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Private Information in the Chinese Stock Market: Evidence from Mutual Funds and Corporate Insiders

I find evidence of valuable private information in the Chinese stock market. First, Chinese actively managed stock mutual funds outperform passive benchmarks including market, size, value, and momentum factors. Most funds appear to have skill, and much of that skill consists of stock-picking ability. Second, Chinese corporate insiders also outperform the market. Private information associated with insider trades is more valuable for stocks of state-owned enterprises and for more volatile stocks. Third, I find strong correlation patterns between the performance of stock funds and corporate insiders. Funds that trade more in the same direction as insiders perform better. Funds' larger shareholding positions correlate more with insiders and perform better. Funds with a higher portfolio concentration in these large positions outperform funds with a lower concentration. Finally, I find evidence of performance erosion for both stock funds and corporate insiders, a sign of improvement in market efficiency.

Keywords: *market efficiency, private information, Chinese stock market, mutual funds, and insider trading.*

1 Introduction

"The China Securities Regulatory Commission has opened 25 insider trading investigations since the start of the year, up from 22 for all of 2013, and has referred 29 cases to police and prosecutors, up from 21 in 2013…At least 178 fund managers have left their jobs in the first six months of this year, compared with 150 in all of 2013…The large number of fund managers leaving this year has a direct relationship with the probes…Insider trading is seen as common on China's domestic bourses."

Financial Times, July 7, 2014

The primary role of a financial market is to allocate the economy's capital stock. To do so efficiently, the market must rely on prices that provide accurate signals for resource allocation. Fama (1965, 1970) defines an efficient market as a market in which prices always fully reflect available information. Strong-form efficiency is concerned with whether given investors have monopolistic access to any information relevant to price formation. Subsequent studies on insider trading such as Jaffe (1974), Finnerty (1976), Seyhun (1986) and Lakonishok and Lee (2001), have presented evidence that suggests violation of strong-form efficiency in the U.S. stock market. Corporate insiders in the United States seem to possess private information that helps them generate trading profits. Semi-strong form efficiency is concerned with whether prices efficiently adjust to publicly available information. Performance evaluation of U.S. mutual fund managers has lent support to this hypothesis. For example, Fama and French (2010) show that, in aggregate, actively managed U.S. stock mutual funds do not beat the market, and very few funds produce benchmark-adjusted returns sufficient to cover their costs.

Thus, the extent to which private information is exploited in the U.S. stock market seems limited. That so few mutual fund managers can beat the market suggests that the U.S. stock market is not grossly inefficient in semi-strong form. A well-developed legal system and harsh punishment for insider trading have contributed to this efficiency.[1] The U.S. stock market is probably the most efficient marketplace in the world. There are many other financial markets around the world. An interesting question then is to ask how private information is exploited in a less developed financial market.

With a short history, a weak legal system, and a significant retail-investor presence, the Chinese stock market provides an excellent target for this study. Established in 1990, the Chinese stock market has a short history, but it has seen tremendous growth. It is currently the second largest stock market in the world. Meanwhile, financial laws and regulations have been introduced gradually to address new developments in the Chinese financial markets. However, as is common in emerging markets, the legal system in China is not as fully developed as that in the United States. For example, regulations on insider trading and reporting were introduced only recently, in April 2007. Meanwhile, Chinese retail investors represent a large fraction of the stock market. In 2003, they held over 87% of the total stock market capitalization.

In this paper, I focus on two groups of investors in China: actively managed stock mutual funds and corporate insiders. Actively managed stock mutual funds represent a substantial portion of the Chinese stock market. For example, in 2007, their aggregate holdings represented

[1] For example, in 2011, Galleon Group hedge fund founder Raj Rajaratnam was sentenced in New York to 11 years for illegal trading on inside information. He was ordered to pay a $10 million fine and forfeit $53.8 million.

16.6% of the Chinese stock market capitalization. Chinese corporate insiders trade a substantial amount of their own company stocks. From April 2007 to June 2014, their aggregate trading volume amounted to nearly RMB900 billion, which represented about 0.3% of the total trading volume in the market.[2]

The first part of my analysis focuses on the performance evaluation of Chinese actively managed stock mutual funds (for the rest of my paper, I use 'stock mutual funds', 'mutual funds', or 'stock funds' interchangeably with 'actively managed stock mutual funds'). I find that despite representing a substantial share of the Chinese stock market, the aggregate portfolio of stock funds outperforms passive benchmarks including market, size, value, and momentum factors. First, I show results based on the aggregate portfolio of stock funds. Second, I perform bootstrap simulations based on a zero-α return sample and find that most managers have sufficient skill to cover all costs. Finally, I investigate their stock holdings and find evidence of stock-picking skill that helps explain a substantial amount of the funds' outperformance.

These findings are in sharp contrast to Fama and French (2010)'s result on U.S. stock mutual funds. They show that U.S. actively managed stock mutual funds do not outperform the market. Only the managers in the right tail of the distribution seem to possess skill that help them generate positive α. Therefore, the evidence of Chinese fund managers' outperformance suggests that either they are good at interpreting public information, or they are able to exploit private information. The former explanation is at least partly true, because mutual fund managers presumably have better investment knowledge and skill than an average market participant. Attributing some of their outperformance to their skill at interpreting public information is reasonable. The more relevant question for my study is the latter explanation, that is, to what extent are the fund managers exploiting private information?

To answer this question, I first study the trading activities of Chinese corporate insiders, the group of investors that intrinsically have access to private information about their own company. I discover strong evidence of information asymmetry in the Chinese stock market. Chinese corporate insiders are able to reap large profits by trading their own company stocks. Insider buys possess predictive power for stock returns, whereas insider sells lack predictive power for stock returns. This finding is consistent with the intuition that reasons other than negative private information, such as liquidity and diversification needs, may motivate insider sells. Insider buys, on the other hand, are much more likely driven by positive private information. Moreover, I find stronger predictive power of insider trades from state-owned-enterprises (SOEs) than those from non-SOEs. I also find that insiders benefit more from trading more volatile stocks. In aggregate, the value of insiders' private information is economically significant. A simple insider-mimicking trading strategy produces a significantly positive annual alpha of 14.43% (t=3.08) against the market benchmark.

Having established that Chinese corporate insiders possess valuable private information, I then turn to the investigation of possible connections between the performance of corporate insiders and stock funds. I find evidence that points to some intersection between these two groups' information sets. First, I show a strong return correlation between stock funds' trading portfolio and the insider-mimicking trading portfolio, after adjusting for common risk benchmarks. Second, I find that funds that trade more in the same direction as insiders deliver better performance. Next, I refer to a fund's large shareholding positions (holdings that represent a large fraction of the stocks' market capitalization) as its qualified holdings. In other words, a

[2] RMB is the official currency of China. The RMB/USD exchange rate prior to July 2005 was pegged at 8.28RMB/USD. Since then, RMB has appreciated to about 6.16RMB/USD by June 2014.

fund's qualified holdings represent a significant share percentage of the corresponding stocks. I show a significant correlation between the insider-mimicking portfolio and the stock funds' aggregate qualified-holding portfolio. Qualified holdings outperform the non-qualified holdings, especially around earnings announcements. Furthermore, I calculate a fund's concentration in these qualified holdings as a proxy for the fund's access to inside information. I find that funds with a higher concentration in qualified holdings outperform funds with a lower concentration in qualified holdings.

Finally, I present evidence of performance erosion in Chinese stock mutual funds and corporate insiders. Stock funds' aggregate benchmark-adjusted returns exhibit a significantly negative time trend. Insider trades' predictive power for stock returns has substantially declined over time. These results suggest that the Chinese stock market is becoming more efficient and harder to beat. It is also consistent with the fact that a growing institutional presence in the Chinese stock market has introduced more competition. The retail fraction of the Chinese stock market has decreased from 88% in 2003 to 37% in 2013. The decline in the retail fraction coincides with the rise in the institutional fraction, which has grown from 12% to 63% in just over 10 years.[3]

This paper contributes to several strands of the finance literature. First, it adds to the literature on mutual fund performance evaluation by studying a novel data set on Chinese mutual funds and showing very different results in the Chinese data from the U.S. data. Since Jensen's 1968 study on U.S. mutual funds, papers in this literature have attempted to get a better understanding and more accurate assessment of their performance (e.g. Grinblatt and Titman (1989), Carhart (1997), Chen, Jegadeesh and Wermers (2000), Wermers (1999, 2000), Pastor and Stambaugh (2002), Berk and Green (2004), Cohen, Coval, and Pastor (2005), Busse and Irvine (2006), Fama and French (2010), Pastor and Stambaugh (2012), Linnainmaa (2013), and Pastor, Stambaugh, and Taylor (2014)). However, the U.S. literature has given little attention to Chinese mutual funds. The finance literature in China has some coverage of mutual fund performance, but with very limited data[4]. In this paper, I construct and study a comprehensive data set since the inception of the Chinese stock mutual fund industry. My data set covers 418 Chinese actively managed stock mutual funds for a sample period from 1998 to 2014.

Fama and French (2010) conclude that the aggregate portfolio of actively managed U.S. stock funds is very close to the stock market portfolio, and few funds produce benchmark-adjusted returns sufficient to cover their costs. By contrast, I find widespread skill among Chinese stock funds. I present strong evidence of outperformance, both in aggregate fund returns through a regression framework, and in individual fund returns through a bootstrap simulation approach. Using the methodology of Berk and Binsbergen (2014), I find that the aggregate outperformance of Chinese stock mutual funds amounted to over RMB233 billion (in Y2010 RMB), for the sample period from July 2003 to June 2014. Moreover, I show that managers possess stock-picking abilities that help them generate positive α. Furthermore, funds that trade more frequently tend to outperform funds that trade less frequently, suggesting intra-period trading skill beyond those reflected by their semiannual stock holdings.

[3] Pastor, Stambaugh, and Taylor (2014) find similar evidence of rising competition in the U.S. stock market. They find that the rising competition is offset by the rising skill of active mutual funds, so that the net effect on the performance of U.S. active funds is approximately neutral. In contrast, I find that competition in China has risen so fast that the performance of Chinese funds has declined over time.

[4] For example, Su et al. (2012) had a sample of only 42 funds. Earlier works such as Li, Chen, and Mao (2007) and Luo, Wang, and Tian (2003) had even smaller sample sizes.

Second, this paper adds to the literature on the informational efficiency of financial markets by studying information asymmetry in the Chinese stock market. Fama (1965, 1970) introduced the efficient-market hypothesis. Subsequent studies on insider trading, such as Jaffe (1974), Finnerty (1976), Seyhun (1986), and Lakonishok and Lee (2001), have presented evidence that suggests violation of strong-form efficiency in the U.S. stock market. In this paper, I assemble and study a novel data set on the Chinese corporate insiders' trading activities. I find that insider buys possess predictive power for stock returns, whereas insider sells lack predictive power for stock returns. This finding confirms the intuition that a variety of reasons may motivate insiders to sell. But the main reason for insiders to buy has to be to make money. Moreover, I find that trades of insiders from SOEs have stronger predictive power than those from non-SOEs. SOEs are generally perceived to be operationally inefficient due to its state-owned nature (e.g. Shleifer and Vishny (1998), Fan, Wong, and Zhang (2007), and Fisman and Wang (2011)). My results suggest that in addition to operational inefficiency, SOEs in China may also suffer from informational inefficiency. Government policies have a strong impact on stock prices in China, especially SOEs, so it is not surprising that SOE insiders' information is more valuable. I also find that insider trades of high-volatility stocks have stronger predictive power than those of low-volatility stocks. Higher volatility suggests a higher degree of investor uncertainty and information asymmetry. And insiders profit more under such circumstances.

Third, this paper adds to the literature on mutual fund performance attribution by studying an interesting information overlap between Chinese mutual funds and corporate insiders. Papers in this literature try to understand channels from which mutual fund managers derive their alphas. Kacperczyk, Sialm, and Zheng (2005) offer evidence of manager skill by showing that funds with higher industry concentration outperform. Cohen, Coval, and Pastor (2005) find a relationship between stock quality and manager skill and design a new performance measure incorporating a fund's stock holdings' qualities. Kacperczyk and Seru (2007) focus on the manager-skill channel that depends on the degree to which a fund manager relies on public information. Cohen, Frazzini, and Malloy (2008) discover an informational advantage based on social networks between fund managers and corporate board members. In my Chinese data, I show that a substantial amount of manager skill can be attributed to stock-picking ability. In addition, I discover strong correlation patterns between stock funds and corporate insiders. By studying both groups' return series and trading activities, I find a significant correlation between the performance of the stock funds' aggregate trading portfolio and the insider-mimicking portfolio. Cross-sectionally, funds that trade more in the same direction as insiders tend to outperform those that trade less in the same direction as insiders. Lastly, stock funds' qualified holdings (large stock holdings measured by the holding's value divided by the stock's market capitalization) show a significantly positive return correlation with the insider-mimicking portfolio. Qualified holdings outperform non-qualified holdings, especially around earnings announcements. Funds more concentrated in such holdings outperform those less concentrated in such holdings. All evidence is consistent with the intuition that Chinese stock fund managers may be exploiting similar private information that corporate insiders possess.

Finally, this paper also contributes to the understanding of Sharpe's (1991) arithmetic of active investing in the context of the Chinese stock market. Retail investors in China account for over 87% of the stock market capitalization in 2003. Most of these retail investors actively manage their portfolios and trade frequently. According to the official statistics by Chinese stock exchanges, in 2012, retail investors had an average holding period of only 39.1 days and constituted 85.6% of the trading volume. This market environment aids the institutional money managers in their pursuit to beat the market at the expense of retail investors. Consistent with this intuition, I find that Chinese stock funds and corporate insiders both outperform the market. Barber et al. (2012) document similar evidence from Taiwanese individual day traders. They find that less than 1% of the total population of day traders is able to predictably and reliably earn positive abnormal returns net of fees. Odean (1999) and Barber and Odean (2000) document evidence of excessive trading among U.S. retail investors. They conclude that these investors pay a tremendous performance penalty for active trading. I find similar results that Chinese retail investors in aggregate underperform passive benchmarks. This observation is not surprising, given that institutional investors are equipped with better financial knowledge and a vaster amount of resources, not to mention their potential access to private information. Consequently, Chinese retail investors are paying a tremendous performance penalty for active trading.

Closest to my research is a contemporaneous paper by Choi, Jin, and Yan (2014). They study a different data set on Chinese stock ownership (1996-2007) and show that institutional accounts have a strong information advantage over retail accounts. They rely on the stock exchange's definition of account ID to differentiate institutional accounts from retail accounts. My data and empirical methodology are very different. Specifically, I assemble and study two novel data sets on stock mutual funds (1998-2014) and corporate insiders (2007-2014). I show that both stock funds and corporate insiders outperform the market portfolio. In this dimension, Choi, Jin, and Yan's (2014) results on Chinese institutional accounts' outperformance are consistent with and complementary to my results on stock funds and corporate insiders. Moreover, my paper has a research focus beyond the outperformance results. In particular, I discover strong correlation patterns between stock funds and corporate insiders. I find evidence that points to some intersection between these two groups of active investors' information sets. Furthermore, I present evidence of performance erosion for both stock funds and corporate insiders.

The rest of the paper is organized as follows. Section 2 offers background information on the Chinese stock market and mutual funds. Section 3 describes the data. Section 4 evaluates the performance of Chinese actively managed stock mutual funds in three different ways: (1) aggregate return analysis, (2) bootstrap simulation analysis, and (3) holdings analysis. Section 5 evaluates the performance of Chinese corporate insiders and constructs an insider-mimicking portfolio. Section 6 investigates correlation patterns between stock funds and corporate insiders, in relation to fund performance. Section 7 shows evidence of performance erosion for stock funds and corporate insiders. Section 8 concludes. The appendix includes additional results.

2 Chinese Stock Market and Mutual Funds

Founded in 1990, the Chinese stock market is relatively young compared to many other stock markets in more developed economies. Despite its young age, the Chinese stock market has been growing at a robust pace. Currently, it is the second largest stock market in the world, just behind the U.S. stock market. At the end of 2013, the aggregate Chinese stock market capitalization reached RMB20 trillion, equivalent of $3.3 trillion. More than 2,500 stocks are currently trading on the two Chinese stock exchanges: Shanghai stock exchange and Shenzhen stock exchange. Stocks available for domestic investors are A-share, whereas stocks available for foreign investors are B-share. Stocks listed in Hong Kong are H-share. For my sample period, they are not available to the Chinese mainland investors. That is, H-share stocks are not part of the investment universe for either Chinese stock mutual funds or corporate insiders. The A-H connect program is implemented on November 17, 2014, which should allow Chinese mainland investors to invest in H-share, and foreign investors to invest in A-share subject to some quota. For this paper, I focus on A-share stocks because they constitute the stock investment universe for the subjects I study.

Since the inception of the first stock mutual fund in China in 1998, the growth of the Chinese stock mutual fund industry has been robust. As Table 1 shows, total assets under management (AUM) of actively managed stock mutual funds grew from RMB2 billion in 1998 to over RMB750 billion in 2013. In the meantime, the number of stock funds has increased from only one in 1998 to 380 in 2013.

Table 1 shows the summary statistics of Chinese stock mutual funds and the Chinese stock market. The ratio between stock funds' aggregate AUM to the total stock market capitalization exceeded 16% in 2007. In the 2008 bear market, the aggregate AUM of actively managed stock mutual funds experienced a sharp downturn, from RMB1,515 billion to RMB636 billion. At the end of 2013, the aggregate AUM is RMB758 billion.

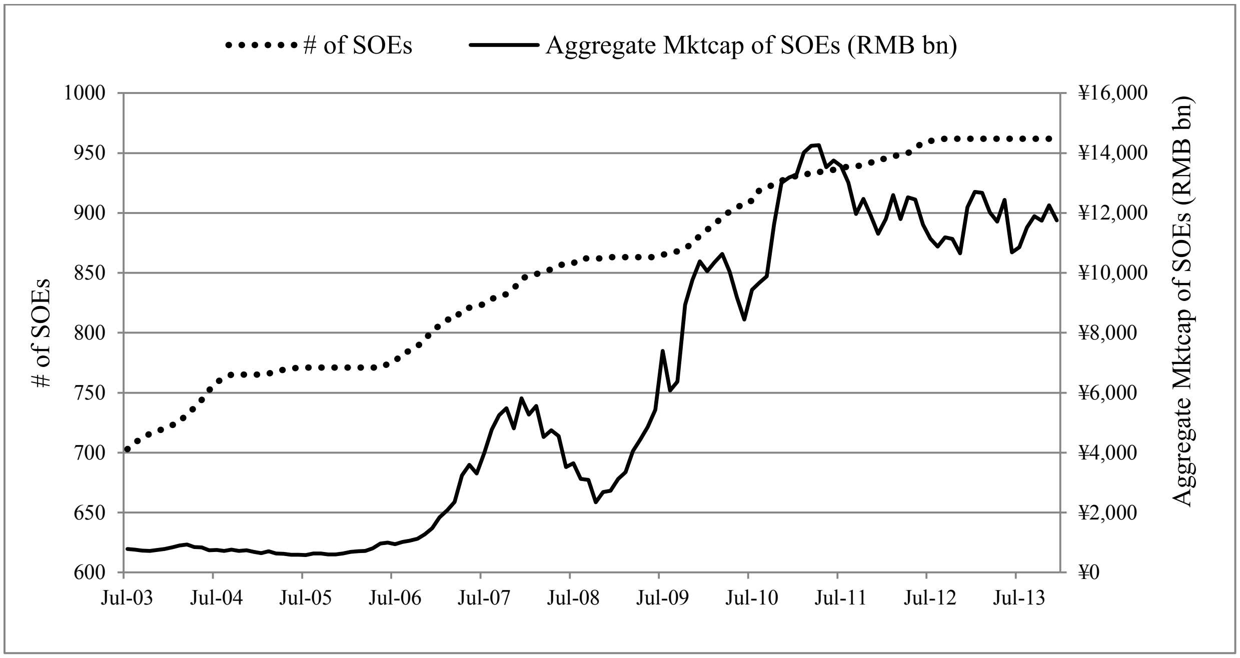
Meanwhile, the Chinese stock market has grown steadily. My measure of the market capitalization is based on the outstanding floating shares in the secondary market. The growth in the aggregate stock market capitalization in China is partly due to the share-reform policy initiated in 2005. The policy is designed to convert the previously restricted/non-tradable shares (mostly shares of SOEs) into floating/tradable shares in the secondary stock exchanges. Since the first stock's share-reform in 2005, there have been more than 1,300 stocks that participated in the share-reform program. Moreover, most of these participating stocks are SOEs, which are usually large-cap stocks. As a result, the restricted-to-floating share conversion has contributed significantly to the growth of the aggregate stock market capitalization. Government-sponsored institutions in China owned most of the previously restricted shares. Consequently, their presence in the secondary stock market has increased dramatically thanks to the share-reform policy. As Figure 1 shows, the aggregate market capitalization of SOEs has grown from RMB779 billion in 2003 to RMB11,751 billion in 2013. At the end of 2013, 962 publicly listed SOEs account for 39.0% of the stock market in terms of number of stocks, and 58.6% in terms of market capitalization.

Table 1: Summary Statistics on the Chinese Stock Market and Mutual Funds

Column 1 records the semiannual reporting periods. Columns 2 to 5 report the number of funds, the total AUM of funds, the aggregate stock market capitalization, and the ratio between the two (column 3/column 4). Stock funds' holdings data start in 2003. Columns 6 to 8 report the total number of stocks held by stock funds in aggregate, the total number of publicly listed stocks, and the ratio between the two (column 6/column 7). The data cover 418 funds from July 1998 to December 2013. AUM and MktCap are in RMB billion. Ratios are in %.

Reporting Period	# of Funds	AUM of Funds (bn)	Aggr. Stock MktCap (bn)	AUM / MktCap	# of Stocks held by MF	# of Stocks Total	MF/Total
2Q/1998	1	¥2	¥596	0.3%		784	
4Q/1998	1	¥2	¥559	0.4%		826	
2Q/1999	7	¥21	¥886	2.3%		873	
4Q/1999	13	¥34	¥801	4.2%		923	
2Q/2000	17	¥45	¥1,291	3.5%		973	
4Q/2000	20	¥51	¥1,566	3.3%		1,060	
2Q/2001	22	¥42	¥1,753	2.4%		1,113	
4Q/2001	33	¥46	¥1,346	3.4%		1,137	
2Q/2002	37	¥56	¥1,473	3.8%		1,164	
4Q/2002	39	¥51	¥1,184	4.3%		1,201	
2Q/2003	43	¥58	¥1,283	4.5%	376	1,227	30.6%
4Q/2003	44	¥63	¥1,245	5.1%	295	1,264	23.3%
2Q/2004	45	¥63	¥1,205	5.2%	426	1,323	32.2%
4Q/2004	47	¥66	¥1,116	5.9%	367	1,354	27.1%
2Q/2005	53	¥67	¥954	7.1%	364	1,368	26.6%
4Q/2005	68	¥88	¥1,020	8.7%	436	1,356	32.2%
2Q/2006	79	¥150	¥1,620	9.3%	505	1,354	37.3%
4Q/2006	105	¥377	¥2,413	15.6%	525	1,416	37.1%
2Q/2007	116	¥813	¥5,418	15.0%	669	1,460	45.8%
4Q/2007	125	¥1,515	¥9,145	16.6%	724	1,533	47.2%
2Q/2008	140	¥873	¥5,922	14.7%	748	1,591	47.0%
4Q/2008	157	¥636	¥4,540	14.0%	743	1,609	46.2%
2Q/2009	179	¥953	¥9,087	10.5%	855	1,607	53.2%
4Q/2009	202	¥1,049	¥15,080	7.0%	1,099	1,702	64.6%
2Q/2010	229	¥846	¥12,672	6.7%	1,306	1,875	69.7%
4Q/2010	254	¥989	¥19,235	5.1%	1,396	2,046	68.2%
2Q/2011	279	¥902	¥20,054	4.5%	1,547	2,211	70.0%
4Q/2011	307	¥747	¥16,520	4.5%	1,882	2,323	81.0%
2Q/2012	335	¥749	¥17,340	4.3%	1,888	2,424	77.9%
4Q/2012	354	¥739	¥18,223	4.1%	1,812	2,473	73.3%
2Q/2013	369	¥724	¥16,982	4.3%	1,774	2,470	71.8%
4Q/2013	380	¥758	¥20,042	3.8%	1,801	2,467	73.0%

Figure 1: Growth of SOEs in the Chinese Stock Market



Actively managed stock mutual funds have been lagging in growth compared to the stock market, which is partly why we observe a decreasing trend in stock funds' share of the total market capitalization since the end of 2007. Nonetheless, as of December 2013, this ratio remained substantial at 3.8% of the Chinese stock market capitalization. In aggregate, these funds still manage over RMB750bn. The last three columns of Table 1 show an increasing trend in the number and percentage of stocks in which the stock mutual funds invest. In 2003, stock funds held 376 stocks or 30.6% of all publicly listed Chinese stocks. By 2013, this number has increased to 1,801 or 73.0% of all publicly listed Chinese stocks.

Clearly, actively managed stock mutual funds represent a substantial portion of the Chinese stock market, both in terms of assets under management and stock market coverage. They represent an even more substantial portion of the Chinese institutional investors. This is because Chinese retail investors represent a large fraction of the stock market. In 2003, they held over 87% of the total stock market capitalization. The retail fraction has steadily decreased to 37% by the end of 2013. That is, Chinese institutional investors hold 63% of the stock market capitalization. Among the institutionally managed stock market assets, actively managed stock mutual funds account for 5.1% in 2013. Data availability is the primary reason I focus on the stock funds for this study. Because they represent a substantial portion of the institutional investors, results on stock funds should also shed light on the performance of other types of institutional money managers. In fact, I also investigate the aggregate institutional investors' stock holdings data and find similar results to the holdings of stock funds.

3 Data Description

Thanks to the data provider Wind Information® (WIND), a leading Chinese financial data provider, I am able to construct several novel data sets on the Chinese financial markets. Founded in 1994, WIND serves more than 90% of the domestic financial enterprises, including securities firms, mutual funds, insurance companies and banks. Overseas, WIND serves 75% of the Qualified Foreign Institutional Investors (QFII). Additionally, most renowned financial research institutions and regulatory committees are on WIND's client list. Media reporters and academic researchers frequently quote WIND data. The other commonly used source for Chinese financial data is CSMAR on WRDS. In comparison, WIND offers more detailed and up-to-date data on stocks and mutual funds. Moreover, WIND collects data on corporate insiders' trading activities, which CSMAR does not provide. For this paper, I construct four data sets covering the following parts of the Chinese financial markets: stock market, mutual funds, corporate insiders, and institutional investors. I will discuss each of the four data sets below.

1. Chinese Stock Market Data Set

For this study, I focus on the Chinese A-share stock market, which comprises 2,555 stocks as of June 2013. The stock mutual funds in my sample can only invest their stock portfolio in the A-share stocks. In particular, I construct daily and monthly series for each stock's price, holding period return and market capitalization. Data on delisted stocks are also appropriately recorded for the time period they existed. But overall, few stocks are delisted.

I further construct the benchmark returns from the Chinese stock market data. In particular, I calculate the excess value-weighted market return $R_m - R_f$, Fama-French factor returns *SMB* and *HML*, as well as the Fama-French version of Carhart's (1997) momentum return *MOM*. All returns are monthly. More details on these factors are presented in section 4.

2. Chinese Mutual Fund Data Set

For this study, I include only those funds that invest primarily in the Chinese stock market. My sample includes 418 eligible funds. The first stock mutual fund was established in March 1998. Its first monthly return was recorded for April 1998, which is the beginning of my data. For my sample period from April 1998 to June 2014, I collect each fund's monthly net return series. Return calculations are based on the fund's net asset value (NAV) adjusted for dividend payout. I use adjusted NAV for calculating returns for both open-end and closed-end funds. Closed-end funds trade on the stock exchange while open-end funds do not. A closed-end fund's trading price may deviate from the fund's NAV due to the effects of supply and demand in the secondary market. I use NAV to calculate fund returns, because NAV more accurately reflects fund performance. I also collect information on each fund's fees and expenses. To calculate gross returns, I add the annual fees and expense ratio divided by 12 to the monthly net returns.

My data set is free of the incubation bias (Evans, 2010). All open-end mutual funds must publicly report their establishment to the Chinese Securities Regulatory Commission (CSRC). WIND starts collecting data on this public disclosure date. All closed-end mutual funds trade on the stock exchange. WIND starts collecting data on the first trading day. In other words, WIND starts collecting fund data as soon as funds are available to the public. My dataset is also free of the survivorship bias, because WIND collects data of dead funds while they are still alive.

For the subsample period from March 2003 to March 2014, I collect each fund's stock-holdings data. Since the beginning of 2003, all stock mutual funds are required to disclose their top-10 stock holdings in quarterly reports, and their entire holdings in semiannual reports. Quarterly reports disclose fund holdings at the end of March, June, September, and December. Semiannual reports refer to interim and yearend reports. Interim reports disclose fund holdings at the end of each June. Year-end reports disclose fund holdings at the end of each December. I collect quarterly holdings data from March 2003 to March 2014, for a total of 45 quarters. I collect semiannual holdings data from June 2003 to December 2013, for a total of 22 reporting periods. WIND has a unique advantage in linking holdings data directly to each fund. So matching stock holdings to a mutual fund is convenient. In addition, from 2004 to 2013, I collect the annual turnover ratio for each fund.

The Chinese actively managed stock mutual funds have an interesting feature: they do not always fully invest fund assets in stocks. From 2003 to 2014, funds in my sample on average invest around 80% of the fund assets in stocks, while holding the rest mainly in cash or bonds.

3. Chinese Corporate Insider Trading Data Set

The data set of insider trades covers the period from January 1, 2004 to June 30, 2014. This data set records three insider types: managers/directors, large shareholding entities, and other relevant individuals. "Large shareholding entities" are those who own more than 5% of shares and are not managers or directors. "Other relevant individuals" are all investors who are required to report their trading to the CSRC but are neither mangers/directors nor large shareholders (e.g. company lawyers, relatives of managers/directors). The current law that regulates insider trading was enacted in April 2007. Before April 2007, insiders disclosed their trades on a voluntary basis. Hence, I use the data after April 2007. The resulting data set records a total of 49,739 trades of insiders from 2,275 publicly listed companies. Insiders are required to report to the CSRC within 2 business days after their trades. My data set contains key variables such as insider identity, stock traded, insider type, direction of trade (i.e. buy or sell), trade-completion date, and shares/amount traded.

4. Chinese Institutional Investor Holdings Data Set

This data set records the percentage ownership of each A-share stock's market capitalization by institutional investors. It covers a sample period from December 2003 to June 2014, for a total of 21 semiannual reporting periods. Institutional investors include but are not limited to government-sponsored institutions, mutual funds, banks, brokerage firms, pension funds, trusts, insurance companies, and QFII's.

4 Performance Evaluation of Chinese Stock Mutual Funds

This section evaluates the performance of Chinese stock mutual funds. First, I evaluate the aggregate performance under a regression framework and show evidence of outperformance of stock funds as a whole. Second, I perform bootstrap simulations and show cross-sectional evidence of positive alpha for most funds. Third, I evaluate the performance of mutual funds' aggregate semiannual stock holdings and attribute a substantial amount of funds' outperformance to managers' stock-picking skill. I also present evidence of managers' intra-period trading skill.

4.1 Aggregate Performance

4.1.1 The Regression Framework

The three benchmark models used for evaluating stock fund performance is the CAPM, Fama and French's (1993) three-factor model (FF3F), and Carhart's (1997) four-factor model

(FF3F+MOM). To measure performance, these models use variants of the time-series regression:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}\left(R_{mt} - R_{ft}\right) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + e_{mf,t.} \quad (1)$$

All factor returns are based on the Chinese stock market data. In this regression, R_{mf} is the return on the aggregate fund portfolio for month *t*, and R_{ft} is the risk-free rate for month *t*. As the Chinese government bond market was developed much later than its stock market, I use the three-month household deposit rate as a proxy for risk-free rate. R_{mt} is the market return (the return on a value-weighted portfolio of all Chinese A-share stocks), SMB_t and HML_t are the size and value returns as in Fama and French (1993), MOM_t is the Fama-French version of Carhart's (1997) momentum return, α_{mf} is the average return left unexplained by the benchmark model, and $e_{mf,t}$ is the residual. Table 2 contains details on the factor construction.

The regression with $R_{mt} - R_{ft}$ as the only regressor is the CAPM model. The regression with $R_{mt} - R_{ft}$, SMB_t, and HML_t as regressors is the FF3F model. The regression with $R_{mt} - R_{ft}$, SMB_t, HML_t, and MOM_t as regressors is the FF3F+MOM model. Table 2 shows the summary statistics for the explanatory returns in Regression (1) for the sample period of July 2003 to June 2014 (henceforth 2003 to 2014). $R_{mt} - R_{ft}$ has an average return of 0.89% per month (t=1.15). Average monthly returns of SMB_t and HML_t are also large at 0.73% (t=1.82) and 0.50% (t=1.89) respectively. MOM_t shows a small average monthly return of 0.07% (t=0.22). Wang (2004) and Wang (2013) show that the size and value factors in China work in a way similar to those in the United States. The momentum factor in China is not statistically significant. But as I will show next, it is still a useful explanatory variable in the performance evaluation of stock funds.

4.1.2 Regression Results for Equal- and Value-Weighted Portfolios of Stock Funds

Under the adding-up constraint, the value-weighted aggregate of all Chinese stock portfolios is the Chinese stock market portfolio. It has a market slope of 1 in Regression (1), zero slopes on all other factors and zero intercept – before investment cost. If the value-weighted aggregate portfolio of passive investors has a zero intercept before costs, the value-weighted aggregate portfolio of active investors must also have a zero intercept. Thus, positive and negative intercepts among active investors balance out before costs.

The above statement applies to the aggregate stock portfolio of all active investors, which is not the same as the aggregate portfolio of all active stock mutual funds. In fact, the active stock mutual funds represent a subset of the active-investor universe. Passive investors hold cap-weighted portfolios. Active investors tilt away from cap weights, and must be balanced by other active investors with the opposite tilts. Therefore, as only part of the active-investor universe, the active stock funds may tilt away from cap weights.

Table 3 shows estimates of Regression (1) for monthly returns of July 2003 to June 2014 on equal- and value-weighted portfolios of the funds in my sample. In unreported results, I find similar regression results for the whole sample period from 1998 to 2014. June 2003 marks the first time stock funds report semiannual holdings. I use the same sample period (July 2003 to June 2014) for the holdings-based analysis later. By overlapping sample periods, I can better compare results here with holdings-based results later.

Table 2: Summary Statistics for Monthly Benchmark Factor Returns

The table reports the average monthly returns and t-statistics (in parentheses) of the factors considered in Regression (1). The sample period is July 2003 to June 2014.

For the market risk premium $R_m - R_f$, R_m is taken as the value-weighted one-month return on A-share stocks publicly listed on the Shanghai and Shenzhen stock exchanges, which represent all eligible stocks for Chinese stock mutual funds. Weights are monthly market-cap values. R_f is the risk-free return, proxied by the three-month Chinese household deposit rate. Because this rate is reported as an annual rate, I divide it by 12 to get a monthly R_f. Finally, the excess market return factor was constructed as the market return R_m less the risk-free rate R_f.

For the size factor *SMB*, each stock is categorized as "big" or "small" based on whether it is above or below the median market cap at the end of June each year. For the value factor *HML*, stocks are also classified as "high," "medium," or "low" BE/ME ratio based on June BE/ME ratio for each stock. Stocks with BE/ME ratios in the top 30th percentile of all BE/ME ratios for publicly listed Chinese A stocks were classified as "high," whereas stocks with BE/ME ratios in the bottom 30th percentile were classified as "low." Stocks with BE/ME ratios in the remaining percentiles (30th to 70th percentile) were classified as "medium." Six portfolios were formed annually, namely, Small/High, Small/Medium, Small/Low, Big/High, Big/Medium, and Big/Low. The value-weighted monthly returns for each portfolio were computed using monthly market-cap data, and the monthly factors are determined as follows: *SMB* is the equal-weighted average of returns on the "Small" portfolios minus the equal-weighted average of returns on the "Big" portfolios. *HML* is similarly the equal-weighted average of returns on the "High" portfolios minus the equal-weighted average of returns on the "Low" portfolios.

The momentum factor (*MOM*) was constructed by forming six portfolios monthly, using monthly market cap to construct small and big portfolios much like in the computation of *SMB* and *HML*. However, for the momentum factor, the size portfolios are formed monthly instead of annually. Next, the total return from 12 months prior to 2 months prior is computed for each stock. Monthly momentum portfolios are formed based on this prior return measure, with the bottom 30th percentile of stocks (i.e. those stocks with the lowest return from 12 months ago to 2 months ago) being classified as "low" and the top 30th percentile of prior return stocks being classified as "high." The remaining stocks, from the 30th percentile to 70th percentile, are classified as "medium" momentum stocks. Then six portfolios are formed by intersecting the momentum portfolios with the size portfolios. The monthly momentum factor itself is MOM = 1/2 *(return on Big/High + return on Small/High) – 1/2 *(return on Big/Low + return on Small/Low).

Average Monthly Return

Sample Period	Rm-Rf	SMB	HML	MOM
07/2003 ~ 06/2014	0.89	0.73	0.50	0.07
	(1.15)	(1.82)	(1.89)	(0.22)

Value-weighted (VW) portfolio is weighted by fund AUM at the beginning of each month. Equal-weighted (EW) portfolio weights funds equally each month. The intercepts in (2) for EW fund returns inform us about whether the average returns differ from their exposures to common factors, whereas VW returns inform us about the return of aggregate wealth invested in funds. I report results based on both net and gross returns. Net returns are returns calculated based on funds' adjusted NAV. Gross returns are equal to net returns plus 1/12 of a fund's annual expense ratio.

Chinese actively managed stock funds in aggregate do not have a market slope close to 1. Moreover, they load negatively on *SMB* and *HML* and positively on *MOM*. The VW fund portfolio loads 0.78 (t=−13.40, calculated from 1 but not 0) on $R_m - R_f$, −0.22 (t=−6.75) on *SMB*, −0.34 (t=−6.52) on *HML*, and 0.23 (t=5.49) on *MOM*. The coefficients show that in aggregate, Chinese stock funds load more on large growth stocks and tend to chase winners. The market loading of 0.78 is consistent with the institutional feature that Chinese actively managed stock funds on average invest about 80% of the fund net assets in stocks. In Appendix A, I include the Chinese Treasury bond index as an additional regressor. I find an insignificant loading on the bond index and little change in the regression's R-square and coefficients on existing factors. In unreported results, I use the Chinese corporate bond index as an additional regressor and find similar results. The two bond indices have highly correlated returns.

Table 3: Intercepts and Slopes in Regression (1) for Stock Mutual Funds

The table shows the annualized intercepts (12*α) and t-statistics (in parentheses) for the CAPM, FF3F, and FF3F+MOM versions of Regression (1) estimated on equal-weighted (EW) and value-weighted (VW) net and gross returns on the portfolios of actively managed stock mutual funds. The table also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. Net returns are those received by investors. Gross returns are net returns plus 1/12 of a fund's expense ratio for the year. The data cover 418 funds from July 2003 to June 2014.

	12*α						
	Net	Gross	Rm-Rf	SMB	HML	MOM	R-sq
Equal-Weighted Returns							
CAPM	6.30	8.05	0.71				0.86
	(2.35)	(3.01)	(-11.81)				
FF3F	10.66	12.41	0.76	-0.24	-0.46		0.93
	(5.36)	(6.23)	(-12.88)	(-6.84)	(-8.42)		
FF3F+MOM	8.94	10.68	0.77	-0.17	-0.34	0.26	0.94
	(5.00)	(5.98)	(-13.66)	(-5.21)	(-6.38)	(6.01)	
Value-Weighted Returns							
CAPM	4.75	6.50	0.72				0.86
	(1.78)	(2.43)	(-11.39)				
FF3F	9.34	11.08	0.77	-0.28	-0.45		0.93
	(4.91)	(5.83)	(-12.82)	(-8.27)	(-8.52)		
FF3F+MOM	7.80	9.55	0.78	-0.22	-0.34	0.23	0.95
	(4.49)	(5.49)	(-13.40)	(-6.75)	(-6.52)	(5.49)	

Both EW and VW fund portfolios produce statistically and economically significant alphas. Due to the factor-loading pattern, multi-factor models produce a higher α than CAPM. For example, the VW fund portfolio's net returns have an annual CAPM intercept of 4.75% (t=1.78), a FF3F intercept of 9.34% (t=4.91), and a FF3F+MOM intercept of 7.80% (t=4.49). Results are better for gross returns. The VW fund portfolio's gross returns have an annual CAPM intercept of 6.50% (t=2.43), a FF3F intercept of 11.08% (t=5.83), and a FF3F+MOM intercept of 9.55% (t=5.49).

As argued earlier, for a subset of active investors, their aggregate performance does not have to equal the performance of the market portfolio. Indeed, the aggregate gross returns of Chinese actively managed stock funds exhibit a statistically and economically significant positive alpha. These funds are benefiting from active investment, compared to the passive benchmarks.

4.2 Cross-sectional Performance

I now turn to bootstrap simulations that use individual fund returns to infer the existence of superior and inferior managers. Kosowski (2006), Fama and French (2010), and Barras, Scaillet, and Wermers (2010) have employed simulation methods to study cross-sectional performance. I replicate Fama and French's (2010) procedure to draw inferences about the cross-section of true α. In particular, I test whether the cross-section of α estimates suggests a world in which true α is zero for all funds.

In contrast to Fama and French's (2010) results for U.S. stock funds, I find widespread evidence of manager skill in Chinese stock funds. Cross-sectionally, Chinese stock funds outperform the market, size, value, and momentum benchmarks. I include detailed analysis in Appendix B. Whereas results in section 4.1 show that Chinese stock funds in aggregate outperform passives benchmarks, results in Appendix B show that the outperformance is prevalent across funds.

4.3 Holdings-based Analysis

4.3.1 Summary Statistics on Funds' Stock Holdings

Semiannual disclosure of funds' entire stock holdings allows me to evaluate the performance of their stock portfolios at a six-month frequency. In particular, at the end of each semiannual period from June 2003 to December 2013, I compute the fraction of the market capitalization of each stock that is held by the stock funds in aggregate. Equivalently, we can consider a single big fund that holds the aggregate of stock portfolios from all the funds in my sample. The variable *mfmkt%* measures the fraction of the market capitalization of each stock that is held by this big fund. I sort stocks into quartile portfolios based on *mfmkt%* at the end of each semiannual period. I exclude those stocks with zero *mfmkt%*.

I then compute the equal-weighted average characteristic scores for quartile portfolios formed based on rankings on *mfmkt%*. In particular, I sort all stocks separately by their market capitalization and book-to-market ratio at the beginning of each semiannual holding period. For momentum, I sort all stocks by the six-month cumulative return prior to the beginning of each semiannual holding period.

Table 4: Characteristics of Stocks Held by Mutual Funds

At the end of each semiannual period from June 30, 2003 to December 31, 2013, I compute the fraction of the market capitalization of each stock that is held by the universe of mutual funds (*mfmkt%*). I compute the equal-weighted average characteristic scores for quartile portfolios formed based on separate rankings on *mfmkt%*. To compute the rank score of a given stock on a given characteristic, I sort all stocks separately by their market capitalization, book-to-market ratio and momentum at the beginning of each semiannual period. I assign each stock a rank score on each characteristic, where the rank lies between zero (low) and one (high). For example, if N stocks are available at the end of a period, I assign the ith-ranked stock (on a particular characteristic) a rank score of $(i\text{-}1)/(N\text{-}1)$ for that period. Finally, I report the time-series average of all measures across all periods. The data cover 418 funds.

	mfmkt%	Size Rank	Book-to-Market Rank	Momentum Rank
Quartile 1 (Bottom)	0.41	0.45	0.55	0.46
Quartile 2	2.23	0.46	0.54	0.47
Quartile 3	6.48	0.51	0.50	0.50
Quartile 4 (Top)	18.42	0.58	0.41	0.56

I then assign each stock a rank score on each characteristic, where the rank lies between zero (low) and one (high). For example, if N stocks are available at the end of a period, the ith-ranked stock (on a particular characteristic) is assigned a rank score of $(i\text{-}1)/(N\text{-}1)$ for that semiannual period. Finally, I report the time-series average of all measures across all periods.

Table 4 shows these summary statistics. A substantial amount of variation occurs in *mfmkt%* among the quartile portfolios. For stocks in the bottom quartile, stock funds hold only 0.41% of their market capitalization on average. For stocks in the top quartile, stock funds hold 18.42% of their market capitalization on average. This large variation suggests stock funds in aggregate deviate from the market portfolio, which is consistent with the regression results from Table 3. Summary statistics based on the other characteristics suggest stock funds in aggregate invest more in large growth stocks and tend to chase winners. All these results are consistent with the regression outcome in Table 3, where we see negative loadings on *SMB* and *HML*, but a positive loading on *MOM*.

4.3.2 Performance Evaluation of Funds' Stock Holdings

At the end of each semiannual period from June 2003 to December 2013, I construct a stock portfolio ("All Holdings") that aggregates stock holdings of all the stock funds. I appropriately adjust the portfolio's value weights monthly to create a buy-and-hold return series for the six months following the portfolio formation. I then paste the six-month return series together to create a longer time series of monthly returns. This portfolio tracks the aggregate stock funds' stock holdings every six months without any lag. Of course, for an investor, who has to wait three months for the public disclosure of a stock fund's portfolio holdings, implementing this strategy is impossible. Instead, my objective is to evaluate the actual performance of stock funds' aggregate stock holdings, updated at a six-month frequency.

Table 5: Performance of Stocks Held by Stock Mutual Funds

At the end of each semiannual period from June 30, 2003 to December 31, 2013, I compute the fraction of the market capitalization of each stock that is held by the universe of mutual funds (*mfmkt%*). Next, I compute the buy-and-hold return on the aggregate portfolio of all stocks held by the sample of funds (All Holdings). I also compute buy-and-hold returns on quartile portfolios, which are formed by rankings on *mfmkt%* (all stocks with zero *mfmkt%* are excluded). Quartile 1 stocks have the lowest *mfmkt%*. Quartile 4 stocks have the highest *mfmkt%*.
At the end of each semiannual period, I create a six-month return series following the portfolio formation, for each portfolio discussed above. I appropriately adjust portfolio value weights monthly to create a buy-and-hold monthly return series for the six months following the portfolio formation. Then I paste the six-month return series together to create a longer time series of monthly returns. I run the CAPM, FF3F, and FF3F+MOM versions of Regression (1) to obtain a monthly α for each portfolio, as well as a long-short portfolio constructed from subtracting Quartile 1 returns from Quartile 4 returns. I report α and t(α). The data cover 418 funds.

	CAPM		FF3F		FF3F+MOM	
	α	t(α)	α	t(α)	α	t(α)
mfmkt%						
All Holdings	0.40	(1.58)	0.84	(4.88)	0.69	(4.48)
Quartile 1 (bottom)	0.21	(0.93)	0.09	(0.41)	0.07	(0.33)
Quartile 2	-0.06	(-0.37)	-0.02	(-0.15)	-0.01	(-0.07)
Quartile 3	0.21	(1.02)	0.46	(2.68)	0.43	(2.46)
Quartile 4 (top)	0.47	(1.49)	1.01	(4.46)	0.80	(4.01)
4-1	0.26	(0.60)	0.91	(2.67)	0.73	(2.18)

Similarly, I construct the monthly return series for the quartile stock portfolios sorted by stocks' *mfmkt%* measure. Quartile 1 stocks have the lowest *mfmkt%*. Quartile 4 stocks have the highest *mfmkt%*. I also construct the return series of a long-short portfolio (4−1) by subtracting Quartile 1 returns from Quartile 4 returns. For each return series, I run the CAPM, FF3F, and FF3F+MOM versions of Regression (1). In Table 5, I report monthly α and t(α) from each regression model.

For the "All Holdings" portfolio, we see an economically significant monthly α at 0.40% (t=1.58) under CAPM, and a both economically and statistically significant α under the FF3F and FF3F+MOM models, at 0.84% (t=4.88) and 0.69% (t=4.48) respectively. In addition, when sorted by *mfmkt%*, the quartile portfolios exhibit a rising trend in α from the bottom to top quartile. That is, the stocks held more heavily by the funds in aggregate tend to perform better. The last row in Table 5 (4−1) shows a positive α for the return difference between the top and bottom quartile. Under the FF3F model, it is yielding a large monthly α at 0.91% (t=2.67).

In Appendix C, I perform similar analysis on the semiannual stock holdings of Chinese institutional investors. I show similar evidence on holding patterns and return outperformance of Chinese institutional investors in aggregate. Their outperformance against passive benchmarks directly implies the underperformance of Chinese retail investors in aggregate. This finding is not surprising, because Chinese retail investors are much less sophisticated than institutional

Table 6: Intercepts and Slopes in Regression (1) for Stock Funds and "All Holdings" Portfolio

The "All Holdings" portfolio is formed as follows: at the end of each semiannual reporting period, the portfolio is rebalanced to mimic the exact aggregate holdings of the stock mutual funds in my sample. It is then held for the next six month before the next rebalancing takes place. As a result, this portfolio mimics the aggregate mutual fund holdings at six-month intervals. The top panel copies the statistics for stock funds' aggregate value-weighted gross returns from Table 3. The bottom panel shows the value-weighted statistics for the "All Holdings" portfolio. Gross returns are appropriate for the comparison because fees/expenses are not deducted from the "All Holdings" portfolio's returns. The table shows the annualized intercepts (12*α) and t-statistics (in parentheses) for the CAPM, FF3F, and FF3F+MOM versions of Regression (1) estimated on the value-weighted (VW) returns on the "All Holdings" portfolio. The table also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. The data cover 418 funds from July 2003 to June 2014.

	Gross (12*α)	Rm-Rf	SMB	HML	MOM	R-sq
Actual VW Gross Returns						
CAPM	6.50	0.72				0.86
	(2.43)	(-11.39)				
3-Factor	11.08	0.77	-0.28	-0.45		0.93
	(5.83)	(-12.82)	(-8.27)	(-8.52)		
4-Factor	9.55	0.78	-0.22	-0.34	0.23	0.95
	(5.49)	(-13.40)	(-6.75)	(-6.52)	(5.49)	
VW "All Holdings" Returns						
CAPM	4.74	0.90				0.89
	(1.58)	(-3.55)				
3-Factor	10.03	0.96	-0.31	-0.54		0.95
	(4.88)	(-1.90)	(-8.52)	(-9.42)		
4-Factor	8.25	0.98	-0.24	-0.41	0.27	0.96
	(4.48)	(-1.36)	(-6.99)	(-7.42)	(6.04)	

investors, who are equipped with better financial knowledge and a vaster amount of resources, not to mention their potential access to private information.

Next, I evaluate the performance of the "All Holdings" portfolio under the framework of Regression (1). Table 6 offers a performance comparison between the VW fund portfolio and the "All Holdings" portfolio. I use the fund portfolio's gross returns for this comparison because fees and expenses are not deducted from the "All Holdings" portfolio's returns. I see similar loading patterns on the *SMB*, *HML*, and *MOM* factors. However, the "All Holdings" portfolio's loading on the market factor is much closer to 1. For example, under the FF3F+MOM model, the market loading is 0.98 (t=−1.36, measured from 1 instead of 0). This result is expected because the "All Holdings" portfolio comprises only stock investments, whereas the overall fund portfolio on average comprises 80% of stock investments and 20% of cash and bonds. Also, the "All Holdings" portfolio is rebalanced every six months. The returns on this portfolio do not capture any intra-period trading activity. Stock funds' intra-period trading may cause their market-factor loading to further deviate from 1.

Comparisons between the two portfolios' alphas suggest that managers' stock-picking skill captures a substantial amount of their outperformance. For example, under the FF3F+MOM model, the "All Holdings" portfolio has an annualized alpha of 8.25% (t=4.48), compared with the VW fund portfolio's annualized alpha of 9.55% (t=5.49). Nonetheless, across all three models, I see a stronger α and t(α) for the VW fund portfolio than the "All Holdings" portfolio. This finding shows that stock fund managers may possess skills beyond those reflected by their semiannual stock holdings.

4.3.3 Return Gap, Turnover and Performance

To further understand fund managers' skill in intra-period trading, I investigate a return gap measure introduced by Kacperczyk, Sialm, and Zheng (2005). Specifically, I define the return gap as the difference between a fund's gross return and the return on a portfolio that invests in the previously disclosed fund holdings. Kacperczyk, Sialm, and Zheng (2005) define the return gap as the difference between the net fund return and the net return of the fund's holdings. My calculation just adds back the management fees and other expenses to both net returns, which does not affect the value of return gap. I define it this way because most of my other analyses are based on gross returns. It captures both the hidden benefits and hidden costs of a fund. Hidden benefits may be generated from unobserved interim trades by skilled fund managers who use their informational advantage to time the purchases and sales of stocks optimally. Hidden costs may come in the form of trading costs, agency costs, and negative investor externalities. In the Chinese sample, the return gap is very small when measured by raw returns. But it becomes more positive after adjusting for common risk factors. On average, the Chinese stock fund managers have intra-period trading skill that creates sufficient value to offset trading costs and other hidden costs. I include detailed analysis in Appendix D.

Next, I turn to the investigation of the cross-sectional relationship between fund turnover and fund performance. In my sample, stock funds report their annual turnover ratios from 2004 to 2013. Each year, I sort funds into quartile portfolios by their turnover ratios in that year. Quartile 1 funds have the lowest turnover. Quartile 4 funds have the highest turnover. I then calculate the monthly equal-weighted average gross returns of each quartile portfolio during the same year. Next, for each quartile portfolio, I paste the monthly return series to form a longer return series from January 2004 to December 2013, for a total of 120 months. I also construct the returns of a long-short portfolio by subtracting Quartile 1 returns from Quartile 4 returns. I then evaluate each portfolio's performance by the CAMP, FF3F, and FF3F+MOM models.

Table 7 first reports the time-series average of turnover ratios for each quartile portfolio. The turnover measure exhibits a large cross-sectional variation. The bottom-quartile funds have an average turnover of 130%. The top-quartile funds have an average turnover of 602%. Chinese stock funds have a median turnover of 282% and a mean turnover of 350%. On average, they hold a stock for only about three and a half months. By contrast, the U.S. stock mutual funds have a much lower turnover. Kacperczyk, Sialm and Zheng (2005) study the U.S. stock funds over the period 1984-2003 and report a median turnover of 65% and a mean turnover of 88%. The frequent interim trading of Chinese stock funds may help explain their deviation from the market portfolio. Recall from Table 3, under the FF3F+MOM model, the VW fund portfolio loads 0.78 (t=−13.40, measured from 1 instead of 0) onto the market benchmark.

Next, Table 7 summarizes the performance results for the quartile portfolios and the long-short (4−1) portfolio. An increasing trend is clear in the quartile performance. That is, funds with higher turnover ratios deliver better performance. Quartile 4 funds significantly outperform the Quartile 1 funds. Under the CAMP, FF3F, and FF3F+MOM models, the long-short (4−1) fund portfolio produces a significantly positive monthly α of 0.41% (t=2.67), 0.39% (t=2.54), and 0.32% (t=2.16) respectively. Funds that trade more frequently tend to outperform, which suggests intra-period trading skill beyond those reflected by funds' semiannual holdings.

So far, I have shown results in the return space. But it is also important to understand the economic magnitudes of Chinese stock mutual funds' outperformance. Using the methodology advocated by Berk and Binsbergen (2014), I estimate the RMB-value of each stock fund's outperformance against the market benchmark. The average fund outperforms an economically significant RMB7.17 million per month (in Y2010 RMB). The standard error of this cross-sectional mean is only RMB0.68 million, implying a t-statistic of 10.54. For my sample period from July 2003 to June 2014, the aggregate outperformance of Chinese stock mutual funds amounted to over RMB233 billion (in Y2010 RMB). Now that I have shown evidence of manager skill in Chinese stock mutual funds, I will investigate another group of active investors – Chinese corporate insiders.

Table 7: Performance of Quartile Fund Cohorts Sorted by Fund Turnover

Each year, I sort funds into quartile cohorts by their turnover ratios for the year. I follow the quartile cohorts for these twelve months and calculate each quartile's monthly equal-weighted average gross return series. Then I paste the twelve-month return series together to create a longer return series for each quartile cohort. Quartile 1 funds have the lowest turnover ratios. Quartile 4 funds have the highest turnover ratios. I run the CAPM, FF3F, and FF3F+MOM versions of Regression (1) to obtain a monthly α for each quartile cohort, as well as a long-short portfolio constructed from subtracting Quartile 1 returns from Quartile 4 returns. The table reports, for each quartile portfolio, the average turnover ratio and the regression statistics on α for the CAPM, FF3F, and FF3F+MOM models. The data cover 391 funds from January 2004 to December 2013.

	turnover	CAPM		FF3F		FF3F+MOM	
		α	t(α)	α	t(α)	α	t(α)
Quartile 1 (bottom)	130%	0.19	(0.91)	0.49	(3.07)	0.47	(2.92)
Quartile 2	221%	0.28	(1.28)	0.58	(3.55)	0.53	(3.29)
Quartile 3	329%	0.46	(2.08)	0.74	(4.37)	0.66	(4.10)
Quartile 4 (top)	602%	0.60	(2.56)	0.88	(4.67)	0.78	(4.42)
4-1	472%	0.41	(2.67)	0.39	(2.54)	0.32	(2.16)

5 Performance Evaluation of Chinese Corporate Insiders

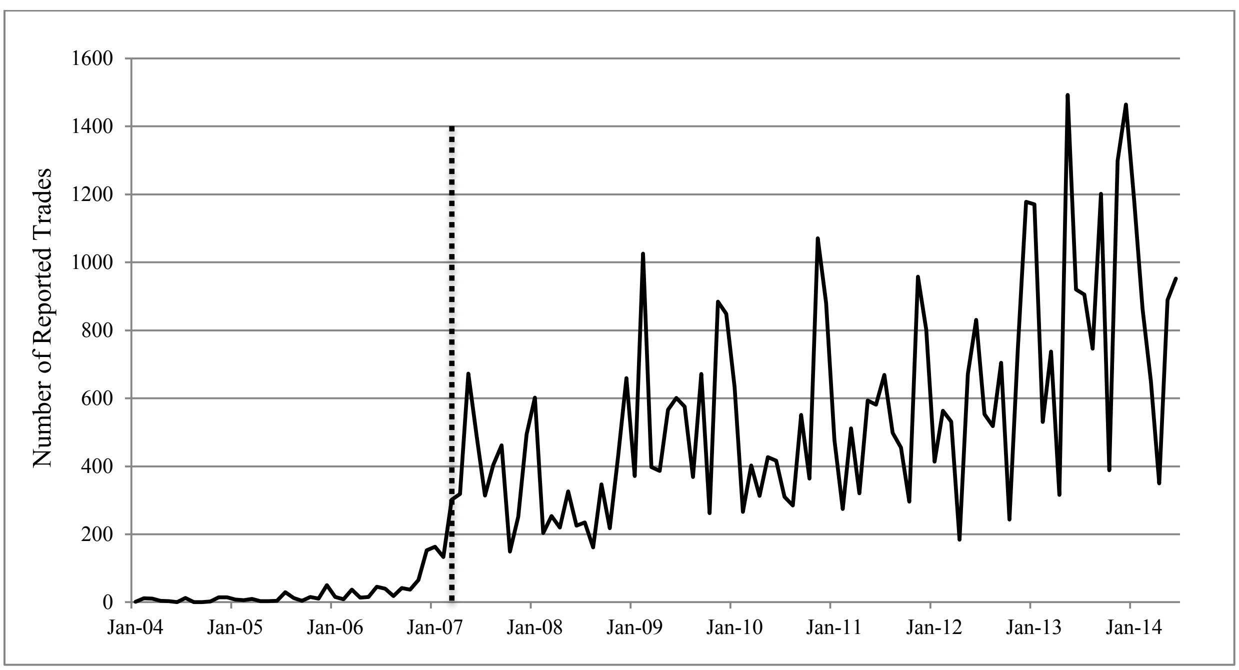
In this section, I study Chinese corporate insiders' trading activities. I discover strong evidence of information asymmetry in the Chinese stock market. Insider buys have strong predictive power for stock returns, whereas insider sells lack such predictive power. Moreover, private information associated with insider trades is more valuable for stocks of state-owned enterprises and for more volatile stocks. A simple insider-mimicking trading strategy produces a significantly positive annual alpha of 14.43% (t=3.08) against the market benchmark.

5.1 Summary Statistics

As discussed in section 3, the law that regulates insider trading was not in effect until April 2007. Figure 2 plots the monthly number of reported insider trades from 2004 to 2014. Before April 2007 (marked by the dashed vertical line), insider reports were voluntary and few in numbers. The sudden increase in reported trades took place right around April 2007. Hence, I use the data after April 2007. The resulting data set records a total of 49,739 trades of insiders from 2,275 publicly listed companies. This data set records three insider types: managers/directors, large shareholding entities, and other relevant individuals.

Table 8 shows the summary statistics on Chinese insiders' trading activities. In terms of number of trades, 74.3% of all insider trades are sells (36,977), about three times as many as insider buys (12,762). In terms of amount of trades, 79.6% are insider sells (RMB715 billion), and only 20.4% are buys (RMB184 billion).

Figure 2: Monthly Number of Reported Insider Trades



The top panel is grouped by insider type. In terms of number of trades, managers and directors account for 71.0% (35,329) of all insider trades. Large shareholding entities account for 26.0% (12,915). Other relevant individuals account for only 3.0% (1,495). In terms of amount of trades, large shareholding entities account for 76.6% (RMB689 billion). Managers and directors account for 18.0% (RMB162 billion). Other relevant individuals account for only 5.4% (RMB48 billion). The bottom panel is grouped by firm size, defined as the stock's average market capitalization at the time of trades in my insider-trade sample. I break the firms into five size groups with cutoffs at 1 billion, 2 billion, 3 billion, and 5 billion. For each group of firms, the insider sells still far exceed the insider buys both in terms of number and amount of trades. The fact that insider sells outnumber and outweigh insider buys in my sample is not surprising, because there are many reasons for insiders to sell their own company stocks, such as liquidity and diversification needs. But the main reason for insiders to buy is to make money.

5.2 Insider Performance

To evaluate the performance of insider trades, I investigate the returns associated with insider buys and insider sells. In other words, I test to see if insider trades have predictive power for stock returns. In particular, I conduct two panel regressions as follows:

$$R_{i,t+1\sim t+k} = a + b * Num\_Buy_{i,t} + s * Num\_Sell_{i,t} + e_{i,t+1\sim t+k} \quad and \tag{2}$$

$$R_{i,t+1\sim t+k} = a + b * (\frac{Amt\_Buy}{Mktcap})_{i,t} + s * (\frac{Amt\_Sell}{Mktcap})_{i,t} + e_{i,t+1\sim t+k}. \tag{3}$$

At the end of each month *t* in my sample period, I group insider buys and insider sells on the stock (*i*) level for the prior six months including month *t*. I then create variables $Num\_Buy_{i,t}$ and $Num\_Sell_{i,t}$ to capture the number of insider buys and insider sells of stock *i* during the prior six months. Similarly, I create variables $(\frac{Amt\_Buy}{Mktcap})_{i,t}$ and $(\frac{Amt\_Sell}{Mktcap})_{i,t}$ to capture the amount of insider buys and insider sells adjusted by stock *i*'s market capitalization at the time of trades during the prior six months. For example, if a total of two insider buys took place for stock *i* during the prior six months up to month *t*, and the two trades respectively represented *x%* and *y%* of stock *i*'s market capitalization at the time of trades, $(\frac{Amt\_Buy}{Mktcap})_{i,t}$=(*x*+*y*)*%*.

I then follow stock *i* for the next *k* months (from month *t+1* to *t*+*k*) and calculate its cumulative return $R_{i,t+1\sim t+k}$. I regress this future return under a panel setting, on the number of buys and sells during the prior six months. Table 9a reports results under this specification. I study different holding periods by choosing *k*=1, 3, 6, 9, and 12. Results based on different holding periods are reported in different rows. Similarly, I regress this future return on the amount of buys and sells adjusted by stock *i*'s market cap at the time of trades during the prior six months. Table 9b reports results under this specification. When I use longer holding periods, I end up with overlapping periods. Therefore, in calculating t-statistics, I use the Newey-West autocorrelation- and heteroscedasticity-consistent covariance estimates (see Newey and West, 1987).

Table 8: Insider Trading Summary Statistics

The table reports the summary statistics of the insider-trade sample. The top panel groups insider trades by insider type, i.e. managers/directors, large shareholding entities, and other relevant individuals. The bottom panel groups trades by firm size, i.e. the stock's average market capitalization at the time of insider trades. The sample period is April 1, 2007 to June 30, 2014. The data cover a total of 49,739 trades of insiders from 2,275 publicly listed firms.

	Grouped by Insider Type			
	Managers /Directors	Large Shareholding Entities	Other Relevant Individuals	Total
Number of Trades				
Buys	10,173	2,252	337	12,762
Sells	25,156	10,663	1,158	36,977
Total	35,329	12,915	1,495	49,739
Amount of Trades (RMB million)				
Buys	21,682	156,064	6,022	183,768
Sells	140,540	532,619	42,144	715,303
Total	162,222	688,683	48,166	899,071

	Grouped by Firm Size					
	<1 billion	1~2 billion	2~3 billion	3~5 billion	>5 billion	Total
Number of Firms	319	638	430	386	502	2,275
Number of Trades						
Buys	878	2,991	2,186	2,093	4,614	12,762
Sells	4,375	11,124	7,774	5,410	8,294	36,977
Total	5,253	14,115	9,960	7,503	12,908	49,739
Amount of Trades (RMB million)						
Buys	2,418	14,122	12,110	21,182	133,937	183,768
Sells	25,032	122,410	110,455	129,541	327,865	715,303
Total	27,449	136,532	122,565	150,723	461,801	899,071

Tables 9a and 9b show strong predictive power for stock returns from insiders' buying activities across all holding periods. Table 9a shows that each additional insider buy during the prior six months on average corresponds to a 0.09%/0.22%/0.38%/0.55%/0.70% increase in a stock's return for the next 1/3/6/9/12 months. All t-statistics are significant at the 1% level. Similarly, Table 9b shows that each additional percent of insider buys per market cap on average corresponds to a 0.31%/0.93%/1.94%/2.73%/3.30% increase in a stock's return for the next 1/3/6/9/12 months. All t-statistics are significant at the 1% level. In unreported results, I also investigate the 18- and 24-month forecasting horizons. The coefficients of both insider-buy measures flatten out beyond the twelve-month period.

In contrast to insider buys, insider sells do not have any significant predictive power for stock returns. The lack of predictive power is observed across all forecasting horizons. For example, for a one-month holding period, Table 9a shows that each additional insider sell on average corresponds to a 0.00% (t=−0.30) change in a stock's return; Table 9b shows that each additional percent of insider sells per market cap on average corresponds to a −0.01% (t=−0.74) change in a stock's return. For a twelve-month holding period, each additional insider sell on average corresponds to a −0.03% (t=−0.28) change in a stock's return; each additional percent of insider sells per market cap on average corresponds to a 0.06% (t=0.40) change in a stock's return. As robustness checks, in unreported results, I calculate the insider-trading measures based on a shorter period, such as the prior one-month and three-month period. In general, results are similar in that insider buys have strong predictive power for stock returns, whereas insider sells lack such predictive power. For the remaining parts of the paper, I define the insider-trade measures on the prior six-month period.

The difference in the predictive power of insider buys and insider sells is not too surprising, because there are a variety of reasons for an insider to sell, but the main reason to buy has to be to make money. An insider may sell his company shares for reasons other than negative private information on the stock, such as liquidity or diversification needs. But an insider would buy his company shares only when he discovers positive information on the stock. The empirical evidence from the Chinese stock market is consistent with the results found in the United States. For example, Lakonishok and Lee (2001) examine insiders' trading activities in the United States from 1975 to 1995 and find that informativeness of insiders' activities comes from purchases, whereas insider selling appears to have no predictive ability.

Next, I investigate insider trades' predictive power in relation to stock characteristics. In particular, I focus on the SOE status and volatility of a stock. I divide my insider-trade sample into subsamples according to these stock characteristics and perform Regressions (2) and (3) on each subsample. I report coefficients and t-statistics related to the two insider-buy measures in Table 10, for the three-, six-, and twelve-month forecasting horizons.

First, I divide the sample by the SOE status of a stock. As discussed in section 2, SOEs constitute a large part of the Chinese stock market. In my insider-trade sample, insiders from SOEs account for 28.5% in terms of number of trades, and 41.1% in terms of trading volume. As the top panel of Table 10 shows, the insider trades from SOEs seem to be able to predict future stock returns better than those from non-SOEs. For a three-month holding period, each additional SOE-insider buy on average corresponds to a 0.33% (t=3.50) change in a stock's return, larger than a 0.15% (t=2.31) change from non-SOE-insider buys. For a six-month holding period, each additional SOE-insider buy on average corresponds to a 0.60% (t=3.25) change in a stock's return, larger than a 0.24% (t=1.77) change from non-SOE-insider buys. For a twelve-month holding period, each additional SOE-insider buy on average corresponds to a 0.93% (t=3.21) change in a stock's return, larger than a 0.57% (t=2.36) change from non-SOE-insider buys. Similarly, the SOE-insiders' outperformance persists when I use the volume-based insider-trade measure, across all forecasting horizons.

Despite its economic reforms in recent years, the Chinese government has been known to exert pervasive political control over the economy. Its various government-sponsored institutions control a large stake of many SOEs. Corporate insiders from these SOEs may possess private information not available to general market participants. Indeed, their trades reflect their information advantage. On average, insiders from SOEs have more valuable private information than insiders from non-SOEs, as measured by their trades' predictive power for stock returns.

Table 9: Panel Regression Results on Insider Trade Performance

$Num\_Buy_{i,t}$ and $Num\_Sell_{i,t}$ correspond to the number of insider buys and insider sells of stock i during the prior six months including month t. Similarly, $(\frac{Amt\_Buy}{Mktcap})_{i,t}$ and $(\frac{Amt\_Sell}{Mktcap})_{i,t}$ correspond to the amount of insider buys and insider sells, divided by stock i's market capitalization at the time of trades during the prior six months. $R_{i,t+1\sim t+k}$ is the cumulative return of stock *i* over *k* months starting from month *t+1*. Table 9a reports results from Regression (2), and Table 9b reports results from Regression (3). The data cover insider trades from April 2007 to June 2013, for a total of 52,605 data points. I base t-statistics on the Newey-West autocorrelation- and heteroscedasticity-consistent standard errors. The number of lags I use in the estimation of Newey-West standard errors are *k-1* months for *k*-month holding period returns, where *k*=1, 3, 6, 9, and 12.

Table 9a: Panel Regression Results using Num_Buy & Num_Sell

Holding Period	Constant	Num_Buy	Num_Sell	Sample Size	R-sq
1m	0.77	0.09	0.00	52,605	0.0%
	(9.98)	(4.26)	(-0.30)		
3m	2.75	0.22	0.00	52,605	0.1%
	(14.35)	(4.13)	(-0.12)		
6m	5.61	0.38	-0.01	52,605	0.1%
	(14.71)	(3.54)	(-0.15)		
9m	8.91	0.55	0.00	52,605	0.1%
	(16.39)	(3.71)	(0.05)		
12m	13.39	0.70	-0.03	52,605	0.1%
	(19.64)	(3.78)	(-0.28)		

Table 9b: Panel Regression Results using (Amt_Buy/Mktcap) & (Amt_Sell/Mktcap)

Holding Period	Constant	Amt_Buy/Mktcap (%)	Amt_Sell/Mktcap (%)	Sample Size	R-sq
1m	0.81	0.31	-0.01	52,605	0.1%
	(11.11)	(5.20)	(-0.74)		
3m	2.75	0.93	0.00	52,605	0.2%
	(15.24)	(6.06)	(-0.02)		
6m	5.57	1.94	-0.02	52,605	0.4%
	(15.30)	(5.93)	(-0.28)		
9m	8.89	2.73	-0.02	52,605	0.4%
	(17.15)	(6.47)	(-0.17)		
12m	13.14	3.30	0.06	52,605	0.5%
	(19.97)	(6.16)	(0.40)		

Standard errors are Newey-West adjusted.

Next, I divide the sample by the idiosyncratic volatility of a stock. I define the idiosyncratic volatility as the volatility of a stock's market-model residuals calculated from the 252 daily returns prior to the insider trade. In particular, I run the market-model regression for each stock i as follows, where t=0 marks the day when the insider trade takes place:

$$R_{it} = a_i + b_i * R_{mt} + \varepsilon_{it}, \quad t = -252, -251, \ldots, -1. \tag{4}$$

R_{it} is stock i's return on day t. R_{mt} is the market return on day t. I define the volatility of ε_{it} as the idiosyncratic volatility of stock i. I sort my insider-trade sample by each traded stock's idiosyncratic volatility, and then divide it equally into the low-, medium-, and high-tertile.

The bottom panel of Table 10 shows the regression results for each volatility tertile. The insider trades in the high-volatility tertile seem to be best at predicting stock returns, and the insider trades in the low-volatility tertile seem to be worst at predicting stock returns. For a twelve-month holding period, each additional insider buy from the high-volatility tertile on average corresponds to a 2.82% (t=5.07) change in a stock's return, compared with a 1.09% (t=2.47) change from the medium-volatility tertile, and a −0.01% (t=−0.05) change from the low-volatility tertile. This outperformance by the higher volatility tertile is robust for all forecasting horizons (three-, six- and twelve-month). Similarly, the outperformance results persist when I use the volume-based insider-trade measure. The predictive power of an insider buy on the stock's future returns seems to be positively correlated with the stock's volatility. In unreported results, I define the total volatility of a stock as the standard deviation of the 252 daily stock returns prior to the insider trade. I find similar results when using the total volatility instead of the idiosyncratic volatility.

High volatility in a stock's returns reflects a great amount of uncertainty of investor opinions about the stock. That is, the degree of information asymmetry may be high. Inside information under these circumstances may be more valuable. I find results that are consistent with this intuition. Insider trades from companies with higher stock-return volatility outperform those from companies with lower stock-return volatility, as measured by their trades' predictive power for stock returns.

In unreported results, I also divide the sample by the size of a stock. At the end of June each year, I sort stocks by their market capitalization into tertiles. I then compare the predictive power of each size tertile's insider trades. Lakonishok and Lee (2001) find that in the U.S. data, insider trading is a stronger indicator in small-cap stocks, a segment of the market that is often perceived to be less efficient. However, I don't observe this small-cap effect in my data. In China, SOEs tend to be large-cap stocks. As earlier results show, insiders from SOEs possess more valuable private information than insiders from non-SOEs. This SOE-effect negates the small-cap effect, which may explain the absence of a stronger indicator in small-cap stocks in the Chinese data.

5.3 Insider-Mimicking Strategy

Motivated by the regression results in the last section, I create a trading strategy that mimics the insider trades. Because insider buys have significant predictive power for stock returns, whereas insider sells lack such predictive power, I choose to follow the insider buys only in constructing this mimicking strategy. In particular, at the end of each month (starting from April 2007), I invest one unit of capital equally among all insider buys that took place during the past

Table 10: Panel Regression Results on Subsamples of Insider Trades

The table reports the coefficients on $Num\_Buy_{i,t}$ in Regression (2) and $(\frac{Amt\_Buy}{Mktcap})_{i,t}$ in Regression (3), their t-statistics (in parentheses), and the sample size of each subsample. I calculate the insider-trade measures based on the prior six-month period. The first panel divides by the SOE status of a stock. Top subpanel ('Yes') reports results for the trades of insiders from SOEs. Bottom subpanel ('No') reports results for the trades of insiders from non-SOEs. The second panel divides by the idiosyncratic volatility of a stock, defined as the volatility of a stock's market-model residuals from the prior 252 daily returns. The three subpanels report results for the insider trades from each idiosyncratic-volatility tertile, respectively. The data cover insider trades from April 2007 to June 2013. I base t-statistics on the Newey-West autocorrelation- and heteroscedasticity-consistent standard errors. The number of lags I use in the estimation of Newey-West standard errors are *k-1* months for *k*-month holding period returns, where *k*=3, 6, and 12.

		Num_Buy			Amt_Buy/Mktcap (%)			Sample Size
		3-month	6-month	12-month	3-month	6-month	12-month	
SOE Status	Yes	0.33	0.60	0.93	1.32	2.58	3.83	18,981
		(3.50)	(3.25)	(3.21)	(4.82)	(4.59)	(3.74)	
	No	0.15	0.24	0.57	0.72	1.62	3.10	33,624
		(2.31)	(1.77)	(2.36)	(3.83)	(3.94)	(5.08)	
Volatility (Idiosyncratic)	Low	-0.09	-0.19	-0.01	0.06	0.11	1.17	19,664
		(-1.99)	(-2.42)	(-0.05)	(0.31)	(0.29)	(1.54)	
	Medium	0.39	0.51	1.09	1.08	1.87	3.18	19,195
		(3.28)	(2.18)	(2.47)	(4.36)	(3.94)	(3.59)	
	High	0.87	1.95	2.82	1.68	3.93	6.03	20,298
		(5.33)	(5.55)	(5.07)	(5.30)	(5.14)	(5.28)	

Standard errors are Newey-West adjusted.

month. I hold these stocks in my portfolio for the next twelve months and then sell them. I update my portfolio at the end of each month following this strategy. Due to the twelve-month holding period of the stock positions, the portfolio takes twelve months to fully form. As a result, I conduct my analysis based on the portfolio returns from April 2008 to June 2014.

By law, Chinese insiders are not allowed to make more than two round-trip transactions a year. That is, they cannot sell (buy) within the six months since their last buy (sell). Because they are legally prohibited from trading on any short-term information, it is reasonable to expect insider buys to profit from a longer holding period. Thus, a twelve-month holding period is sensible for the insider-mimicking strategy.

To evaluate the performance of the insider-mimicking portfolio, I run Regression (5) below, where $R_{insider,t}$ is the insider-mimicking portfolio's return for month t, R_{ft} is the risk-free rate for month t, and R_{mt} is the market return for month t:

$$R_{insider,t} - R_{ft} = \alpha_{insider} + b_{insider}\left(R_{mt} - R_{ft}\right) + e_{insider,t}. \quad (5)$$

I report the regression results in Table 11. I first report the results based on an insider-mimicking strategy constructed from trades of all types of insiders. This insider-mimicking strategy produces a significantly positive annualized α of 14.43% (t=3.08). In aggregate, insiders clearly outperform the market. From April 2008 to June 2014, 1 unit of initial investment in the insider-mimicking portfolio has grown to 1.70, whereas 1 unit of initial investment in the market portfolio has declined to 0.79.

Next, I divide the insider-trade sample into two subsamples by insider type: manager/directors and other relevant individuals, and large shareholding entities. I group the managers/directors and other relevant individuals together because the latter type represents relatively few trades. Moreover, other relevant individuals have special relationships with company managers and directors, so they are likely to have access to similar inside information. Insider-mimicking strategies constructed from both subsamples significantly outperform the market. The annualized α for managers/directors and other relevant individuals is 14.74% (t=2.99). The annualized α for large shareholding entities is 15.93% (t=3.26).

It is reasonable to assume that corporate insiders have better information than the average market participant. For example, managers and directors run a company and have access to inside information that is not shared with general market participants. Other relevant individuals may have access to such inside information through their special relationships with managers and directors. Large shareholders may be able to extract such inside information from their regular communications with the company. As a result, corporate insiders benefit greatly from their superior information by trading their own company stocks.

The substantial outperformance of the insider-mimicking strategy echoes the significant predictive power of insider buys. Chinese corporate insiders seem to possess valuable private information that helps them beat the market. Recall that Chinese stock funds also outperform the

Table 11: Intercepts and Slopes in Regression (5) for the Insider-Mimicking Portfolio

The table shows the annualized intercepts (12*α) and t-statistics (in parentheses) for Regression (5) estimated on returns of the insider-mimicking portfolio. The table also shows the slope for the market factor, whose t-statistic tests whether b is different from 1 instead of 0. The three panels respectively show results based on an insider-mimicking strategy constructed from trades of (1) all insiders, (2) managers/directors and other relevant individuals, and (3) large shareholding entities. The sample period is April 2008 to June 2014, a total of 75 months.

	12*α	b	R-sq	Sample Size
All Insiders	14.43	1.13	0.89	75
	(3.08)	(2.83)		
Managers/Directors & Other Relevant Individuals	14.74	1.14	0.88	75
	(2.99)	(2.86)		
Large Shareholding Entities	15.93	1.09	0.87	75
	(3.26)	(1.83)		

market portfolio. For example, their VW gross annualized α is 6.50% (t=2.43). In the next section, I investigate the correlation patterns between these two groups of active investors.

6 Correlations between Corporate Insiders and Stock Funds

In this section, I study the correlations between corporate insiders and stock funds. I first show correlation evidence between the return series of stock funds' trading portfolio and the insider-mimicking portfolio (for the rest of my paper, I refer to the insider-mimicking portfolio as the one constructed from the whole insider-trade sample in section 5.3). I then show that stock funds that trade more in the same direction as insiders deliver better performance. Finally, I offer more correlation evidence between stock funds' large holdings and the insider-mimicking portfolio. Funds with a higher concentration in such holdings outperform those with a lower concentration.

6.1 Return Correlation

To track the insiders' performance, I use the insider-mimicking portfolio constructed from the whole insider-trade sample. This portfolio consists only of insider buys because they contain valuable private information. To make proper comparisons, I construct a trading portfolio for stock funds based on their buying activities.

6.1.1 Aggregate-level Evidence

At the end of each semiannual period, I aggregate all stock funds' holdings to form a big portfolio. Equivalently, I can think of it as a big fund that holds the aggregate portfolio of all stock funds. I track this big fund's trading activities at the semiannual frequency. In particular, I compare this fund's stock holdings of adjacent periods and back out the stocks it has bought and sold during the past six months. More specifically, I measure its holding of a stock by the holding's value divided by the stock's market capitalization. If this measure increases (or decreases) from last period to this period, I consider it a buy (or a sell).

I focus on the buys to construct the stock funds' aggregate trading portfolio. After I form the trading portfolio at the end of each semiannual period, I follow it for the next six months and calculate the value-weighted buy-and-hold monthly portfolio returns. I then paste together the six-month return series to form a longer monthly return series $R_{mf,t}$.

For the insider-mimicking portfolio, I first run the FF3F+MOM performance evaluation regression, and then define an outperformance variable $outperf_{insider}$:

$$R_{insider,t} - R_{ft} = \alpha_{insider} + b_{insider}\left(R_{mt} - R_{ft}\right) + s_{insider}SMB_t + h_{insider}HML_t + m_{insider}MOM_t + e_{insider,t} \quad and \tag{6}$$

$$outperf_{insider,t} = \alpha_{insider} + e_{insider,t}. \tag{7}$$

$outperf_{insider,t}$ is the monthly outperformance series for the insider-mimicking strategy. $\alpha_{insider}$ and $e_{insider,t}$ are the intercept and residuals of Regression (6). Because $e_{insider,t}$ has mean zero, $outperf_{insider,t}$ should have mean $\alpha_{insider}$, which is the monthly alpha of the insider-mimicking portfolio. The monthly outperformance series helps capture the time-series variation of the insider-mimicking portfolio's performance, after adjusting for the market, size, value, and momentum factors.

Next, for the stock funds' aggregate trading portfolio, I also run the FF3F+MOM performance evaluation regression. I then add the insider factor $outperf_{insider,t}$ to this regression:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}\left(R_{mt} - R_{ft}\right) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + e_{mf,t} \qquad (8)$$

and

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}\left(R_{mt} - R_{ft}\right) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t$$
$$+c_{mf} * outperf_{insider,t} + e_{mf,t}. \qquad (9)$$

Table 12 shows the performance evaluation results of the stock funds' trading portfolio. The top panel reports results under the FF3F+MOM model. I observe a marginally significant monthly α of 0.56% (t=1.63). This result is consistent with the aggregate outperformance of Chinese stock funds. The bottom panel reports results for Regression (9), where the insider factor is included as an additional regressor. By OLS mechanics, the insider factor is orthogonal to the market, size, value, and momentum factors. I observe a significant loading of 0.68 (t=5.32) on the insider factor. The monthly α of the stock funds' trading portfolio is reduced to 0.29 (t=0.96) after incorporating this new factor. Adding the insider factor accounts for a 49.2% drop in the monthly α from 0.56 to 0.29. R-square of the regression also increases from 92.1% to 94.4%.

This evidence shows that in aggregate, corporate insiders and stock funds are significantly correlated in their performance. The insider factor $outperf_{insider,t}$ serves as a proxy for insiders' private information. One interpretation of this result is that stock funds have similar private information that helps them beat the passive benchmarks. In other words, there is an important overlap between the privation information sets of stock funds and corporate insiders in China. In Appendix E, I present similar correlation results when I use the CAPM and FF3F models instead of the FF3F+MOM model in the above analysis.

Table 12: Intercepts and Slopes in Regressions (8) and (9)

The table shows the monthly intercepts α and t-statistics (in parentheses) for Regressions (8) and (9) estimated on returns of the mutual funds' aggregate trading portfolio. The table also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. Top panel shows results for Regression (8). Bottom panel reports results for Regression (9). The sample period is April 2008 to June 2014, a total of 75 months.

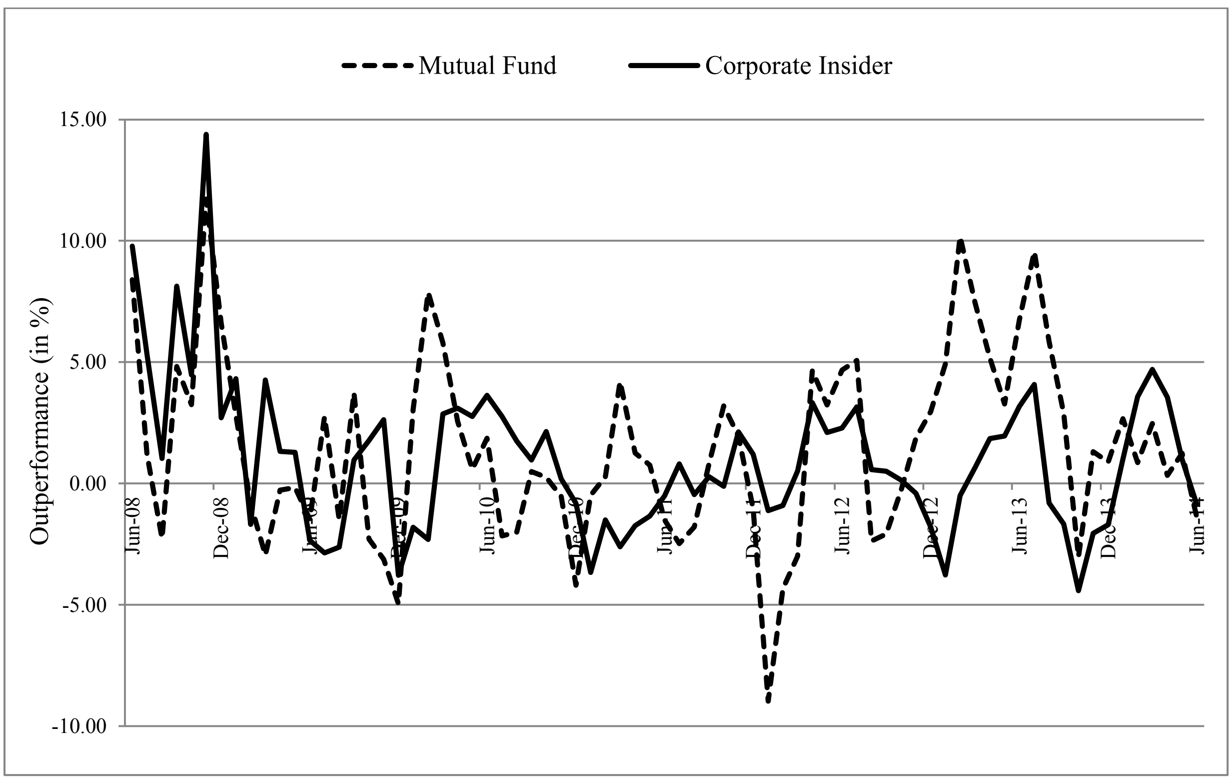
Mutual Fund Trading Portfolio	α	b	s	h	m	c	R-sq.
FF3F+MOM	0.56	1.15	0.01	-0.33	0.53		92.1%
	(1.63)	(3.53)	(0.10)	(-2.49)	(4.96)		
FF3F+MOM+Insider	0.29	1.15	0.01	-0.33	0.53	0.68	94.4%
	(0.96)	(4.16)	(0.11)	(-2.94)	(5.85)	(5.32)	

From Regression (8), I now define the outperformance series for stock mutual funds:

$$outperf_{mf,t} = \alpha_{mf} + e_{mf,t}. \tag{10}$$

α_{mf} and $e_{mf,t}$ are the intercept and residuals of Regression (8). Similar to $outperf_{insider,t}$, $outperf_{mf,t}$ captures the time-series variation of the mutual funds' trading portfolio's performance, after adjusting for the market, size, value, and momentum benchmarks. The correlation between $outperf_{insider,t}$ and $outperf_{mf,t}$ is 0.54 with a t-statistic of 5.48. This significantly positive correlation suggests that stock funds and corporate insiders tend to win and lose to the passive benchmarks at the same time. Figure 3 plots the three-month moving average of both outperformance series. They have a correlation of 0.41 with a t-statistic of 3.82 (standard errors are Newey-West adjusted with two lags).

Figure 3: Outperformance Series (3-Month Moving Average)



So far, I have accounted for common risk factors such as market, size, value, and momentum. But I still cannot rule out the case that corporate insiders and stock funds are both loading onto some other omitted common risk factor. To address this concern, in Appendix F, I replace the stock funds' trading portfolio with randomly simulated placebo portfolios and repeat the analysis in this subsection. I show that the placebo portfolios on average do not outperform the passive benchmarks. Moreover, the placebo portfolios on average show no statistically significant correlation with the insider factor. The placebo test offers additional support to my conjecture that Chinese stock funds and corporate insiders have similar private information, which is not accounted for by common risk factors.

6.1.2 Fund-level Evidence

I now turn to study the fund-level correlations with the insider factor $outperf_{insider,t}$. First, for each fund i in my sample, I construct its trading portfolio from its semiannual holdings data. I then follow this portfolio for the next six months and calculate the value-weighted buy-and-hold monthly portfolio returns. Next, I paste together the fund's six-month return series to form a longer monthly return series R_{it}. Basically, I apply the same methodology as in section 6.1.1, but to each fund i in my sample instead of the aggregate fund portfolio.

To study the correlations between individual funds' trading portfolios and the insider-mimicking portfolio, I run the following regression for each fund i in my sample:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + b_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t \\ + m_i MOM_t + c_i * outperf_{insider,t} + e_{it}. \end{aligned} \tag{11}$$

Table 13 exhibits the percentile distribution for coefficient c_i, its t-statistic and the fraction of explained variance due to the insider factor $outperf_{insider,t}$. Specifically, this fraction is defined as $({c_i}^2 * {\sigma_{outperf_{insider,t}}}^2)/[var(R_{it} - R_{ft}) - var(e_{it})]$. The average fund loads significantly (c=0.91, t=2.00) on the insider factor. The fraction of explained variance due to the insider factor has a median/mean value of 3.40%/5.86%, with a fairly wide range from 0.00% to 51.99%. Consistent with the aggregate-level correlation evidence, I observe that cross-sectionally, about half of the funds correlate significantly with the insider-mimicking portfolio.

Table 13: Summary Statistics for Correlation Coefficient in Regression (11)

For a given fund i, I perform Regression (11) to obtain its coefficient c_i on the $outperf_{insider,t}$ term. Defined in equation (7), $outperf_{insider,t}$ is a monthly time series of the insider-mimicking strategy's outperformance against benchmarks including market, size, value, and momentum factors. The table shows the distribution summary statistics of coefficient c_i, its t-statistics, and the fraction of explained variance due to the insider factor $outperf_{insider,t}$. I require the funds to report at least two years of holdings data to be considered in this exercise. The sample includes a total of 271 funds.

Distribution	c	*t(c)*	fraction_insider
min	-1.20	-1.56	0.00
10%	0.11	0.23	0.28
25%	0.44	1.05	1.30
50%	0.77	1.90	3.40
mean	0.91	2.00	5.86
75%	1.31	2.87	8.08
90%	1.94	3.91	14.08
max	3.58	6.19	51.99

6.2 Trading Correlation

In this section, I investigate the trading activities of stock funds and corporate insiders. I show that stock mutual funds that exhibit more correlated trading patterns with corporate insiders deliver better performance.

Stock mutual funds report their entire stock holdings every six months. As a result, I observe what a fund i has traded during a six-month period t. If a fund's holding in a stock increases/decreases during the period, it is considered a buy/sell. If a fund's holding in a stock does not change during the period, it is considered no action.

For the same six-month period t, I generate the list of stocks that have had at least one insider buy during the period. As discussed in section 5, insider buys are much more likely than insider sells to contain valuable private information. Therefore, I focus on the stocks with at least one insider buy and ignore the insider-sell information. I call this stock sample the insider-buy sample for period t.

Next, for a given fund i and period t, I count fund i's overlapped stocks with the insider-buy sample for the period. I impose a threshold of 15 for a fund to be considered in this exercise. I then create a variable equal to the fraction of fund i's overlapped stocks it has bought in period t. I call this variable $trade\_corr_{i,t}$, which is designed to reflect the correlation in trading patterns between fund i and corporate insiders during period t. For example, if during period t, fund i has 25 overlapped stocks with the insider-buy sample, and it has increased its holdings in 20 out of these 25 stocks, $trade\_corr_{i,t}$=80%.

My sample for this exercise starts with the six-month period July2007-Dec2007 and ends with July2013-Dec2013. For each six-month period t, I create a fund sample following the procedure described above. I then sort funds into quartile portfolios by $trade\_corr_{i,t}$. Quartile 1 funds have the lowest $trade\_corr_{i,t}$. Quartile 4 funds have the highest $trade\_corr_{i,t}$. I then calculate the monthly equal-weighted average gross returns of each quartile portfolio during period t. Next, for each quartile portfolio, I paste the monthly return series to form a longer return series from July 2007 to December 2013, for a total of 78 months. I also construct the returns of a long-short portfolio by subtracting Quartile 1 returns from Quartile 4 returns. I then evaluate each portfolio's performance by the CAMP, FF3F, and FF3F+MOM models.

Table 14 first reports the time-series average of $trade\_corr_{i,t}$ for each quartile portfolio. The trading-correlation measure exhibits a large cross-sectional variation. The bottom-quartile funds on average buy 29% of the stocks that insiders are buying. The top-quartile funds on average buy 62% of the stocks that insiders are buying. Next, Table 14 summarizes the performance results for the quartile portfolios and the long-short $(4-1)$ portfolio. An increasing trend is present in the quartile performance. The more correlated a fund's trading is with the insiders, the better performance it delivers. Under the CAMP, FF3F, and FF3F+MOM models, the long-short $(4-1)$ fund portfolio produces a significantly positive monthly α of 0.20% (t=2.62), 0.19% (t=2.31), and 0.18% (t=2.26) respectively.

This trading-correlation evidence corroborates the return-correlation evidence discovered in section 6.1. The return-correlation evidence suggests some intersection between the private information sets of stock funds and corporate insiders. As a result, these two groups of active investors tend to win or lose against the passive benchmarks at the same time. The trading-correlation evidence confirms the valuable private information associated with insider buys. Furthermore, funds that trade more in the same direction as insiders seem to reap larger profits from such private information. If we consider the trading correlation a proxy for access to inside

Table 14: Performance of Quartile Fund Cohorts Sorted by Trading Correlation with Insiders

For a given semiannual period *t* and a given fund *i*, I calculate the fund's trading correlation with insiders as $trade\_corr_{i,t}$. To calculate $trade\_corr_{i,t}$, I compare the overlapped stocks between fund *i* and the insiders during period *t,* defined as those stocks that are bought by at least one insider and show up in the fund's holdings. I define $trade\_corr_{i,t}$ as the fraction of these overlapped stocks that fund *i* has bought during period *t*.
For each semiannual period, I sort funds into quartile cohorts by the $trade\_corr_{i,t}$ measure. I follow these quartile cohorts for these six months and calculate each quartile's monthly gross return series. Then I paste the six-month return series together to create a longer return series for each quartile cohort. Quartile 1 funds have the lowest $trade\_corr_{i,t}$. Quartile 4 funds have the highest $trade\_corr_{i,t}$. I run the CAPM, FF3F, and FF3F+MOM versions of Regression (1) to obtain a monthly α for each quartile cohort, as well as a long-short portfolio constructed from subtracting Quartile 1 returns from Quartile 4 returns. The table reports, for each quartile portfolio, the average $trade\_corr_{i,t}$, and the regression statistics on α for the CAPM, FF3F, and FF3F+MOM models. The data cover 418 funds from July 2007 to December 2013.

	trade_corr	CAPM		FF3F		FF3F+MOM	
		α	t(α)	α	t(α)	α	t(α)
Quartile 1 (bottom)	0.29	0.23	(1.07)	0.46	(2.59)	0.43	(2.65)
Quartile 2	0.41	0.33	(1.45)	0.52	(2.72)	0.50	(2.68)
Quartile 3	0.49	0.29	(1.28)	0.54	(2.79)	0.51	(2.88)
Quartile 4 (top)	0.62	0.43	(1.91)	0.65	(3.42)	0.62	(3.58)
4-1	0.33	0.20	(2.62)	0.19	(2.31)	0.18	(2.26)

information, funds with better access to inside information clearly outperform those with worse access to inside information.

The fact that a fund trades in the same direction as insiders does not necessarily imply trading on material inside information. The fund's trading decisions could be derived from research on public information. I am merely claiming that more correlated trading patterns point to a higher likelihood of private information shared by stock funds and corporate insiders. Due to the limitation of my data, I cannot make a further claim on how fund managers obtain such private information.

6.3 Qualified Holdings

Conceivably, a fund is more likely to gain access to insiders' private information if it is a large shareholder of the company. For example, large shareholders are more likely to have regular communications with corporate management. Through meetings, phone calls, and other forms of communication, large shareholders of a company can obtain private information. To capture this notion, I create a variable *mfmkt%* defined as the value of a mutual fund's holding of a stock divided by the stock's market capitalization. Furthermore, I define a fund's qualified holdings as those stock holdings with *mfmkt%* exceeding a given threshold. In other words, qualified holdings reflect large shareholding status. If the threshold on *mfmkt%* is 1.00% and a fund holds more than 1.00% of a company's shares (a qualified holding), the fund is considered a large shareholder of the company.

Note that my definition of large shareholders in this fund-holding context is based on the threshold I choose for *mfmkt%* (0.50%, 1.00%, 1.50%, or 2.00%), whereas the definition of the insider type "large shareholding entities" requires a minimum of 5.00% stake. My definition of large shareholders in this fund-holding context is less strict. Moreover, mutual funds are exempt from the insider-reporting requirement even if they hold more than 5.00% of shares, as long as they acquired the shares without the purpose of changing or influencing the control of the company. Hence, little overlap exists between my insider-trade sample and my qualified-holding sample, which alleviates the concern of a mechanical relationship between the insider-mimicking portfolio and the qualified-holding portfolio. Next, I investigate the correlation between the insider-mimicking portfolio and the stock funds' aggregate qualified-holding portfolio.

6.3.1 Aggregate-level Evidence

I construct a portfolio of stock funds' aggregate qualified holdings. Specifically, from each fund's semiannual holdings, I keep the stocks with *mfmkt%* exceeding a given threshold (0.50%, 1.00%, 1.50%, or 2.00%). I then aggregate these qualified stock holdings across all funds to form a single portfolio that I buy and hold for the next six months. I update this portfolio of aggregate qualified holdings every six months. I then paste the six-month return series together to form a longer monthly return series $R_{holding,t}$. I evaluate this portfolio's performance under the FF3F+MOM model and calculate its outperformance series:

$$R_{holding,t} - R_{ft} = \alpha_{holding} + b_{holding}(R_{mt} - R_{ft}) + s_{holding}SMB_t + h_{holding}HML_t + m_{holding}MOM_t + e_{holding,t} \quad and \quad (12)$$

$$outperf_{holding,t} = \alpha_{holding} + e_{holding,t}. \quad (13)$$

Next I study the correlation between this portfolio's performance and the insider-mimicking portfolio's performance. I use the same definition for $outperf_{insider,t}$ as in equation (7). I perform the following regression to study their correlation at different *mfmkt%* thresholds:

$$outperf_{holding,t} = a + b * outperf_{insider,t} + e_t. \quad (14)$$

Table 15 reports results for Regression (14). When no threshold is imposed (*mfmkt%*=0.00%), the correlation (0.16, t=1.42) is not significant between the stock funds' aggregate holdings and the insider-mimicking portfolio. The R-square is low at 2.7%. However, after I filter out the unqualified holdings by imposing a 0.50% threshold on *mfmkt%*, the correlation becomes statistically significant at 0.33 (t=2.97), with R-square of 10.8%. As I increase the *mfmkt%* threshold to 2.00%, the correlation increases to 0.39 (t=3.60), with R-square of 15.1%. Whereas the stock funds' aggregate holdings do not significantly correlate with the insider portfolio, once I filter out the unqualified holdings and focus on the qualified holdings, I discover a statistically

Table 15: Correlation between Qualified-Holding Portfolio and Insider-Mimicking Portfolio

The table reports results from Regression (14), including coefficient b, its t-statistic (in parentheses), the correlation between $outperf_{holding,t}$ and $outperf_{insider,t}$, and R-square of the regression. The sample period is April 2008 to June 2014.

mfmkt%	*b*	Correlation	R-sq
0.00%	0.09 (1.42)	0.16	2.7%
0.50%	0.23 (2.97)	0.33	10.8%
1.00%	0.28 (3.56)	0.38	14.8%
1.50%	0.27 (3.34)	0.36	13.2%
2.00%	0.29 (3.60)	0.39	15.1%

significant correlation. These results are consistent with the intuition that large shareholders may have better access to insiders' private information.

6.3.2 Outperformance of Qualified Holdings

Furthermore, I study the performance of qualified holdings and non-qualified holdings around earnings announcements. For each stock in the semiannually updated aggregate qualified--holding portfolio, I study its performance around the next two quarterly earnings announcements. In particular, I focus on a 21-trading-day window (t–10, t+10) around the earnings announcement at day t. I choose this time window for two reasons: (1) due to rampant insider trading, material inside information tends to leak before earnings announcements, so a 10-day window before the announcement helps to incorporate this effect; (2) due to a less efficient market, information may take longer to be fully processed, so a 10-day window after the announcement is reasonable to fully capture the information. I calculate the stock's compound return during this time window. I call it the stock's earnings-period return, which is a monthly return because a calendar month contains about 21 trading days.

Next, I calculate an earnings-period return for each stock and earnings announcement. Furthermore, I calculate a value-weighted earnings-period return for the qualified-holding-portfolio, by weighing each stock's earnings-period return by its holding's RMB value at t–10, where t is the corresponding earnings announcement date. I perform the same calculation for non-qualified holdings. I then compare the performance of qualified holdings and non-qualified holdings around earnings announcements. The top panel of Table 16 reports the results. Across various specifications, the qualified holdings significantly outperform the non-qualified holdings around earnings announcements. For example, given a lower (upper) bound of *mfmkt%*=1.00% (0.10%) for the qualified (non-qualified) holdings, the value-weighted average earnings-period return is 2.60% (0.35%) per month for the qualified (non-qualified) holdings. The qualified

Table 16: Performance of Qualified Holdings and Non-Qualified Holdings

The table compares the performance of qualified holdings and non-qualified holdings. The top panel compares their performance during earnings periods. The bottom panel compares their performance during non-earnings periods. A stock's earnings period is defined as the month (21 trading days) surrounding the stock's quarterly earnings announcement date *t*: (*t*–10, *t*+10). A stock's non-earnings period is defined as the month before its earnings period and the month after its earnings period: (*t*–31, *t*–11) & (*t*+11, *t*+31). For qualified holdings, I use *mfmkt%* lower bounds of 0.50%, 1.00%, 1.50%, and 2.00%. For non-qualified holdings, I use *mfmkt%* upper bounds of 0.50%, 0.10%, and 0.05%. For each *mfmkt%* threshold combination, I report the value-weighted average monthly returns of qualified-holdings and non-qualified holdings, their average monthly return difference, and its t-statistics. Returns are reported in %.

Table 16a: Earnings-Period Returns of Qualified Holdings vs. Non-Qualified Holdings

Non-Qualified Holdings *mfmkt%*	Qualified Holdings *mfmkt%* 0.50%	1.00%	1.50%	2.00%
0.50%	2.46	2.60	2.62	2.76
	1.22	1.22	1.22	1.22
	1.25	1.38	1.40	1.54
	(1.89)	(2.08)	(2.10)	(2.29)
0.10%	2.46	2.60	2.62	2.76
	0.35	0.35	0.35	0.35
	2.12	2.25	2.27	2.41
	(2.57)	(2.71)	(2.72)	(2.89)
0.05%	2.46	2.60	2.62	2.76
	0.11	0.11	0.11	0.11
	2.36	2.49	2.51	2.65
	(2.66)	(2.79)	(2.79)	(2.95)

Table 16b: Non-Earnings-Period Returns of Qualified Holdings vs. Non-Qualified Holdings

Non-Qualified Holdings *mfmkt%*	Qualified Holdings *mfmkt%* 0.50%	1.00%	1.50%	2.00%
0.50%	1.56	1.53	1.34	1.28
	1.23	1.23	1.23	1.23
	0.33	0.31	0.12	0.06
	(0.77)	(0.70)	(0.27)	(0.12)
0.10%	1.56	1.53	1.34	1.28
	0.77	0.77	0.77	0.77
	0.79	0.76	0.58	0.51
	(1.43)	(1.37)	(1.03)	(0.90)
0.05%	1.56	1.53	1.34	1.28
	0.65	0.65	0.65	0.65
	0.91	0.88	0.70	0.63
	(1.52)	(1.47)	(1.15)	(1.03)

holdings outperform the non-qualified holdings by 2.25% for the 21-trading-day window, with a t-statistic of 2.71.

This result that qualified holdings outperform non-qualified holdings is consistent with the intuition that qualified holdings are more likely informed. Around earnings announcements, the outperformance ranges between 1.25% and 2.65% under various specifications. As an interesting comparison, I also calculate the returns of the qualified and non-qualified holdings during non-earnings periods, which are defined to be (t–31, t–11) and (t+11, t+31) around a given earnings announcement date t. In other words, a stock's non-earnings period is defined as the month before its earnings period and the month after its earnings period. I report the comparison results in the bottom panel of Table 16. The outperformance of qualified holdings over non-qualified holdings still persists, though with much weaker and insignificant t-statistics. During periods away from earnings announcements, the outperformance ranges between 0.06% and 0.91% under various specifications. This suggests that the better information associated with qualified holdings are more concentrated around earnings announcements.

6.3.3 Fund-level Evidence

Based on last two subsection's results, I make an assumption that large shareholders of a company are more likely to have access to insiders' private information than small shareholders. In my notation, a stock fund is a large shareholder if it has a qualified holding in the company's stock. My assumption then implies that within a fund's portfolio, those qualified holdings are more likely associated with insiders' private information. From section 5, I have already shown that insiders' private information leads to superior performance. Therefore, I test the following hypothesis:

> *Funds with a higher average concentration in qualified holdings outperform funds with a lower average concentration in qualified holdings.*

I construct a qualified-holding-concentration variable that serves as a proxy for the amount of inside information a fund accesses. For a given fund and reporting period, the qualified-holding concentration is defined as the weight of a fund's portfolio that is invested in qualified holdings, adjusted by the qualified stocks' weights in the market portfolio.

A simple example will illustrate the calculation for the qualified-holding concentration. The *mfmkt%* threshold is set at 1.00%. A fund holds N qualified stocks with *mfmkt%*>1.00% in a given period. The fund's holdings in these N stocks account for $x_1\%, x_2\%, \dots, x_N\%$ of its stock portfolio. The market capitalization of these N stocks account for $y_1\%, y_2\%, \dots, y_N\%$ of the market portfolio. Then the qualified-holding concentration of the fund for the given period is defined as $\sum_{n=1}^{N}(x_n\% - y_n\%)$. If N is zero (i.e. no qualified stock), I assign a value of zero to the fund's qualified-holding concentration for the period.

The adjustment for the qualified stocks' market-portfolio weights is important. As a thought experiment, think of a large index fund that holds 5.00% of the market. That is, this fund holds 5.00% of each stock's market capitalization. If no adjustment is made, given a *mfmkt%* threshold of 1.00%, this fund's qualified-holding concentration will be 100%. This is not sensible because an index fund unlikely accesses any inside information: it never tilts away from the market portfolio's weights. Now if I adjust by the market portfolio's weights, the qualified-holding concentration will correctly become zero for the index fund.

I define each fund's average qualified-holding concentration as the equal-weighted average of its qualified-holding concentrations across all available periods. The qualified-holding concentration captures a given fund's asset concentration in qualified holdings, adjusted by those qualified stocks' weights in the market portfolio. It measures the fund's deviation from the market portfolio on those qualified holdings. A fund would have a high qualified-holding concentration if it invests a large portion of its portfolio in qualified holdings, and it overweighs those stocks relative to the market portfolio.

I then perform a cross-sectional test to see if funds with a higher average concentration in qualified holdings outperform funds with a lower average concentration in qualified holdings. I first run the FF3F+MOM regression for each fund *i* and record the t-statistics of α. I focus on t(α), rather than estimates of α, to control for differences in precision due to differences in residual variance and in the number of months funds are available in my sample:

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + m_i MOM_t + e_{it}. \qquad (15)$$

I then regress these $t(\alpha)_i$ on the funds' average qualified-holding concentrations (HC_i):

$$t(\alpha)_i \; = \; constant + \gamma * HC_i + \varepsilon_i. \qquad (16)$$

I calculate the qualified-holding concentration at two reporting frequencies: quarterly and semiannual. Stock mutual funds report their top-10 holdings at the quarterly frequency and their entire holdings at the semiannual frequency. On average, a fund's top-10 holdings accounts for 49.8% of the fund's stock portfolio. I present quarterly and semiannual results in Tables 16a and 16b respectively.

Table 17a first shows the results when I impose no threshold on *mfmkt%*. For quarterly data, this condition corresponds to top-10 holdings, which may not be qualified holdings. The loading on the top-10-holding concentration (γ=−0.59, t=−0.79) implies that the relationship between stock funds' performance and their top-10-holding concentrations is statistically non-significant. More interestingly, when I impose a 0.50% threshold on *mfmkt%*, results become statistically significant: γ=4.92 (t=9.37). R-square increases substantially from 0.2% (top-10) to 18.6%. As I increase the *mfmkt%* threshold, I observe similar results that funds' qualified-holding concentrations correlate significantly with funds' performance.

Table 17b shows similar results from semiannual holdings data. The first row reports results for the top-10-holding concentration. The loading γ=0.29 (t=0.41) implies that the relationship between stock funds' performance and their top-10-holding concentrations is statistically non-significant. When I impose a 0.50% threshold on *mfmkt%*, results become statistically significant: γ=3.31 (t=12.02). R-square increases substantially from 0.0% (top-10) to 27.4%. As I increase the *mfmkt%* threshold, I observe similar results that funds' qualified-holding concentrations correlate significantly with funds' performance.

Under the assumption that a higher *mfmkt%* implies better access to inside information, a fund's qualified-holding concentration reflects the fund's overall access to inside information. A fund with a higher concentration in qualified holdings would have better access to inside information. Because insiders' private information is valuable, better access to such information should help improve fund performance. The significantly positive correlation between funds' performance and their qualified-holding concentrations is consistent with this intuition. Moreover, the non-significant correlation between funds' performance and their top-10-holding

Table 17: Fund Performance and Holding Concentration

As in Regression (15), I compute the t-statistics of FF3F+MOM monthly α for each fund in my sample. Next, I compute a fund's average holding concentration (in decimal). The table shows the coefficients and their t-statistics (in parentheses) from Regression (16). I report the quarterly results in the top panel and the semiannual results in the bottom panel. In each panel, I report results for holding concentrations based on the top-10 holdings and various *mfmkt%* threshold conditions: 0.50%, 1.00%, 1.50%, and 2.00%. The quarterly data cover 386 funds. The semiannual data cover 385 funds. The sample period is July 2003 to June 2014.

Table 17a: Fund FF3F+MOM t(α) vs. Holding Concentration (Quarterly)

mfmkt%	Constant	Holding Concentration	R-sq.	Sample Size
Top 10	1.32 (3.76)	-0.59 (-0.79)	0.2%	386
0.50%	0.22 (1.90)	4.92 (9.37)	18.6%	386
1.00%	0.34 (3.33)	6.88 (9.79)	20.0%	386
1.50%	0.44 (4.62)	8.59 (9.57)	19.2%	386
2.00%	0.53 (5.84)	10.00 (9.00)	17.4%	386

Table 17b: Fund FF3F+MOM t(α) vs. Holding Concentration (Semiannual)

mfmkt%	Constant	Holding Concentration	R-sq.	Sample Size
Top 10	0.94 (2.88)	0.29 (0.41)	0.0%	385
0.50%	0.10 (0.98)	3.31 (12.02)	27.4%	385
1.00%	0.31 (3.41)	4.34 (11.58)	25.9%	385
1.50%	0.44 (5.00)	5.38 (10.87)	23.6%	385
2.00%	0.54 (6.35)	6.41 (10.10)	21.0%	385

concentrations further corroborates this intuition. Top-10 holdings may represent a fund's core positions, but they are not necessarily qualified holdings. Therefore, a fund with a higher concentration in top-10 holdings does not necessarily have better access to inside information.

Consequently, I observe no significant correlation between funds' performance and their top-10-holding concentrations.

As discussed earlier, a fund would have a high qualified-holding concentration if it invests a large fraction of its portfolio in qualified holdings, and it overweighs those stocks relative to the market portfolio. Bigger funds are more likely to have qualified holdings than smaller funds, because they can invest more in each position. Therefore, bigger funds are also more likely to have a higher qualified-holding concentration. Next, I control for fund size by adding each fund's average size ($Size_i$) into the regression:

$$t(\alpha)_i = constant + \gamma * HC_i + \theta * Size_i + \varepsilon_i. \tag{17}$$

Table 18 reports results for Regression (17). Under all four *mfmkt%* threshold conditions, the significant correlations between funds' performance and their qualified-holding concentrations persist, after controlling for fund size. The fund-size coefficients are statistically insignificant. The magnitudes of the holding-concentration coefficients are slightly lower than those reported in Table 17b. For example, when I impose a 1.00% threshold on *mfmkt%*, the fund-size loading is 0.00 (t=0.10); the holding-concentration loading is 4.30 (t=7.34), compared with 4.34 (t=11.58) when not controlling for fund size.

In this section, I have presented evidence that points to some intersection between the private information sets of stock funds and corporate insiders. Over the whole sample period, both stock funds and corporate insiders beat the market, thanks to their valuable private information. An interesting question to ask is how the informational environment has evolved in the Chinese stock market during the same sample period. Next, I study the time-series pattern of the performance of Chinese stock mutual funds and corporate insiders. In particular, I examine performance erosion of these two groups of active investors.

Table 18: Fund Performance and Holding Concentration, Controlling for Fund Size

As in Regression (15), I compute the t-statistics of FF3F+MOM monthly α for each fund in my sample. Next, I compute each fund's average semiannual holding concentration (in decimal) and average size (in RMB billion). The table shows the coefficients and their t-statistics (in parentheses) from Regression (17). I report results for holding concentrations based on various *mfmkt%* threshold conditions: 0.50%, 1.00%, 1.50%, and 2.00%. The semiannual data cover 385 funds. The sample period is July 2003 to June 2014.

mfmkt%	Constant	Holding Concentration	Fund Size	R-sq.	Sample Size
0.50%	0.11 (1.06)	3.16 (7.92)	0.01 (0.54)	27.4%	385
1.00%	0.31 (3.41)	4.30 (7.34)	0.00 (0.10)	25.9%	385
1.50%	0.44 (4.97)	5.08 (6.38)	0.02 (0.48)	23.6%	385
2.00%	0.52 (6.09)	5.36 (5.37)	0.04 (1.37)	21.4%	385

7 Performance Erosion of Stock Funds and Corporate Insiders

In this section, I present evidence of performance erosion for Chinese stock mutual funds and corporate insiders, in connection with the growth of the institutional money-management industry. Performance erosion results suggest that the Chinese stock market is becoming more efficient and harder to beat.

7.1 Performance Erosion of Stock Funds

I add a time trend to Regression (1) to capture the performance erosion of stock mutual funds. I use stock funds' aggregate VW gross returns $R_{mf,t}$ in Regression (18):

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}\left(R_{mt} - R_{ft}\right) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \rho_{mf}Month_t + e_{mf,t}. \quad (18)$$

Table 19 shows results for the CAPM, FF3F, and FF3F+MOM versions of Regression (18). Under all three specifications, I observe a negative time trend in benchmark-adjusted returns. For example, under CAPM, the monthly performance decay is -0.010% (t=-1.75), which amounts to an annual performance decay of -0.12%. For my sample period from 2003 to 2014, the performance decay amounts to -1.32%. Under the FF3F and FF3F+MOM models, monthly performance erosion is -0.009% (t=-2.12) and -0.008% (t=-2.23) respectively. Although the stock mutual funds outperform passive benchmarks during my sample period from 2003 to 2014, their performance seems to have been decaying over time.

Table 19: Performance Erosion of Stock Mutual Funds

The table shows the monthly intercepts α and t-statistics (in parentheses) for the CAPM, FF3F, and FF3F+MOM versions of Regression (18) estimated on aggregate value-weighted (VW) gross returns of actively managed stock mutual funds. The table also shows the slopes for benchmark factors and time trend. For the market slope, t-statistic tests whether b is different from 1 instead of 0. The data cover 418 funds from July 2003 to June 2014.

	α	RmRf	SMB	HML	MOM	Time (Month)	R-sq.
CAPM	1.22	0.71				-0.010	86.7%
	(2.73)	(-11.56)				(-1.75)	
FF3F	1.50	0.77	-0.27	-0.46		-0.009	93.7%
	(4.77)	(-13.08)	(-7.83)	(-8.84)		(-2.12)	
FF3F+MOM	1.35	0.78	-0.21	-0.35	0.23	-0.008	94.9%
	(4.73)	(-13.70)	(-6.37)	(-6.85)	(5.53)	(-2.23)	

7.2 Performance Erosion of Corporate Insiders

I divide my insider-trade sample into two halves: April 2007 to May 2010 and June 2010 to June 2013. I then run Regressions (2) and (3) on each subsample. I report coefficients and t-statistics related to the two insider-buy measures in Table 20, for the three-, six-, and twelve-month forecasting horizons.

The predictive power associated with insider buys is much stronger in the first half of my sample. Each additional insider buy during the prior six months on average corresponds to a 2.13% (t=5.16) increase in a stock's return for the next twelve months; each additional percent of insider buys per market cap on average corresponds to a 5.63% (t=6.18) increase in a stock's return for the next twelve months. For the second half of my sample, the predictive power of insider buys decreased substantially. Each additional insider buy on average corresponds to a 0.27% (t=1.65) increase in a stock's return for the next twelve months; each additional percent of insider buys per market cap on average corresponds to a 0.91% (t=2.12) increase in a stock's return for the next twelve months. For the three- and six-month forecasting horizons, insider trades from the first half possess economically and statistically significant predictive power, whereas insider trades from the second half lack any statistically significant predictive power.

The evidence of performance erosion for both mutual funds and corporate insiders is consistent with the intuition that the Chinese stock market is becoming more efficient. The decreasing value of insider's private information suggests that the informational environment in the Chinese stock market may be becoming less asymmetric. Stricter legal enforcement and harsher punishment against trading on material inside information may have contributed to this

Table 20: Performance Erosion of Corporate Insiders

The table reports the coefficients on $Num\_Buy_{i,t}$ in Regression (2) and $(\frac{Amt\_Buy}{Mktcap})_{i,t}$ in Regression (3), their t-statistics (in parentheses), and the sample size of each subsample. I calculate the insider-trade measures based on the prior six-month period. The first panel summarizes results on insider trades from the first half of my sample: April 2007 to May 2010. The second panel summarizes results on insider trades from the second half of my sample: June 2010 to June 2013. I base t-statistics on the Newey-West autocorrelation- and heteroscedasticity-consistent standard errors. The number of lags I use in the estimation of Newey-West standard errors are *k-1* months for *k*-month holding period returns, where *k*=3, 6, and 12.

	Num_Buy			Amt_Buy/Mktcap (%)			Sample Size
	3-month	6-month	12-month	3-month	6-month	12-month	
04/2007 ~ 05/2010	0.80	1.48	2.13	1.64	3.47	5.63	22,793
	(6.49)	(5.79)	(5.16)	(6.73)	(6.25)	(6.18)	
06/2010 ~ 06/2013	-0.03	-0.04	0.27	0.13	0.30	0.91	30,448
	(-0.63)	(-0.48)	(1.65)	(0.92)	(1.11)	(2.12)	

improvement in market efficiency. The declining alpha of stock mutual funds suggests that the Chinese stock market is becoming more difficult to beat. This is another sign of improvement in the Chinese stock market's efficiency. The increasing competition among market participants, especially institutional money managers, may have contributed to this improvement in market efficiency. Next, I investigate the growth of Chinese institutional investors.

7.3 Growth of Institutional Money-Management Industry

I compile the semiannual stock holdings data of the Chinese institutional investors. Table 21 reports the summary statistics of Chinese institutional investors' stock holdings, in relation to the aggregate stock market capitalization and stock mutual funds' holdings. At the end of 2003, Chinese institutional investors represented only 12.4% of the aggregate stock market capitalization. Within the institutional holdings, stock mutual funds represented a substantial 30.7%. Chinese retail investors were dominant in the stock market, holding 87.6% of the stock market. This period was a great time for professional money managers because the competition from other institutional investors was low and the retail-investor presence was high. Professional money managers had more knowledge and resources than retail investors. Consequently, they could beat the market easily at the expense of less sophisticated retail investors.

Over time, two trends have been taking place simultaneously. First, the institutional investors are managing more and more assets. Stocks held by Chinese institutional investors have grown from RMB154 billion to RMB12,595 billion in just over 10 years. The institutional fraction of the stock market has increased from 12.4% to 62.8%. Various types of institutional investors other than stock mutual funds have been entering the stock market. Examples include banks, insurance companies, pension funds, trusts, brokerage firms, hedge funds, and QFII's. Additionally, as discussed in section 2, the share-reform policy initiated in 2005 has helped fuel the growth of government-owned fraction in the secondary stock market.

Second, within institutional investors, stock mutual funds' fraction has decreased from 30.7% in 2003 to 5.1% in 2013. This means other types of institutional investors are gaining clout in the stock market. On the one hand, Chinese retail investors are being offered more investment options by various institutions other than stock mutual funds: brokerage firms, banks, and trusts have been creating and issuing investment products to their retail clients at a growing pace in recent years. The investment-delegation business is becoming more and more competitive. On the other hand, institutional investors such as insurance companies, pension funds, hedge funds, and QFII's are becoming a new force in the Chinese stock market. In addition, the government-sponsored institutions are growing in size thanks to the share-reform policy. Due to these reasons, stock funds' fraction of the institutional holdings has been declining in recent years.

Both trends are likely hurting the performance of stock mutual funds. A declining retail presence in the market must be accompanied by a rising institutional presence. Institutional investors such as those professional money managers from the private sector present competition not only in processing public information, but also in acquiring private information. Institutional investors such as those from government-sponsored institutions may be naturally at an advantage in accessing valuable private information. Facing more competition from these fellow institutional investors, stock fund managers are seeing their performance erode over time.

Pastor, Stambaugh, and Taylor (2014) find similar evidence of rising competition in the U.S. stock market. They find that the rising competition is offset by the rising skill of active mutual

Table 21: Summary Statistics of Institutional Stock Holdings

The table reports the summary statistics on Chinese institutional stock holdings, in relation to the aggregate stock market capitalization and stock funds' holdings. The institutional holdings data start in the fourth quarter of 2003. Column 1 records the semiannual reporting periods. Column 2 shows the aggregate Chinese stock market capitalization. Column 3 shows the value of aggregate Chinese institutional stock holdings. Column 4 shows the institutional fraction of the stock market (column 3/column 2). Column 5 shows the value of aggregate stock holdings of Chinese stock mutual funds. Column 6 shows the stock funds' fraction of the stock market (column 5/column 2). Column 7 shows the stock funds' fraction of the institutional holdings (column 5/column 3).

Reporting Period	Aggr. Stock MktCap (bn)	Institutional Stock Holdings (bn)	Institutional Holdings / Aggr. Stock MktCap	Stock Fund Holdings (bn)	Stock Fund Holdings / Aggr. Stock MktCap	Stock Fund Holdings / Institutional Holdings
4Q/2003	¥1,245	¥154	12.4%	¥47	3.8%	30.7%
2Q/2004	¥1,205	¥175	14.5%	¥43	3.6%	24.5%
4Q/2004	¥1,116	¥202	18.1%	¥47	4.2%	23.5%
2Q/2005	¥954	¥196	20.5%	¥49	5.1%	24.9%
4Q/2005	¥1,020	¥228	22.3%	¥59	5.8%	26.0%
2Q/2006	¥1,620	¥348	21.5%	¥96	5.9%	27.6%
4Q/2006	¥2,413	¥745	30.9%	¥232	9.6%	31.2%
2Q/2007	¥5,418	¥1,864	34.4%	¥636	11.7%	34.1%
4Q/2007	¥9,145	¥3,772	41.2%	¥1,240	13.6%	32.9%
2Q/2008	¥5,922	¥2,421	40.9%	¥643	10.9%	26.6%
4Q/2008	¥4,540	¥2,023	44.6%	¥463	10.2%	22.9%
2Q/2009	¥9,087	¥4,555	50.1%	¥818	9.0%	18.0%
4Q/2009	¥15,080	¥9,284	61.6%	¥904	6.0%	9.7%
2Q/2010	¥12,672	¥7,748	61.1%	¥639	5.0%	8.2%
4Q/2010	¥19,235	¥12,360	64.3%	¥838	4.4%	6.8%
2Q/2011	¥20,054	¥12,986	64.8%	¥748	3.7%	5.8%
4Q/2011	¥16,520	¥10,985	66.5%	¥612	3.7%	5.6%
2Q/2012	¥17,340	¥11,289	65.1%	¥632	3.6%	5.6%
4Q/2012	¥18,223	¥11,969	65.7%	¥641	3.5%	5.4%
2Q/2013	¥16,982	¥10,794	63.6%	¥590	3.5%	5.5%
4Q/2013	¥20,042	¥12,595	62.8%	¥639	3.2%	5.1%

funds, so that the net effect on the performance of U.S. active funds is approximately neutral. In contrast, I find that competition in China has risen so fast that the performance of Chinese stock mutual funds has declined over time.

Last but not least, the Chinese regulatory authority's harsher punishment for insider trading may have also contributed to the improvement in the Chinese stock market's efficiency. The decreasing predictive power associated with insider trades suggests that the informational environment may be becoming less asymmetric. The private information channel that used to help some stock fund managers beat the market is being gradually shut down. As a result, those fund managers may suffer performance erosion.

8 Conclusion

In this paper, I investigate private information in the Chinese stock market by studying two groups of Chinese investors: actively managed stock mutual funds and corporate insiders. First, in aggregate, stock funds outperform passive benchmarks including market, size, value, and momentum factors. Cross-sectionally, most fund managers have sufficient skill to cover all costs and generate positive α. Managers' stock-picking skill helps explain a substantial amount of their outperformance. Moreover, managers have intra-period trading skill that creates sufficient value to offset trading costs and other hidden costs. Funds with higher turnover ratios outperform funds with lower turnover ratios.

Next, I discover evidence of information asymmetry in the Chinese stock market. Chinese corporate insiders reap large profits by trading their own company stocks. Insider buys possess significant predictive power for stock returns. Private information associated with insider trades is more valuable for stocks of state-owned enterprises and for more volatile stocks. Moreover, I construct a simple insider-mimicking portfolio that produces a significantly positive annual alpha of 14.43% (t=3.08) against the market benchmark.

Next, I find strong correlation patterns between stock funds and corporate insiders. First, I show a significant correlation between the performance of stock funds' trading portfolio and the insider-mimicking portfolio. Second, I find that funds that trade more in the same direction as insiders deliver better performance. Third, I find that stock funds' large shareholding positions (as measured by the stock holding's value divided by the stock's market capitalization) exhibit a significant return correlation with the insider-mimicking portfolio. Furthermore, funds with a higher concentration in these positions outperform funds with a lower concentration.

Finally, I present evidence of performance erosion for both stock funds and corporate insiders, showing that the Chinese stock market is becoming more efficient and harder to beat. This result is consistent with recent trends in the Chinese stock market, such as more competition among institutional investors, better financial regulation, and harsher crackdowns on insider trading. I see this improvement in market efficiency as an encouraging sign for the future development of Chinese financial markets.

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Appendices

A Mutual Fund Performance Evaluation with Bond Index

Table 22: Intercepts and Slopes in Regression (1) with Bond Benchmark

The top panel shows the annualized intercepts (12*α) and t-statistics (in parentheses) for the CAPM, FF3F, and FF3F+MOM versions of Regression (1) estimated on the aggregate value-weighted (VW) net and gross returns of actively managed stock mutual funds. It also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. The bottom panel includes an additional bond index: the Chinese Treasury bond index (Bond). Net returns are those received by investors. Gross returns are net returns plus 1/12 of a fund's expense ratio for the year. The data cover 418 funds from July 2003 to June 2014.

	12*α							
	Net	Gross	Rm-Rf	SMB	HML	MOM	Bond	R-sq
VW Returns without Bond Index								
CAPM	4.75	6.50	0.72					0.86
	(1.78)	(2.43)	(-11.39)					
3-Factor	9.34	11.08	0.77	-0.28	-0.45			0.93
	(4.91)	(5.83)	(-12.82)	(-8.27)	(-8.52)			
4-Factor	7.80	9.55	0.78	-0.22	-0.34	0.23		0.95
	(4.49)	(5.49)	(-13.40)	(-6.75)	(-6.52)	(5.49)		
VW Returns with Bond Index								
CAPM+Bond	4.82	6.57	0.72				-0.02	0.86
	(1.71)	(2.33)	(-11.31)				(-0.08)	
3-Factor+Bond	9.85	11.59	0.77	-0.28	-0.45		-0.15	0.94
	(4.92)	(5.79)	(-12.83)	(-8.27)	(-8.54)		(-0.82)	
4-Factor+Bond	8.36	10.11	0.78	-0.22	-0.34	0.23	-0.17	0.95
	(4.58)	(5.54)	(-13.44)	(-6.76)	(-6.56)	(5.51)	(-1.02)	

B Cross-sectional Performance: Bootstrap Simulation

B.1 Setup

For my fund sample from 1998 to 2014, I run Regression (1) to estimate each fund's CAPM, FF3F, and FF3F+MOM α for net and gross returns. To get zero-α returns, I simply subtract a fund's α estimate from all its monthly returns. For example, to compute FF3F zero-α net returns for a fund, I subtract its estimated FF3F α from the fund's monthly net returns. Thus, when I run Regression (1) with the resulting zero-α returns as the dependent variable, I get back a zero intercept. I calculate zero-α returns for net and gross returns, under CAMP, FF3F, and FF3F+MOM models. The result is 6 populations of zero-α returns.

Setting true α to zero builds different assumptions about skill into the tests on net and gross fund returns. The zero-α net return sample implies a world in which every manager has sufficient skill that generates expected returns that cover all costs. The zero-α gross return sample corresponds to a world in which every manager has sufficient skill that generates expected returns that cover costs missed in expense ratios.

A simulation run/pseudo-sample is then generated from bootstrapping with replacement. There are in total 195 calendar months in my sample period from April 1998 to June 2014. So the pseudo-sample for all the funds is a random sample (with replacement) of 195 months, drawn from the 195 calendar months of April 1998 to June 2014. The pseudo-sample is the same random sample of months, for net and gross returns, under the CAPM, FF3F, and FF3F+MOM benchmark models.

For each of the 6 sets of zero-α returns, I estimate, fund by fund, the relevant benchmark model on the simulation draw of months of zero-α returns, dropping funds that are in the simulation run for less than 8 months. Funds with less than 8 months of returns in 10,000 pseudo-samples account for less than 0.05%, thus unlikely to affect results. I use zero-α returns as the dependent variable in Regression (1) and produce cross-sections of α estimates. I do 10,000 simulation runs to produce 6 distributions of t(α), for a world in which true α is zero. I focus on t(α), rather than α, to control for differences in precision due to differences in residual variance and in the number of months funds are in a pseudo-sample.

To analyze simulation results, I first compare the percentiles of the cross-section of t(α) estimates from actual fund returns with the average values of the percentiles from the simulations. I then look at the likelihood statements to see whether the cross-section of t(α) estimates for actual fund returns points to the existence of skill.

B.2 Comparison of t(α) Percentiles and Cumulative Distribution Function (CDF)

When I estimate a benchmark model on the returns of each fund, I get a cross-section of t(α) estimates that can be ordered into a cumulative distribution function (CDF) of t(α) estimates for actual fund returns. A simulation run for the same benchmark model also produces a cross-section of t(α) estimates and its CDF for a zero-α world. Table 23, 24, and 25 show the CDF of t(α) estimates for actual returns and the average of the 10,000 simulation CDFs.

Table 23, 24, and 25 respectively report results for the CAPM, FF3F, and FF3F+MOM models. First, I compare (i) the values of t(α) at selected percentiles of the CDF of the t(α) estimates from actual fund returns (Act) and (ii) the averages across the 10,000 simulation runs of the t(α) estimates at the same percentiles (Sim). Note the average simulated distribution of t(α) is fairly symmetric and centered around 0. This is not surprising since we simulate from zero-α returns.

The left panel shows results for net returns. Managers seem to have sufficient skill to cover their costs. For all benchmark models, the average simulated t(α) is lower than the actual t(α) for all percentiles. Under CAPM benchmark model, for example, the 5th percentiles of the actual t(α) estimates −0.59 is larger than the average estimates from the simulation −1.50. The 50th percentiles of the actual t(α) estimates 1.20 is larger than the average estimates from the simulation −0.01. The 95th percentiles of the actual t(α) estimates 3.05 is larger than the average estimates from the simulation 1.43.

The right panel shows results for gross returns. Not surprisingly, gross returns produce better actual t(α) estimates. For all benchmark models, the average simulated t(α) is always lower than the actual t(α) for all percentiles. Clearly, fund managers have sufficient skill to cover costs missing from expense ratios.

B.3 Likelihood Analysis

%<Act column in Table 23, 24, and 25 shows the fraction of the 10,000 simulation runs that produce lower values of t(α) at the selected percentiles than actual fund returns. These likelihoods allow me to judge more formally whether the tails of the cross-section of t(α) for actual fund returns are extreme relative to what we observe when true α is zero.

At the left tail for the worst managers, I infer some managers lack sufficient skill to cover all costs if %<Act is low, i.e. large fractions of the simulation runs beat the t(α) estimates from actual net fund returns. The intuition goes the other way too. At the right tail for the best managers, I infer some managers possess sufficient skill to cover costs if %<Act is high, i.e. large fractions of the simulation runs are below the t(α) estimates from actual net fund returns. It is similar for gross fund returns, but the question is whether managers possess sufficient skill to cover costs missing from expense ratios.

Fama and French (2010) pointed out two issues with likelihood analysis: multiple comparison and correlation across different likelihoods. To cope with these issues, I will focus on a given percentile of each tail (5th and 95th percentiles) in the following analysis. Under CAPM, at 5th percentile, actual t(α) is −0.59. The likelihood that simulated t(α) is less than −0.59 out of 10,000 simulations is 97.08%. At 95th percentile, actual t(α) is 3.05. The likelihood that simulated t(α) is less than 3.05 out of 10,000 simulation runs is 99.57%. At both tails, there is dominant evidence of manager skill sufficient to cover costs.

For gross returns, results look better. There is widespread evidence of manager skill sufficient to cover costs missing from expense ratios. For example, under CAPM, at 5th percentile, actual t(α) is −0.28. The likelihood that simulated t(α) is less than −0.28 out of 10,000 simulations is 99.56%. At 95th percentile, actual t(α) is 3.38. The likelihood that simulated t(α) is less than 3.38 out of 10,000 simulation runs is 99.88%. At both tails, there is clear evidence of manager skill sufficient to cover costs missing from expense ratios.

Table 23: Performance Estimates for Actual and Simulated Fund Returns (CAPM)

The table shows values of t(α) at selected percentiles (Pct) of the distribution of t(α) estimates for actual (Act) net and gross stock fund returns. Calculations of t(α) are based on the CAPM. The table also shows the percent of the 10,000 simulation runs that produce lower values of t(α) at the selected percentiles than those observed for actual fund returns (%<Act). Sim is the average value of t(α) at the selected percentiles from the simulations. The data cover 418 funds from April 1998 to June 2014.

Stock Funds	Net Return CAPM			Gross Return CAPM		
Pct	Sim	Act	%<Act	Sim	Act	%<Act
1	-2.25	-1.53	88.33	-2.25	-1.12	98.48
2	-1.93	-1.09	94.53	-1.93	-0.65	99.68
3	-1.74	-0.79	97.41	-1.74	-0.39	99.89
4	-1.61	-0.64	97.74	-1.61	-0.36	99.66
5	-1.50	-0.59	97.08	-1.50	-0.28	99.56
10	-1.15	-0.30	95.77	-1.15	0.02	99.40
20	-0.75	0.14	96.08	-0.75	0.52	99.63
30	-0.47	0.57	97.85	-0.47	0.89	99.66
40	-0.23	0.90	98.56	-0.23	1.24	99.77
50	-0.01	1.20	98.87	-0.01	1.54	99.85
60	0.21	1.43	98.84	0.21	1.80	99.82
70	0.45	1.83	99.30	0.45	2.13	99.82
80	0.72	2.13	99.34	0.72	2.46	99.82
90	1.10	2.59	99.31	1.10	3.00	99.86
95	1.43	3.05	99.57	1.43	3.38	99.88
96	1.52	3.17	99.58	1.52	3.63	99.91
97	1.64	3.41	99.60	1.64	3.78	99.93
98	1.80	3.59	99.57	1.80	4.06	99.91
99	2.08	3.84	99.15	2.08	4.38	99.79

Table 24: Performance Estimates for Actual and Simulated Fund Returns (FF3F)

The table shows values of t(α) at selected percentiles (Pct) of the distribution of t(α) estimates for actual (Act) net and gross stock fund returns. Calculations of t(α) are based on the FF3F model. The table also shows the percent of the 10,000 simulation runs that produce lower values of t(α) at the selected percentiles than those observed for actual fund returns (%<Act). Sim is the average value of t(α) at the selected percentiles from the simulations. The data cover 418 funds from April 1998 to June 2014.

Stock Funds	Net Return FF3F			Gross Return FF3F		
Pct	Sim	Act	%<Act	Sim	Act	%<Act
1	-2.60	-1.63	95.61	-2.60	-1.35	99.21
2	-2.20	-1.35	96.01	-2.20	-1.14	98.96
3	-1.98	-1.22	95.00	-1.98	-0.97	98.98
4	-1.83	-1.12	94.05	-1.82	-0.83	99.03
5	-1.71	-0.97	95.35	-1.70	-0.65	99.53
10	-1.31	-0.41	98.82	-1.31	-0.08	99.96
20	-0.85	0.19	99.58	-0.85	0.46	99.98
30	-0.53	0.60	99.79	-0.53	0.92	99.99
40	-0.27	0.96	99.89	-0.26	1.26	99.99
50	-0.02	1.41	99.99	-0.01	1.71	100.00
60	0.23	1.78	100.00	0.24	2.16	100.00
70	0.50	2.25	100.00	0.51	2.71	100.00
80	0.82	2.74	100.00	0.82	3.24	100.00
90	1.26	3.39	100.00	1.27	3.83	100.00
95	1.64	4.11	100.00	1.66	4.58	100.00
96	1.76	4.24	100.00	1.77	4.75	100.00
97	1.90	4.35	99.99	1.91	4.91	100.00
98	2.11	4.64	99.89	2.12	5.12	99.92
99	2.48	4.75	99.06	2.49	5.26	99.32

Table 25: Performance Estimates for Actual and Simulated Fund Returns (FF3F+MOM)

The table shows values of t(α) at selected percentiles (Pct) of the distribution of t(α) estimates for actual (Act) net and gross stock fund returns. Calculations of t(α) are based on the FF3F+MOM model. The table also shows the percent of the 10,000 simulation runs that produce lower values of t(α) at the selected percentiles than those observed for actual fund returns (%<Act). Sim is the average value of t(α) at the selected percentiles from the simulations. The data cover 418 funds from April 1998 to June 2014.

Stock Funds	Net Return FF3F+MOM			Gross Return FF3F+MOM		
Pct	Sim	Act	%<Act	Sim	Act	%<Act
1	-3.00	-2.01	89.20	-3.00	-1.75	96.38
2	-2.37	-1.66	90.72	-2.37	-1.38	98.21
3	-2.09	-1.49	90.41	-2.08	-1.28	97.12
4	-1.91	-1.33	90.85	-1.91	-1.13	97.43
5	-1.78	-1.23	90.36	-1.78	-0.89	99.29
10	-1.37	-0.65	97.65	-1.36	-0.34	99.94
20	-0.89	-0.11	98.65	-0.89	0.17	99.97
30	-0.56	0.37	99.65	-0.56	0.68	99.99
40	-0.29	0.72	99.78	-0.28	1.04	99.99
50	-0.03	1.20	99.97	-0.03	1.51	100.00
60	0.22	1.63	99.99	0.23	2.04	100.00
70	0.49	2.17	100.00	0.50	2.59	100.00
80	0.81	2.65	100.00	0.82	3.17	100.00
90	1.26	3.32	100.00	1.27	3.78	100.00
95	1.65	3.91	100.00	1.66	4.44	100.00
96	1.77	4.06	99.99	1.78	4.63	100.00
97	1.93	4.26	99.96	1.93	4.78	99.97
98	2.16	4.43	99.64	2.17	4.90	99.68
99	2.69	4.60	96.57	2.69	5.21	97.36

C Institutional Investors' Aggregate Stock Holding

Table 26: Characteristics of Stocks Held by Institutional Investors

At the end of each semiannual period from June 30, 2003 to December 31, 2013, I compute the fraction of the market capitalization of each stock that is held by the universe of Chinese institutional investors (*instmkt%*). I compute the equal-weighted average characteristic scores for quartile portfolios formed based on separate rankings on *instmkt%*. To compute the rank score of a given stock on a given characteristic, I sort all stocks separately by their market capitalization, book-to-market ratio, and momentum at the beginning of each semiannual period. I assign each stock a rank score on each characteristic, where the rank lies between zero (low) and one (high). For example, if *N* stocks are available at the end of a period, I assign the *i*th-ranked stock (on a particular characteristic) a rank score of (*i*-1)/(*N*-1) for that period. Finally, I report the time-series average of all measures across all periods.

	instmkt%	Size Rank	Book-to-Market Rank	Momentum Rank
instmkt%				
Quartile 1 (Bottom)	3.90	0.33	0.48	0.47
Quartile 2	14.53	0.44	0.51	0.49
Quartile 3	27.29	0.54	0.53	0.50
Quartile 4 (Top)	51.41	0.69	0.48	0.54

Table 27: Performance of Stocks Held by Institutional Investors

At the end of each semiannual period from June 30, 2003 to December 31, 2013, I compute the fraction of the market capitalization of each stock that is held by the universe of Chinese institutional investors (*instmkt%*). Next, I compute the buy-and-hold return on the aggregate portfolio of all stocks held by the institutional investors (All Holdings). I also compute buy-and-hold returns on quartile portfolios, which are formed by rankings on *instmkt%* (all stocks with zero *instmkt%* are excluded). Quartile 1 stocks have the lowest *instmkt%*. Quartile 4 stocks have the highest *instmkt%*.

At the end of each semiannual period, I create a six-month return series following the portfolio formation, for each portfolio discussed above. I appropriately adjust portfolio value weights monthly to create a buy-and-hold monthly return series for the six months following the portfolio formation. Then I paste the six-month return series together to create a longer time series of monthly returns. I run the CAPM, FF3F, and FF3F+MOM versions of Regression (1) to obtain a monthly α for each portfolio, as well as a long-short portfolio constructed from subtracting Quartile 1 returns from Quartile 4 returns.

	CAPM		FF3F		FF3F+MOM	
	α	*t(α)*	α	*t(α)*	α	*t(α)*
instmkt%						
All Holdings	0.20	(1.13)	0.48	(4.08)	0.41	(3.62)
Quartile 1 (bottom)	0.01	(0.05)	-0.49	(-3.61)	-0.51	(-3.75)
Quartile 2	0.02	(0.06)	-0.36	(-2.28)	-0.34	(-2.13)
Quartile 3	0.16	(1.15)	0.05	(0.40)	0.02	(0.18)
Quartile 4 (top)	0.19	(0.87)	0.52	(3.99)	0.46	(3.56)
4-1	0.17	(0.35)	1.01	(4.76)	0.97	(4.51)

D Stock Mutual Funds' Return Gap Analysis

Table 28 presents the equal- and value-weighted averages of the return gaps for my sample. I obtain the returns by first computing the cross-sectional means in each month and then reporting the time-series means along with the corresponding t-statistics. The equal-weighted average of funds' gross return is 1.49% per month. The equal-weighted average of holdings return is 1.46% per month. Thus, the return gap equals 2.4 basis points per month and is not significantly away from zero. Similarly, the value-weighted return gap equals −1.9 basis points per month and is not significantly away from zero. Once I adjust for common risk factors, the return gap becomes more significant. The equal-weighted return gap under CAPM equals 20 basis points (t=1.96) per month. Similarly, the value-weighted return gap under CAPM equals 15 basis points (t=1.56) per month.

Table 28: Performance of Fund Gross Returns and Holdings Returns

The table summarizes the performance of monthly fund gross returns, the holdings returns, and the return gaps for the equal-weighted and value-weighted portfolio of all stock funds in my sample. The return gap is defined as the difference between the fund gross returns and the holdings returns of the portfolio disclosed in the previous period. I report the raw returns, the CAPM α, FF3F α, and FF3F+MOM α. The returns are expressed in percent per month and the t-statistics are summarized in parentheses. The sample period is July 2003 to June 2014.

	Fund Gross Returns	Holdings Returns	Return Gap
Equal-weighted returns			
Raw return	1.49	1.46	0.02
	(2.20)	(1.72)	(0.13)
CAPM α	0.67	0.47	0.20
	(3.01)	(1.85)	(1.96)
FF3F α	1.03	0.90	0.13
	(6.23)	(5.06)	(1.31)
FF3F+MOM α	0.89	0.74	0.15
	(5.98)	(4.69)	(1.48)
Value-weighted returns			
Raw return	1.37	1.39	-0.02
	(1.98)	(1.62)	(-0.11)
CAPM α	0.54	0.40	0.15
	(2.43)	(1.58)	(1.56)
FF3F α	0.92	0.84	0.09
	(5.83)	(4.88)	(0.94)
FF3F+MOM α	0.80	0.69	0.11
	(5.49)	(4.48)	(1.16)

E Correlations under CAPM and FF3F

CAPM specification:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{mt} - R_{ft}) + e_{mf,t} \qquad and \qquad (E1)$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{mt} - R_{ft}) + c_{mf} * outperf_{insider,t} + e_{mf,t}. \qquad (E2)$$

FF3F specification:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{mt} - R_{ft}) + s_{mf}SMB_t + h_{mf}HML_t + e_{mf,t} \quad and \qquad (E3)$$

$$\begin{aligned} R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{mt} - R_{ft}) + s_{mf}SMB_t + h_{mf}HML_t \\ + c_{mf} * outperf_{insider,t} + e_{mf,t}. \end{aligned} \qquad (E4)$$

Similar to the FF3F+MOM results in section 6.1.1, I observe a significant loading on the insider factor c=0.54 with t=4.84 (under CAPM), and c=0.77 with t=5.26 (under FF3F). R-square increases after including the insider factor under both models: 85.4% to 89.0% under CAPM, and 89.3% to 92.4% under FF3F. Finally, α decreases substantially after including the insider factor. It decreases from 0.49 (t=1.15) to −0.16 (t=−0.40) under CAPM, and from 0.65 (t=1.63) to 0.32 (t=0.93) under FF3F.

Table 29: Intercepts and Slopes in Regression (E1) to (E4)

The table shows the monthly intercepts α and t-statistics (in parentheses) for Regressions (E1), (E2), (E3), and (E4) estimated on returns of the mutual funds' aggregate trading portfolio. The table also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. Top panel shows results for Regressions (E1) and (E2). Bottom panel reports results for Regressions (E3) and (E4). The sample period is April 2008 to June 2014, a total of 75 months.

Mutual Fund Trading Portfolio	α	b	s	h	c	R-sq.
CAPM	0.49	1.06				85.4%
	(1.15)	(1.11)				
CAPM+Insider	-0.16	1.06			0.54	89.0%
	(-0.40)	(1.27)			(4.84)	
FF3F	0.65	1.08	-0.05	-0.64		89.3%
	(1.63)	(1.74)	(-0.44)	(-4.82)		
FF3F+Insider	0.32	1.08	-0.05	-0.64	0.77	92.4%
	(0.93)	(2.04)	(-0.52)	(-5.65)	(5.26)	

F Placebo Test

In the analysis in section 6.1.1, I have accounted for common risk benchmarks by including market, size, value, and momentum factors. But I still cannot rule out that the insider factor $outperf_{insider,t}$ may be capturing some other common risk factor, instead of insiders' private information. If mutual funds and corporate insiders were both loading onto an omitted common risk factor, I would have generated the same results in section 6.1.1, but with a different interpretation. To get a better understanding of the results, I replace the mutual funds' trading portfolio with a placebo portfolio and repeat the analysis in section 6.1.1. The placebo portfolio can be considered as a fund that randomly allocates assets to stocks.

To construct the placebo portfolio, I randomly simulate each stock's *mfmkt%* weights (stock holding's value divided by the stock's market capitalization) from a uniform distribution every month. I create each stock's value weights as its stock market capitalization multiplied by its simulated *mfmkt%*. I then calculate a value-weighted monthly return series of this portfolio. It covers the same sample period as the stock funds' trading portfolio: April 2008 to June 2014. I simulate the placebo portfolio for 1,000 times and run Regressions (8) and (9) using the placebo portfolio's return as the dependent variable. I report the average regression statistics in Table 30.

The placebo portfolio is not significantly correlated with the insider factor. Its coefficient *c* on the insider factor in Regression (9) is 0.02 (t=1.01). It is both economically and statistically insignificantly away from zero, compared with a significantly positive loading by the mutual fund portfolio of 0.68 (t=5.32).

The placebo test offers additional support to my conjecture that Chinese stock mutual funds and corporate insiders have similar private information, which is not accounted for by common risk factors.

Table 30: Placebo Portfolio's Intercepts and Slopes in Regressions (8) and (9)

The table shows the monthly intercepts α and t-statistics (in parentheses) for the intercept for Regression (8) and (9) estimated on returns of the average placebo portfolio. The also shows the slopes for factors. For the market slope, t-statistic tests whether b is different from 1 instead of 0. Top panel shows results for Regression (8). Bottom panel reports results for Regression (9). 1,000 placebo portfolios are simulated. All coefficients reported in the table represent the average values of the 1,000 simulated trials. The sample period is April 2008 through June 2014, a total of 75 months.

Placebo Portfolio	α	b	s	h	m	c	R-sq.
FF3F+MOM	0.00	1.02	0.00	-0.02	-0.01		99.8%
	(0.06)	(2.77)	(0.10)	(-0.81)	(-0.40)		
FF3F+MOM+Insider	-0.01	1.02	0.00	-0.02	-0.01	0.02	99.8%
	(-0.18)	(2.83)	(0.10)	(-0.82)	(-0.40)	(1.01)	