Are Hedge Funds More Skilled than Other Institutional Investors?

Evidence from Their Use of Insider Trading Information

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Abstract

This study examines the use of insider trading information by hedge funds. We find that hedge funds tend to trade in the same direction as insiders when insider trading is likely driven by information, but do not respond to likely liquidity-driven insider trades. This finding is consistent with hedge funds being able to decipher insider trading information and trade accordingly. In contrast, mutual funds, pension funds and other institutional investors (mostly banks and insurance companies) are more likely to trade in the opposite direction as insiders, acting as liquidity providers regardless of the trading motives of insiders. Further, there is evidence that a hedge fund's ability to exploit insider trading information helps improve its performance. Our study contributes to the literature on hedge fund skills by showing their ability to exploit insider information and linking such ability to performance.

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1. Introduction

Compared with other institutional investors like mutual funds, hedge funds are generally found to deliver superior performance and thus viewed as skilled investors (e.g., Ackermann, McEnally, and Ravenscraft (1999); Brown, Goetzmann, and Ibbotson (1999); Agarwal and Naik (2000); Kosowski, Naik, and Teo (2007); Jagannathan, Malakhov, and Novikov (2010)).[1] However, there is relatively limited evidence on hedge funds' specific skills and sources for their superior performance. Recent studies on hedge funds' confidential holding filings find that their hidden holdings are typically associated with information-sensitive events and deliver superior future returns, suggesting that hedge funds possess private information (Agarwal, Jiang, Tang, and Yang (2013); Aragon, Hertzel, and Shi (2013)).[2]

We explore one potential source of hedge funds' information advantage relative to other institutional investors – insider trading information. Although corporate insiders frequently trade for non-information motives, such as portfolio diversification and liquidity, they may also trade on their private information given their incomparable access to information about firm's operations and significant corporate events. There is a long list of studies finding

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[1] Most of these studies find positive alphas for hedge funds on average and performance persistence for superior funds. And part of the hedge funds' superior performance could be attributed to their risk takings, such as tail risk (Agarwal and Naik (2004); Jiang and Kelly (2012)), liquidity risk (Sadka (2010)), and macroeconomic risk (Bali, Brown, and Caglayan (2014)). There are also studies suggesting no superior performance of hedge funds. For example, Amin and Kat (2003) find no evidence of superior performance for a sample of 77 hedge funds and 13 hedge fund indices from May 1990 to April 2000. Fung, Hsieh, Naik, and Ramadorai (2008) find that the average funds-of-funds deliver alpha only in the period October 1998 to March 2000 out of their sample period 1995 to 2004.

[2] Massoud, Nandy, Saunders, and Song (2011) find that hedge funds short-sell the equity of firms that borrow from them prior to public announcement of both loan originations and loan amendments. Klein, Saunders, and Wong (2014) find evidence that hedge funds gain favored access to analysts' stock recommendation information. Qiang and Zhong (2014) find that hedge funds' abnormal holdings of IPO stocks, especially those "connected" stocks underwritten by their prime brokers, predict these stocks' future returns.

evidence for profitability of insider trading.[3] As insiders are required to disclose their trades timely, it allows sophisticated investors to analyze their trades and decipher insiders' private information.[4] In this study, we examine whether hedge funds are more skilled than other institutional investors at using insider trading information, and further link such skill to their performance.

We follow Cohen, Malloy and Pomorski (2012) to identify likely informative insider trades. They argue that trading by routine insiders with consistent patterns in the timing of trades is unlikely to be informative about firms' futures, and find that the predictive power for returns exists only for trades by opportunistic insiders not trading routinely. We adopt their method to classify insider trades into opportunistic ones, which are likely driven by insiders' private information, and routine ones, which are likely for liquidity motive, and aggregate them within each group to calculate the net insider trading measures for each firm each quarter.

We identify hedge fund companies as those money management companies with the majority of their business in hedge fund operations. We further classify the remaining institutional investors into two categories: mutual fund companies and other independent

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[3] For the early evidence of profitability of insider trades, please see Seyhun (1986), Lakonishok and Lee (2001), and Jeng, Metrick, and Zeckhauser (2003), among others. Cohen, Malloy and Pomorski (2012) differentiate between routine insider trades and opportunistic insider trades, i.e., trades by those insiders who don't trade routinely, and find that only opportunistic trades are informative about firms' futures.

[4] Empirical evidence is mixed regarding whether outsiders can earn abnormal profits by mimicking insider trades after the disclosure of these trades (see e.g., Bettis, Vickrey, and Vickrey (1997); Gelband (2005)). Catalyst Funds launched in 2012 the first legal insider trading mutual fund to take advantage of legal insider trading (http://www.reuters.com/article/idUS135757+20-Jun-2012+MW20120620).

investment advisors (referred as mutual funds hereinafter), and other institutions.[5] For each category of institutional investors, we first aggregate their holdings of a stock at the quarter ends, and then calculate the quarterly net trading in the stock from the change in aggregate holdings from quarter to quarter.

We infer the use of insider information by each category of institutional investors from the relation between their quarterly net trading and the quarterly net insider trading. Using a large sample of U.S. stocks over the period 1995 to 2013, we find that hedge fund trading is on average in the same direction as opportunistic insider trading but unrelated to routine insider trading. The finding is consistent with hedge funds being able to identify likely informative insider trades and trade on such insider information. On the other hand, the trading by mutual funds and other institutional investors is inversely related to insider trading, regardless of opportunistic or routine one, suggesting that these investors are not able to differentiate information-driven insider trades from liquidity-motivated ones and provide liquidity to both types of insider trades.

Our analysis with quarterly institutional holdings to infer institutional trading leaves two issues which might weaken our inference regarding the ability of hedge funds to decipher insider information. First, it is difficult to verify that hedge funds indeed trade after observing and analyzing inside trades, which is critical for our inference. Second, we cannot rule out the

[5] We refer hedge fund companies as hedge funds hereafter. Mutual fund companies and other independent investment advisors include asset management companies, investment banks, brokers, and private wealth management companies, after excluding the identified hedge fund companies. Other institutions include banks, insurance companies, corporate or private pension funds, public pension funds, university foundations and endowments, and miscellaneous, after excluding the identified hedge fund companies. More details about institutional investor classification could be found in section 2.2 and Appendix B.

possibility that both insiders and hedge funds process similar information and trade consistently. We conduct two further tests to address these issues. The first test uses a regulation change in 2002 by the Securities and Exchange Commission (SEC) that requires corporate insiders to report their trades within 2 days of the transactions (instead of 10 days after the month of trading). If the positive relation between hedge fund trading and opportunistic insider trading is driven primarily by hedge funds' ability to process insider trading information, we should expect this relation to be stronger after the regulation, as the insider trade information is more timely and thus more informative. We find that the positive relation exists only in the post-regulation period when insiders are required to disclose their trades promptly, making it more profitable for sophisticated investors to mimic informative insider trades.

In the second test, we provide further evidence regarding whether hedge funds are able to identify informative insider trades. The opportunistic versus routine trading approach in Cohen et al. (2012) only noisily identifies informative insider trading. If hedge funds are indeed able to decipher information in insider trading, we should expect opportunistic insider trades with confirming hedge fund trading to be more informative about firms' futures and predict future returns better than those without. And this is exactly what we find – stocks most heavily bought by opportunistic insiders (in the top decile in terms of quarterly net opportunistic insider purchase) outperform those with heaviest sale by opportunistic insiders (in the bottom decile) by about 3% in the next quarter, if insider trades are accompanied with hedge fund trades in the same direction, and when there is no confirming hedge fund trading, the next quarter return difference between the two groups of stocks diminishes to a statistically insignificant 30 basis points.

Given the evidence that hedge funds are skilled at identifying informative insider trades, it is natural to ask whether such skill contributes to their performance. We test this relation via a similar two-step regression framework as in Kacperczyk and Seru (2007) and find supporting evidence. For each fund each quarter, we first regress its quarterly changes of individual stocks' holdings on stocks' quarterly net opportunistic insider purchases, and extract the coefficient (RIC – responsiveness to insider information coefficient) to measure its ability to exploit insider information. We then link this skill measure to hedge funds' future performance in a panel regression using quarterly fund observations. The regression result suggests that hedge funds that are most responsive to informative insider trades (in the top decile of RIC in a quarter) outperform least responsive funds (in the bottom decile) by about 40 basis points per quarter, after controlling various fund characteristics.

Our study contributes to the growing literature discovering various skills of hedge funds that contribute to their superior performance. Hedge funds are found to be better than other institutions at timing the market (Chen and Liang (2007) and Cao, Chen, Liang, and Lo (2014))[6], sophisticatedly using options in their portfolios (Aragon and Martin (2012)), and front-running distressed mutual funds (Chen, Hanson, Hong and Stein (2007)). Some recent studies find that hedge funds trade on their superior private information obtained from their participation in syndicated loans (Massoud et al. (2011)) and their connected brokers about

[6] Chen and Liang (2007) provide evidence of market timing ability for hedge funds self-labelled as "market timers". And Cao, Chen, Liang, and Lo (2014) find that hedge funds are able to time market liquidity through adjusting their portfolios' market exposure based on aggregate liquidity conditions. On the other hand, Griffin and Xu (2009) find no evidence for hedge funds' market timing ability by analyzing their stock holdings disclosed in 13F filings.

analyst recommendations and IPO stocks (Klein et al. (2014) and Qiang and Zhong (2014), respectively). We add to this line of study by discovering another source of hedge funds' information advantage – their superior ability to decipher insider trade information.

By analyzing the response to insider trades by hedge funds and other institutional investors, our study also contributes to the long literature on insider trading and especially the interaction between insiders and institutional investors. Sias and Whidbee (2010) find a pervasive inverse relationship between insider trading and aggregate institutional trading. However, they don't differentiate insider trades potentially driven by private information from liquidity-motivated ones, and potentially more sophisticated investors like hedge funds from other institutional investors. On the other hand, Cohen et al. (2012) identify potential informative insider trades and find consistent aggregate institutional trading in the same direction. Our findings complement theirs by showing heterogeneous responses by different categories of institutional investors to different types of insider trades.

The rest of this paper is organized as follows. Section 2 introduces data and our sample. Section 3 reports the response by hedge funds and other institutional investors to different types of insider trading. Section 4 relates hedge funds' skill to decipher insider information to their performance. And finally section 5 concludes.

2. Data and Sample

2.1. Corporate insiders' data

The corporate insider trading data are drawn from Thomson Reuters insider filings database. We choose data from the Form 4 filings during the year 1995 to 2013. The year 1995 has been selected as the starting year, due to the reason that the amount of insider trading data before 1995 is significantly less. This paper applies previous studies' procedure to clean the insider trading data[7].

To separate insiders' trades into informative, non-informative and all other insider trades, this paper follows the methodology by Cohen, Malloy and Pomorski (2012) to identify "opportunistic" and "routine" trades. The previous category of insiders' trades potentially contain information for predicting future return, while the latter category are trades made by insiders for liquidity or diversification reasons, i.e., trades without information. Specifically, if insiders' trades in the first 3-year classifying period are placed randomly in different calendar months, then the subsequent transactions have been regarded as insiders' opportunistic trades. Insiders' routine trades have been defined as the subsequent transactions after the 3-year classifying period, where trades in the classifying period are placed in the same calendar month. The detailed methodology of identification has been listed in the Appendix A.

Following Sias and Whidbee (2010), we limit the role of insiders as officers and directors, and measure different categories of insiders' demand (e.g., routine, opportunistic and all the others) in each quarter as the net fraction of shares purchased by insiders. Specifically, the net insider demand is defined as the difference between shares purchased and sold by insiders divided by share outstanding.

2.2. S34 institution holding data

[7] Our analysis focuses on shares in the open market purchased and sold by insiders, and hence options exercises and private transactions have been excluded. We exclude duplicated filings, transactions with missing security id by Thomson Reuters, missing ownership and transaction date, transactions with prices that deviate from the CRSP ask-high and bid-low by more than 10%, and transactions involving more than 20% of the shares outstanding.

Institutions' stock holding data is drawn from the mandatory institutional quarterly portfolio holding reports (13F). The Security Exchange Commission (SEC) requires that all institutions with investment discretion of over $100 million in qualified securities report their holding, and the data is compiled by Thomson Reuters (previously known as CDA/Spectrum S34 Thomson Financial sets)[8]. We separate institutions into different groups including (1), hedge funds; (2), mutual funds and independent investment advisors (hereinafter mentioned as mutual funds & IIA), e.g., asset management companies, investment banks, brokers and private wealth management companies and (3), other institutions (hereinafter mentioned as other institutions), which include banks, insurance companies, corporate or private pension funds, public pension funds, miscellaneous, and university foundations and endowments.

Following previous literature (see, e.g., Brunnermeier and Nagel, 2004; Griffin and Xu, 2009; Jame, 2013), we classify the institution as hedge fund if the majority of its business consists of hedge fund operations. The business component of institutional investor is identified via the Form ADV on the SEC website. Specifically, an institution has been classified as hedge fund if more than half of its clients are categorized as "high net worth individuals" or "other pooled investment vehicles". In addition, we require the manager to charge a performance-based fee. After identifying the hedge funds from the ADV form, we manually map them with the S34 institutions via their names. In the end, we identify 985 hedge fund management companies in our sample. This number is close to the amount of

[8] We map the S34 data to Brian Bushee's cleaned institutional investor classification data to get a constant institution code and a more accurate institution type code, which solves the problems that CDA/Spectrum uses recycled manager number and institutional type is wrong after the year 1998. The S34 data are carefully cleaned of reporting errors (including staled and duplicated records) and adjusted of the number of shares holding when calculating the net institutional demand.

hedge fund identified from the S34 data disclosed by previous research (e.g., Agarwal et al. (2013) identify 942 hedge funds; Jame (2013) identifies 1013 hedge funds). We then use the reliable institution's type code from the S34 data and Brian Bushee's cleaned institution type code to further divide the rest of institutions into group (2) and (3) mentioned above. We put all the detailed process of identifying different institutions' types in Appendix B.

2.3. Sample

Our final sample combines both the insider and institution data at firm-quarter level. Following previous literature (e.g., Lakonishok and Lee, 2001; Sias and Whidbee, 2010; Cohen et al., 2012), we firstly limit the sample to the quarters that have insider's trading, and then focus on the combined sample with insiders' opportunistic- and routine-trades only. We apply the CRSP share code of 10 or 11 and exchange code of 1, 2 or 3 to exclude non-ordinary securities and securities not traded in NYSE, AMEX and Nasdaq. We also require securities traded with price larger than \$1 and trading amount bigger than or equal to 100, stock quarters with quarterly absolute net insider demand less than or equal to 20% of the shares outstanding, and securities with a book-to-market value larger than 0 and less than or equal to 100.

Table 1 reports the summary statistics of pooled average over all firm-quarter observations of our final sample.[9] Insiders' opportunistic-trading demand is more fluctuate than their routine-trading demand, which indicates that insiders tend to trade more if the transaction is driven by information. Compared to mutual fund and other institutions, the net

[9] We winsorize all the measures regarding to net insider demand and net institutional demand cross-sectionally within each quarterly cohort at 1 and 99 percentile values.

hedge fund institution's demand is less fluctuated. This result is consistent with Agarwal et al. (2013) and partially caused by the reason that hedge fund companies are smaller in size[10] compared to other types of institutions.

[Insert Table 1 here]

3. The use of insider information by hedge funds and other institutional investors

In this section we check the relationship between different categories of insiders' and institutions' trading demand. At every quarter, insider trading (overall insiders' trades), non-informative trading (insiders' routine trades) and informative trading (insiders' opportunistic trades) at stock-quarter level are sorted into four portfolios by their net insider demands. We then compute the cross-sectional average of net insider demand (for different categories of insiders), and focus on the different categories of net institutional demand (net fraction of outstanding shares moving to institutional investors) at the same quarter (quarter t). After computing the cross-sectional average for every quarter, we then calculate the time-series average for each of the four portfolios.

[Insert Table 2 here]

Our early findings in Table 2 are consistent with Sias and Whidbee (2010)'s results that there is a strong and significant inverse relation between overall net insider demand and institutional investors' demand. Specifically, when the overall net insider demand increases

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[10] Institutions' size is measured as the product of stocks' prices and the reported shares in the quarter-end equity portfolio reported by different categories of institutions. The actual difference in the total assets under management between hedge fund and other types of institution could be less, due to the reason that hedge funds could hold different types of assets, without the constraint to hold long positions in public stocks.

from -0.63% to 0.292%, the overall institutions' demand decreases from 1.058% to 0.39%. Turning to hedge funds, however, we could not find the significant inverse trading relationship documented above.

3.1. Hedge funds' and insiders' informative trades

In this sub-section we further focus on the interaction between hedge funds' and insiders' trades. Our results indicate that hedge funds tend to trade in the same direction as those insider transactions likely driven by information (insiders' opportunistic transactions), and do not respond significantly when insiders trade routinely for liquidity reasons. Specifically, when insiders' routine-trading demand increases from -0.41% to 0.13%, the hedge funds' demand remain approximately constant around 0.02%, with an insignificant t-statistic. On the other hand, hedge funds' demand increase significantly from -0.01% to 0.12% when insiders' opportunistic-trading demand increases from -0.50% to 0.18%. Meanwhile, our supplementary finding is also consistent with Cohen et al. (2012) that insiders' opportunistic trades could be utilized to predict future return. Both the quarterly market-excess return (defined as the difference between stock's return and the value-weighted CRSP all equity market return) and the DGTW abnormal return (defined as the difference between stock's return and one of the 125 portfolios aggregated by size, book-to-market and momentum it belongs to) have the consistent increasing pattern across all the four quartiles sorted by the insiders' opportunistic-trading demand. On the contrary, there is no significant relationship between insider's routine-trading demand and stocks' future performance.

We then replicate the empirical results above by further controlling some well-known firm characteristics (e.g., stock's size, book-to-market value and momentum) in the pooled multivariate regression:

$$Net\ Institutional\ Demand_{i,c,t} = \alpha_0 + \beta_1 * Decile\ Rank\ Net\ Insider\ Demand_{i,c,t} + \beta_2 * Control_{\ i,t-1} \quad (1)$$

For each stock (i) at time t we calculate its different categories of institutions' (c) demand. For each category (c) of insiders' trades (i.e., routine or opportunistic), we sort the raw value of the net insider demand into deciles[11] at every quarter and apply the decile rank as the key independent variable. T-values in all the regressions of this study are calculated based on coefficients' standard errors clustered by firm, and quarter fixed effect has been included.[12]

[Insert Table 3 here]

Consistent with our previous results, we document a significant positive relationship between insiders' likely informative trading and hedge funds' demand. On the contrary, the relationship between likely liquidity-driven insider trades and hedge fund trades is slightly inverse and statistically insignificant. There exists an inverse pattern between mutual fund & IIA and insiders' trades, and the inverse relation is much stronger and highly significant between all the other institutions' demand (e.g., pension fund, insurance companies) for insider trades regardless of information or liquidity driven.

[11] The reason we use the decile ranks of insiders' opportunistic- and routine-trading demand instead of the raw value as the key independent variable in the regression is to reduce the noise in the data.

[12] We follow Cohen et al. (2012) to cluster standard error at the firm level and include time fix effect. Our empirical results are consistent if we calculate the T-values based on coefficients' standard errors clustered by both firm and quarter.

3.2. Regulation change

Though the results in the previous sub-section are suggestive, they tend to demonstrate that hedge funds' and insiders' likely informative trades have a consistent trading direction. To confirm that hedge funds are more likely to follow and mimic insiders' informative trades, we exploit a further test by utilizing an important regulation change occurred in our sample period. The event we applied in this study is the shrink of reporting deadline for insiders' trades. In 2002, SEC requires corporate insiders to report their trading within 2 days (instead of 10 days after the trading month, which could be as long as 40 days) after the transaction happens. We conjecture that institutions tend to have more mimicking activities of insiders' information after the regulation, since the information is easier to track.

[Insert Table 4 here]

We set a regulation dummy as 1 if the date in our sample is after August 29th, 2002 (the date when the regulation change begins), and replicate the regression analysis in table 3 by adding an interaction term among decile rank of insiders' demand and dummy-regulation. Table 4 presents the results that the coefficient on the interaction of the (decile rank of) insiders' opportunistic-trading demand with dummy-regulation interaction is highly significant in explaining hedge funds' demand. The same effect does not exist for the interaction term if we change insiders' opportunistic-trading demand to insiders' routine-trading demand, which is consistent with our previous finding that hedge funds tend to discard insiders' non-informative trades throughout our sample period.

3.3. Hedge funds' transaction, insiders' trades and future return

In this sub-section we apply hedge funds' mimicking as a filter and further hypothesize that insiders' likely informative-driven (opportunistic) trades mimicked by hedge fund have additional predictive power for future return. Specifically, we generate a hedge fund mimic dummy, which equals to 1 if the net hedge fund demand has a same trading sign with insider's opportunistic trading-demand at the same quarter, and 0 otherwise. After that, we interact the insiders' informative trading rank with hedge funds' mimic dummy in the following regression model:

$$\begin{aligned} Ret_{i,t+1} = \alpha + \ & \beta_1 * Decile\ Rank\ Insider's\ Oppo.Demand_{i,t} + \beta_2 \\ & * Decile\ Rank\ Insider's\ Oppo.Demand_{i,t} * HF\ Mimic\ Dm_{i,t} + \beta_3 \\ & * HF\ Mimic\ Dm_{i,t} + \beta_4 * Net\ HF\ demand_{i,t} + \beta_5 * Net\ MF\ demand_{i,t} \\ & + \beta_6 * Net\ other\ institution\ demand_{i,t} + \beta_7 * Control_{i,t} \end{aligned} \quad (2)$$

[Insert Table 5 here]

Table 5 demonstrates that slope coefficients on the interaction terms of (the decile rank of) insiders' opportunistic-trading demand with hedge fund mimic dummy are highly significant at 0.28 and 0.35 respectively for market- and DGTW-adjusted future stock return. This result is consistent with our conjecture that hedge funds' mimicking could be further applied as a filter to select insiders' informative trades. Our result further indicates that the empirical measure of insiders' opportunistic trade is only a proxy for informative trades, and hedge funds tend to be able to identify insiders' trades motivated by information from the overall insider transactions, instead of mimicking insiders' opportunistic trades only.

4. Hedge funds' skill to identify information and their future performance

Our results in section 4 raise the question of whether the ability (or the extent) of mimicking insiders' informative trades matters for hedge funds' future performance. We follow Kacperczyk and Seru (2007) to generate the empirical proxies of hedge funds' extent to mimic insiders' informative trades by running a two-stage regression. Specifically, we generate empirical measures close to the RPI (reliance on public information) measure in Kacperczyk and Seru (2007) from the first stage regression. After that, we apply the second stage regression to test whether there is a significant relation between these measures and hedge funds' future buy-and-hold return.

4.1. Measuring hedge funds' ability to identify informative inside trades

Following the intuition of Kacperczyk and Seru (2007), we construct an empirical measure named RIC (response to informative insider trades coefficient). Specifically, we need to evaluate the magnitude of the percentage change of average stock holding driven by insiders' informative trading. For each institution at every quarter, we firstly calculate the percentage change of stock holding (for each stock), and then sort its portfolio of stocks into deciles [13] by insiders' opportunistic-trading demand. We then estimate the following cross-sectional regression for each institution (m) at quarter (t) by using all the stocks (i) it

[13] We have two reasons to use decile rank as the key independent variable in our regression model. First, as the same reason mentioned in footnote 9 above, the raw value of insiders' opportunistic-trading demand could be noisy. Second, it will be more consistent with Kacperczyk and Seru (2007)'s regression if we use the rank of insiders' opportunistic-trading demand, since their key independent variable in the similar regression is a change in the recommendation of the consensus forecast of stock, i.e., also a scaled variable.

holds[14]:

$$Change\ holding_{m,i,t} = \alpha_{0,t} + \beta_{1,t} * Decile\ rank\ insider's\ oppo.demand_{i,t} \quad (3)$$

where $Change\ holding_{m,i,t}$ demotes a percentage change in stock split-adjusted holdings by an institutional investor m from the previous quarter to the current quarter t, $Decile\ rank\ insider's\ oppo.demand_{i,t}$ measures the decile rank of insider's opportunistic-trading demand across each institution at quarter t.

We use the slope coefficient of model (3) as the main empirical proxy to represent the magnitude of institutions' mimicking activity to informative insider trading (RIC).[15] Kacperczyk and Seru (2007) document that the RPI measure (i.e., the unadjusted R-square from their first stage regression) does not discriminate between investors who trade in the same or in the opposite direction as public information. In our paper the trading direction is important, since we are interested in whether the institution is sophisticated enough to follow insider's informative trades. Thus, the slope coefficient β (RIC) represents both the magnitude and direction of information mimicking by institutions.

4.2. RIC and hedge funds' future performance

In the second-stage regression we explore the relation between RIC and hedge funds' future performance. Specifically, hedge funds' future buy-and-hold return is calculated based on the

[14] Compared to Kacperczyk and Seru (2007), the reason we do not include the change or the lagged change of opportunistic demand is we believe that timing is a very important factor for institutions to mimic insiders' informative trading.

[15] Close to the RPI measure by Kacperczyk and Seru (2007), we generate another measure of RIR (reliance on informative insider's trading measured by signed R-square) by calculating the product of the coefficient sign and the R-square in the first-stage regression, and find similar results in the second-stage regression.

most recent disclosure of holding information. We then sort RIC into decile ranks at every quarter across the institutions:

$$Hedge\ funds'return_{m,t+1} = \alpha_0 + \beta_1 * Decile\ Rank\ RIC_t + \beta_2 * Control_{m,t} \tag{4}$$

We focus on the relation between hedge funds' extent of mimicking insiders' informative trades and their future performance by limiting our sample into hedge funds institution only in the two-stage regression analysis.[16] Our second-stage regression results in table 6 demonstrate that hedge funds' future performance is better if they could utilize insiders' information. We thus provide some direct evidence that hedge funds could benefit from mimicking insiders' informative transaction.

[Insert Table 6 here]

In summary, our results in section 4 document a connection between the managers' skill to mimic insiders' informative trades and hedge funds' future return. These findings are consistent with our earlier regression results at stock level.

5. Conclusion

The existing evidence generally suggests that hedge funds are more skilled than other institutional investors on average. More and more studies attempt to discover the sources for superior performance by hedge funds. We add to this line of literature by exploring a new source contributing to hedge funds' information advantage – insider trading information.

By classifying insider trades into potentially informative ones and others likely driven

[16] Our results are robust if we extend the hedge fund sample to the overall institutional investors.

by liquidity motives, we find supporting evidence for hedge funds' ability to identify potentially informative insider trades and mimic such trades. In contrast, mutual funds and other institutional investors on average act as liquidity providers to insiders, regardless of insiders' trade motives. We further develop a measure of hedge funds' ability to use insider trade information, and link such ability to their performance in the cross-section. We find that hedge funds more skilled at identifying informative insider trades tend to outperform others.

References

Agarwal, V., Fos, V., and Jiang, W., 2013, "Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings," *Management Science*, Vol.59, 1271-1289.

Agarwal, V., Jiang, W., Tang, Y. and Yang, B., 2013, "Uncovering hedge fund skill from the portfolio holdings they hide," *The Journal of Finance*, Vol. 68, 739–783.

Aragon, G.O., and Strahan, P.E., 2012, "Hedge funds as liquidity providers: evidence from the Lehman bankruptcy," *Journal of Financial Economics* Vol. 103, 570-587.

Baik, B., Kang, J.-K., Kim, J.-M., 2010, "Local institutional investors, information asymmetries, and equity returns," *Journal of Financial Economics* Vol. 97, 81-106.

Ben-David, I., Franzoni, F., Landier, A. and Moussawi, R., 2013, "Do hedge funds manipulate stock prices?," *The Journal of Finance*, Vol. 68, 2383–2434.

Bettis, C., Vickrey, D. and Vickrey, D.W., 1997, "Mimickers of corporate insiders who make large volume trades," *Financial Analysts Journal*, Vol. 53 (5), 57-66.

Brunnermeier, M., and Lasse P., 2009, "Market liquidity and funding liquidity," *Review of Financial Studies*, Vol. 22(6), 2201-2238.

Brunnermeier M. and Nagel, S., 2004, "Hedge funds and the technology bubble," *Journal of Finance*, Vol. 59, 2013-2040.

Bushee, B.J. and Goodman, T., 2007, "Which institutional investors trade based on private information about earnings and returns?," *Journal of Accounting Research*, Vol. 45(2), 289–322.

Campbell, John Y., Tarun R., and Allie S., 2008, "Caught on tape: institutional trading, stock returns, and earnings announcements," *Journal of Financial Economics*, Vol. 92(1), 66-91.

Chakrabarty, B. and Shkilko, A, 2014, “Information leakage and learning in financial markets,” *Working paper*.

Cohen, L., Malloy, C. and Pomorski, L., 2012, “Decoding inside information,” *The Journal of Finance*, Vol. 67: 1009–1043.

Collin-Dufresne, P. and Fos, V., 2015, “Do prices reveal the presence of informed trading?,” *Journal of Finance*, Vol. 70(4), 1555–1582.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997, “Measuring mutual fund performance with characteristic-based benchmarks,” *The Journal of Finance*, Vol. 52, 1035–1058.

Daniel, K. and Titman, S., 2006, “Market reactions to tangible and intangible information,” *The Journal of Finance*, Vol. 61, 1605–1643.

Easley, D., and M. O’Hara, 2004, “Information and the cost of capital,” *The Journal of Finance*, Vol. 59, 1552–1583.

Fung, W., Hsieh, D., Naik, N, and Ramadorai, T., 2008, “Hedge funds: performance, risk and capital formation,” *Journal of Finance,* Vol. 63, 1777-1803.

Goldstein, M., P. Irvine, E. Kandel, and Z. Wiener., 2009, “Brokerage commissions and institutional trading patterns,” *Review of Financial Studies*, Vol. 22, 5175–5212.

Griffin, J., and Xu, J. 2009. “How smart are the smart guys? A unique view from hedge fund stock holdings,” *Review of Financial Studies*, Vol. 22, 2531–2570.

Ibbotson, R., Chen, P. and Zhu, K., 2011, “The ABCs of hedge funds: alphas, betas and costs,” *Financial Analyst Journal*, Vol. 67, 15-25.

Indjejikian, R., Lu, H and Yang, L., 2014, “Rational information leakage,” *Management Science*, Vol. 60(11), 2762–2775.

Ivashina, V., and Sun. Z., 2011, “Institutional stock trading on loan market information,” Journal of Financial Economics, Vol. 100(2), 284-303.

Jame, R., 2013, “How do hedge fund "stars" create value? Evidence from their daily trades,” *Working paper.*

Kacperczyk, M. and Seru, A., 2007, “Fund manager use of public information: new evidence on managerial skills,” *The Journal of Finance*, Vol. 62, 485–528.

Ke, B. and Petroni, K., 2004, “How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases,” *Journal of Accounting Research*, Vol. 42(5), 895–927.

Khan, M. and Lu, H., 2013, “Do Short Sellers Front-Run Insider Sales?,” *The Accounting Review*, Vol. 88(5), 1743-1768.

Klein, A., Saunders, A. and Wong, Y., 2014, “Do hedge funds trade on private information? Evidence from upcoming changes in Analysts’ stock recommendations,” *Working paper.*

Kosowski, R., Naik, N. and Teo, M., 2007, “Do hedge funds deliver alpha? A Bayesian and bootstrap analysis,” *Journal of Financial Economics,* Vol. 84, 229-264.

Lakonishok, J., and Lee, I., 2001, “Are insider trades informative?,” *Review of Financial Studies*, Vol. 14,79–111.

Martin, J.M. and Oliver, J.P., 2008, “The dog that did not bark: insider trading and crashes,” *Journal of Finance*, Vol. 73(5), 2429–2476.

Massoud, N., Nandy, D., Saunders, A., and Song, K., 2011. “Do hedge funds trade on private information? Evidence from syndicated lending and short-selling,” *Journal of Financial Economics*, Vol. 99(3), 477-499.

Morgenson, G. 2012, “Surveys Give Big Investors an Early View From Analysts,” *The New York Times*, July 16, 2012.

Qian, H. and Zhong, Z., 2014, “Do hedge funds possess private information in IPO stocks? Evidence from post-IPO holdings,” *Working paper.*

Shive, S., and Hayong Y., 2013, “Are mutual funds sitting ducks?,” *Journal of Financial Economics*, Vol. 107, 220-237.

Sias, R., and Whidbee, D., 2010, “Insider trades and demand by institutional investors,” *Review of Financial Studies*, Vol. 23, 1544–1595.

Yan, X., Zhang, Z., 2009, “Institutional investors and equity returns: are short-term institution better informed?,” *Review of Financial Studies*, Vol. 22, 893-924.

Appendix A: Identifying opportunistic and routine trades made by insiders

This paper follows the method by Cohen, Malloy and Pomorski (2012) to differentiate opportunistic and routine trades made by insiders. Insiders' trades have defined as either routine or opportunistic at the beginning of each calendar year based on their preceding 3-year classifying period of trades. Transactions *after* the classification period are placed into one of two buckets: routine and opportunistic trades. Insiders' routine-trading have been defined as the transactions after the consecutive three-year classification periods if insiders placed a trade in the same calendar month (during the classification periods). Insiders' opportunistic-trading have been defined as the transactions after the consecutive three-year classification periods if insiders placed trades randomly in different calendar months (during the classification periods). Using the same sample period with Cohen et al. (2012), the ratios of insiders' routine- and opportunistic-trading are 54.86% and 45.14% respectively. In Cohen's paper, the same ratios are 54.81% and 45.19%.

Appendix B: The classification process of 13F filing institutions

Thomson Reuters database uses manager number as the key identifier for every institution managers, and divides the institution types into different categories. Unfortunately, both of these two measures are problematic: [1], the manager number does not serve as unique and permanent identifier for every manager; [2], the type code is unreliable since the year 1998. Type codes 1, 2, 3, 4, 5 stand for bank, insurance company, investment companies and their managers, investment advisors, and all others (pension funds, university endowments, foundations). Since 1998, type code 5 includes many misclassified institutions from all other categories listed above.

To solve problem [1], Brian Bushee has created a permanent key to tie together the holdings history for fund managers that change manager numbers. For problem [2], he has taken the "reliable" 13F type codes and carried them forward in time for institutions still in existence after 1998. For new institutions, he has attempted to assign a type code based on searches for information about the fund manager. He merges type code 3 and 4 into the same group. In addition, he has taken the type code 5 group ("other") and attempted to determine whether the fund manager was a private pension, public pension, or an endowment. All other institutions were classified as "miscellaneous".

We apply Bushee's permanent key to identify institution managers, and use reliable 13F type code, Bushee's institutional type code and ADV form to classify institutions into different categories. We believe that hedge fund identified by ADV form should belong to the corrected 13F type code 4 or 5 (independent investment advisors or others). Thus, we firstly select 13F type code 4 and 5 and use Bushee's code as a filter to remove institutions that he classifies as banks, insurance companies, corporate or private pension funds, public pension funds, and university foundations and endowments (S34 potential hedge fund list). After that, we select a hedge fund list from the ADV form by requiring more than half of the institution's clients are categorized as "high net worth individuals" or "other pooled investment vehicles", and the institution charges a performance-based fee (ADV hedge fund list). We then use institution's names to map the "S34 potential hedge fund list" with the "ADV hedge fund list" and get the final hedge fund list in this study. After that, we remove all the hedge funds from the S34 data and apply Bushee's code to classify the rest of institutions into two groups: mutual fund and independent investment advisor (other than hedge funds), and all the other institution managers (e.g., banks, insurance companies, corporate or private pension funds, public pension funds, miscellaneous, and university foundations and endowments).

Appendix C: Variable definitions

This table lists all the variables and their definitions in the current paper.

Variable	Definition
Net insider demand (%)	The difference between shares purchased and sold by insiders, and divided by share outstanding. The measure indicates the net fraction of firm's shares purchased by insiders.
Hedge fund (institutions)	We identify hedge fund institutions through the way of ADV form, by requiring 1), the institution belongs to either independent investment advisors or other unclassified type of institutions according to the 13F type code; 2), using Brian Bushee's code as a filter to remove banks, insurance companies, corporate or private pension funds, public pension funds, and university foundations and endowments; 3), more than half of the institution's clients are categorized as "high net worth individuals" or "other pooled investment vehicles", and 4), the institution charges a performance-based fee. We then map the ADV hedge fund list with S34 dataset via the institutions' name to identify the hedge fund within S34 data.
Mutual fund and I.I.A .	Mutual fund and independent investment advisors, identified by requiring 1), all the identified hedge funds are eliminated from the S34 sample; 2), apply Brian Bushee's code to select the rest of institutions from two groups: mutual fund and independent investment advisor (other than hedge funds).
All other institutions	All the other institutions including banks, insurance companies, corporate or private pension funds, public pension funds, miscellaneous, and university foundations and endowments, identified by Brian Bushee's code.
Net institutional demand (%)	We firstly sum the share-holding (after carefully adjust the share split) of both quarter t and quarter t-1 for each type of institutional investor, each stock at each quarter, and then calculate the (summation) difference of share-holding from the previous quarter to current quarter in the aggregated way. Finally we

	scale the change of institutional holding by the share outstanding.
Market adjusted return (%)	Stocks' quarterly return minus the return on the CRSP value-weighted index over the same period.
DGTW adjusted return (%)	We follow Daniel, Grinblatt, Titman, and Wermers (1997) and subtract each stock's return from the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles.
Size	Market capitalization, defined as the price per share of each firm at the end of quarter multiple the number of share-outstanding.
BM	Book-to-market value. Market value is defined as market capitalization. This paper follows Daniel and Titman (2006)'s definition to calculate book value. We subtract from shareholders' equity the preferred stock value, where we use redemption value (item 56), liquidating value (item 10), or carrying value (item 130), in that order, as available. If all of the redemption, liquidating, or par values are missing from COMPUSTAT, then we treat the book equity value as missing for that year; if they are not missing, we add to this value balance sheet deferred taxes (item 35) and subtract off the postretirement benefit asset (item 330). Finally, we assume book value has at least a 3-month ahead of the market value.
Momentum	Return of the given stock over the prior four quarters, and aggregated at the yearly level.
Hedge fund mimic dummy	A dummy which equals to 1 if hedge fund's demand and opportunistic insider's demand have a same trading sign (either positive or negative). This dummy indicates whether hedge fund has a mimicking activity with opportunistic insiders' demand.
Change of institutional holding (%)	A percentage change in split-adjusted holdings of stock held by an institutional investor from the previous quarter to the current quarter. We set the

	measure as 100% for adding a new stock position into a fund portfolio.
RIC	Decile rank-transformed measure as reliance on informative insider's trading measured by coefficient (RIC). We follow the intuition of Kacperczyk and Seru (2007) and apply a two-stage regression to test the hypothesis that whether institutions which have a better ability to identify and follow informative insiders' trades could have a better future performance (at the institutional return level). In the first-stage regression, for each institution/qtr we regress the change of institutional holding on the decile rank-transformed opportunistic insiders' demand. We then extract the slope coefficient of first-stage regression for each institution/qtr, and rank-transform the coefficient into decile values at every quarter. The final decile rank-transformed coefficient is RIC.
RIR	Following the procedures of the first-stage regression above, we extract the R-square and the sign of the coefficient and then calculate the product of them. For every quarter we then transform the signed R-square into decile ranks as RIR.
Institutional buy and hold return (%)	For each institution at every quarter, we compute the value-weighted (the mkt cap. of shares holding) quarterly market-adjusted or DGTW-adjusted return, assuming it holds the most recently disclosed quarter-end holdings.
Institutional age	The difference between the year 2013 and the inception year that the institution's first appearance in Thomson Reuters dataset.
Institutional annual turnover	We first calculate quarterly turnover rates as the lesser of purchases and sales, divided by the average portfolio size of the last and the current quarters. Purchases and sales are proxied by the product of 1), positive/negative changes in the number of split-adjusted share-holding from the previous to current quarter end, and 2), the average share price between the previous and current quarter end. After

	getting quarterly turnover rates we then aggregate them to annual turnover rates.
Institutional size	The total value of quarter-end equity portfolio, calculated by the product of reported shares and corresponding quarter-end CRSP stock prices.
Institutional BM	For each institution at every quarter, we compute the value-weighted (by the size of stock-holding) aggregated BM value at institutional level, assuming the institution holds the most recently disclosed quarter-end stock holdings.

Table 1: Summary statistics

This table reports the summary statistics for the combined sample of corporate insider and institutional investor at firm-quarter level. The sample period ranges from 1995 to 2013. Following previous literature (e.g., Lakonishok and Lee, 2001; Sias and Whidbee, 2010; Cohen et al., 2012), we firstly limit the sample to the quarters that have insider's trading, and then focus on the combined sample with insiders' opportunistic and routine trades only. According to Sias and Whidbee (2010), net insider demand is defined as the net proportion of shares of firm i purchased by insiders in quarter t. For net institutional demand, we firstly sum the share-holding (after carefully adjust the share split) of both quarter t and quarter t-1 for each type of institutional investor, each stock at each quarter, and then calculate the difference of share-holding from the previous quarter to current quarter. Finally we scale the change of institutional holding by the share outstanding. For each stock at every quarter, we generate its market-adjusted return and DGTW-adjusted return. We calculate size (in billions), book-to-market and momentum and apply them as control variables in the regression. Appendix A, B and C provide detailed definition of different variables. We winsorize variables within each quarterly cohort at 1 and 99 percentile values.

Variable	Mean	Std Dev	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Net insider demand %	-0.114	0.521	-0.846	-0.127	-0.018	0.012	0.281
Insiders' routine-trading demand %	-0.066	0.300	-0.459	-0.067	-0.006	0.006	0.130
Insiders' opportunistic-trading demand %	-0.070	0.369	-0.511	-0.059	-0.008	0.006	0.145
Net institution demand %	0.493	3.781	-4.696	-0.846	0.169	1.715	6.302
Hedge funds' demand %	0.028	1.173	-1.814	-0.294	0.000	0.337	1.875
Mutual fund & IIAs' demand %	0.316	2.933	-4.023	-0.754	0.090	1.319	5.091
Other institutions' demand %	0.162	1.823	-2.548	-0.385	0.025	0.717	3.120
Mkt adj. ret	0.014	0.243	-0.307	-0.105	-0.004	0.105	0.374
DGTW adj. ret	0.003	0.238	-0.320	-0.112	-0.009	0.096	0.346
Size	4.943	23.552	0.025	0.132	0.543	2.029	17.429
BM	0.658	0.720	0.100	0.282	0.483	0.802	1.710
Momentum	0.194	0.667	-0.532	-0.142	0.093	0.369	1.185

Table 2: Univariate test for the relationship of trading demand between different categories of corporate insiders and institutions

We divide our sample into different segments according to the category of corporate insider trading. At every quarter, all the insider trading in the sample at stock-quarter level (overall insiders), insider trading for liquidity reasons (routine) and insiders' informative trading (opportunistic) are further sorted into four portfolios by the fraction of outstanding shares purchased by different categories of insiders (Net Insider Demand). We then compute the cross-sectional average of net insider demand (among different categories of insiders), net institutional demand over the same quarter as the insider trading (quarter t), as well as the next quarter's market-adjusted return for securities within each insider demand quartile. After computing the cross-sectional average we calculate the time-series average for each of the four portfolios. Following Sias and Whidbee (2010), we provide the p-value from an F-test of the null hypothesis that the values do not differ across the insider demand quartiles (computed from the time series of the cross-sectional means). We also provide the result of a T-test of the null hypothesis that the values for the fourth portfolio and for the first portfolio do not differ from each other.

	Insider Sell	**Quartile2**	**Quartile3**	**Insider Buy**	**Pr > F**	**Pr > |t|**
			Overall			
Overall net insider demand (t) %	-0.630	-0.026	0.003	0.292	<.0001	<.0001
Overall net institution demand (t) %	1.058	0.528	0.437	0.390	<.0001	<.0001
HF net institution demand (t) %	0.069	0.018	0.041	0.100	0.010	0.268
MF & IIA net institution demand (t) %	0.687	0.317	0.296	0.312	<.0001	<.0001
Other net institution demand (t) %	0.333	0.206	0.118	0.022	0.000	<.0001
Mkt adj. ret (t+1) %	-0.070	0.200	0.980	2.540	0.024	0.020
DGTW adj. ret (t+1) %	-0.600	-0.200	0.300	1.510	<.0001	<.0001
			Opportunistic			
Oppo. net insider demand (t) %	-0.497	-0.030	-0.001	0.182	<.0001	<.0001
Overall net institution demand (t) %	0.747	0.465	0.464	0.479	0.355	0.154
HF net institution demand (t) %	-0.010	0.020	0.024	0.118	0.009	0.003
MF & IIA net institution demand (t) %	0.473	0.251	0.306	0.435	0.429	0.829
Other net institution demand (t) %	0.288	0.201	0.150	-0.014	0.077	0.027
Mkt adj. ret (t+1) %	0.290	0.760	0.940	3.210	0.099	0.049
DGTW adj. ret (t+1) %	-0.780	-0.060	0.080	1.800	0.023	0.014
			Routine			
Routine net insider demand (t) %	-0.412	-0.032	0.000	0.126	<.0001	<.0001
Overall net institution demand (t) %	0.867	0.575	0.396	0.182	0.018	0.005
HF net institution demand (t) %	0.021	0.012	-0.004	0.017	0.977	0.952
MF & IIA net institution demand (t) %	0.485	0.271	0.262	0.172	0.361	0.122
Other net institution demand (t) %	0.341	0.269	0.146	0.028	0.013	0.004
Mkt adj. ret (t+1) %	1.910	0.350	0.750	2.570	0.432	0.712
DGTW adj. ret (t+1) %	0.630	-0.250	-0.110	0.370	0.838	0.844

Table 3: Multivariate regression for the pattern between different categories of institutions' and insiders' trades

This table reports the OLS regression result for the pattern between different categories of institutions' and insiders' trades during the period 1995 to 2013. Dependent variable is the net institutional demand by different categories of institutions (i.e., hedge fund, mutual fund & IIA, and all the other institutions such as bank, insurance companies, etc). We then sort the net insider demand (opportunistic or routine) into decile ranks each quarter and use the decile values as the key independent variable. Following Cohen et al. (2012), we control stock's size, book-to-market value and momentum at the previous time period. We report slope coefficient and P-values in the table. T-values of each variable are calculated based on coefficients' firm-clustered standard errors. We also include quarter fixed effect into all of the regressions in the table. *, **, and *** indicate statistical significance at 10%, 5% and 1% respectively.

	HF demand (t) %			MF & IIA demand (t) %			Other institution demand (t) %		
Intercept	0.324***	0.397***	0.330***	0.837***	0.806***	0.911***	0.093	0.062	0.217*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.433)	(0.613)	(0.096)
Decile rank oppo (t)	0.007**		0.007**	-0.009		-0.010*	-0.014***		-0.014***
	(0.012)		(0.012)	(0.102)		(0.099)	(0.000)		(0.000)
Decile rank rt (t)		-0.001	-0.001		-0.006	-0.006		-0.010***	-0.011***
		(0.790)	(0.840)		(0.298)	(0.285)		(0.005)	(0.004)
Log(size) (t-1)	-0.020***	-0.021***	-0.020***	-0.034***	-0.034***	-0.036***	-0.002	-0.001	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.747)	(0.804)	(0.403)
Log (bm) (t-1)	-0.024**	-0.021*	-0.024**	-0.130***	-0.131***	-0.127***	-0.078***	-0.079***	-0.073***
	(0.026)	(0.057)	(0.031)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum (t-1)	-0.073***	-0.077***	-0.073***	-0.048	-0.043	-0.049	0.219***	0.226***	0.217***
	(0.000)	(0.000)	(0.000)	(0.267)	(0.320)	(0.257)	(0.000)	(0.000)	(0.000)
Nobs.	31229	31229	31229	34240	34240	34240	34568	34568	34568
R-square	0.020	0.019	0.020	0.028	0.028	0.028	0.068	0.068	0.068
Adjusted R-square	0.017	0.017	0.017	0.026	0.026	0.026	0.066	0.066	0.066

Table 4: The relationship between the institutions' and insiders' trades under the 2002 regulation change

This table reports the OLS regression result for testing the impact of regulation change on different categories of institutions' and insiders' trades during the period 1995 to 2013. In 2002, SEC requires corporate insiders to report their trading within 2 days (instead of 10 days after the end of month) when the transaction happens. We set the Dm as 1 if the date in our sample is after August 29th, 2002 (the date when the regulation change begins). Following Cohen et al. (2012), we control stock's size, book-to-market value and momentum at the previous time period. We report slope coefficient and P-values in the table. T-values are calculated based on coefficients' standard errors clustered by firm. We also include quarter fixed effect into the regression. *, **, and *** indicate statistical significance at 10%, 5% and 1% respectively.

	HF demand (t) %			MF & IIA demand (t) %			Other institution demand (t) %		
Intercept	0.400***	0.397***	0.398***	1.590***	1.599***	1.884***	0.693***	0.596***	0.788***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile rank oppo (t)	-0.005		-0.005	-0.051***		-0.047***	-0.023***		-0.024***
	(0.279)		(0.266)	(0.000)		(0.001)	(0.002)		(0.001)
Decile rank rt (t)		0.001	0.001		-0.052***	-0.048***		-0.008	-0.006
		(0.827)	(0.848)		(0.000)	(0.000)		(0.300)	(0.453)
Decile rank oppo (t) * Dm	0.014**		0.014**	0.050***		0.047***	0.011		0.012
	(0.012)		(0.012)	(0.001)		(0.003)	(0.162)		(0.156)
Decile rank rt (t) * Dm		-0.005	-0.004		0.144***	0.134***		-0.007	-0.015
		(0.688)	(0.751)		(0.000)	(0.000)		(0.729)	(0.499)
Dm	-0.088	0.004	-0.078	-0.798***	-0.877***	-1.110***	-0.610***	-0.529***	-0.572***
	(0.221)	(0.960)	(0.326)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control (t-1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs.	31229	31229	31229	34240	34240	34240	34568	34568	34568
R-square	0.020	0.019	0.020	0.029	0.029	0.029	0.068	0.068	0.068
Adjusted R-square	0.018	0.017	0.017	0.027	0.027	0.027	0.066	0.066	0.066

Table 5: Multivariate regression for testing the relationship between future return and insiders' informative-trading demand with hedge fund mimicking

This table reports the OLS regression result of testing the relationship between future return and insiders' informative-trading demand with hedge fund mimicking during the period 1995 to 2013. We create a hedge fund mimic dummy, which equals to 1 if both hedge fund managers' and insiders' opportunistic-trading demand have the same trading direction. Dependent variable is the market (DGTW)-adjusted return at quarter t+1. For each quarter, we sort the net insider demand (opportunistic or routine) into decile ranks, and create an interaction term as the product of decile ranks of insiders' opportunistic-trading demand and the hedge fund mimic dummy. Following Cohen et al. (2012), we control stock's size, book-to-market value and momentum at the previous time period. We report coefficient and P-values in the table. We also include quarter fixed effect into all of the regressions in the table. *, **, and *** indicate statistical significance at 10%, 5% and 1% respectively.

	Mkt adj. qtrly return (t+1) %		DGTW adj.qtrly return (t+1) %	
Intercept	3.057***	7.755***	-0.129	0.812
	(0.000)	(0.000)	(0.864)	(0.699)
Decile Oppo nid (t)	0.083	0.035	0.025	0.020
	(0.274)	(0.659)	(0.754)	(0.806)
Decile Oppo nid (t) * HF mimic dm (t)	0.279**	0.271**	0.345***	0.344***
	(0.018)	(0.021)	(0.004)	(0.005)
HF mimic dm (t)	-1.194*	-1.146*	-1.824***	-1.815***
	(0.081)	(0.093)	(0.009)	(0.009)
Decile Rt nid (t)	0.161	-0.236	0.410	0.361
	(0.835)	(0.765)	(0.609)	(0.656)
HF net institution demand (t) %	0.306**	0.299*	0.189	0.192
	(0.046)	(0.052)	(0.218)	(0.213)
MF & IIA net institution demand (t) %	0.011	0.012	-0.039	-0.038
	(0.889)	(0.883)	(0.596)	(0.611)
Other net institution demand (t) %	-0.145*	-0.139	-0.149*	-0.153*
	(0.090)	(0.100)	(0.073)	(0.065)
Log(size) (t)		-0.196**		-0.046
		(0.023)		(0.607)
Log (bm) (t)		0.687***		0.195
		(0.003)		(0.403)
Momentum (t) %		0.007*		0.005
		(0.097)		(0.333)
Nobs.	31005	31005	28595	28595
R-square	0.032	0.032	0.006	0.006
Adjusted R-square	0.029	0.030	0.004	0.004

Table 6: Multivariate regression for testing the relationship between hedge funds' ability to mimic insiders' informative trades and their future performance

This table reports the 2nd-stage regression results of testing the relationship between the hedge funds' ability to mimic insiders' informative trades and their future performance. In the 1st-stage regression, we regress the change of hedge funds' holding on the decile rank of insiders' net opportunistic-trading demand for each hedge fund institution/quarter, and extract the slope coefficients. After that we sort the coefficients into decile rank at every quarter (RIC). For each hedge fund/quarter, we compute the value-weighted (by the mkt cap. of shares holding) quarterly market- or DGTW-adjusted return, assuming it holds the most recently disclosed quarter-end holdings. For the 2nd-stage regression, we regress the hedge funds' return at the next quarter on the decile rank of slope coefficients (RIC) from the 1st-pass regression. We report slope coefficient and P-values in this table. T-values are calculated based on coefficients' standard errors clustered by firm. We include quarter fixed effect into all of the regressions in the table. *, **, and *** indicate statistical significance at 10%, 5% and 1% respectively.

	Mkt adj. qtrly ret (t+1) %		DGTW adj.qtrly ret (t+1) %	
Intercept	1.165***	2.677**	2.704	2.348**
	(0.000)	(0.011)	(0.145)	(0.028)
RIC(t)	0.045*	0.036	0.057**	0.043*
	(0.094)	(0.205)	(0.017)	(0.095)
Log(age) (t)		-0.256		-0.490***
		(0.112)		(0.003)
Log(size) (t)		-0.047		0.029
		(0.346)		(0.502)
Log (bm) (t)		-2.077***		-1.935***
		(0.000)		(0.000)
Annual turnover (t)		0.015		-0.098
		(0.496)		(0.874)
Mkt/DGTW adj. qtrly ret (t) %		-0.032**		0.023
		(0.044)		(0.309)
Mkt/DGTW adj. qtrly ret (t-1) %		0.025		-0.030*
		(0.126)		(0.092)
Mkt/DGTW adj. qtrly ret (t-2) %		-0.005		0.019
		(0.795)		(0.271)
Mkt/DGTW adj. qtrly ret (t-3) %		0.514		0.009
		(0.426)		(0.571)
Nobs.	6389	5612	5818	5110
R-square	0.100	0.112	0.091	0.105
Adjusted R-square	0.092	0.102	0.082	0.093