpha stocks at the fund level, especially stocks that are not included in the top 10 outstanding shareholders data.

To estimate the hedge fund shareholding ratio of different alpha portfolios, we follow Chen and Chi (2018) and build a composite return based on different alpha portfolios and minimize the squared difference between the hedge fund return series and the composite return series. Furthermore, we obtain the global optimized weights of different alpha portfolios in the composite return, which are the estimated fund holdings in different alpha portfolios. Using this model, we can estimate the fund holdings of different daily alpha portfolios and obtain economically meaningful estimations. The specific form of the model is as follows:

$$\text{Min } \left\|R_{j,t} - R_{p,t}\right\|_2^2 = \frac{1}{T}\sum_{t=1}^{T}(R_{j,t} - R_{p,t})^2 \ ,$$

$$R_{p,t} = \beta_h * R_{High,t} + \beta_m * R_{Medium,t} + \beta_L * R_{Low,t} + \beta_f * R_f \ ,$$

$$\text{s.t. } \beta_h + \beta_m + \beta_L + \beta_f = 1 \ and \ \beta_h, \beta_m, \beta_L, \beta_f \geq 0 \tag{14}$$

in which $R_{j,t}$ is the net return of each hedge fund j in day t, $R_{p,t}$ is the composite return in day t. $R_{High,t}$, $R_{Medium,t}$, and $R_{Low,t}$ are the returns on different alpha portfolios. The global optimized parameters: $\beta_h,\ \beta_m, and\ \beta_L$ are hedge funds' estimated holdings in different alpha portfolios. β_f is hedge fund's estimated holdings of riskless assets. The model assumes that hedge funds cannot short stocks.

Specifically, we use the following method to calculate returns on different alpha portfolios. First, we construct annual formed alpha portfolios based on the FF3 (FF5) alpha of the stocks at the end of the previous year. Stocks with an alpha in the top 30th percentile of all alphas for publicly listed Chinese A-share stocks are classified as high, while stocks with an alpha in the bottom 30th percentile are classified as low. Stocks with an alpha between the 30th to 70th percentiles are classified as medium. We then calculate issuance size weighted daily returns for each portfolio (RHigh, RMedium, RLow) using annual alpha.

[Insert Table 11 Here]

Table 11 reports the fund position estimation for different alpha portfolios. For hedge fund holdings, the average position is 0.153 (0.114) on high-alpha portfolios and 0.191 (0.205) on low-alpha portfolios in Panel A (Panel B). When testing for the difference in the average position between high and low alpha portfolios, the *p*-value strongly rejects the null that the average positions are the same for high and low alpha portfolios (i.e., High-Low = –0.038, *t*-statistic = 6.46 in Panel A; High-Low = 0.091, *t*-statistic = –16.43 in Panel B). These results suggest that hedge funds prefer to hold overvalued stocks at the fund level, which is consistent with the results of Section 4.1 and supports Hypothesis 1 at the fund level.

5.2 Excluding the Financial Crisis Period

Our sample period is relatively short and starts before the financial crisis of 2007-2008, we exclude the financial crisis period and again run the regression on the hedge fund holdings and alpha to further check the robustness of our results[10].

[Insert Table 12 Here]

Table 12 shows the results of the Fama-MacBeth cross-sectional regressions (eq. (7)) of hedge fund holding on a one-quarter lagged significant alpha excluding the financial crisis period. For positive alpha, hedge fund holdings are insignificantly related to the magnitude of positive alpha. For negative alpha, hedge fund holdings are significantly and positively related to the absolute value of negative alpha $(i.e. \beta = 0.412, t - statistic = 3.15)$. This suggests again that hedge fund holdings increase with the degree of overpriced stocks after excluding the financial crisis period, which is consistent with our main findings.

6. Conclusions

We use a comprehensive dataset of Chinese hedge fund holdings covering all major hedge fund management companies from 2007 to 2016 to examine the role of hedge funds in the stock price formation process. Our empirical analysis shows that based on different valuation models, in the cross-section of stocks, hedge funds holdings of stocks are positively related to the degree of stock overpricing, and this is not the case for non-hedge funds holdings. In addition, hedge fund holdings are significantly negatively related to idiosyncratic volatility. We further find that stocks with high hedge fund holdings generate an abnormal return to 1.78% per month, resulting in a return spread of approximately 4.8% per year compared with low hedge fund holdings.

Further, hedge fund holdings and trades impede the dissipation of stock mispricing, and hedge fund performance is mainly driven by trend chasing. This seems to suggest that the trend-chasing behavior of hedge funds in China may be why hedge funds prefer to hold overvalued stocks. Finally, we examine hedge fund holdings around stock price peaks and the short-selling ban lifts. Hedge funds reduce their holdings before price collapses, but there are no significant changes before or after the short-selling ban lifts. This suggests that hedge funds intentionally hold overvalued stocks.

Distinct from the findings that hedge funds bring prices closer to fundamental values (Cao, Liang, et al. 2018; Y. Chen, Da, and Huang 2019), hedge funds play a different role in the asset pricing formation process in China. First, stock price may deviate from fundamental values for a long time, because the Chinese stock market is dominated by noise traders and lacks of a strong link to fundamentals. Second, different regulatory framework as we compared in Appendix A, shorter locked period, limited leverage ratio and derivatives hamper the Chinese hedge funds to implement long-term investment strategies that long undervalued stocks. Third, fund managers have the skills to time the market and to identify mispriced stocks to make money (Dong and Doukas 2020). Our results directly challenge the view that sophisticated investors consistently move against mispricing, and it enriches the research on the role of sophisticated investors in asset pricing and shed new lights on the information content and potential investment value of hedge funds holdings in emerging markets.

Notes

1. The underlying index, the CSI 300 Index, is the stock index that China Securities Index Co., Ltd. composed with the 300 largest A-Shares listed on the Shanghai Stock Exchange (179 stocks) and Shenzhen Stock Exchange (121 stocks).

2. In Appendix A, we give a full account of privately offered funds in China (Chinese hedge funds), which includes privately offered funds' characteristics, such as establishment conditions, qualified investors, operation modes, investment restrictions, etc. The following website also provides an overview of Chinese hedge funds' the regulatory framework: *https://uk.practicallaw.thomsonreuters.com/w-015-9140?transitionType=Default&contextData=(sc.Default)&firstPage=true* We also summarize the difference between privately offered funds and general hedge funds.

3. The speech reported by CCTV in 2001: *http://www.cctv.com/financial/ fengyun/sanji/20010114.html.*

4. Data from Shanghai stock exchange statistics annual in 2017.

5. Data from the U.S. Securities and Exchange Commission: *https://www.sec.gov/news/public-statement/statement-roisman-2019-11-05-14a-2b*

6. We note that our data set of hedge fund holdings based on the top 10 shareholder's quarterly holdings has its limitations. These partial holdings may result in biased results. For example, hedge funds may separate risk and diversify their investments by having small holdings among various undervalued stocks. We use an optimization method to investigate hedge fund holdings at the whole fund level in Section 5.1, especially stocks that are not included in the top 10 outstanding shareholders data.

7. The CSI 300 Index consists of the 300 largest and most liquid A-share stocks, and CSI 300 Index futures were introduced in 2010.

8. The results are available upon request.

9. We thank an anonymous reviewer for suggesting the use of the Stambaugh, Yu, and Yuan (2015) mispricing measure.

10. We thank an anonymous reviewer for suggesting to exclude the financial crisis period.

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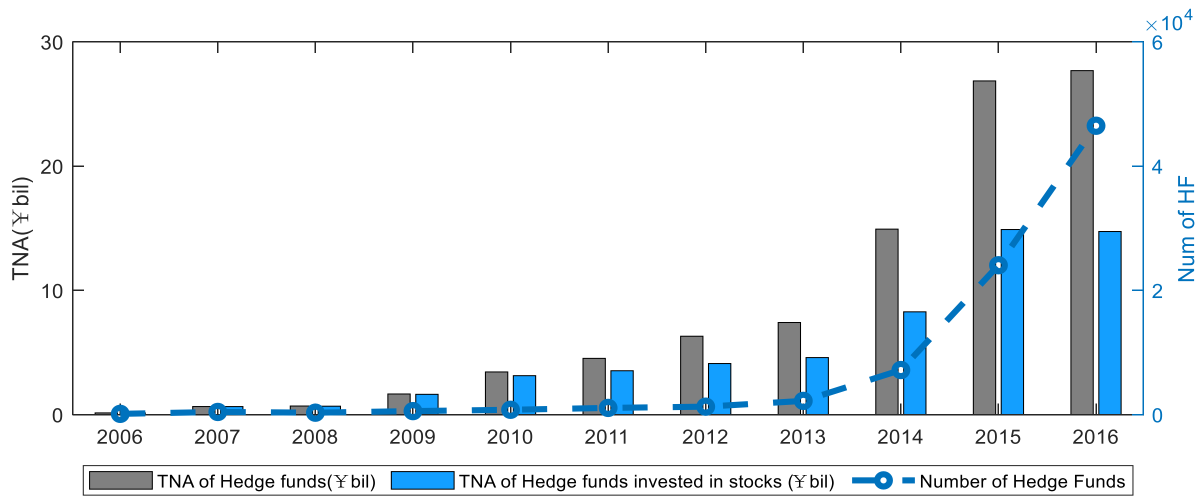
Panel A: The Development of All Hedge Funds



Panel B: The Development of Hedge Funds and Mutual Funds in the Stock Market

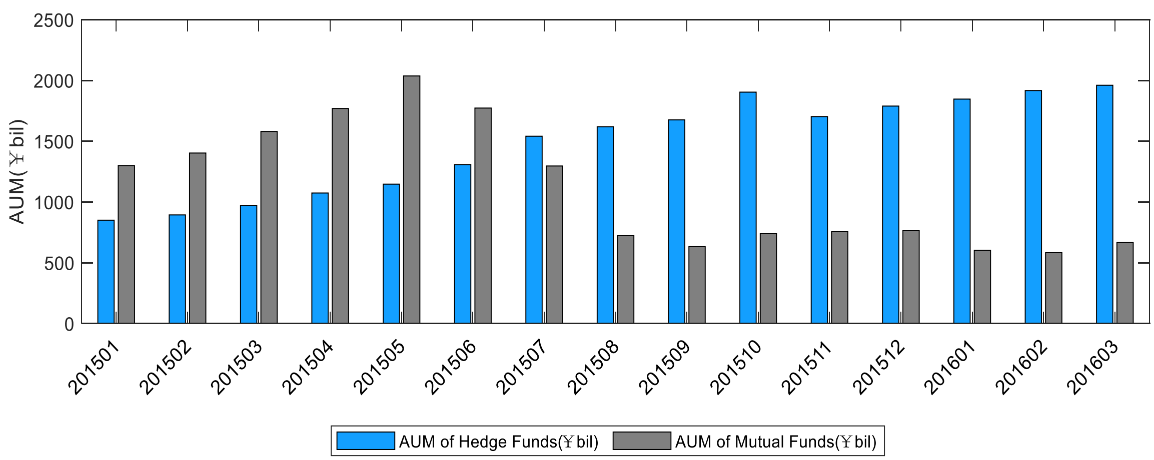


Figure 1. The Development of Hedge Funds in China

Note: Figure 1 shows the development of hedge funds and mutual funds. Panel A reports the development of all hedge funds during 2006 to March 2016, and the data are from the WIND database. Specifically, "all hedge funds" include those invested in the stock market, unlisted companies, VC, bonds and so on. Panel B shows the development of hedge funds and mutual funds that only invest in the stock market. The data are from the AMAC for the January 2015 to March 2016 period.

Table 1. Summary Statistics of Stock Characteristics

	Mean	Std. Dev.	25%	Median	75%	Min	Max	Skewness	Kurtosis'
				Panel A: All stocks in the full sample					
Book/Market	0.80	0.72	0.36	0.58	0.96	0.13	3.75	2.22	8.35
Market cap (¥ bil)	4.97	4.63	2.32	3.59	5.86	1.14	42.23	3.49	20.85
Dividend yield (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.02	2.99	11.27
Age(month)	179.64	60.86	135.00	176.00	223.00	63.00	316.00	0.21	2.46
Price (¥)	14.38	9.92	7.53	11.46	17.60	3.57	48.05	1.65	5.59
				Panel B: Stocks Belong to the top decile of hedge fund holdings					
Book/Market	0.71	0.66	0.32	0.54	0.83	0.13	3.75	2.75	11.77
Market cap (¥ bil)	4.96	4.43	2.21	3.61	6.06	1.14	42.23	3.09	17.43
Dividend yield (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.02	2.96	11.11
Age (month)	176.83	62.45	134.00	171.00	219.00	63.00	316.00	0.23	2.51
Price (¥)	15.31	9.44	8.58	13.06	18.78	3.57	48.05	1.53	5.39
				Panel C: Stocks Belong to the top decile of non-hedge fund holdings					
Book/Market	0.53	0.49	0.26	0.40	0.62	0.13	3.75	3.41	18.59
Market cap (¥ bil)	6.36	4.86	3.28	4.91	7.81	1.14	42.23	2.47	11.89
Dividend yield (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.02	3.58	16.28
Age (month)	172.22	60.50	128.00	167.00	210.00	63.00	316.00	0.39	2.71
Price (¥)	20.69	10.96	12.72	17.64	26.44	3.57	48.05	1.03	3.32

Note: Table 1 provides the summary statistics for all stocks owned by hedge funds (Panel A), and for stocks that belong to the top decile of hedge fund holdings (Panel B), and for stocks that belong to the top decile of non-hedge fund holdings (Panel C) in each quarter. The reported statistics include book-to-market ratio, market capitalization (in ¥ billion), dividend yield per quarter (in %), firm age (in months), and share price (in ¥). The full sample is based on a merged AMAC hedge fund list, top 10 outstanding shareholders' holdings in Chinese A-share stock data, and stock characteristics from January 2007 to March 2016.

Table 2. Regression of Hedge Fund (Non-Hedge Fund) Holdings on Lagged Dummy Significant Alpha

	(1)	(2)	(3)	(4)
	HF_SH_t	$Non\_HF\_SH_t$	HF_SH_t	$Non\_HF\_SH_t$
D(PostiveAlpha)_FF3$_{t-1}$	-0.032	0.056		
	(-0.43)	(0.63)		
D(NegativeAlpha)_FF3$_{t-1}$	0.505***	-0.058**		
	(4.84)	(-2.40)		
D(PostiveAlpha)_FF5$_{t-1}$			-0.080	0.060
			(-1.09)	(0.68)
D(NegativeAlpha)_FF5$_{t-1}$			0.425***	-0.039
			(4.52)	(-1.61)
Ln(Book/Market)$_{t-1}$	-0.030**	-0.021**	-0.032**	-0.022**
	(-2.29)	(-2.10)	(-2.39)	(-2.14)
Ln(Market Cap)$_{t-1}$	-0.059***	0.190***	-0.058***	0.191***
	(-3.56)	(8.10)	(-3.44)	(8.02)
Ln(Dividend yield)$_{t-1}$	0.005	-0.013	0.005	-0.012
	(0.62)	(-1.20)	(0.58)	(-1.13)
Ln(Age)$_{t-1}$	0.008	0.023**	0.008	0.022**
	(0.55)	(2.22)	(0.57)	(2.14)
Ln(Price)$_{t-1}$	0.075***	0.268***	0.077***	0.268***
	(3.89)	(22.92)	(3.81)	(23.07)
constant	-0.042***	-0.041***	-0.037***	-0.040***
	(-4.80)	(-2.79)	(-4.51)	(-2.75)
avg. R-squared	0.062	0.169	0.058	0.168
N	17834	17834	17834	17834

Note: Table 2 shows the results from Fama-MacBeth cross-sectional regressions of hedge fund holdings and non-hedge fund holdings on one-quarter lagged dummy significant alpha. $D(PositiveAlpha)_{i,t-1}$ is a dummy variable equaling one if the stock i had a significant positive alpha in quarter $t-1$ and equals zero otherwise, $D(NegativeAlpha)_{i,t-1}$ is a dummy variable equaling one if the stock i had a significant negative alpha in quarter $t-1$ and equals zero otherwise. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Regression of Hedge Fund (Non-Hedge Fund) Holdings on Lagged Significant Alpha

	(1)	(2)	(3)	(4)
	HF_SH_t Positive Alpha	$Non\_HF\_SH_t$ Positive Alpha	HF_SH_t Negative Alpha	$Non\_HF\_SH_t$ Negative Alpha
		Panel A: Alpha Estimated by FF3		
$alpha\_FF3_{t-1}$	-0.074	-0.069	0.346***	-0.011
	(-1.34)	(-1.26)	(3.43)	(-0.41)
constant	0.016	0.447	4.231***	-0.277**
	(0.09)	(0.59)	(5.55)	(-2.13)
Control variables	YES	YES	YES	YES
avg. R-squared	0.592	0.627	0.564	0.459
N	563	563	1021	1021
		Panel B: Alpha Estimated by FF5		
$alpha\_FF5_{t-1}$	-0.037	-0.063	0.477***	0.042
	(-0.89)	(-1.08)	(3.09)	(0.98)
constant	-0.042	0.145	2.987***	-0.131*
	(-0.45)	(0.67)	(4.54)	(-1.85)
Control variables	YES	YES	YES	YES
avg. R-squared	0.578	0.592	0.513	0.437
N	537	537	1130	1130

Note: Table 3 shows the results from Fama-MacBeth cross-sectional regressions of hedge fund (non-hedge) fund holdings on one-quarter lagged significant alpha. In quarter t, $alpha_{t-1}$ is the absolute value of significant intercept from the FF3 (FF5) and is estimated using each stock's daily returns in quarter t-1. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Regression of Hedge Fund (Non-Hedge Fund) Holdings on Lagged Mispricing

	(1) HF_SH_t	(2) $Non\_HF\_SH_t$
Firm-Mispring $_{t-1}$	0.072***	-0.002
	(3.52)	(-0.18)
Ln(Book/Market)$_{t-1}$	0.022	-0.025*
	(1.54)	(-2.03)
Ln(Market Cap)$_{t-1}$	-0.103***	0.195***
	(-5.20)	(7.59)
Ln(Dividend yield)$_{t-1}$	0.008	-0.013
	(1.24)	(-1.14)
Ln(Age)$_{t-1}$	0.001	0.025**
	(0.07)	(2.32)
Ln(Price)$_{t-1}$	0.080***	0.268***
	(3.90)	(21.70)
constant	-0.017**	-0.042***
	(-2.25)	(-2.89)
avg. R-squared	0.040	0.163
N	17834	17834

Note: Table 4 reports the results from Fama-MacBeth cross-sectional regressions of hedge fund and non-hedge fund holdings on one quarter lagged mispricing. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. In quarter *t*, Firm-Mispricing$_{t-1}$ is the regression error from the Rhodes-Kropf et al. (2005) model and is estimated by quarterly, firm-level, cross-sectional regressions in quarter *t*-1. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Regression of Hedge Fund (Non-Hedge Fund) Holdings on Lagged Anomaly mispricing

	(1) HF_SH $_t$	(2) Non_HF_SH $_t$
Misp_Score $_{t-1}$	0.041***	-0.057**
	(3.61)	(-2.89)
Ln(Book/Market)$_{t-1}$	-0.056**	0.001
	(-2.88)	(0.07)
Ln(Market Cap)$_{t-1}$	-0.041***	0.141***
	(-4.37)	(4.64)
Ln(Dividend yield)$_{t-1}$	0.012	-0.042*
	(0.88)	(-1.87)
Ln(Age)$_{t-1}$	-0.007	0.045**
	(-0.30)	(2.37)
Ln(Price)$_{t-1}$	0.052**	0.289***
	(2.28)	(23.96)
constant	0.000	-0.000
	(1.20)	(-0.75)
avg. R-squared	0.032	0.154
N	8743	8743

Note: Table 5 reports the results from Fama-MacBeth cross-sectional regressions of hedge fund and non-hedge fund holdings on one quarter lagged anomaly mispricing. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. Following Stambaugh, Yu, and Yuan (2015), Misp_Score$_{t-1}$ is the equal-weigth average of the ranking percentile for each stock based on the 10 return anomalies except for the net operating assets anomaly in quarter *t*-1. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Regression of Hedge Fund (Non-Hedge Fund) Holdings on Lagged Idiosyncratic Volatility

	(1)	(2)	(3)	(4)
	HF_SH_t	$Non\_HF\_SH_t$	HF_SH_t	$Non\_HF\_SH_t$
Idio_vol_FF3	-0.045***	-0.043***		
	(-4.45)	(-4.80)		
Idio_vol_FF5			-0.034***	-0.037***
			(-3.26)	(-3.98)
$Ln(Book/Market)_{t-1}$	-0.033**	-0.027**	-0.034**	-0.027***
	(-2.46)	(-2.63)	(-2.59)	(-2.73)
$Ln(Market\ Cap)_{t-1}$	-0.059***	0.198***	-0.059***	0.198***
	(-3.50)	(8.46)	(-3.50)	(8.43)
$Ln(Dividend\ yield)_{t-1}$	0.003	-0.015	0.002	-0.016
	(0.43)	(-1.41)	(0.28)	(-1.48)
$Ln(Age)_{t-1}$	0.003	0.023**	0.003	0.023**
	(0.23)	(2.19)	(0.21)	(2.18)
$Ln(Price)_{t-1}$	0.082***	0.277***	0.084***	0.279***
	(4.00)	(23.01)	(4.04)	(23.47)
constant	-0.016**	-0.040***	-0.015**	-0.040***
	(-2.24)	(-2.74)	(-2.15)	(-2.73)
avg. R-squared	0.039	0.166	0.039	0.166
N	17834	17834	17834	17834

Note: Table 6 presents the results from the Fama-MacBeth cross-sectional regressions of hedge fund and non-hedge fund holdings on one-quarter lagged idiosyncratic risk. The control variables are lagged stock characteristics, including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. In quarter t, IdioVolt-1 is the standard deviation of return residuals from the FF3 or FF5 and estimated using each stock's daily returns in quarter t-1. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Logit Regression of Alpha Dissipation on Institutional Holdings

	(1)		(2)	
	Alpha_FF3		Alpha_FF5	
	Coef.	z-Score	Coef.	z-Score
Panel A: Dependent variable = D (Negative Alpha dissipation) $_t$				
HF_SH_{t-1}	0.009	0.26	-0.003	-0.07
$Non\text{-}HF\_SH_{t-1}$	-0.146	-2.98	-0.115	-2.58
ΔHF_SH_{t-1}	-0.059	-1.70	-0.067	-2.02
$\Delta Non\_HF\_SH_{t-1}$	-0.042	-0.85	-0.026	-0.59
Control variables	Yes		Yes	
Quarter dummies	Yes		Yes	
Stock-quarter obs.	15473		15429	
Pseudo R-squared	0.017		0.017	
Panel B: Dependent variable = D (Positive Alpha dissipation) $_t$				
HF_SH_{t-1}	-0.107	-1.49	-0.163	-2.31
$Non\text{-}HF\_SH_{t-1}$	0.000	0.01	-0.006	-0.10
ΔHF_SH_{t-1}	-0.092	-1.58	-0.121	-1.72
$\Delta Non\_HF\_SH_{t-1}$	0.027	0.55	0.024	0.48
Control variables	Yes		Yes	
Quarter dummies	Yes		Yes	
Stock-quarter obs.	15341		15270	
Pseudo R-squared	0.069		0.058	

Note: Table 7 presents the results from logit regressions of alpha dissipation on the level and change in stock holdings by hedge and non-hedge funds. For each stock in each quarter *t*, dependent variable is a dummy variable that equals 1 if the stock was a positive-alpha (negative-alpha) share in quarter *t*-1 but not in quarter *t* and 0 other wise. The control variables are lagged stock characteristics, including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Summary Statistics of Portfolio Returns (decimals per month)

	Portfolios based on ∆ HF_SH	
	Low_portfolio	High_portfolio
Mean return	0.0138	0.0178
Median return	0.0134	0.0167
Standard Dev.	0.0717	0.0724
Adjusted return (FF3)	-0.0010	0.0036
Adjusted return (FF5)	-0.0027	0.0009
Sharpe ratio （Rf benchmark）	0.1487	0.2037
Information ratio （CSI 300 benchmark）	0.1486	0.2034
Information ratio （Rf benchmark）	0.0138	0.0178

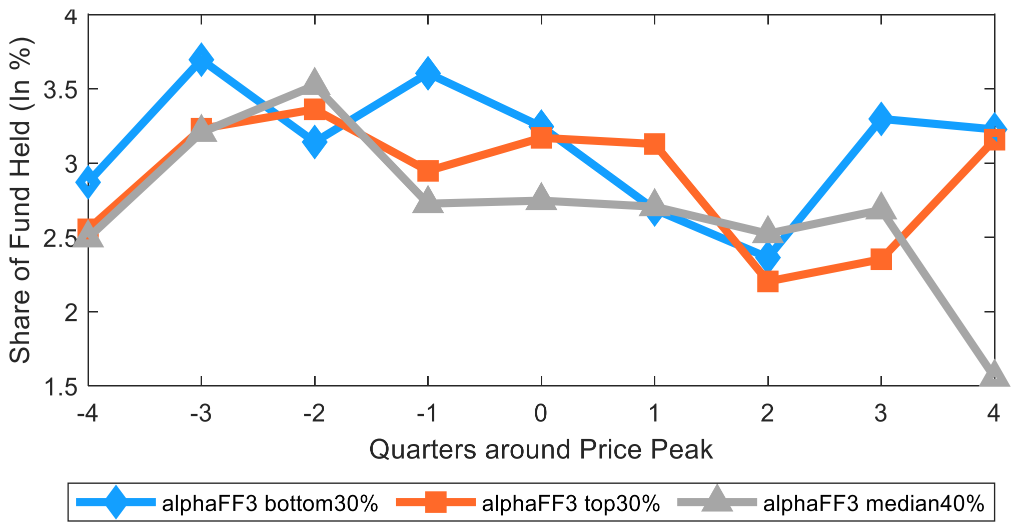
Note: Table 8 reports the "out of sample" performance of two equally weighted portfolios: the first investing in stocks with a top 30% changes in hedge fund holdings, and the second investing in stocks with a bottom 30% changes in hedge fund holdings. In each quarter *t*, we sort stocks into two equally weighted portfolios based on their change in hedge fund holdings (△ HF_SH) in quarter *t*. The portfolios are held for three months before rebalancing. The monthly return is decomposed by quarterly return (Liu and Strong, 2008) and adjusted by market return, i.e., minus the CSI 300 monthly return. The monthly return series for the portfolios is from January 2007 to June 2016.

Table 9. Regression of Hedge Fund Monthly Return and Factors

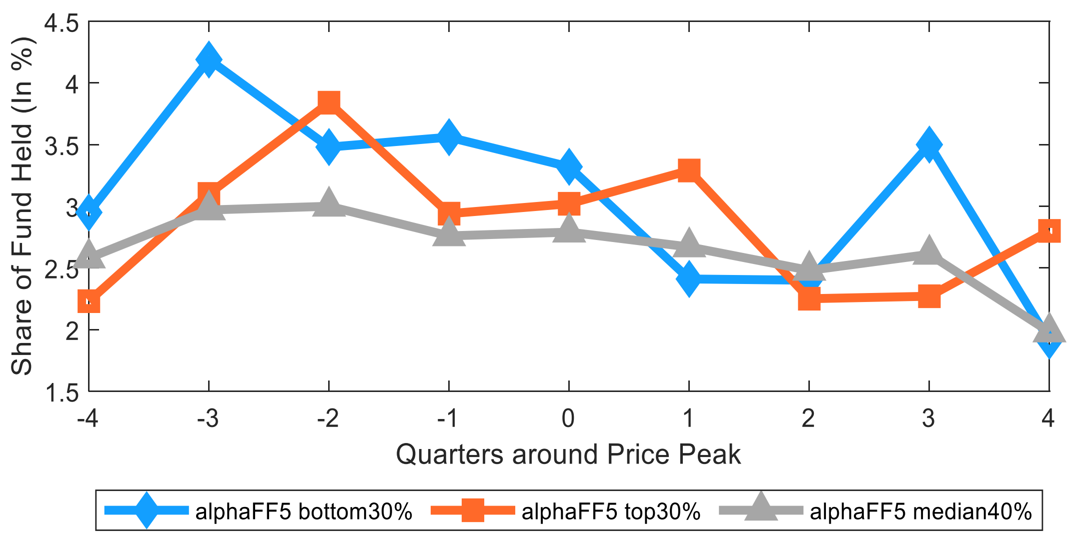
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EW	EW	EW	EW	SW	SW	SW	SW
Rm-Rf_FF3	0.271***	0.285***			0.306***	0.318***		
	(12.37)	(12.79)			(13.91)	(14.07)		
SMB_FF3	0.118***	0.102***			0.138***	0.125***		
	(3.12)	(2.70)			(3.65)	(3.28)		
HML_FF3	-0.081	-0.069			0.000	0.010		
	(-1.29)	(-1.12)			(0.00)	(0.17)		
MOM		0.084**		0.089**		0.070*		0.074**
		(2.33)		(2.46)		(1.91)		(2.07)
Rm-Rf_FF5			0.265***	0.279***			0.296***	0.308***
			(11.08)	(11.61)			(12.49)	(12.82)
SMB_FF5			0.044	0.022			0.055	0.037
			(0.57)	(0.29)			(0.72)	(0.48)
HML_FF5			-0.151**	-0.141*			-0.075	-0.067
			(-2.03)	(-1.94)			(-1.02)	(-0.93)
RMW_FF5			-0.070	-0.074			-0.089	-0.092
			(-0.55)	(-0.59)			(-0.71)	(-0.74)
CMA_FF5			0.123	0.128			0.166	0.171
			(1.02)	(1.09)			(1.39)	(1.45)
alpha	-0.009***	-0.008***	-0.009***	-0.008***	-0.012***	-0.011***	-0.012***	-0.011***
	(-4.32)	(-4.07)	(-4.04)	(-3.77)	(-5.69)	(-5.47)	(-5.45)	(-5.21)
adj. R-squared	0.640	0.655	0.638	0.655	0.685	0.693	0.691	0.701
F	64.544	51.820	38.716	34.877	78.690	61.430	48.915	42.780
N	108	108	108	108	108	108	108	108

Note: Table 9 reports the intercepts of alpha, the slopes of the factors, and *t*-statistics (in parentheses) for the FF3, FF3 + MOM, FF5, and FF5 + MOM estimated on the monthly portfolios of hedge funds. The data cover 24,290 funds from January 2007 to March 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Hedge fund holdings around price peaks of individual stocks: grouped stocks by alpha estimated using the Fama-French three-factor model



Panel B. Hedge fund holdings around price peaks of individual stocks: grouped stocks by alpha estimated using the Fama-French five-factor model



Panel C. Hedge fund holdings around price peaks of individual stocks: grouped stocks by mispricing calculated using the Rhodes-Kropf et al. (2005)

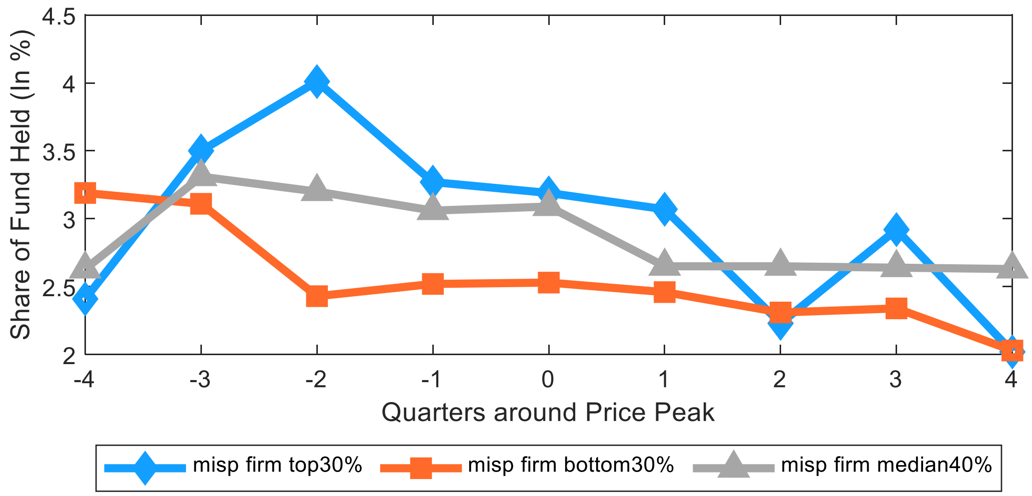


Figure 2 Hedge Fund Holdings Around Price Peaks of Individual Stocks

Note: For each stock, we construct a quarterly total return index from 2013 to 2015 and determine each stock's price peak during that period. Each quarter, we also calculate the proportion of outstanding shares held by hedge funds. For stocks with peaks in 2014 or 2015, we align the time-series of holdings with the event time (value-weighted), in which the price peak is the event-time quarter 0. We then average hedge fund holdings in event time across all stocks in the sample. The figure presents these event-time averages for three samples of stocks, based on the degree of mispricing. In Panel A of Figure 2, we divide stocks into three groups based on the alpha estimated using the Fama-French three-factor model. In Panel B of Figure 2, we divide stocks into three groups based on the alpha estimated using the Fama-French five-factor model. In Panel C of Figure 2, we divide stocks into three groups based on mispricing calculated using Rhodes-Kropf et al. (2005).

Table 10. DID Regression Results

	(1) alpha_FF3<0 HF_SH	(2) alpha_FF3>0 HF_SH	(3) alpha_FF5<0 HF_SH	(4) alpha_FF5>0 HF_SH
$Short_{i,t} * Time_{i,t}$	0.326	-2.562***	0.169	-2.188***
	(0.76)	(-4.65)	(0.41)	(-3.69)
$Short_{i,t}$	-0.126	0.808***	0.188	0.540**
	(-0.56)	(3.44)	(0.87)	(2.50)
$Time_{i,t}$	0.927***	3.247***	0.984***	2.943***
	(3.54)	(6.84)	(3.95)	(5.92)
$Ln(Book/Market)_{t-1}$	-0.728***	-0.100	-0.695***	-0.147
	(-4.33)	(-0.47)	(-4.14)	(-0.68)
$Ln(Market\ Cap)_{t-1}$	0.326*	-0.110	0.186	0.050
	(1.86)	(-0.62)	(1.08)	(0.31)
$Ln(Dividend\ yield)_{t-1}$	5.730	-3.190	-9.484	-1.280
	(0.27)	(-0.12)	(-0.46)	(-0.05)
$Ln(Age)_{t-1}$	0.079	0.407	0.043	0.436
	(0.21)	(1.14)	(0.12)	(1.18)
$Ln(Price)_{t-1}$	0.472**	0.456*	0.402*	0.530**
	(2.13)	(1.87)	(1.86)	(2.11)
constant	-6.779**	0.749	-3.552	-2.996
	(-1.98)	(0.20)	(-1.08)	(-0.84)
adj. R-squared	0.027	0.022	0.022	0.021
N	3070	2752	3273	2548

Note: Table 10 reports the results from DID regression of hedge fund holdings around the short-selling ban lifts. $Short_{i,t}$ is a dummy variable, in which 1 represents stocks that are added to the shorting list, and 0 represents stocks that are not added. $Time_{i,t}$ is a dummy variable, for which 1 indicates that stocks can be shorted during the period, and 0 indicates that stocks cannot be shorted. $Short_{i,t} * Time_{i,t}$ is an interaction term whose coefficient measures the net effect of short-selling policy on hedge fund holdings. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Estimated Hedge Fund Positions in Small and Large Alpha Portfolios

Panel A: Alpha Calculated by FF3

	N	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis	25%	Median	75%
R_{High}	4965	0.000	1.000	0.153	0.249	2.010	6.372	0.001	0.020	0.212
R_{Median}	4965	0.000	1.000	0.089	0.202	2.866	10.937	0.000	0.003	0.043
R_{Low}	4965	0.000	1.000	0.191	0.284	1.610	4.556	0.001	0.028	0.301
R_f	4965	0.000	1.000	0.568	0.355	-0.321	1.681	0.265	0.626	0.917

Panel B: Alpha Calculated by FF5

	N	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis	25%	Median	75%
R_{High}	4965	0.000	1.000	0.114	0.214	2.487	9.000	0.001	0.009	0.122
R_{Median}	4965	0.000	1.000	0.106	0.213	2.469	8.641	0.000	0.004	0.080
R_{Low}	4965	0.000	1.000	0.205	0.290	1.496	4.148	0.001	0.042	0.313
R_f	4965	0.000	1.000	0.576	0.353	-0.354	1.704	0.278	0.640	0.922

Note: Table 11 shows the results of return-based fund-position estimation in various alpha portfolios. First, we construct daily formed alpha portfolios based on the alpha of the stocks at the end of last year. Stocks with an alpha in the top 30th percentile of all alphas for publicly listed Chinese A stocks are classified as high, while stocks with an alpha in the bottom 30th percentile are classified as low. Stocks with an alpha between the 30th to 70th percentiles are classified as medium. We then use annual alpha data to calculate issuance scale -weighted daily returns for each portfolio: R_{High}, R_{Medium}, and R_{Low}. We get rid of funds with zero returns and have 4,965 funds from 2007 to 2016. In Panel A, the alpha is estimated using the FF3. In Panel B, the alpha is estimated using the FF5.

Table 12. Regression of Hedge Fund Holdings on Lagged Significant Alpha Excluding the Financial Crisis Period

	（1）	（2）	（3）	（4）
	HF_SH_t Positive Alpha	HF_SH_t Negative Alpha	HF_SH_t Positive Alpha	HF_SH_t Negative Alpha
alpha $\_FF3_{t-1}$	-0.097	0.378**		
	(-1.32)	(3.27)		
$alpha\_FF5_{t-1}$			-0.052	0.412**
			(-0.89)	(3.15)
$Ln(Book/Market)_{t-1}$	0.043	0.247	-0.004	0.030
	(0.49)	(0.69)	(-0.09)	(0.20)
$Ln(Market\ Cap)_{t-1}$	0.196	0.787	0.169	0.435
	(1.27)	(1.18)	(1.15)	(0.70)
$Ln(Dividend\ yield)_{t-1}$	-0.004	0.181	0.046	0.152
	(-0.07)	(2.03)	(1.02)	(1.86)
$Ln(Age)_{t-1}$	-0.123	-0.559	0.009	-0.715
	(-1.46)	(-1.63)	(0.27)	(-1.94)
$Ln(Price)_{t-1}$	0.262	0.482	0.065	-0.211
	(1.66)	(0.69)	(1.26)	(-0.61)
constant	-0.075	4.616***	0.002	3.440***
	(-0.50)	(6.18)	(0.02)	(4.88)
avg. R-squared	0.549	0.522	0.534	0.472
N	552	993	530	1102

Note: Table 12 shows the results from Fama-MacBeth cross-sectional regressions of hedge fund holdings on one-quarter lagged significant alpha excluding the financial crisis period. In quarter t, $alpha_{t-1}$ is the absolute value of significant intercept from the FF3 (FF5) and is estimated using each stock's daily returns in quarter t-1. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, and share price. All of the variables (except dummy variables) are standardized each quarter based on the full sample. The sample period is from 2007 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Privately Offered Funds in China

In this appendix, we introduce privately offered funds' characteristics, establishment conditions, qualified investors, operation modes and investment restrictions in China. On this basis, we summarize the differences between private equity funds and general hedge funds.

China's privately offered funds are offered through nonpublic sources for specific investors (institutional or retail investors) and are mainly invested in the secondary market. China's first privately offered funds were born in the late 1990s.

Privately offered funds have the following characteristics. First, the threshold for purchase is high, and they are only privately issued to qualified institutions and individuals; not the public, nor are they publicly promoted. Generally, each investment is not less than one million yuan (about 145,380 USD). Second, privately offered fund managers generally charge 20% excess performance compensation every time the net value of the fund reaches a high return. Third, the fund pursues absolute positive returns. Because fixed management fees are small and the fund depends on excess performance fees, the interests of private equity fund managers and investors are relatively consistent. Therefore, privately offered funds need to pursue absolute positive returns and strictly control downside risks. Fourth, the proportion of stock investment is flexible, from 0% to 100%, which enables partial or complete avoidance of the systemic risk of the market. Fifth, the funds have flexible operations. Compared with mutual funds, the size of privately offered funds, usually tens of millions to hundreds of millions, is small, and the requirements for industry concentration and equity concentration are lower. Sixth, they have limited liquidity. Privately offered funds generally have a 6 to 12-month closure or share lock-in period. Seventh, there is less information disclosure. Funds usually publish their net value weekly, biweekly, or monthly. In addition, funds up to 50 million yuan in size must disclose their information monthly and all products each quarter.

Establishment of a privately offered fund requires adoption of a filing system. After fundraising is complete, the fund manager files a record with the fund industry association. Private fund managers are required to have registered capital of no less than 100 million yuan and must have paid-in monetary capital.

Investors in privately offered funds are restricted to qualified investors, that is, a unit or individual with the corresponding risk identification ability and risk bearing ability to invest in a single privately offered fund with an amount of not less than 1 million yuan and meets the following relevant standards: (1) a unit whose net assets are not less than 10 million yuan; (2) an individual whose financial assets are not less than 3 million yuan or whose annual average income in the recent three years is not less than 500,000 yuan. The total number of investors in a fund cannot exceed 200.

There are three operation modes of privately offered funds. The most popular mode is entrusted management, such as sunshine privately offered funds. These funds let investors hand over their money to a trust company that signs a management agreement with a privately offered fund manager. The manager buys a certain proportion of the funds, such as 20%, to achieve mutual benefits and avoid a transfer of benefits caused by inconsistent benefits. This kind of privately offered fund relies on the trust laws, which are clearly defined, and a standard trust plan. According to the 2017 China's Privately Offered Funds Industry Development Report published by AMAC, the number and assets of privately offered funds with entrusted management mode were 99.6% and 98.3%, respectively, by 2016.

The second operation mode is self-management. These funds manage themselves by building internal management teams. In general, several people contribute to set up a company as a limited partnership, in which one or more parties give money and other parties gives expertise. The distribution proportion is stipulated in the articles of the contract and may not be in accordance with the proportion of investment. By 2016, the number and assets of privately offered funds with self-management were just 0.4% and 1.7%, respectively.

The third operation mode is the consultant mode. These privately offered fund managers provide investment advisory services for asset management products managed by other financial institutions (i.e., trust companies, securities companies, futures companies, etc.). As investment advisers or research consultants, fund managers must meet the requirements of the China Securities Regulatory Commission, the AMAC, and corresponding regulatory authorities for investment advisers. In addition, asset management products (i.e., trust plans, securities capital management plans, futures capital management plans, etc.) can be sold directly by financial institutions or entrusted to other eligible financial institutions for sale.

The securities that privately offered funds are allowed to invest in include publicly issued stocks, bonds, fund shares, and other securities and derivatives specified by the security regulatory authority under the State Council. The main investments are stocks and bonds on exchanges and interbank markets. However, hedge funds can usually invest in a wider range of asset classes, including but not limited to stocks, bonds, derivatives, currencies, real estate, etc.

In terms of investment strategies, Chinese privately offered funds suffer from greater restrictions than hedge funds. Chinese privately offered funds are not allowed to short selling, and their leverage multiples and underlying asset types are also strictly restricted. In the regulations on the operation and management of privately offered funds, the leverage ratio must not be more than 1 times the funds that are invested in stocks. Moreover, total assets in structured funds cannot exceed 140% of net assets, and total assets in unstructured collective funds cannot exceed 200% of net assets. We present a clearer comparison of privately offered funds and hedge funds in Table A.1.

In summary, privately offered funds share many of the same characteristics as hedge funds in the U.S. and other developed markets (Eling and Faust, 2010). They have a similar fee structure. Privately offered funds issue products known as Private Asset Management Plans and sell them to a limited number of investors who satisfy income and minimum investment thresholds. The lock-in period for this investment is usually long-term compared with that of mutual funds. There are no specific restrictions on the strategies used by the issued products. The management team of a privately offered fund faces fewer restrictions and agency problems, which is like hedge funds.

Table A.1. Comparison of Privately Offered Funds and Hedge Funds

	Privately Offered Funds	Hedge Funds
Country	China	U.S.
Register	Issuers must register and put their funds on record within 20 working days after fundraising completion.	Issuers must register if their AUM exceed $1 million and investors exceed 500. Hedge fund issuance does not require registration.
Fundraising Type	Nonpublic	Nonpublic
Qualified Investors	1) Personal net assets exceed ¥ 3,000,000. 2) Personal annual income exceeded ¥500,000 in the last 3 years. 3) Institutional investors' total assets exceed ¥10,000,000	1) Personal net assets exceed $1,000,000. 2) Personal annual income is stable and has exceeded $200,000 in the last 2 years. 3) Institutional investors' total assets exceed $5,000,000.
Maximum Number of Investors	200	500
Minimum Investment Amount	¥1,000,000	$250,000~$1,000,000
Lock-in Period	3~12 months	12~24 months
Fees	1) Subscription fees are 1-3% of investment amount. 2) Redemption fees are 3-5% of the redemption amount. 3) Management fees are 2% of investment amount per year. 4) Performance fees are 20% of funds' NAV increment.	1) Management fees are 2% of investment amount per year. 2) Performance fees are 20% of funds' NAV increment.
Investment Strategies	Use of short selling, derivatives, leverage ratio are relatively limited.	Funds can execute any investment strategy and adapt them accordingly.