The Role of Hedge Funds in the Asset Pricing：Evidence from China

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This is an Accepted Manuscript of an article published by Taylor & Francis in The European Journal of Finance on 20th May 2021, available online: http://www.tandfonline.com/10.1080/1351847X.2021.1929373

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Abstract

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

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

1. Introduction

Whether arbitrageurs are a stabilizing force that keeps stock prices close to fundamental values is controversial. Many studies focus on hedge funds to examine 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. As representative arbitrageurs, hedge funds are expected to engage in securities trading based on price deviations from fundamental values (Cao, Chen, Goetzmann, and Liang 2018).

However, whether hedge funds' trading corrects asset pricing errors remains controversial. 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 level (Cao, Chen, Goetzmann, and Liang 2018) and the market levels (Kokkonen and Suominen 2015). In contrast, other studies find that rational speculators may also ride a trend and drive a bubble. Speculators may initiate or contribute to price movements, expecting positive-feedback traders to 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 arbitrageurs engage in a coordinated selling effort. 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 on whether hedge funds drive stock prices to converge their fundamental values by investigating hedge fund holdings and trades in China. Specifically, we examine whether hedge funds hold more undervalued or overvalued stocks. Furthermore, we clarify the drivers of hedge fund performance to obtain a better understanding of their holdings and trades. We also examine the effect of market friction alleviation on hedge fund holdings and trades.

The Chinese hedge fund dataset used in this paper has its advantages. Market conditions in China make Chinese hedge funds better representative arbitrageurs of securities trading based on price deviations from fundamental values than the U.S. hedge funds studied in Cao, Chen, Goetzmann, and Liang (2018), because the Chinese stock market has a limited number of derivative instruments which limits the means of hedging. As an emerging market, the Chinese stock market is gradually perfecting hedging instruments. For example, 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. Unlike in developed stock markets which have numerous futures for indices and individual stocks, excluding index constituents has relatively little impact on sophisticated investors' trading behavior in the Chinese stock market. In addition, since 2010, the Chinese stock market has progressively eased its restrictions on short selling, which allows us to compare hedge fund behavior before and after the alleviation of that market friction. Moreover, the conflicting empirical results in the literature on hedge fund behavior may be because hedge funds hold and trade stocks for both value arbitrage and hedging, and because they may be forced to hold overpriced stocks due to friction in the stock market, such as short-selling restrictions (Miller 1977; Scheinkman and Xiong 2003; Chen, Da, and Huang 2019). Disentangling arbitrage effects from hedge effects in empirical studies. A study of Chinese hedge funds would provide new evidence for the behavior of arbitrageur and contribute to the debate on whether hedge funds drive stocks prices to converge on their fundamental values.

In this paper, focusing on hedge funds in China, we investigate the role of sophisticated investors in the security price formation process. No funds are explicitly named as "hedge funds" in China. Therefore, following Huang, Yao, and Zhu (2018), we define privately offered funds in China as hedge funds for the purposes of this study.[2] Except for the lack of instruments to hedge, the privately offered funds in China and hedge funds in the U.S. share similar characteristics (e.g. establishment conditions, qualified investors, operation modes, management and performance fees). For convenience, we refer to these privately offered funds as "hedge funds" in the rest of this paper. The hedge fund industry in China has grown considerably over the past decade. According to 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 Chinese stock market, and the assets under management (AUM) 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 these hedge funds, such as the number of hedge funds, the total net AUM (TNA), and the TNA of hedge funds that invest in the stock market. We can see that hedge funds in China have grown rapidly since 2014. In May 2014, the Chinese State Council issued official documents to foster the hedge fund. In response, the AMAC promptly implemented a series of policies to register and manage hedge funds. Consequently, we observe a boom in hedge funds, with some prominent mutual fund managers such as Lu Guoqiu and Wang Xiaoming moving to the hedge fund industry. Since 2015, the AMAC has reported in detail the number and AUM of hedge funds that only invest in the stock market.

Panel B suggests that since 2015, hedge funds have accounted for an increasing proportion of the Chinese stock market.

All hedge funds in China must be registered in the AMAC. Therefore, we obtain hedge fund data from 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 on the Chinese stock market. We match hedge funds with the top 10 outstanding shareholders reported by the listed companies each quarter. Because the Chinese government has only allowed the trading of futures contracts in the CSI 300 Index since 2010, we exclude the CSI 300 stocks from the sample to ensure that our sample includes only stocks without hedging instruments. Finally, 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 as measured using relative and absolute valuation models. We find strong evidence that hedge funds tend to hold overvalued stocks with low 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 data on top 10 outstanding shareholders. The results of this estimation suggest that hedge funds tend to hold overvalued stocks at the fund level. We find that hedge fund holdings nurture mispricing in the emerging financial market. Moreover, we find that hedge fund holdings and trades impede stocks from converging the security market line in the following quarter.

Next, we investigate whether hedge funds profit from holding overvalued stocks. We separately track the price movements for stocks with previous high versus low levels of hedge fund holdings. The results show that stocks with high hedge fund holdings generate an abnormal return of 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, implying that trend-chasing behavior is the key reason hedge funds prefer to hold overvalued stocks.

Third, we investigate changes in hedge fund holdings around market bubbles and the easing of restrictions on short-selling, respectively. We find that hedge funds reduce their holdings before prices collapse, but no significant changes are observed before or after a short-selling ban lift, suggesting that hedge funds deliberately hold overvalued stocks. Their decision to ride the bubble is not driven by market friction, which is consistent with the results of 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 stock prices to converge on their fundamental values. Using a unique Chinese hedge fund dataset in which the holdings mainly come from arbitrage and not hedging, our research provides a better understanding of the behavior of arbitrageurs and offers new evidence for the role of hedge funds in the security price formation process. Furthermore, the lifting of the ban on short-selling in China allows us to study the behavior of hedge funds before and after the alleviation of that market friction, 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 clarifies the information content and potential investment value of hedge fund holdings in emerging markets.

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

2. Related Literature and Hypothesis 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. As 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 researchers challenge this view and find 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 research also provides evidence that institutions have a strong tendency to buy overvalued stocks (Edelen, Ince, and

Kadlec 2016) and that the increase in the number of sophisticated investors does not necessarily lead to greater market efficiency (Stein 2009). Brunnermeier and Nagel (2004) and Griffin et al. (2011) show that hedge funds rode with the bubble and destabilized the market during the tech bubble period.

These conflicting results may be attributable to the ambiguous rationale for hedge fund holdings and trades (Cao, Chen, Goetzmann, and Liang 2018). In this research, we study hedge funds in China, where their stock holdings are mainly for arbitrage, with limited or no hedging effect.

Two potential factors may explain why it is more difficult to pick undervalued stocks in China than in developed markets. First, the Chinese stock market is highly speculative, and stock prices have weak links to their fundamentals and the macroeconomy. In addition, both the market and regulators are immature and imperfect, with the well-known Chinese economist Wu Jinglian dubbing the market a "casino" in 2001.[3] The 1990s, 2000s, and 2010s saw major incidents in which spectacular price rallies were followed by severe market crashes, trends that cannot be easily explained by market fundamentals. As reported by Bloomberg in April 2015, during the price peak in March 2000, the average price–earnings ratio of Chinese tech stocks was 41% higher than that of their U.S. counterparts. Compared with the much developed Hong Kong market, 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 creates a price risk that deters rational arbitrageurs from aggressively betting against them (De Long et al. 1990b). In the Shanghai Stock Exchange, as of 2016, retail investors held 25.18% of the market value, while investment funds held only 2.93%. Of these retail investors, 74.7% do not have a college education, which means that it might be hard for them to calculate the fundamental value[4]. In contrast, in the U.S., institutional investors own 80% of the market value, much higher than what retail investors own.[5]

Therefore, in the Chinese stock market, prices may deviate from fundamental values for long periods, 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 the institutional ownership, the lower the idiosyncratic volatility of stocks.

In summary, retail investors in China find it harder to trade overvalued stocks than undervalued stocks because short selling is either not allowed or is costly when allowed in a limited capacity. In contrast, hedge funds can buy overvalued stocks with low idiosyncratic risk and use their skills to ride the trend. They can quickly pull capital out of the market before a crash while retail investors continue to buy and hold them. Thus, we posit the following:

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 the price trend of stocks, the intention is to drive stock prices further away from their fundamental values. Accordingly, we propose the following hypothesis:

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

If the market is efficient, mispricing will be quickly corrected, and abnormal stock performance will not persist. However, when the market is inefficient and mispricing persists, holding stocks with abnormal past performance might be profitable (Y. Chen, Da, and Huang 2019). In the case of Chinese hedge funds, we propose the following hypothesis:

Hypothesis 3: Hedge fund trades predict stock returns.

We now turn to investigate the drivers of hedge fund performance. In the literature, hedge fund performance is usually measured using 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 of all stock characteristics, hedge funds exhibit a strong preference for stocks with high momentum. Huang, Yao, and Zhu (2018) show that Chinese hedge funds outperform the stock market despite regulatory disruptions and that their performance is significantly and positively associated with the momentum factor.

With a large number of young and inexperienced retail investors, the Chinese stock market is generally regarded as speculative. The demand shocks of retail investors can be easily correlated with the rise of strong and persistent mispricing over time (Baker and Wurgler 2006; Han and Li 2017), providing hedge funds with the opportunity to profit from trend-chasing strategies. Hedge funds that prefer to hold overpriced stocks will profit by riding trends. Thus, hedge fund returns should be positively associated with the momentum factor. Therefore, it would be interesting to test the following hypothesis:

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

Finally, we analyze whether hedge funds intentionally hold overvalued stocks. Studies suggest that market friction, particularly short-selling restrictions, forces sophisticated traders to hold overvalued stocks. If short selling is restricted, stock prices, which mainly reflect investors' heterogeneous expectations, would be higher than their real value (Miller 1977), and rather than holding the shares forever, investors are willing to pay a higher price for the right to resell them to other agents who have more optimistic beliefs (Harrison and Kreps 1978; Scheinkman and Xiong 2003).

Some studies suggest that fund managers have the skills to accurately identify mispriced stocks, which leads to superior fund performance (Dong and Doukas 2020; R. Huang, Asteriou, and Pouliot 2020; Barras, Scaillet, and Wermers 2019). Moreover, hedge funds do not ride bubbles because they fail to notice that stocks are overvalued; instead, hedge funds deliberately ride bubbles (Brunnermeier and Nagel 2004; Griffin et al. 2011) and manipulate stock prices (Ben-David et al. 2013) to earn profits. In summary, if hedge funds deliberately hold overpriced stocks, we would expect the following:

Hypothesis 5: Hedge fund holdings of overvalued stocks decline before a price peak but not after the short-selling ban 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 on the 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 non-hedge 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 database. Our sample comprises all (2,591) publicly listed stocks on the Shanghai and Shenzhen stock exchanges except for the CSI 300[7] stocks as of March 2016. Excluding the SCI 300 stocks ensures that our sample includes only stocks that are less likely to be used as hedging instruments. Our stock dataset includes, but is not limited to, daily data on stock returns, risk-free return rate, trading status, quarterly data on 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, only stocks whose trades have not been suspended in the previous quarter are selected. Our merged panel data contain 19,681 firm-quarter observations for the period from January 2007 to March 2016.[9]

Based on this comprehensive dataset, Panel A of Table 1 reports the stock characteristics (i.e., book-to-market ratio, market capitalization, dividend yield, firm age, and price) at the firm-quarter level for all stocks held by the 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.

[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 are younger (176.83 months vs. 179.64 months) and have higher prices (15.31 CNY vs. 14.38 CNY) than the full sample of stocks in the merged dataset. In contrast, stocks that belong to the top decile of non-hedge fund holdings have a lower book-to-market ratio (0.53 vs. 0.80) and 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: relative mispricing, absolute mispricing, and anomaly mispricing. 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. Anomaly mispricing is determined by the cross-sectional return anomalies shown in financial studies (Stambaugh, Yu, and Yuan 2015). 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. Following Cao, Chen, Goetzmann, and Liang (2018), we use the intercept of the Fama–French three-factor (FF3) and five-factor (FF5) models to measure relative mispricing with the daily stock returns for each quarter. Furthermore, we construct factors in the Chinese stock market (Guo et al. 2017) to estimate the FF3 model:

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

Similarly, we estimate 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 the profitability, and CMA_t represents the investment factors. α_i is the measure of relative mispricing for stock i. The security market line is calculated using beta and factors in the right-hand sides and displays the expected returns of a stock. A stock whose expected return versus its systematic risk (beta) is above the security market line is considered undervalued. Conversely, a stock whose beta is below the security market line is deemed overvalued because the investor would accept a lower return for the amount of systematic risk associated with the stock. The daily data are from the CSMAR database and calculated by weighting all A-share market shares by their 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.

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

in which $\ln(\mathrm{M})_{ijt}$ is the quarterly market value of stock i in quarter t and sector j, $ln(B)_{it}$ is the 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:

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

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

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

Finally, we measure the degree of mispricing based on 10 cross-sectional return anomalies

(Stambaugh, Yu, and Yuan 2015). Because companies in China do not disclose data on their operating assets, we exclude the net operating assets anomaly (Hirshleifer et al. 2004). The 10 return anomalies are 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 ratio (Titman, Wei, and Xie 2004).

On the basis of these 10 return anomalies, we first score all stocks in our sample for each quarter according to their future returns predicted by each of these anomalies. This score ranges from 0 to 100 and increases with overpricing. Specifically, if high momentum, gross profitability premium, or return on assets are followed by high future returns, then the degree of overpricing is low and thus the stock is assigned a low score. Similarly, if high O-Score or high values of the five other anomalies are followed by low future returns, then the degree of overpricing is high and the stock is thus assigned a high score. Each stock's aggregate score is the equal-weighted average of the ranking percentile computed for the previous quarter.

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, and 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:

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

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 equal to 1 if stock i's alpha is significant and positive in quarter $t-1$, and 0 otherwise. $D(NegativeAlpha)_{i,t-1}$ is a dummy variable equal to 1 if stock i's alpha is significant and negative in quarter $t-1$, and 0 otherwise. $X_{i,t-1}$is a vector of control variables for stock characteristics, namely one-quarter lagged values of the 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 in 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), which ensures 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 hedge fund holdings to increase with significantly overvalued stocks and β_{2t} to be significant and positive.

[Insert Table 2 Here]

Table 2 reports the relationship between fund holdings and two dummy variables lagged by one quarter, 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 columns (1) and (3), but the average coefficient on $D(PostiveAlpha)_{i,t-1}$ is non-significant. These results suggest that stocks with significantly negative alpha in the previous quarter are associated with significantly higher hedge fund holdings in the current quarter, which supports Hypothesis 1. However, the relationship between non-hedge fund holdings and the lagged dummy variables of significant alpha estimated with the FF5 in column (4) is not significant.

Regarding 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)). Furthermore, 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 examine the relationship between hedge fund holdings and the degree of mispricing for stocks with significant alpha:

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

in which $|Alpha_{i,t-1}|$ is the absolute value of the significant intercept of the FF3 or FF5 measuring the deviation from the security market line for stock *i* at the end of quarter $t-1$, which is estimated using each stock's daily returns in quarter $t-1$. Thus, Hypothesis 1 expects hedge fund holdings to increase with an increase in $|Alpha_{i,t-1}|$ when stocks are overpriced; specifically, b_t is significant and 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 $(i.e.\ \ \beta = 0.346\ ,t - statistic\ = 3.43\ in\ Panel\ A; \beta = 0.477\ ,t - statistic\ = 3.09\ in\ Panel\ B)$, indicating that stocks with overvalued alpha in the previous quarter are associated with significantly higher hedge fund holdings in the current quarter, which again supports Hypothesis 1. Our results are consistent with those of Abreu and Brunnermeier (2003), who report that rational investors invest in overpriced securities.

However, our results are inconsistent with the evidence presented by Cao, Chen, Goetzmann, and Liang (2018), likely for the following three reasons. First, the Chinese stock market is dominated by retail traders. Stock prices may be affected by noise trading and may deviate from fundamental values for long periods. Thus, hedge funds incur high arbitrage costs if they wait for the price increase of undervalued stocks. Second, hedge fund managers can easily predict the irrational trading behaviors of retail investors, such as herding and trend-chasing. Therefore, hedge funds find it profitable to time the market, deliberately hold overpriced stocks, and ride bubbles. We formally test this hypothesis in Section 4.4. Finally, Chinese hedge funds have a short lock-up period, meaning that they can easily abandon long-term investment strategies.

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 the fundamental values of stocks. We again test whether hedge fund stock holdings are cross-sectionally related to the magnitude of mispricing. We run the following Fama–MacBeth regression:

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

where $misp\_firm_{i,t-1}$ is the measure of the 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 if Hypothesis 1 is supported.

[Insert Table 4 Here]

Table 4 shows the results from the 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 the stocks are overvalued in the previous quarter, the higher the hedge fund holdings of these stocks in the current quarter. However, no significant relationship is observed 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 consistent 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

Finally, we use the Stambaugh, Yu, and Yuan (2015) mispricing measure to further test Hypothesis 1. With the aforementioned 10 return anomalies, we compute the equal-weighted average of the ranking percentile for each stock in each quarter. We again examine whether hedge fund holdings are positively related to the degree of mispricing. We run the following Fama–MacBeth regression:

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

where $misp\_score_{i,t-1}$ 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 if Hypothesis 1 is supported.

[Insert Table 5 Here]

Table 5 shows the results from the Fama-MacBeth cross-sectional regressions of fund holdings on the one-quarter lagged overvalued score[10]. In column (1), the more the stocks are overvalued in the previous quarter, the higher the hedge fund holdings in the present quarter ($\beta = 0.041, t - statistic = 3.61$). Column (2) shows a significant and negative relationship between non-hedge fund holdings and the mispricing score ($\beta = -0.057, t - statistic = -2.89$). Thus, we find that hedge fund holdings increase with the degree of overvaluation, which is consistent 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. Accordingly, hedge funds should not bear the cost of arbitrage. We now examine the relationship between hedge fund holdings and value arbitrage costs measured by idiosyncratic volatility.

We run the following Fama–MacBeth regression:

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

where $SH_{i,t}$ is the hedge fund shareholding ratio (or non-hedge fund shareholding ratio) of stock i at the end of quarter t, $IdioV_{i,t}$ is idiosyncratic volatility for stock i and measured by the standard deviation of the 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 columns (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 and 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 of the FF3 or FF5 model estimated using each stock's daily returns in the last quarter.

In summary, hedge fund holdings are significantly and negatively related to lagged idiosyncratic volatility, which is 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). However, these results are inconsistent with those presented by Cao, Chen, Goetzmann, and Liang (2018), because the Chinese stock market is dominated by noise traders whose beliefs create risk for asset pricing (De Long et al. 1990b) and prices may deviate from fundamental values for long periods, which discourages rational hedge funds from bearing the costs 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 Hypothesis 2. Following Cao, Chen, Goetzmann, and Liang (2018), we use the following logit regressions to determine whether hedge fund holdings and trades are associated with the dissipation of negative alpha and positive alpha, respectively.

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

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

where $D(Negative\ \ Alpha\ \ dissipation)_t$ ($D(Positive\ \ Alpha\ \ dissipation)_t$) is a dummy variable equal to 1 if the stock's alpha is significant and negative (positive) in quarter $t-1$ but is no longer significant in quarter t, and 0 otherwise. alpha_t is the intercept of the FF3 or FF5 model and is estimated using each stock's daily returns in quarter $t-1$. $\Delta SH_{i,t-1}$ represents 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 the logit regression results with standard errors clustered across stocks. The results in Panel A indicate that hedge fund trades in a quarter are significantly and negatively related to the likelihood that negative alpha will dissipate in the next quarter ($\beta = -0.067$, $Z-score = -2.02$). Non-hedge fund holdings in a quarter are also significantly and negatively related to the likelihood that negative alpha will dissipate in the next quarter ($\beta = -0.115, Z-score = -2.58$).

Panel B of Table 7 shows that both hedge fund holdings and trades in a quarter are significantly and negatively related to the likelihood that positive alpha will dissipate in the next quarter. In particular, the coefficient on hedge fund holdings is -0.163 ($Z-score = -2.31$), and the coefficient on hedge fund trades is $-0.121 (Z-score = -1.72)$ in column (2), suggesting that their holdings and trades 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 will dissipate 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 that of Brunnermeier and Nagel (2004), who find that rational arbitrageurs do not exert a correcting force on stock prices. Non-hedge fund holdings also exacerbate mispricing, and the effect is more obvious on overpriced stocks; this result is consistent with that of 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 whether hedge fund trades exploit market inefficiency by examining Hypothesis 3: hedge fund trades predict future stock returns. 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 the top 30% changes in holdings to build a high hedge fund holding portfolio and use stocks with the bottom 30% changes in holdings to build a low hedge fund holding 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, adjusted for market return (i.e., minus monthly returns for CSI 300 stocks).

[Insert Table 8 Here]

Table 8 reports the portfolios' performance based on hedge fund trades. Portfolios with larger hedge fund holdings outperform their counterparts with smaller hedge fund holdings. For example, the high hedge fund holding portfolio has an average return of 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. Even after adjusting for the FF3 (FF5) factors, the average return for the high hedge fund holding portfolio is higher than that for the low hedge fund holding portfolio (FF3 adjustment: 0.36% vs. −0.10%; FF5 adjustment: 0.09% vs. −0.27%). 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 preferred by hedge funds have more attractive risk–return trade-offs.

Therefore, the results support Hypothesis 3 that hedge fund trades predict stock returns. Specifically, stocks with heavy hedge fund trades tend to have large abnormal returns. This finding is also consistent with the negative relationship between idiosyncratic volatility and subsequent stock returns (Hou and Loh 2016), and in testing Hypothesis 1, we find that hedge fund holdings are significantly and negatively related to lagged idiosyncratic volatility. Therefore, our finding implies that hedge funds buy overvalued stocks with low idiosyncratic volatility not only for lower risk of loss 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. Next, we identify the drivers of hedge fund returns (Hypothesis 4).

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

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

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

where $R_{HF,t}$ 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, that is, buying stocks that were past winners and selling past losers (Carhart 1997). The other variables are the same as in Models (1) and (2).

[Insert Table 9 Here]

Table 9 reports the regression results. We find that both the EW and SW portfolios load significantly and positively on 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 performs well in explaining fund returns, with R^2 values of 0.655 in the EW portfolio and 0.675 in the SW portfolio. These results support Hypothesis 4 and show that both the EW and SW portfolios load significantly and positively 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 stocks with high momentum than any other characteristic.

Overall, our results show that hedge fund returns mainly come from MOM and market factors and that trend-chasing behavior may explain 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, to test Hypothesis 5, we now examine whether hedge funds do so deliberately or whether they simply fail to eliminate bubbles caused by frictions such as short-selling restrictions.

4.4.1 Hedge Fund Holdings Around Stock Price Peaks

First, 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 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 the event study method, we align these quarterly series of hedge fund holdings with the event time, with event-time quarter 0 being 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 shows the results. For highly overvalued stocks (i.e., stocks with the bottom 30% alpha as estimated using the FF5 (Panel A) or FF3 (Panel B) models and stocks with the top 30% mispricing as calculated by Rhodes-Kropf et al. (2005; Panel C)), hedge funds owned a greater proportion of the outstanding equity before the (quarterly) price peak than after.

[Insert Figure 2 Here]

As shown in Panel A of Figure 2, hedge funds hold a larger share, 3.6%, one quarter before a price peak, which decreases to 3.25% at the end of the peak-quarter and further decreases in the subsequent quarters. Consistent with Brunnermeier and Nagel (2004), hedge funds appear to be more successful in timing their investments in overvalued stocks than in undervalued and other stocks. These stock-by-stock results suggest that hedge funds are successful in exiting before prices collapse, which supports Hypothesis 5. Hedge fund managers stop increasing the share of overvalued stocks in their portfolios when stock prices near their peak, leaving other investors to bear most of the losses from a price collapse.

4.4.2 Hedge Fund Holdings Around 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 of over- and undervalued stocks before and after a short-selling ban lift with those of a control group around the same ban lift.

Since 2010, restrictions on short selling in the Chinese stock market have been progressively lifted. Specifically, 90 stocks could be sold short from February 12, 2010, onward, and another 190 stocks from November 25, 2011, onward. The five major ban lifts occurred on February 12, 2010; November 25, 2011; January 25, 2013; September 6, 2013; and September 12, 2014. As of

March 2016, 982 Chinese A-share stocks could be shorted. In our study, each of the short-selling ban lifts can be considered a treatment, and the differences in changes in hedge fund holdings of stocks that can and cannot be shorted are the outcomes. The experimental groups are stocks that can be shorted. We test the effect of market friction, that is, short-selling policy, by comparing the changes in hedge fund holdings before and after each ban lift. We estimate the following DID model:

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

where $Short_{i,t}$ is a dummy variable that equals 1 and 0 if stock i is present in or absent from the shorting list, respectively. $Time_{i,t}$ is a dummy variable of time that equals 1 and 0 if the stocks can and cannot be shorted during this period, respectively. $\text{Short}_{i,t} * \text{Time}_{i,t}$ is an interaction term whose coefficient (i.e., β_3) measures the net effect of the 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 due to short-selling restrictions. If hedge funds are forced to hold overvalued stocks, hedge fund holdings in the negative alpha (overvalued stocks) subsample should decrease after the short-selling restrictions are relaxed, and β_3 should be significantly negative. Conversely, hedge fund holdings in the positive alpha (undervalued stocks) subsample should increase after the short-selling restrictions are relaxed, and β_3 should be significantly positive.

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

[Insert Table 10 Here]

Table 10 summarizes the DID analysis with alpha estimated using the FF3 and FF5 models. In the negative alpha subsample, the coefficient on $\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$ is not significant, and no significant change is observed in hedge fund holdings before or after a short-selling ban lift for the alpha estimated using the 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. Furthermore, 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) $(\beta = -2.188, t - statistic = -3.69)$, meaning 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 Abreu and Brunnermeier (2003).

5. 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 and cross-sectional analysis, based on different valuation models, shows that hedge fund holdings of stocks (but not non-hedge fund holdings) are positively related to the degree of stock overpricing. In addition, hedge fund holdings are significantly and negatively related to idiosyncratic volatility. We further find that stocks with high hedge fund holdings generate an abnormal return of 1.78% per month, resulting in a return spread of approximately 4.8% per year compared with low hedge fund holdings.

Furthermore, hedge fund holdings and trades impede the dissipation of stock mispricing, and hedge fund performance is mainly driven by trend-chasing. These results suggest that the trend-chasing behavior of hedge funds in China may explain why hedge funds prefer to hold overvalued stocks. Finally, we examine hedge fund holdings around stock price peaks and short-selling ban lifts. Hedge funds reduce their holdings before prices collapse, but no significant changes are observed before or after short-selling ban lifts, suggesting that hedge funds intentionally hold overvalued stocks.

Contrary to the findings that hedge funds bring prices closer to fundamental values (Cao, Liang, et al. 2018; Cao, Chen, Goetzmann, and Liang 2018; Y. Chen, Da, and Huang 2019), we find that hedge funds play a different role in the asset pricing formation process in China. First, stock prices may deviate from fundamental values for long periods because the Chinese stock market is dominated by noise traders and trading lacks a strong link to stock fundamentals. Second, compared with the U.S. stock market, different regulatory frameworks (see Appendix A), shorter lock-up periods, a limited leverage ratio, and the limited availability of derivatives in the Chinese market prevent Chinese hedge funds from implementing long-term investment strategies that long undervalued stocks. Third, fund managers have the skills to identify mispriced stocks (Dong and Doukas 2020) and profit from riding bubbles (Abreu and Brunnermeier 2003). Our results directly challenge the view that sophisticated investors consistently move against mispricing. This study enriches research on the role of sophisticated investors in asset pricing and provides a new perspective on the information content and potential investment value of hedge fund holdings in emerging markets.

Notes

1. The underlying index, the CSI 300 Index, is a stock index compiled by China Securities Index Co., Ltd., and includes the 300 largest A-share stocks listed on the Shanghai Stock Exchange (179 stocks) and the Shenzhen Stock Exchange (121 stocks).
2. In Appendix A, we discuss the privately offered funds in China (Chinese hedge funds), and their characteristics, such as establishment conditions, qualified investors, operation modes, and investment restrictions. The following website also provides an overview of the regulatory framework of Chinese hedge funds: *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 Quote from the speech carried by CCTV in 2001: *http://www.cctv.com/financial/fengyun/sanji/20010114.html.*
4. Data from the 2017 annual report of the Shanghai Stock Exchange.
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 shareholders' 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 investing in small holdings of various undervalued stocks. We use an optimization method to investigate hedge fund holdings at the whole fund level in Appendix B.1, especially for stocks that are not included in the data on the top 10 outstanding shareholders.
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 the anonymous reviewer who recommended excluding data from the financial crisis period as a robustness test. In Appendix B.2, we exclude data from the financial crisis period (2007–2008) and rerun the regression on hedge fund holdings and alpha. The results are consistent with our main results.
10. We thank the anonymous reviewer for who recommended using the Stambaugh, Yu, and Yuan (2015) mispricing measure.

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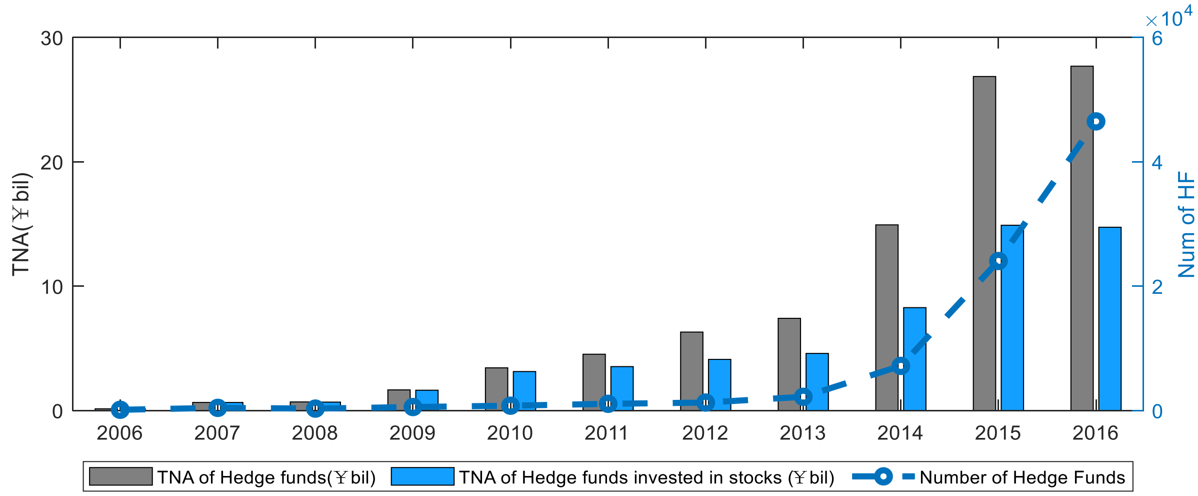
Panel A: The Development of All Hedge Funds



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

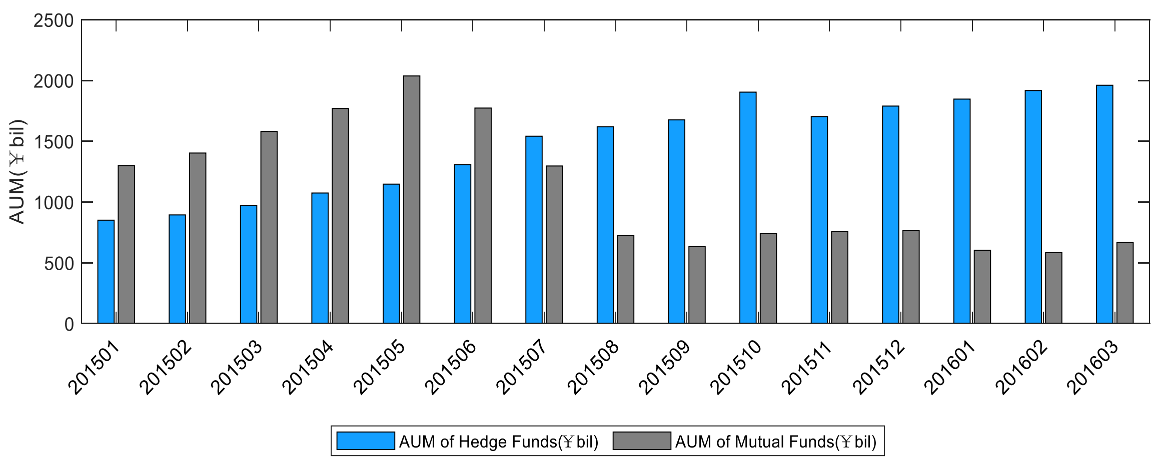


Figure 1. The Development of Hedge Funds in China

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)	(2)
	HF_SH_t	$Non\_HF\_SH_t$
$Misp\_Score_{t-1}$	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 Δ 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

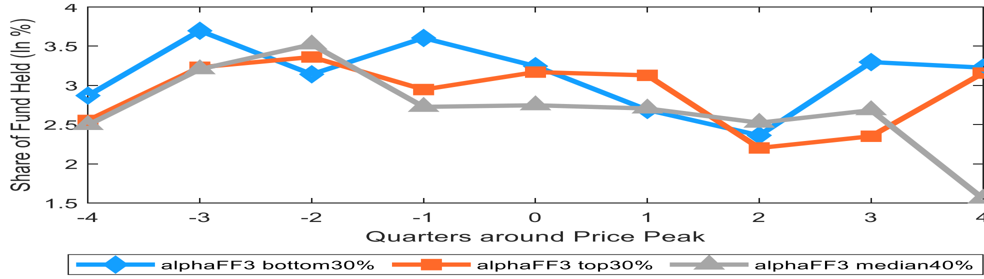
Note: Table 8 reports the "out of sample" performance of two equally weighted portfolios: the first investing in stocks with a top 30% changes in hedge fund holdings, and the second investing in stocks with a bottom 30% changes in hedge fund holdings. In each quarter *t*, we sort stocks into two equally 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

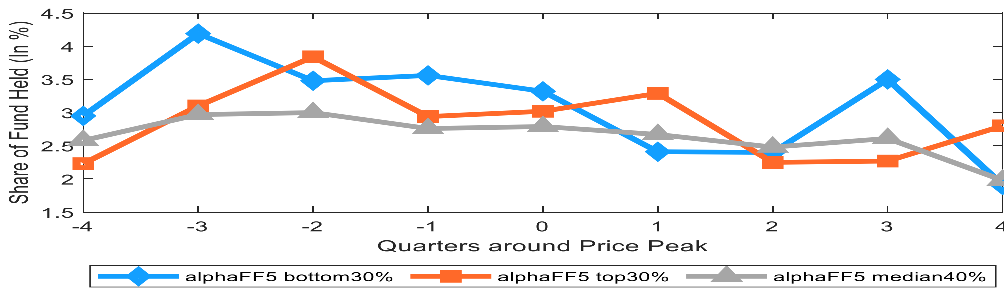
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EW	EW	EW	EW	SW	SW	SW	SW
Rm-Rf_FF3	0.271***	0.285***			0.306***	0.318***		
	(12.37)	(12.79)			(13.91)	(14.07)		
SMB_FF3	0.118***	0.102***			0.138***	0.125***		
	(3.12)	(2.70)			(3.65)	(3.28)		
HML_FF3	-0.081	-0.069			0.000	0.010		
	(-1.29)	(-1.12)			(0.00)	(0.17)		
MOM		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)

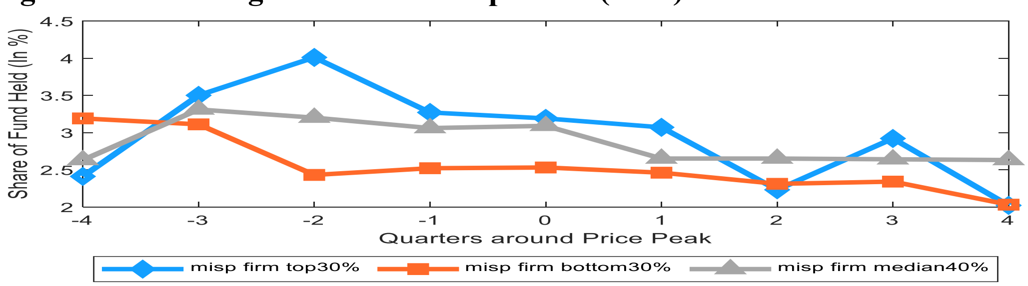


Figure 2 Hedge Fund Holdings Around Price Peaks of Individual Stocks

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
$\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$	0.326	-2.562***	0.169	-2.188***
	(0.76)	(-4.65)	(0.41)	(-3.69)
$\mathrm{Short}_{i,t}$	-0.126	0.808***	0.188	0.540**
	(-0.56)	(3.44)	(0.87)	(2.50)
$\mathrm{Time}_{i,t}$	0.927***	3.247***	0.984***	2.943***
	(3.54)	(6.84)	(3.95)	(5.92)
$\mathrm{Ln(Book/Market)}_{t-1}$	-0.728***	-0.100	-0.695***	-0.147
	(-4.33)	(-0.47)	(-4.14)	(-0.68)
$\mathrm{Ln(Market\ Cap)}_{t-1}$	0.326*	-0.110	0.186	0.050
	(1.86)	(-0.62)	(1.08)	(0.31)
$\mathrm{Ln(Dividend\ yield)}_{t-1}$	5.730	-3.190	-9.484	-1.280
	(0.27)	(-0.12)	(-0.46)	(-0.05)
$\mathrm{Ln(Age)}_{t-1}$	0.079	0.407	0.043	0.436
	(0.21)	(1.14)	(0.12)	(1.18)
$\mathrm{Ln(Price)}_{t-1}$	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. $\mathrm{Short}_{i,t}$ is a dummy variable, in which 1 represents stocks that are added to the shorting list, and 0 represents stocks that are not added. $\mathrm{Time}_{i,t}$ is a dummy variable, for which 1 indicates that stocks can be shorted during the period, and 0 indicates that stocks cannot be shorted. $\mathrm{Short}_{i,t} * \mathrm{Time}_{i,t}$ 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.