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Institutional Ownership and Stock Returns

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Institutional Ownership and Stock Returns

Abstract

This paper investigates the relation between changes in institutional ownership (IO) and cross-section stock returns. By using the monthly IO data in Taiwan from 2001 to 2014, we justify the linearity covariance decomposition of Sias, Starks, and Titman 2006 and provide empirical evidence to show the short-term positive and long-term negative correlations between changes in IO and returns controlling for other characteristics of stock and double clustering standard errors. We also propose an investment strategy by ranking the stocks according to their changes in IO. The investment portfolio can generate, at least, annually 9.51% relative to the momentum strategy.

Does the institutional investor invest in the same stocks as everyone else? Are institutional investors different from others in their demand for asset characteristics? What is the correlation between institutional money managers' trading and stock returns? These questions have been the focus of a large empirical literature, but the conclusions are not clear.

Studying the trading behavior and potential price impact of institutional money managers is of great interest because the increasing prevalence of institutional investors in stock markets. Figure 1 shows the holding compositions of corporate equities in different categorical investors in the U.S. from 1950 to 2010.[1] It shows that the holding percentages by household investors have dramatically decreased from 90.2% in 1950 to 36.6% in 2010. Instead, the ownership became more highly concentrated over the past 60 years: institutional investors increase their share of the market from 4.3% in 1950 to 42.9% in 2010. Moreover, global assets under management totaled approximately $79.3 trillion until 2010, of which the U.S. accounts nearly for 45%.[2]

[Place Figure 1 about here]

In the U.S., institutional investors are requested to report their quarterly equity positions in 13-F filings to the Securities and Exchange Commission (SEC). Most of studies in finance literature use this quarterly data to investigate the relation between institutional trading behaviors and stock returns, answering the questions of whether institutional investors are important in stabilizing or destabilizing influence on stock prices. They find the trading behavior of institutional money managers tend to herd, that is, to imitate each others' stock trades and have also determined positive correlation between the direction of institutional herding and future stock returns. For example, Nofsinger and Sias 1999 show that stocks experiencing the largest increase in institutional ownership per year outperform those experiencing the largest decrease and reveal a positive relation between annual changes in institutional ownership and stock returns. Sias 2004 finds that institutional demand is positive correlated over adjacent quarters and is positively related to returns over the following year.[3] However, some authors have indicated that the positive relationship holds only for institutional purchase and not for sales (Cai and Zheng 2004), only for new institutional position in a stock (Badrinath and Wahal 2002), and only for stock with high past returns (Grinblatt, Titman, and Wermers 1995). Moreover, Dasgupta, Part, and Verardo 2011 investigate the trading persistence of institutional investors over multiple periods and find that institutional trading persistence negatively predicts long-term returns on sold stocks.

The ambiguous empirical findings arise because institutional trading, by itself, can induce price movements or might simply react to price frustration within one quarter. Therefore, the determination of the relation between quarterly institutional flows and lagged quarterly stock returns is severely handicapped only depending on the low frequency of data. That is, the data limitation introduces difficulties in identifying the effect of institutional trading on prices. In order to understand institutional investors' trading patterns depending on the only available quarterly data, many studies also try to propose methodologies in decomposing quarterly changes of institutional ownership to evaluate the relation between intraquarter pattern and stock returns. For example, Sias, Starks, and Titman 2006 develop a method to exploits covariance linearity of changes in institutional ownership. They find strong positive correlation between quarterly changes in institutional ownership and returns. Campbell, Ramadorai, and Schwartz 2009 use the TAQ database to define institutional investors' herding by inferring daily institutional trading behavior. Their study finds that institutional trades are persistent and positively respond to recent daily returns but negatively to longer-term past daily returns according to the choices of cutoff rules for institutional trades.

Instead of decomposing the quarterly holdings of institutional investors to make inference on the changing pattern of institutional ownership (IO) and analyze its role in explaining and predicting stock returns, in this paper, we use a data set from Taiwan that contains monthly holding percentages of institutional investors for each stock from 2001 to 2014, in which these institutional investors can be classified as foreign institutions, investment trusts, or dealers to directly test the correlations of IO changes and returns. In this study, we first consider the IO changes over the past one month until past 12 months and calculate the time-varying correlations of these institutional investors. We find, in Figure 5, foreign IO changes are positive in the short-term and negative in the long-term. The correlations of IO changes for investment trusts are positive only for the very short-term period and the correlations of IO changes for dealers tend to negative all the time. One step further in Figure 6, we find the correlations of IO changes between foreign institutions and investment trusts are close to zeros, as are the correlations between foreign institutions and dealers. If we consider the correlations of IO changes between investment trusts and dealers, they are more likely to be positive. This finding suggests that the trading patterns have large variety in different institutional investors and provide an empirical justification for the correlation decomposition in Sias, Starks, and Titman 2006.

In the regression analysis of Section 2, we examine the correlation between lag IO changes and observable monthly returns in current month and following 12 months. We argue that if IO change for particular stock is positive (negative), this denotes that there are some institutional investors are motivated to buy (sell) the stock within that month. When the IO changes persistently remain positive and increase (decrease) for a period, these institutional investors are likely accorded *conformity* (as in Devenow and Welch (1996)) which indicates institutional investors might disregard their own beliefs and blindly follow others in the market, driving by an intrinsic preference for conformity with market consensus. The *conformity* shifts the demand of stock and pushes the price up. In line with our argument, we find changes in IO indeed can explain the cross-sectional stock returns even if we control for market excess return and a number of stock characteristics including firm size, trading volume, shares turnover, and idiosyncratic volatility, along with other several value characteristics of a firm such as price-to-book (P/B) ratio and past one-month and 12-month stock returns. We show that short-term IO change is significantly positive correlated to the cross-sectional stock returns while the long-term IO change is significantly negative correlated.

We further test the predictability of IO changes for forecasting lead 1-12 months cross-sectional stock returns. Consistent with previous findings in the literature, we find firms with small size, higher trading volume, and lower turnover rate have higher future stock returns. In addition, higher past 12-month stock return indicates lower future stock returns, suggesting that the momentum effect associated with IO changes is not strong in the market. While the most recent IO change of foreign institutions tends to negatively correlate to the future cross-sectional stock returns, IO changes of investment trusts and dealers tend to positively correlate. In particular, past nine-month IO change of investment trusts provides strong predictability power to future cross-section returns.

We next examine the link between IO changes and stock returns by forming portfolios based on the magnitude of IO changes and tracking their performance over periods of future 1-60 months in Section 3. We form a portfolio test by ranking stocks into 10-decile portfolios based on their past J-month ($J = 3$ is the short-term and $J = 12$ is the long-term) IO changes of foreign institutions, investment trusts, and dealers. The stocks in the top (bottom) decile go to 'HIGH' ('LOW') portfolio. The hedge portfolio is constructed by longing the 'LOW' portfolio and shorting the 'HIGH' portfolio. We hold the portfolio for considering the following K^{th} months, $K = 1$, 2, 3, 4, 5, 6, 9, 12, 24, 36, and 60 months and calculate the equally-weighted portfolio returns. We find our proposed strategy by forming IO changes statistically and significantly outperforms the performance of investment portfolio forming by using past 12-month stock returns excluding the recent month, i.e., the momentum strategy. We show the profits of our proposed investment strategy are not only persistent over time in the following three years but also generate monthly 0.76% to 1.05% (9.51% to 13.35% annually) portfolio returns relative to the momentum strategy. In particular, if we consider the compound returns of investing portfolios during the period of 2002 to 2014 as shown in Figure 7, the IO portfolios of foreign institutions and investment trusts can beat over the market and largely improve the performance of momentum strategy.

The reminder of the paper is organized as follows. Section I describes the data and descriptive statistics. Section II presents the regression tests of the link between IO changes and stock returns. Section III shows empirical results for portfolios formed based on IO changes and compares the results to the momentum strategy. Section IV concludes.

1 Data and Sample Statistics

The sample comes from Taiwan Economic Journal (TEJ) which consists of monthly institutional holding percentages for every common stock listed in the Taiwan Stock Exchange during the period from 2001 to 2014, in which three major institutional investors participated in the market: qualified foreign institutions, investment trusts, or dealers.[4] These%ages are calculated based on each stock's monthly shares outstanding. Data on stock prices, returns (adjusted by stock and cash dividends), and other firm characteristics, ex, firm size, P/B ratio, trading volume, and shares turnover are also from the database of TEJ. We construct idiosyncratic volatility by using daily returns for each stock, excluding those stocks that only have 11 trading days within one month. We use returns of Taiwan Stock Exchange Capitalization Weighted Index (TWSI) to represent market returns and define the monthly excess market return ($Mktrf$) as the difference between monthly market return and the three-month commercial fixed deposit rate obtained from the Bank of Taiwan.[5]

1.1 Sample Statistics

Figure 2 plots the numbers of stocks and each stock's holding percentages held by institutional investors.

[Place Figure 2 about here]

In the top panel of Figure 2, we first plot the monthly numbers of stocks holding compositions by these institutional investors. The total number of stocks grows nearly 2.5 times from 2001/01 (612 stocks) to 2014/12 (1524 stocks) where foreign institutional investors hold an average 88.56% (varying from 73.33% to 96.64%) of stocks in the market and continue to increase as the market size grows. However, the monthly numbers of stocks held by investment trusts and dealers change over time, in particular, the the monthly holding numbers of stocks drop 26.31% and 51.25% for investment trusts and dealers, respectively during the 2008 financial crisis. The monthly means of stock holding percentages of institutional investors are shown in the bottom panel of Figure 2. The overall means of holding percentages of foreign institutional investors, investment trusts, and dealers are approximately 8.71%, 2.83%, and 0.59% from 2001 to 2014. It is interesting to notice that the pattern of holding stock numbers and%ages by foreign institutions. After the 2008 financial crisis, the number of stock held by foreign institutional investors did not decrease, but rather increased. Also, the holding%age of each stock increases. It seems some foreign institutional investors pull out the money and flood these cash into a stable emerging stock market, like Taiwan, when the U.S. stock market became volatile during the period of 2008 financial crisis. It could also be the reason that the U.S. government implemented the monetary policy of quantitative easing so that there are may 'easy money' flow around. We won't address too much on this issue and left the discussion for interesting readers since it is not the main scope in this paper.

1.2 Characteristics of Explanatory Variables

Figure 3 illustrates the characteristics of stocks under different institutional investors and total sample, computed as time series average of cross-sectional data.

[Place Figure 3 about here]

The top panel shows the plot for trading volume (in million of New Taiwan Dollars). The institutional investors of dealers tend to hold stocks with high trading volume, following are those institutional investors of investment trusts. Institutional investors of foreign institutions hold stocks with trading volumes that are almost the same as those of the market. A similar finding is the size of stocks held by these institutional investors, as shown in the second top panel. However, for turnover rates and idiosyncratic volatilities of stocks held by institutional investors shown in the top third panel, these institutional investors hold stocks that are quite close to the market. Finally, the bottom panel of Figure 3 shows the P/B ratios of holding stocks by institutional investors. We find that those institutional investors of dealers tend to hold stocks with higher P/B ratios than other institutional investors during the period before the 2008 financial crisis.

1.3 Holding Stock Returns of Institutional Investors

In comparing the holding stock returns by different institutional investors, we plot their time series averages as shown in Figure 4.

[Place Figure 4 about here]

The overall average of market return is 0.63% during our sample period. However, for institutional investors, their average holding stocks returns are 1.51%, 1.97%, and 2.03% for foreign institutions, investment trusts, and dealers, respectively.

1.4 Correlations of IO Changes

In a given stock i, we define the month-t IO change by different institutional investors occurring between month $t-1$ and month t as

$$q_{i,t}^{\kappa} - q_{i,t-1}^{\kappa} \tag{1}$$

where κ=ALL (All institutional investors), F (Foreign institutions), T (Investment trusts) and D (Dealers). At month t, we also define the IO changes during previous $t-m+1$ month to $t-m$ month, $m = 1, 2, ..., 12$ and denote by $ALL(-m), F(-m), T(-m)$, and $D(-m)$. The correlation maps of $ALL(-m), F(-m), T(-m)$, and $D(-m)$ are plotted in Figure 5.

[Place Figure 5 about here]

The top left panel of Figure 5 shows the correlations plot of all institutional investors for every stock over the period from current month t up to the previous 12 months. The same plots in the top right, bottom left, and bottom right panels of Figure 5 indicate the correlations plot of foreign institutions, investment trusts, and dealers. Interestingly, we find that correlations of the holding%age changes for institutional investors are not harmonic; the patterns are quite inconsistent over the short-term and long-term periods. We find that the correlations of the holding%age changes for foreign institutional investors are likely positive over the short-term period in one month up to previous six months. While accounting for long-term correlations of the holding%age changes for foreign institutional investors, they become negative. However, for investment trusts, the correlations behave positively only in a very short-term period within one month and negatively over the period from previous two months to 12 months. The correlations of dealers tend to be negative.

We further define the accumulated IO change for different institutional investors by

$$\kappa.(-n) = \sum_{s=-n}^{-1} \kappa(s) \tag{2}$$

where κ=ALL, F, T, and D and $n = 1, 3, 6, 9$, and 12. $\kappa.(-n)$ measure the time-varying properties of IO changes over the past 1-12 months. The correlation map of $ALL.(-n), F.(-n), T.(-n)$, and $D.(-n)$, $n = 1, 3, 6, 9$, and 12 is in Figure 6.

[Place Figure 6 about here]

In Figure 6, the three blocks 'F T', 'F D', and 'T D' represent the correlations of $F.(-n)$ and $T.(-n)$, correlations of $F.(-n)$ and $D.(-n)$, and correlations of $T.(-n)$ and $D.(-n)$, respectively. We find the correlations are close to zeros except for the positive correlations of 'T D'. It shows the IO changes of foreign institutions are sometimes in conflict with those of investment trusts and dealers. That is, the trading behaviors of foreign institutions are likely to be more compatible than those of investment trusts and dealers. The foreign institutions are more likely to deviate from investment trusts and dealers. Our correlation maps suggest that the trading patterns vary in different type of institutional investors, providing an empirical support for the correlation decomposition as in Sias, Starks, and Titman 2006.

2 Regression Analysis

In this Section, we test the link between the IO changes and current cross-sectional stock returns using regression models control for the market excess return, reversal effect, momentum effect, and a wide variety of other control variables of stock. To conduct more accurate and robust statistical inference, we also estimate the two-way clustering standard errors and calculate the t-statistics proposed by Cameron, Gelbach, and Miller 2011 by considering possible errors being correlated within firm and time clusters.

2.1 Cross-sectional Regression Models

In our regression analysis, we define $\kappa.IC(-m)_{i,t}$ as the cumulated%age changes of IO for stock i at time t in different institutional investors over the past 1-12 months by

$$\kappa.IC(-m)_{i,t} = \sum_{t=-(m-1)}^{0} \frac{q^{\kappa}_{i,t} - q^{\kappa}_{i,t-1}}{q^{\kappa}_{i,t-1}}, m = 1, 3, 6, 9, \text{ and } 12. \tag{3}$$

where κ=F, T, and D. If $q^{\kappa}_{i,t-1}$ is missing or 0, the value of $\kappa.IC(-m)_{i,t}$ is defined as 0.

We consider the specification model:

$$R_{i,t} = \alpha_0 + Mktrf_t + \beta\kappa.IC(-m)_{i,t} + \boldsymbol{\gamma}\mathbf{R_{i,t-1:t-p}} + \boldsymbol{\delta}\mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4}$$

where the dependent variable, $R_{i,t}$ (in %) is the time-t return for stock i. The explanatory variable $Mktrf_t$ denotes the market excess return at time t and $\mathbf{R_{i,t-1:t-p}}$ controls for the reversal effect ($Lag1ret_{i,t}, p = 1$) and the momentum effect ($Lag12ret_{i,t}, p = 12$) of stock documented in DeBondt and Thaler 1985 and Jegadeesh and Titman 1993. The vector $\mathbf{X_{i,t}}$ contains a number of control variables including firm size ($size_{i,t}$), price-to-book (P/B) ratio ($PBR_{i,t}$), trading volume ($Volume_{i,t}$), shares turnover ($Turnover_{i,t}$), and idiosyncratic volatility ($Volatility_{i,t}$). Table I reports the cross-sectional regression results.

[Place Table 1 about here]

We start by focusing on the benchmark model (1) in Table 1. The coefficient estimate of $Mktrf_t$ is significant larger than 1 which comprises the risk premium of individual stock to the whole market. Although the size premium is not statistically significant in our regression, the coefficient estimates of $PBR_{i,t}$ is consistent with the finding as stated in Jensen, Johnson, and Mercer 1997. Moreover, the result shows that shares turnover is positively associated with the cross-sectional returns which is in line with the findings in literature. Amihud and Mendelson 1986, Chalmers and Kadlec 1998, and Rouwenhorst 1999 among others have suggested that one of the particular interest to investors in emerging financial markets is liquidity which is compensated for expected returns. In our study, we find that shares turnover is positively associated with the cross-sectional returns. Moreover, the financial literature has paid considerable attention to study the relation between idiosyncratic volatility and expected returns. In the asset pricing literature, most theories support a positive relation between idiosyncratic risk and expected returns (see in particular Levy 1978; Campbell, Lettau, Malkiel, and Xu 2001; and Guo and Savickas 2008). Consistent with previous studies, our regression coefficient estimate of $Volatility_{i,t}$ finds similar evidence to support the price of risk for the exposure to the idiosyncratic variance risk. In addition, the coefficient estimates of $Lag1ret_{i,t}$ and $Lag12ret_{i,t}$ are both statistically significant negative which indicates the reversal effect is strong but no momentum effect exits in the market.

Our main interests are comparing the separated models (2), (3), and (4) and pooled model (6) to the benchmark model (1). In model (2), we find the recent one-month foreign IC is positively correlated to the cross-sectional returns. The past three-month and past nine-month foreign ICs are negatively correlated. One-standard deviation increase in recent one-month foreign IC increases in return of approximately 0.05%. One-standard deviation increase in past three-month and past nine-month foreign ICs decrease in returns of approximately 0.006% and 0.009%, respectively. Model (3) and (4) also find the short-term positive and long-term negative correlations of investment trusts and dealers ICs to the cross-sectional returns. One-standard deviation increase in recent one-month investment trusts and dealers ICs increase in returns of approximately 0.11% in returns while one-standard deviation increase in recent twelve-month investment trusts and dealers ICs decrease in returns of approximately 0.01% and 0.02%, respectively.

If we pool ICs under different types of institutional investors together in model (5), we can find ICs continue to affect cross-sectional returns, in which short-term ICs are positively correlated to cross-sectional returns and long-term ICs are negative correlated. Moreover, the coefficient estimates of investment trusts and dealers ICs are quite close to each other. This finding reinforces our argument on deviations of foreign institutions in the market.

2.2 Predictive Regression Models

We next estimate predictive cross-sectional regressions for future 1-12 month cross-sectional stock returns as the following specification model:

$$R_{i,t+1:t+n} = \alpha_0 + Mktrf_t + \beta\kappa.IC(-m)_{i,t} + \boldsymbol{\gamma}\mathbf{R_{i,t-1:t-p}} + \boldsymbol{\delta}\mathbf{X_{i,t}} + \epsilon_{i,t} \tag{5}$$

where $n = 1, 3, 6, 9$, and 12 and the explanatory variables are defined the same as in the regression model of Equation (4). The results are presented in model (a)–(e) of Table 2.

[Place Table 2 about here]

Before we discuss the predictability of ICs, we link the findings with the existing finance literature. Our empirical results find that firms with small size and low turnover rate tend to have higher future expected cross-sectional stock returns. This finding is consistent with predictions from a type of transaction cost model in Amihud and Mendelson 1989. Also for trading volume, our empirical evidence is consistent with Gervais, Kaniel, and Mingelgrin 2001, in which they investigate the power of trading volume in predicting the directions of future price movements. They provide the evidence shows that individual stocks whose trading volume is usually large (small) over periods of a day or a week, tend to experience large (small) returns over the subsequent month. The positive correlations is also determined in our regression.

Our ICs indeed predict future cross-sectional stock returns except for lead one month and lead nine months returns. The coefficient estimates indicate mid- and long-term foreign ICs are negatively correlated to future returns. The mid- and long-term ICs of investment trusts and dealers are positively correlated to future returns.

3 IO Portfolios

We further analyze the relationship between ICs and future returns by implementing portfolio evaluation. Specially, we estimate the returns to portfolios of stocks sorted by ICs and examine their performance comparing to the momentum strategy.

3.1 Performance of the Momentum Strategy

Momentum strategies, also known as relative strength strategies, are prevalent among traders propose by Jegadeesh and Titman 1993. The momentum effect has also been confirmed in financial assets such as commodity and currency. However, many researchers, like Barroso and Santa-Clara 2012 and Daniel and Moskowitz 2013, have pointed out some disadvantages of implementing the momentum strategy.

Following most of the literature, we rank the stocks based on their past J-month returns excluding the most recent month where J=6, 9, and 12 and denote them by (6–1), (9–1), and (12–1). This momentum definition is currently most broadly used and readily available through the PR1YR factor of Carhart 1997. The momentum strategy typically disentangles the intermediate horizon momentum effect from the short reversal effect documented by Jegadeesh 1990 and Lehmann 1990. We assign stocks that meet the data criteria into 10 equally weighted portfolios at each formation month. Ten% of firms with the highest ranking period returns are grouped into the 'BUY'-decile portfolio, and those with the lowest ranking period returns are grouped into the 'SELL'-decile portfolio. The return on a zero investment 'B-S' portfolio is the difference between the returns on the 'BUY'-decile portfolio and the 'SELL'-decile portfolio in each period. Each portfolio is held for K months where K=3, 6, 9, and 12, following the formation month. The results are show in Table 3.

[Place Table 3 about here]

From Table 3, we find the momentum strategy performs poorly and tend to be negative in all the combinations of (J, K). Especially, the 'SELL' portfolios behave very strong significant reversal effect during our sample period. It causes the profit of 'B-S' portfolios, the hedged investment portfolios, are almost close to zeros or even worse in negative value.

3.2 Institutional Ownership Portfolios

Instead of ranking the stocks based on their past returns, we rank the stocks by using their past J-month ICs of foreign institutions, investment trusts, and dealers, respectively where J =3 and 12. We assign stocks into 10 (9 in investment trusts and dealers) equally weighted portfolios at each formation month. Top 10% of firms with the highest ranking period ICs are grouped into 'HIGH'-decile portfolio, and bottom 10% lowest ranking period ICs are grouped 'LOW'-decile portfolio. The return on a zero investment 'L-H' portfolio is the difference between the returns on the 'LOW'-decile portfolio and the 'HIGH'-decile portfolio in each period. Each portfolio is considered to hold for (K) months where (K) denotes the equally-weighted portfolio return only in the future K^{th} month, K = 1, 2, 3, 4, 5, 6, 9, 12, 24, 36, and 60. The results for J =3 and 12 are in Table 4 and Table 5, respectively.

[Place Table 4 to 5 about here]

For the long-term IO strategy ($J = 12$), it generates significant and positive monthly portfolio returns following the three months when portfolios are formed by ranking ICs of foreign institutions, investment trusts, and dealers. The profits of IO strategies are also persistent over time in the following three years. For the short-term IO strategy ($J = 3$), the results are different. Only portfolios formed by ranking ICs of foreign institutions can generate significant and positive returns.

3.3 Investment Strategies Evaluation

An interesting result arises if we evaluate the momentum strategy and our proposed IO portfolios over time. We choose the case of $J = 12$ and K=1 in forming these investment portfolios. Figure 6 presents the compound returns for investing \$1 initially in (1) the Taiwan Weighted Stock Index (TWSI) as the market, (2) the momentum strategy, (3)-(5) the IO portfolios of foreign institutions, investment trusts, and dealers, respectively from January 2002 to December 2014.[6]

[Place Figure 6 about here]

On the right side of Figure 6, we show the final dollar values for each of the five portfolios: \$4.24 for (3) the foreign institutions IO portfolio, \$4.23 for (4) the investment trusts IO portfolio, \$1.68 for (1) the market, \$0.81 for (2) the momentum strategy, and \$0.29 for (5) the dealers IO portfolio. Although the compound returns of (5) are quite relatively lower than (3) and (4), the investment performance of (3) and (4) not only beats over the market but also outperforms the momentum strategy. In particular, the compound returns of the portfolios formed by considering the ICs of foreign institutions and investment trusts are about three times more than the market and five times more than the momentum strategy during the period of 2002 to 2014.

4 Conclusions

Motivated by the empirical findings on institutional trading and its potential impact on stock returns, we focus on studying the changes in IO and its relation to cross-sectional stock returns. This study contributes to the literature by overcoming the data limitation and successfully linking the relation in changes of IO to stock returns. We test the effect of IO changes on stock returns by using both regression models and portfolio analysis. In our regression results, we find short-term changes in IO is positively correlated to cross-sectional stock returns while long-term changes in IO is negatively correlated. The regression tests show that the effect of changes in IO on stock returns is not subsumed by the effect of market excess returns, past stock returns or other stock characteristics, such as firm size, P/B ratios, trading volume, shares turnover rate, and idiosyncratic volatility. The empirical results are also considered for the two-way clusterings in firms and dates.

We further test the predictability of the magnitude of IO changes by using the portfolio analysis where the investment portfolios are constructed by ranking the stocks based on their short-term and long-term changes in IOs. Comparing to performance of the momentum strategy, the investment portfolio we proposed can generate returns approximately 9.5% to 13.4% per year.

Moreover, we find, during the period of 2008 financial crisis, some institutional investors flow their money into some stable emerging stock markets. It might because the U.S. stock market became volatile or the monetary policy of quantitative easing. For future work, it is interesting to understand the cash flows and its impact on stock market.

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Notes

[1]The institutional investors' holding percentages of corporate equities in United States over the period from 1950 to 2000 can be found in the NYSE Factbook (http://www.nyxdata.com/nysedata/asp/factbook/v For the statistics in 2010, it can be obtained from The 2012 Statistical Abstract of United States Census Bureau (http://www.census.gov/prod/2011pubs/12statab/banking.pdf).

[2]http://www.thecityuk.com/assets/Uploads/Fund-Management-2011.pdf

[3]Other papers finding evidence of a positive correlation between institutional demand and future returns include Cohen, Gompers, and Vuolteenaho 2002 and Chen, Hong, and Stein 2002, among others

[4]Before 2005, qualified foreign institutional investors contain foreign institutional funds, and oversea compatriots living in Taiwan. Their investment amounts are regulated by $5 millions foreign retail investors.

[5]The historical fixed deposit rates can obtain from http://rate.bot.com.tw/Pages/TWN001/TWN001.aspx

[6]The compound return on an implementable strategy is based on an investment at time 0 and fully reinvested at each subsequent time point. During the investment period, no cash is put in or taken out. $R(t,T)$ denotes the compound return between time t to T, $R(t,T) = \prod_{s=t+1}^{T}(1+R_s)$, where R_s is the s-period portfolio return.

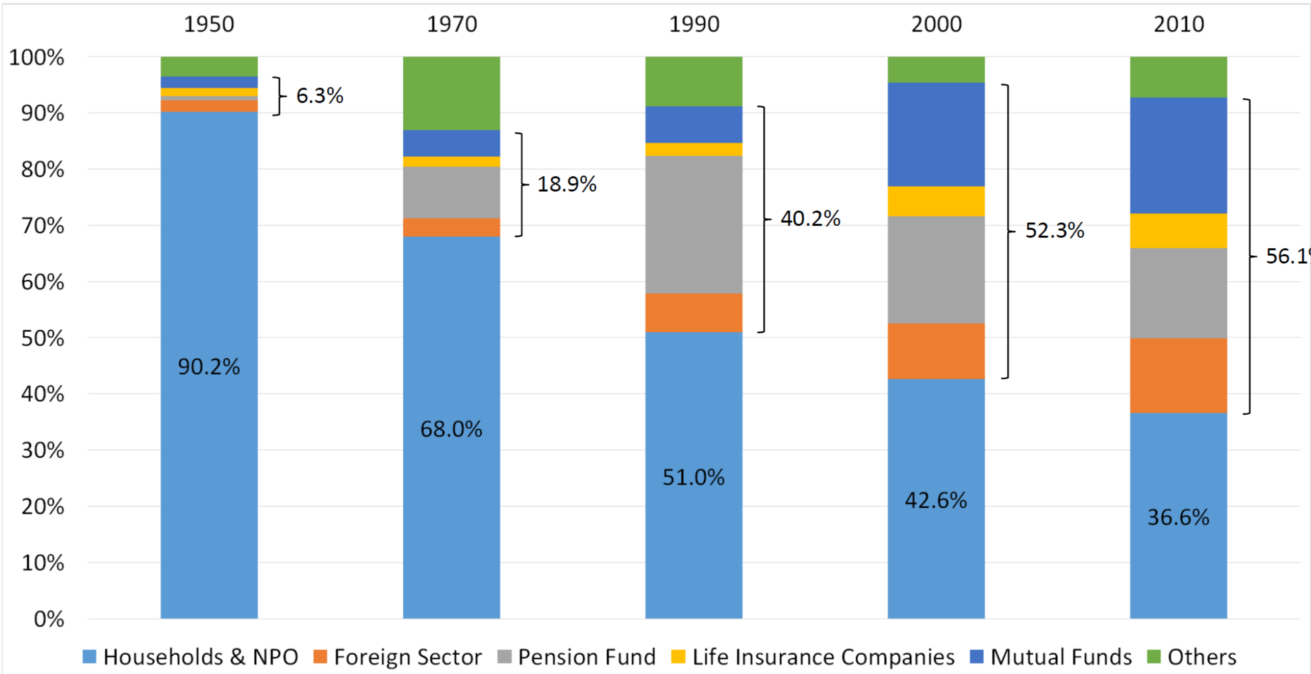

Figure 1. Stock Holding Compositions in the U.S.

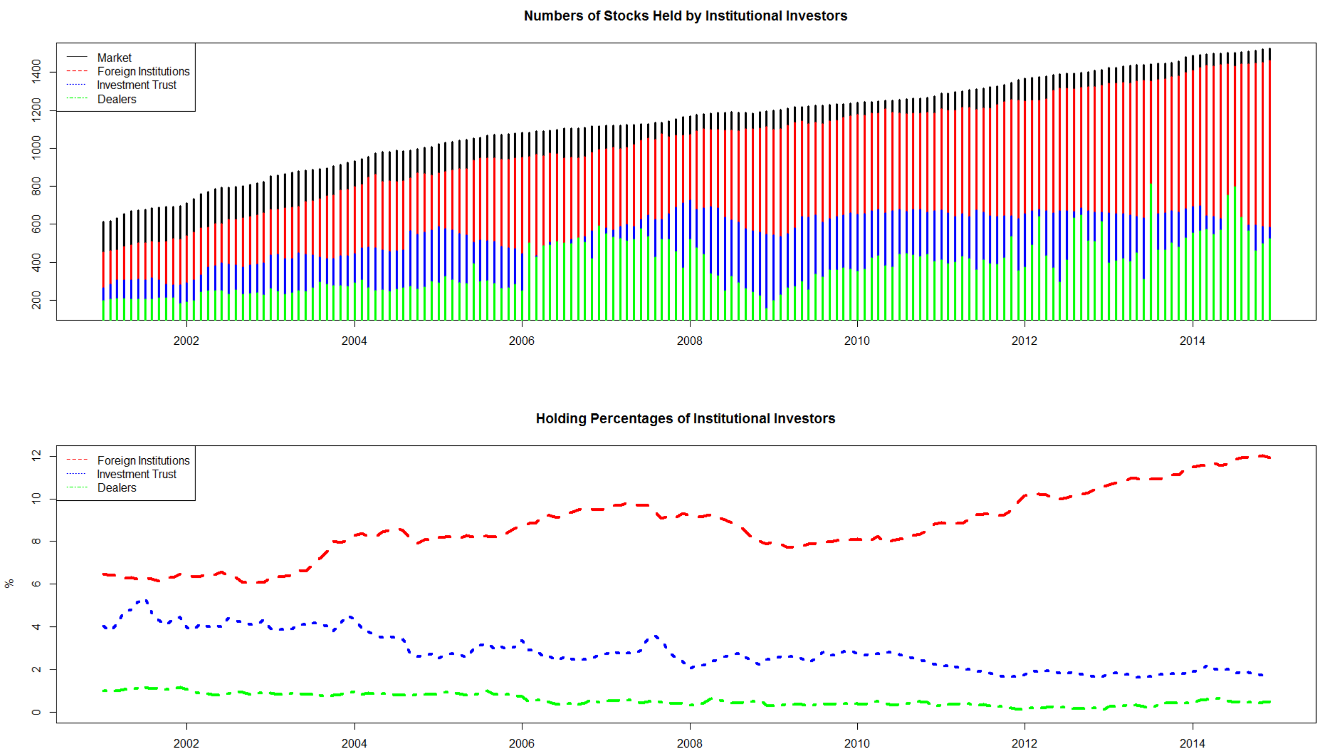

Figure 2. Institutional Investors' Monthly Stock Holding Numbers and percentages in Taiwan from 2001 to 2014

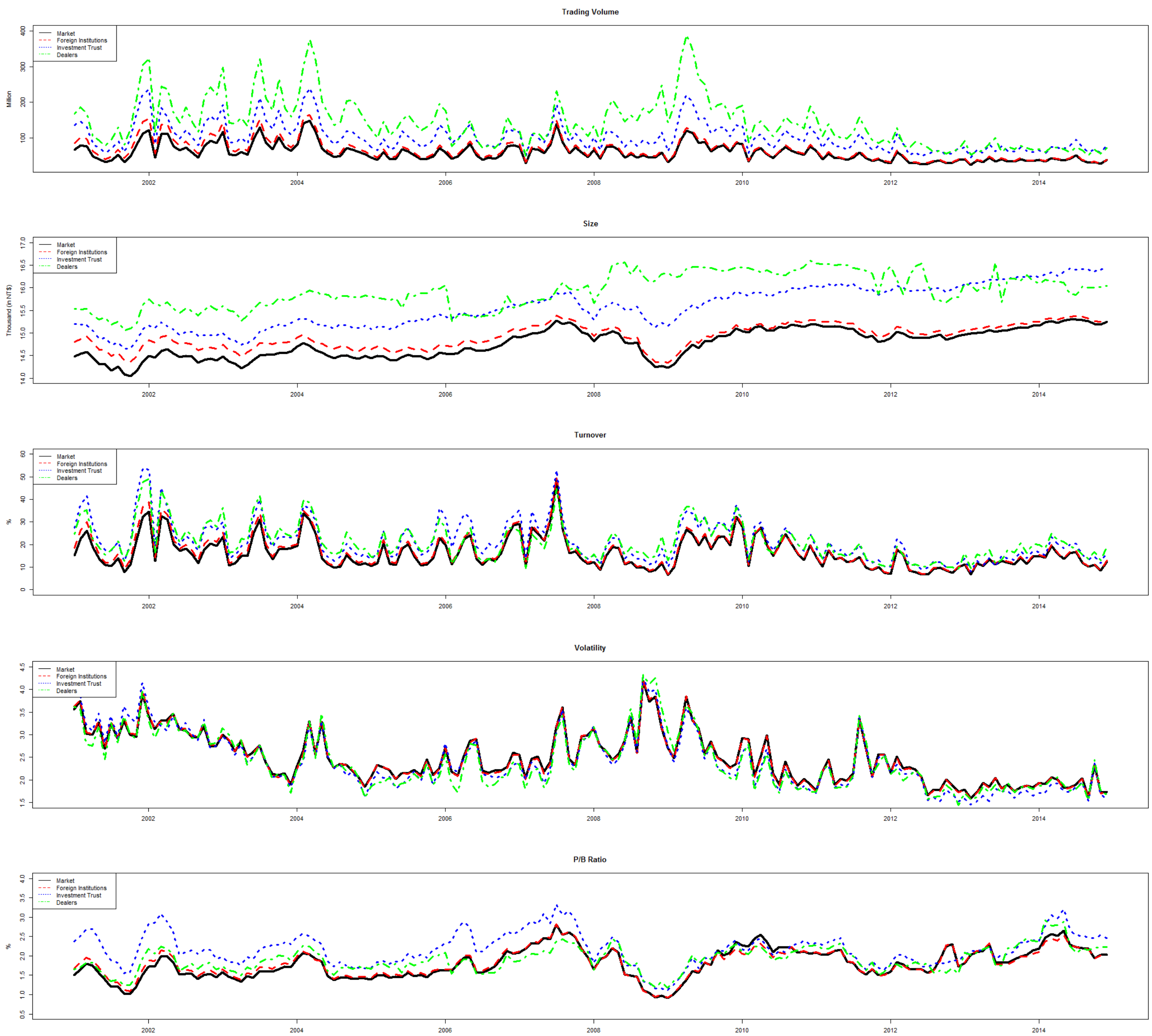

Figure 3. Institutional Investors' Monthly Stock Holding Characteristics

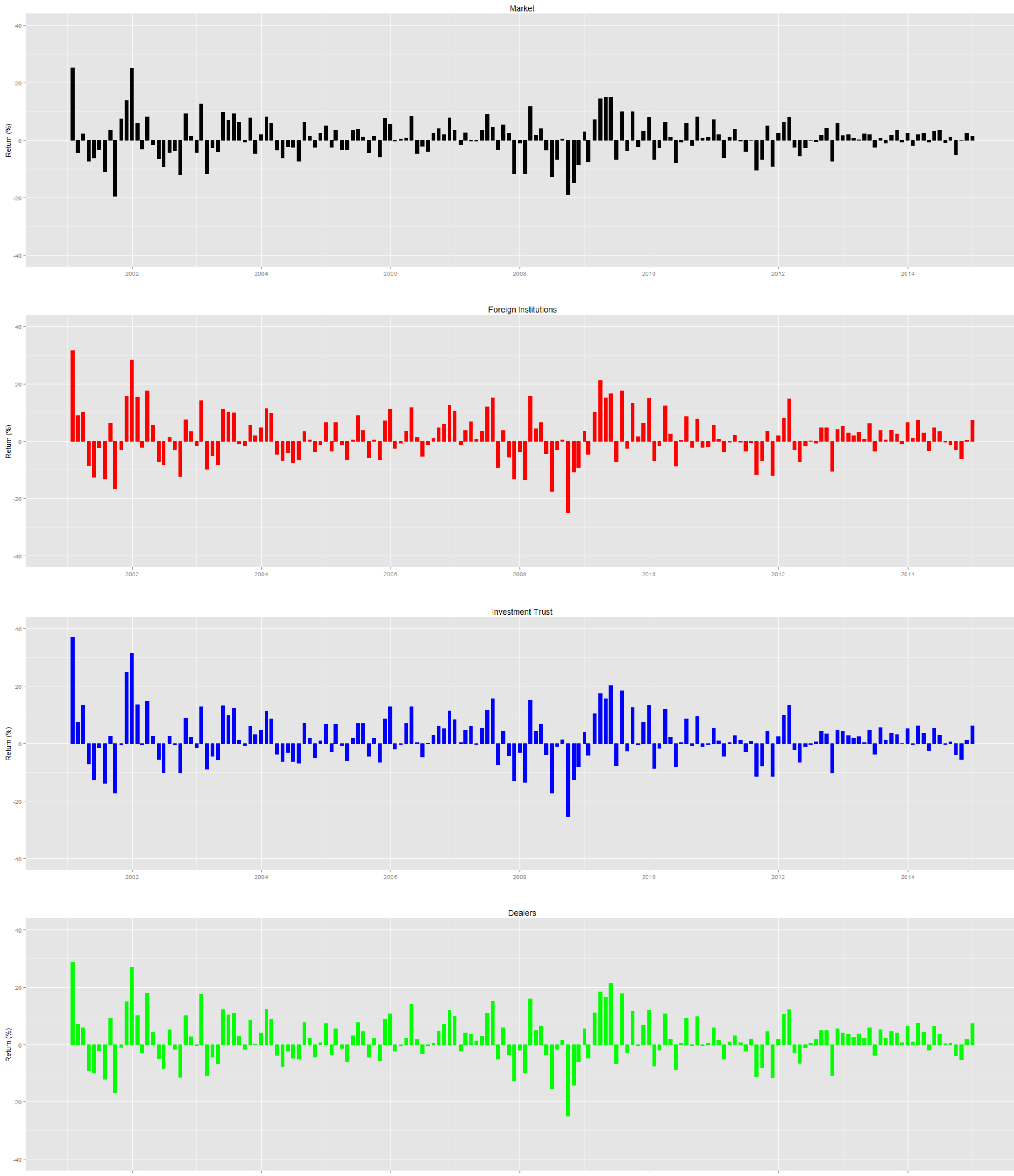

Figure 4. Institutional Investors' Monthly Stock Holding Returns

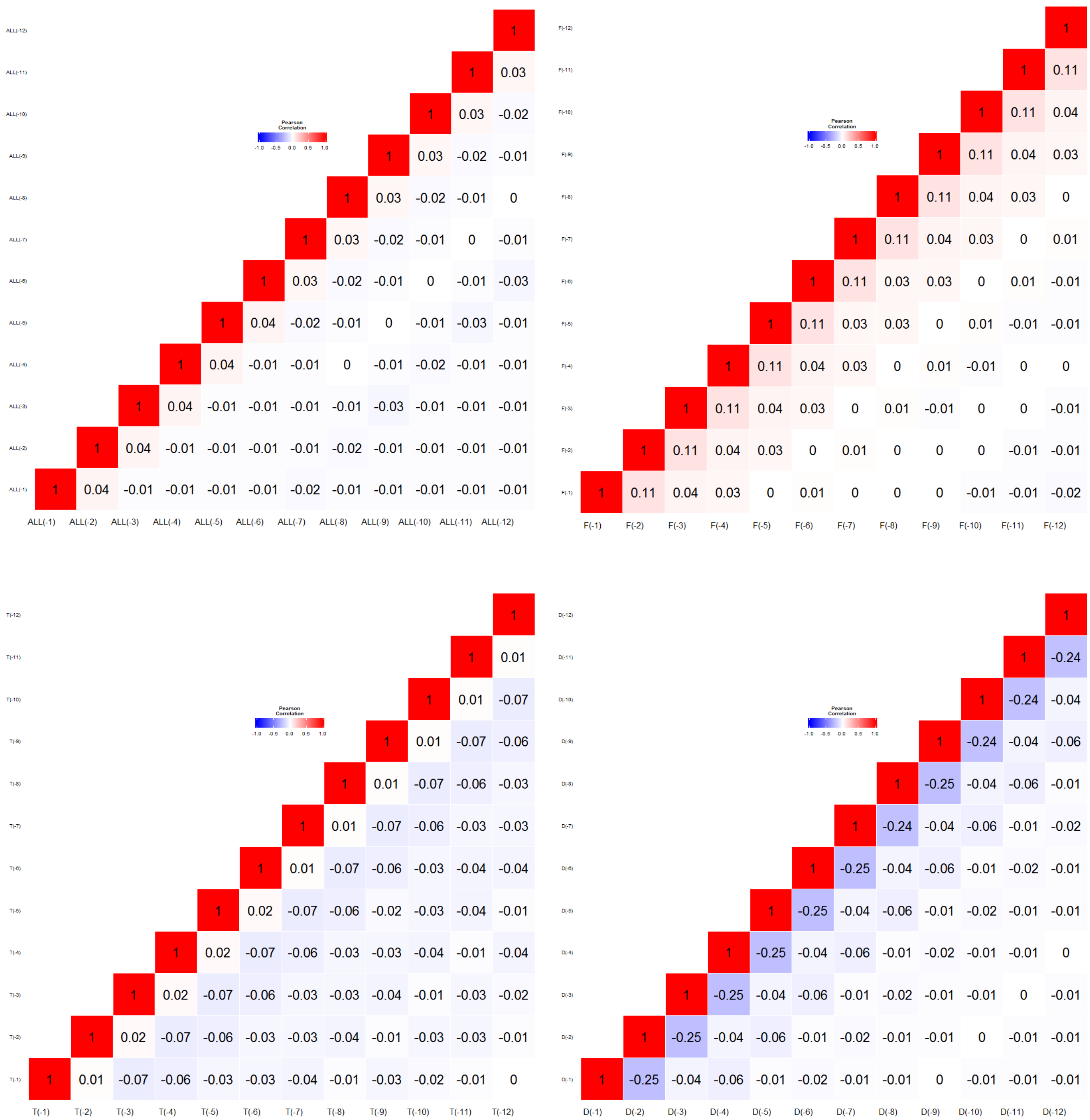

Figure 5. Correlations of IO Changes By All Institutions, Foreign Institutions, Investment Trusts, and Dealers

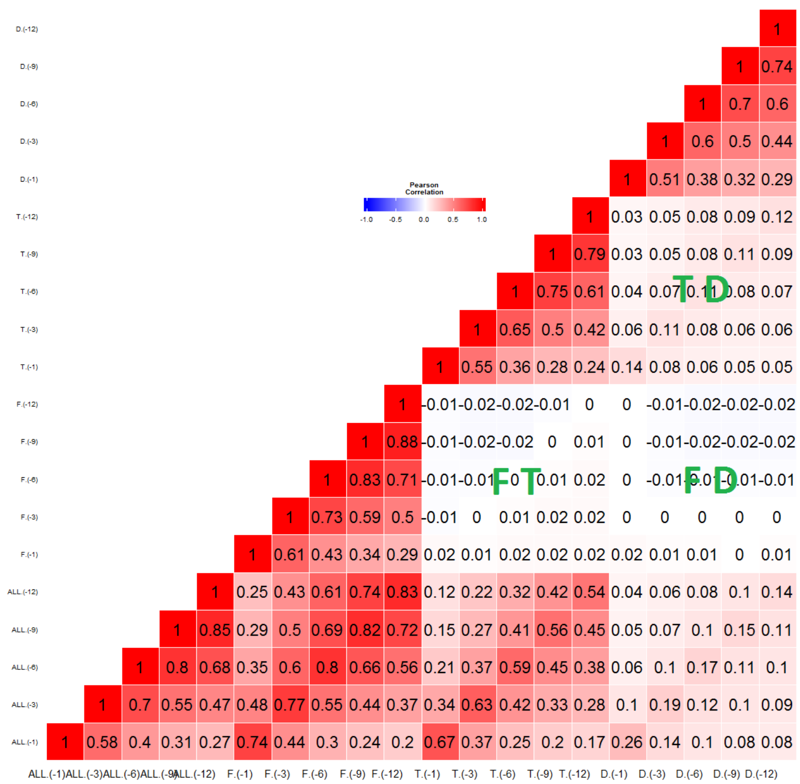

Figure 6. Correlations of Cumulated IO Changes By All Institutions, Foreign Institutions, Investment Trusts, and Dealers

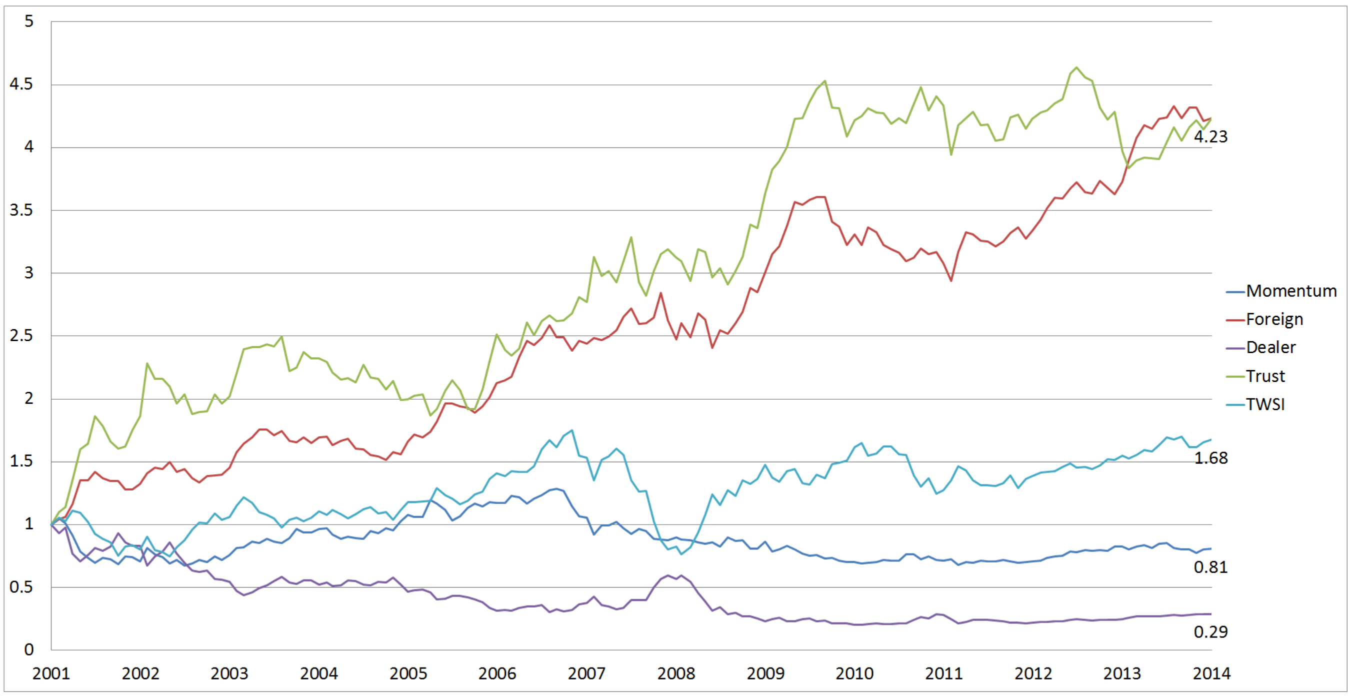

Figure 7. Compound Returns of Investment Portfolios

Table 1. Cross-sectional Regressions of Stock Returns

This table reports coefficient estimates of the specification regression model of Equation (4). We consider the model of using current cross-sectional stock returns to regress on IO changes of foreign institutions ($F.IC(-n)$), investment trusts ($T.IC(-n)$), and dealers ($D.IC(-n)$) defined in Equation (3) combining with past one-month stock return ($Lag1ret$), past 12-month stock returns ($Lag12ret$), and other control variables as described in Figure 3. t-statistics (in parentheses) are adjusted by considering the double clusters (firms and dates) as in Cameron, Gelbach and Miller (2011). *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)
$Intercept_{i,t}$	-4.9508 ***	-4.8947 ***	-5.0006 ***	-5.1217 ***	-5.1034 ***
	(-3.5060)	(-3.4734)	(-3.5536)	(-3.6552)	(-3.6610)
$Mktrf_t$	1.1152 ***	1.1148 ***	1.1145 ***	1.1136 ***	1.1126 ***
	(23.3853)	(23.3815)	(23.4306)	(23.3856)	(23.4250)
$Size_{i,t}$	0.0959	0.0929	0.1014	0.1096	0.1112
	(1.2043)	(1.1690)	(1.2813)	(1.3878)	(1.4173)
$PBR_{i,t}$	0.1449 ***	0.1454 ***	0.1447 ***	0.1447 ***	0.1450 ***
	(3.9136)	(3.9166)	(3.9146)	(3.9145)	(3.9184)
$Volume_{i,t}$	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002
	(-0.1353)	(-0.1453)	(-0.2034)	(-0.1855)	(-0.2613)
$Turnover_{i,t}$	0.1376 ***	0.1376 ***	0.1370 ***	0.1376 ***	0.1370 ***
	(17.3032)	(17.3090)	(17.1617)	(17.3481)	(17.2030)
$Volatility_{i,t}$	1.4825 ***	1.4832 ***	1.4788 ***	1.4798 ***	1.4771 ***
	(5.1980)	(5.1997)	(5.1969)	(5.1962)	(5.1973)
$Lag1ret_{i,t}$	-0.0425 ***	-0.0428 ***	-0.0428 ***	-0.0428 ***	-0.0434 ***
	(-3.3782)	(-3.4058)	(-3.4095)	(-3.4075)	(-3.4636)
$Lag12ret_{i,t}$	-0.0177 ***	-0.0175 ***	-0.0173 ***	-0.0175 ***	-0.0170 ***
	(-4.4626)	(-4.4151)	(-4.3756)	(-4.4332)	(-4.3013)
$F.IC(-1)_{i,t}$		0.0481 ***			0.0479 ***
		(5.1817)			(5.2017)
$F.IC(-3)_{i,t}$		-0.0060 **			-0.0061 **
		(-2.2219)			(-2.2182)
$F.IC(-6)_{i,t}$		0.0008			0.0009
		(0.2905)			(0.3181)
$F.IC(-9)_{i,t}$		-0.0089 ***			-0.0088 ***
		(-4.2891)			(-4.3231)
$F.IC(-12)_{i,t}$		-0.0025			-0.0026
		(-0.6540)			(-0.6758)
$T.IC(-1)_{i,t}$			0.1116 ***		0.1107 ***
			(5.2110)		(5.2242)
$T.IC(-3)_{i,t}$			0.0062		0.0057
			(1.2386)		(1.1506)
$T.IC(-6)_{i,t}$			-0.0023		-0.0023
			(-0.5124)		(-0.5078)
$T.IC(-9)_{i,t}$			-0.0043		-0.0045
			(-1.1123)		(-1.1340)
$T.IC(-12)_{i,t}$			-0.0116 ***		-0.0110 ***
			(-3.3991)		(-3.2968)
$D.IC(-1)_{i,t}$				0.1126 ***	0.1103 ***
				(3.5091)	(3.4912)
$D.IC(-3)_{i,t}$				0.0145	0.0141
				(1.4030)	(1.3570)
$D.IC(-6)_{i,t}$				-0.0076	-0.0075
				(-0.9628)	(-0.9570)
$D.IC(-9)_{i,t}$				-0.0061	-0.0057
				(-0.8911)	(-0.8200)
$D.IC(-12)_{i,t}$				-0.0152 *	-0.0146 *
				(-1.7893)	(-1.7330)

Table 2. Predictive Regressions of Stock Returns

This table reports coefficient estimates of the specification regression model of Equation (5). We consider the model of using future cross-sectional stock returns to regress on IO changes of foreign institutions ($F.IC(-n)$), investment trusts ($T.IC(-n)$), and dealers ($D.IC(-n)$) defined in Equation (3) combining with past one-month stock return ($Lag1ret$), past 12-month stock returns ($Lag12ret$), and other control variables as described in Figure 3. t-statistics (in parentheses) are adjusted by considering the double clusters (firms and dates) as in Cameron, Gelbach and Miller (2011). *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

	(a)	(b)	(c)	(d)	(e)
	$R_{i,t+1}$	$R_{i,t+1:t+3}$	$R_{i,t+1:t+6}$	$R_{i,t+1:t+9}$	$R_{i,t+1:t+12}$
$Intercept_{i,t}$	11.9175 ***	36.2528 ***	65.2874 ***	93.4811 ***	118.4538 ***
	(6.8774)	(10.2603)	(12.3367)	(12.6452)	(13.4712)
$Mktrf_t$	0.2082 *	0.4454 **	0.3485	0.2762	0.0682
	(1.8903)	(2.1575)	(1.1567)	(0.7053)	(0.1529)
$Size_{i,t}$	-0.6814 ***	-2.0852 ***	-3.9214 ***	-5.6640 ***	-7.1215 ***
	(-6.3990)	(-9.5762)	(-11.9288)	(-12.3091)	(-13.0326)
$PBR_{i,t}$	-0.0192	-0.0320	-0.0875 *	-0.0720	-0.0934
	(-1.4456)	(-1.1596)	(-1.7286)	(-0.9630)	(-1.0018)
$Volume_{i,t}$	0.0021 **	0.0054 ***	0.0107 ***	0.0165 ***	0.0203 ***
	(2.4501)	(3.1659)	(3.8067)	(4.2683)	(4.1915)
$Turnover_{i,t}$	-0.0533 ***	-0.1042 ***	-0.1885 ***	-0.2206 ***	-0.3215 ***
	(-4.7332)	(-5.7479)	(-5.3806)	(-6.2089)	(-7.4129)
$Volatility_{i,t}$	0.1336	0.1784	1.6953 *	2.8208 **	3.9017 ***
	(0.3976)	(0.3114)	(1.7085)	(2.2716)	(2.7337)
$Lag1ret_{i,t}$	0.0283	0.0793	0.1161	0.1700 *	0.1880 *
	(1.0351)	(1.5801)	(1.5160)	(1.7341)	(1.8030)
$Lag12ret_{i,t}$	0.0007	-0.0118	-0.0454 *	-0.1032 ***	-0.1535 ***
	(0.0669)	(-0.5995)	(-1.7323)	(-3.3843)	(-4.2045)
$F.IC(-1)_{i,t}$	-0.0083	-0.0038	-0.0037	-0.0097	-0.0020
	(-1.1782)	(-0.3901)	(-0.3312)	(-0.8410)	(-0.1807)
$F.IC(-3)_{i,t}$	0.0012	0.0039	-0.0187 **	-0.0070	-0.0027
	(0.2429)	(0.4478)	(-2.3047)	(-0.8512)	(-0.2150)
$F.IC(-6)_{i,t}$	-0.0070	-0.0214 **	-0.0053	0.0018	-0.0036
	(-1.5560)	(-2.4656)	(-0.6288)	(0.1760)	(-0.4018)
$F.IC(-9)_{i,t}$	0.0015	0.0132	0.0180	0.0114	0.0087
	(0.3074)	(1.2231)	(1.1741)	(1.0431)	(1.5718)
$F.IC(-12)_{i,t}$	-0.0017	-0.0122	-0.0294 *	-0.0375	-0.0369
	(-0.4615)	(-1.3523)	(-1.7539)	(-1.6384)	(-1.6295)
$T.IC(-1)_{i,t}$	0.0085	0.0161	0.0123	0.0061	0.0141
	(0.9122)	(1.1945)	(0.7907)	(0.3582)	(0.8042)
$T.IC(-3)_{i,t}$	0.0035	0.0004	-0.0164	0.0010	0.0019
	(0.6634)	(0.0305)	(-1.2796)	(0.0720)	(0.1445)
$T.IC(-6)_{i,t}$	-0.0063	-0.0166	0.0075	0.0119	-0.0035
	(-1.3428)	(-1.5272)	(0.4817)	(0.8123)	(-0.2420)
$T.IC(-9)_{i,t}$	0.0072	0.0249 **	0.0307 **	0.0142	0.0213 *
	(1.3367)	(2.2236)	(2.4104)	(1.1332)	(1.7477)
$T.IC(-12)_{i,t}$	-0.0002	-0.0063	-0.0157	-0.0086	-0.0026
	(-0.0379)	(-0.5754)	(-1.0843)	(-0.5435)	(-0.1478)
$D.IC(-1)_{i,t}$	0.0174	0.0295	0.0263	0.0287	0.0280
	(1.1656)	(1.2283)	(0.9985)	(0.7656)	(0.8185)
$D.IC(-3)_{i,t}$	-0.0030	-0.0375 *	-0.0219	0.0255	-0.0115
	(-0.2392)	(-1.6971)	(-0.6643)	(0.8227)	(-0.2614)
$D.IC(-6)_{i,t}$	0.0035	0.0188	0.0791 **	0.0376	0.0931 *
	(0.2979)	(0.7116)	(2.4460)	(0.9095)	(1.8814)
$D.IC(-9)_{i,t}$	0.0217	0.0537 *	0.0124	0.0695	0.1037 *
	(1.4090)	(1.8441)	(0.3194)	(1.5659)	(1.7564)
$D.IC(-12)_{i,t}$	-0.0046	-0.0082	0.0246	-0.0014	-0.0492
	(-0.3759)	(-0.3205)	(0.7366)	(-0.0294)	(-0.7354)

Table 3. Momentum Strategy

This table presents the monthly equal-weight portfolio returns (percent) for the momentum strategy. The sample period is from January 2001 to December 2014. We rank the stocks into 10-decile portfolios based on their past J-month returns excluding the most recent month where J = 6, 9, and 12 and denote them as $(6-1), (9-1)$, and $(12-1)$. This momentum definition is currently most used and readily available through the $PR1YR$ factor of Carhart (1997). The stocks in top (bottom) 10% decile go to 'BUY' ('SELL') portfolio. We form the hedge portfolio,'B-S', by longing the 'BUY' portfolio and shorting 'SELL' portfolio and consider its K-month holding returns, K= 3, 6, 9, and 12. Standard errors are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%.

		Holding Periods K			
J	Portfolios	3	6	9	12
(6–1)	BUY	1.319 *	1.340 *	1.263 *	1.141 *
		(0.698)	(0.694)	(0.687)	(0.676)
	SELL	1.361 **	1.298 **	1.326 **	1.403 **
		(0.553)	(0.543)	(0.545)	(0.550)
	B-S	-0.042	0.042	-0.063	-0.262
		(0.323)	(0.288)	(0.266)	(0.237)
(9–1)	BUY	1.602 **	1.480 **	1.370 **	1.256 *
		(0.705)	(0.693)	(0.683)	(0.671)
	SELL	1.333 **	1.407 **	1.445 ***	1.497 ***
		(0.541)	(0.541)	(0.545)	(0.552)
	B-S	0.269	0.073	-0.075	-0.241
		(0.348)	(0.328)	(0.302)	(0.271)
(12–1)	BUY	1.216 *	1.109	0.997	0.921
		(0.693)	(0.681)	(0.672)	(0.660)
	SELL	1.257 **	1.305 **	1.353 **	1.441 ***
		(0.525)	(0.527)	(0.533)	(0.539)
	B-S	-0.040	-0.196	-0.356	-0.520 *
		(0.353)	(0.332)	(0.315)	(0.284)

Table 4. Long-Term IO Portfolios

This table presents the monthly equal-weight portfolio returns (percent) for the long-term IO portfolios. The sample period is from January 2001 to December 2014. We rank the stocks into 10-decile portfolios based on their $\kappa.IC(-12)$ where κ='Foreign Institutions', 'Investment Trusts', and 'Dealers'. The stocks in top (bottom) decile go to 'HIGH' ('LOW') portfolio. We form the hedge portfolio,'L-H', by longing the 'LOW' portfolio and shorting 'HIGH' portfolio and consider its K^{th}-month holding returns, $K = 1 - 36$ months. Standard errors are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%.

J=12	K =	(1)	(2)	(3)	(4)	(5)	(6)	(9)	(12)	(24)	(36)	(60)
Foreign Institutions	LOW	2.23 ***	2.16 ***	2.19 ***	2.06 ***	1.97 ***	2.01 ***	1.94 ***	1.93 ***	1.78 ***	1.89 ***	1.76 **
	(N=156)	(4.07)	(3.90)	(3.91)	(3.76)	(3.63)	(3.69)	(3.49)	(3.41)	(3.16)	(3.21)	(2.55)
	HIGH	1.23 **	1.16 **	1.18 **	1.14 **	1.16 **	1.18 **	1.22 **	1.15 **	1.15 **	1.23 **	1.20 *
	(N=156)	(2.43)	(2.30)	(2.32)	(2.24)	(2.27)	(2.29)	(2.34)	(2.21)	(2.13)	(2.13)	(1.76)
	L-H	1.01 ***	1.00 ***	1.01 ***	0.92 ***	0.80 ***	0.84 ***	0.72 **	0.78 ***	0.63 **	0.66 **	0.55 *
	(N=156)	(3.43)	(3.38)	(3.39)	(3.13)	(2.89)	(2.97)	(2.57)	(2.70)	(2.38)	(2.42)	(1.79)
Investment Trusts	LOW	1.93 ***	1.85 ***	1.80 ***	1.65 **	1.56 **	1.61 **	1.68 **	1.75 ***	1.69 ***	1.70 ***	1.52 **
	(N=153)	(2.99)	(2.86)	(2.78)	(2.61)	(2.48)	(2.55)	(2.59)	(2.69)	(2.64)	(2.57)	(2.04)
	HIGH	0.71	0.69	0.71	0.66	0.68	0.76	0.82	0.95	0.94	1.21	1.06
	(N=156)	(1.14)	(1.10)	(1.12)	(1.03)	(1.06)	(1.19)	(1.28)	(1.45)	(1.35)	(1.65)	(1.27)
	L-H	1.22 ***	1.19 ***	1.13 ***	1.01 **	0.93 **	0.89 **	0.91 **	0.78 *	0.75 **	0.49	0.46
	(N=153)	(2.85)	(2.79)	(2.56)	(2.45)	(2.34)	(2.23)	(2.29)	(1.96)	(2.08)	(1.37)	(1.38)
Dealers	LOW	2.25 ***	2.07 **	2.62 ***	3.07 ***	2.17 *	3.11 **	0.80	1.74	2.81	4.34	5.41
	N=33	(2.93)	(2.43)	(2.83)	(3.36)	(1.79)	(2.67)	(0.72)	(1.29)	(1.08)	(0.91)	(1.80)
	HIGH	1.10 *	1.04 *	1.09 *	0.93	0.88	0.91	0.95	1.09 *	0.99	1.15 *	0.94
	N=156	(1.81)	(1.71)	(1.78)	(1.56)	(1.47)	(1.52)	(1.54)	(1.77)	(1.55)	(1.68)	(1.22)
	L-H	0.87 **	0.97 **	1.37 ***	1.34 ***	1.03 **	0.90 *	0.81	0.86	0.57	2.33	-0.02
	N=33	(2.14)	(2.33)	(3.38)	(3.81)	(2.39)	(1.90)	(1.54)	(1.72)	(0.89)	(1.63)	(-0.02)

Table 5. Short-Term IO Portfolios

This table presents the monthly equal-weight portfolio returns (percent) for the short-term IO portfolios. The sample period is from January 2001 to December 2014. We rank the stocks into 10-decile portfolios based on their $\kappa.IC(-3)$ where κ='Foreign Institutions', 'Investment Trusts', and 'Dealers'. The stocks in top (bottom) decile go to 'HIGH' ('LOW') portfolio. We form the hedge portfolio,'L-H', by longing the 'LOW' portfolio and shorting 'HIGH' portfolio and consider its K^{th}-month holding returns, $K = 1-36$ months. Standard errors are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%.

J=3	K =	(1)	(2)	(3)	(4)	(5)	(6)	(9)	(12)	(24)	(36)	(60)
Foreign Institutions	LOW	1.80 ***	1.91 ***	1.98 ***	1.83 ***	1.85 ***	2.02 ***	1.99 ***	1.87 ***	1.55 ***	1.82 ***	1.44 *
	(N=151)	(3.20)	(3.42)	(3.58)	(3.29)	(3.33)	(3.63)	(3.57)	(3.28)	(2.70)	(2.90)	(1.95)
	HIGH	1.08 **	1.10 **	1.20 **	1.19 **	1.30 **	1.31 **	1.32 **	1.21 **	1.21 **	0.98 *	1.41 **
	(N=165)	(2.06)	(2.10)	(2.27)	(2.24)	(2.44)	(2.43)	(2.53)	(2.37)	(2.29)	(1.78)	(2.14)
	L-H	0.72 **	0.80 ***	0.77 ***	0.77 ***	0.71 **	0.73 ***	0.77 ***	0.61 **	0.51 **	0.65 **	0.51 *
	(N=151)	(2.54)	(2.83)	(2.76)	(2.74)	(2.53)	(2.64)	(2.81)	(2.14)	(2.01)	(2.43)	(1.69)
Investment Trusts	LOW	0.44	0.11	0.26	0.26	0.44	0.50	0.22	1.01	3.56 ***	0.92	2.55 **
	(N=62)	(0.42)	(0.11)	(0.26)	(0.27)	(0.42)	(0.45)	(0.21)	(0.92)	(3.76)	(1.21)	(2.29)
	HIGH	0.85	0.88	0.99	0.93	0.91	0.98	0.79	0.73	0.92	0.88	1.14
	(N=65)	(1.24)	(1.28)	(1.45)	(1.38)	(1.34)	(1.45)	(1.23)	(1.14)	(1.36)	(1.28)	(1.45)
	L-H	0.48	0.63	0.60	0.36	0.32	0.83	0.50	0.27	0.55	0.77 **	0.55
	(N=62)	(0.95)	(1.25)	(1.19)	(0.66)	(0.61)	(1.53)	(1.06)	(0.48)	(1.07)	(2.46)	(1.43)
Dealers	LOW	-0.11	0.23	1.56	4.13 *	5.30 *	4.98 *	2.06	-0.30	N/A	N/A	N/A
	(N=7)	(-0.09)	(0.16)	(0.82)	(2.24)	(2.19)	(2.72)	(1.04)	(-0.25)			
	HIGH	0.97	1.00	1.02 *	1.07 *	1.17 *	1.09 *	1.22 *	1.08 *	N/A	N/A	N/A
	(N=165)	(1.57)	(1.62)	(1.67)	(1.73)	(1.91)	(1.77)	(1.99)	(1.76)			
	L-H	0.17	0.39	0.15	1.61	2.82 **	1.94	0.69	1.44	N/A	N/A	N/A
	(N=7)	(0.26)	(0.64)	(0.20)	(1.54)	(4.46)	(1.45)	(1.96)	(1.41)			