**Title**
Essays in Behavioral Finance



**Author**
Huang, Xing

**Publication Date**
2013

Peer reviewed|Thesis/dissertation

**Essays in Behavioral Finance**

by

Xing Huang

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Stefano DellaVigna, Co-chair
Professor Ulrike Malmendier, Co-chair
Professor Terrance Odean
Professor Nancy Wallace

Spring 2013

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# Abstract


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Professor Stefano DellaVigna, Co-chair

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This dissertation contains three essays in behavioral finance. It explores investors (non-standard) behaviors and their impacts on market efficiency and market valuations. I strive to empirically characterize how market participants behave, and to identify how these behaviors can improve our understanding of the financial market.

The first chapter studies the impact of prior investment experience in an industry on the subsequent purchase of new stocks in the same industry. Using trading records data for households at a large discount broker from 1991 to 1996, I establish that the experience of positive excess returns in a given industry increases the probability of purchasing similar stocks in that industry relative to other industries. This result is robust to industry momentum, wealth effects, and investor heterogeneity. The effect decays when the experience is further in the past. Furthermore, I find that investor sophistication mitigates this experience effect. These results are consistent with mechanisms where investors put more weight on their own experience than on other available historical information when updating the beliefs about an industrys future return. The results are also consistent with investors learning about their stock-picking ability in an industry from their experienced outcomes.

In the second chapter, I ask the question: do investors slow to incorporate return-relevant information if it reflects firms' operations abroad? Using the corresponding industry return in the foreign countries, I show that foreign operations information is slowly incorporated into stock prices. A trading strategy exploiting the foreign operations information of multinational firms generates a monthly abnormal return of approximately 0.80 percentage points, controlling for risk-based factors. The return predictability is not driven by U.S. industry momentum, global industry momentum or foreign country-specific industry momentum.

The third chapter further explores the underlying mechanism to explain the market under-reaction to foreign information identified in the second chapter. The return predictability becomes more pronounced for smaller firms and firms with less analyst coverage, lower institutional holdings, lower fraction of foreign operations and more complicated international operations structure. I also find that stock prices respond more to foreign operations information during the month of a quarterly earnings announcement or when there is more foreign news relative to domestic news appearing in the media. In addition, information about firms' operations in Asia is delayed more than information about operations in Europe and English-speaking countries. These results are consistent with the hypothesis that news about multinational firms' foreign operations diffuses gradually, indicating investors' limited attention and processing capacity for foreign information.

To my family

# Contents

**Contents** iv

**List of Figures** vi

**List of Tables** vii

**1 Mark Twain's Cat: Industry Investment Experience, Categorical Thinking and Stock Selection** 1

1.1 Introduction . . . 2
1.2 Datasets and Methodology . . . 6
1.2.1 Data Description . . . 6
1.2.2 Investors' Investment Experiences and Purchase Decisions . . . 7
1.2.3 Summary Statistics . . . 8
1.3 Industry Investment Experience and Stock Selection . . . 8
1.3.1 Graphical Evidence . . . 9
1.3.2 Baseline Model . . . 9
1.3.3 Robustness Tests . . . 12
1.3.4 Dynamic Effects . . . 13
1.3.5 Summary . . . 14
1.4 Underlying Mechanisms . . . 15
1.4.1 Investor Sophistication . . . 15
1.4.2 Portfolio Diversification . . . 16
1.4.3 Categorization . . . 17
1.4.4 Discussion . . . 20
1.5 Summary Remarks . . . 22

**2 Thinking Outside the Borders (1): Market Underreaction to Foreign Information** 39

2.1 Introduction . . . 40

2.2 Data and Methods . . . . . 44
2.2.1 Data . . . . . 44
2.2.2 Global Segment Information Proxy . . . . . 45
2.2.3 Summary Statistics . . . . . 46
2.3 Return Predictability . . . . . 47
2.3.1 Portfolio Test . . . . . 47
2.3.2 Fama-MacBeth Regression . . . . . 49
2.3.3 Long-horizon Return Pattern . . . . . 53
2.3.4 Real Effects . . . . . 54
2.4 Summary Remarks . . . . . 55

**3 Thinking Outside the Borders (2): Underlying Mechanisms of Investors' Inattention 68**
3.1 Introduction . . . . . 69
3.2 Regression Framework . . . . . 71
3.2.1 Firm Size . . . . . 72
3.2.2 Analyst Coverage . . . . . 72
3.2.3 Institutional Holdings . . . . . 73
3.2.4 Foreign Institutional Ownership . . . . . 74
3.2.5 Total Fraction of Sales from Foreign Operations . . . . . 75
3.2.6 Complexity . . . . . 76
3.2.7 Summary . . . . . 76
3.3 More Mechanisms . . . . . 77
3.3.1 Quarterly Earnings Announcement . . . . . 77
3.3.2 Geographic Segments . . . . . 80
3.3.3 Time-Varying Media Coverage . . . . . 82
3.4 Summary Remarks . . . . . 83

**Bibliography 94**

**A Industry Investment Experience and Stock Selection 100**
A.1 Details on Processing Data . . . . . 100

**B Market Underreaction to Foreign Information 102**
B.1 Global Industry Momentum . . . . . 102
B.2 Robustness Test: Standalone Firms . . . . . 103

**C Underlying Mechanisms of Investors' Inattention 106**
C.1 Regression Results of Effects of Geographic Segments . . . . . 106

# List of Figures

1.1 Motivating Example: Difference in Stock Holdings by Industry of Young and Old Groups vs Difference in Their Experienced Industry Returns . . 23
1.2 The Impact of Personal Investment Experience in an Industry on Subsequent Investment in Experienced Industry vs Other Industry . . . . . . . 24
1.3 Dynamic Effects of Monthly Lagged Industry Experienced Outcomes . . 25
1.4 The Impact of Investment Experience: Variation in Representativeness of Experienced Stocks . . . . . . . . . . . . . . . . . . . . . . . . . . 26
1.5 Performance Analysis (Calendar Time Portfolio) . . . . . . . . . . . . . . 27

2.1 The National Composition of Foreign Sales From 1990 to 2009 . . . . . . 56
2.2 Abnormal Returns of Calendar Time Portfolio . . . . . . . . . . . . . . . . 57
2.3 Annual Raw Return of L/S Portfolio . . . . . . . . . . . . . . . . . . . . . 58
2.4 Average Holding Period Returns to the Long/Short Portfolio Sorted by Foreign Information Proxy . . . . . . . . . . . . . . . . . . . . . . . . . 59
2.5 Average Holding Period Returns to the Long/Short Portfolio Sorted by Domestic Information Proxy . . . . . . . . . . . . . . . . . . . . . . . . 60

3.1 Difference between Cumulative Abnormal Returns of the Top 30% Group and Bottom 30% Group . . . . . . . . . . . . . . . . . . . . . . . . . . 84
3.2 Cumulative Response Ratios: Partition on Geographic Segments . . . . . 85
3.3 Annual Raw Return of L/S Portfolio (Sort on the 2-month Lagged Foreign Information Proxy) . . . . . . . . . . . . . . . . . . . . . . . . . . . 86
3.4 Annual Raw Return of L/S Portfolio and Domestic/Foreign News Coverage Ratio by Year . . . . . . . . . . . . . . . . . . . . . . . . . . . . 87

# List of Tables


1.1 Summary Statistics . . . . . . . . . . . . . . . . . . . . . . . . . . . . 28
1.2 Investment Experience and the Propensity to Purchase New Stocks in the Same Industry (Fama-French 10-industry Classification) . . . . . . . . . . 30
1.3 Robustness Tests . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 31
1.4 Variation in Investor Sophistication . . . . . . . . . . . . . . . . . . . . 34
1.5 Variation in Portfolio Diversification . . . . . . . . . . . . . . . . . . . 35
1.6 The Impact of Personal Investment Experience on Future Purchases in the Experienced Industry vs Other Industries . . . . . . . . . . . . . . . . . 36
1.7 The Impact of Personal Investment Experience: Variation in Categorization 37
1.8 The Impact of Personal Investment Outcomes on Subsequent Trade Frequencies in an Industry . . . . . . . . . . . . . . . . . . . . . . . . . . . . 38

2.1 Summary Statistics . . . . . . . . . . . . . . . . . . . . . . . . . . . . 61
2.2 Predictability by Foreign Information Proxy (1990 – 2010) . . . . . . . . 62
2.3 Calendar Time Portfolio Factor Loadings (1990 – 2010) . . . . . . . . . . . 63
2.4 Fama-MacBeth Regression of Return Predictability by Foreign Information Proxy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 64
2.5 Real Effects of Global, Foreign and Domestic Information Proxies . . . . 67

3.1 Fama-MacBeth Regression of Underlying Mechanisms . . . . . . . . . . . 88
3.2 Response Ratios: Effects of Quarterly Earnings Announcement . . . . . . 92
3.3 Response Ratios: Partition on Geographic Segments . . . . . . . . . . . 93

A.1 Number of Households Retained after Each Refinement . . . . . . . . . . 101

B.1 Fama-MacBeth Regression of Global Industry Momentum . . . . . . . . 104
B.2 Predictability by Foreign Information Proxy: Standalone Firms . . . . . 105

C.1 Fama-MacBeth Regression of Return Predictability: Decomposed by Geographic Segments . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 108

## Acknowledgments

I will always remember the past six years studying and living at Berkeley. There are numerous people who have helped, encouraged, and inspired me, giving me valuable advices on both research and various aspects of my life. I would like to thank them all for making this dissertation possible.

I am deeply indebted to my dissertation committee members Stefano DellaVigna (Co-Chair), Ulrike Malmendier (Co-Chair), Terrance Odean, Adam Szeidl, Nancy Wallace for their guidance, encouragement, support, and patience. Without their help, this dissertation could not be achieved.

I would also like to express my gratitude to Brian Ayash, Matthew J. Botsch, Jing Cai, Francesco D'Acunto, Yuriy Gorodnichenko, Brett Green, Rachita Gullapalli, Paulo Issler, Jian Li, Dmitry Livdan, Matteo Maggiori, Gustavo Manso, Michaela Pagel, Pratish Patel, Haonan Qu, Sungbin Sohn, Changcheng Song, Congyan Tan, Eva Vivalt, Gewei Wang, Michael Weber, Lemin Wu, Li Zeng, Hongyan Zhao for their help and useful discussions. My dissertation also benefited a lot from comments received during various seminars at UC Berkeley and other institutions.

Lastly, and most importantly, I greatly appreciate the endless love, support, and encouragement from my parents and family. I would also like to give special thanks to my husband, Chuan Wang, for growing with me together.

# Chapter 1

# Mark Twain's Cat: Industry Investment Experience, Categorical Thinking and Stock Selection[1]

[1] The cat, having sat upon a hot stove lid, will not sit upon a hot stove lid again. But he won't sit upon a cold stove lid, either. –Mark Twain

## 1.1 Introduction

How do individuals select stocks? Do they incorporate all available historical information and update their beliefs in a Bayesian fashion? Or do they weigh differently their personal investment experiences and other statistical information? A growing body of evidence shows that past experience affects investors' choices in many financial decisions, including household risk taking, mutual fund investment style, and corporate financing decisions[2]. Past experience may influence households' purchase decisions on common stocks as well. Barber et al. (2010) show that the effect of positive past investment experiences in a particular stock increases the likelihood of repurchasing the stock that was owned previously. But do past investment experiences also influence investors' propensity to buy other similar stocks? This question is important because it helps shed light on how investors update their beliefs about stock returns.

In this paper, I explore whether investors put more weight on their idiosyncratic personal experience of investment in an industry when they make decisions about purchasing new stocks. Consider, for example, two individual investors, A and B, who form portfolios in 1991. Investors A and B both invest in the insurance industry, but they invest in different companies. A picks Pioneer Financial Services Inc. while B picks Conseco Inc. One year later, investor A has a paper loss of 30% whereas investor B's investment doubles. Given the idiosyncratic realization of returns, after enjoying a huge gain from investing in insurance industry, will B, when compared to A, be more prone to invest in *other* stocks in that industry? The psychology literature suggests that personally experienced outcomes have a greater impact on personal decisions than information acquired merely by reading, which comes without personal involvement (Weber, Bockenholt, Hilton, and Wallace, 1993; Hertwig, Barron, Weber, and Erev, 2004). The experience hypothesis predicts that in an industry where investors have prior investment experience, it is more likely for them to buy new stocks after they have experienced good rather than bad returns.

This paper exploits data from detailed trading records for households at a large discount broker from 1991 to 1996 (Barber and Odean, 2000) as a measure of investors' personal investment experiences, and explores whether the past experiences of these investors affect their subsequent purchase decisions at the industry level. The results indicate that the likelihood of investors purchasing new stocks in an experienced industry increases with their experienced excess return. Furthermore, the effect of experienced outcomes becomes weaker for the purchase decisions on stocks

[2] Barber, Odean, and Strahilevitz (2010), Chan, Chen, and Lakonishok (2002), Choi, Laibson, Madrian, and Metrick (2009), Graham and Narasimhan (2004), Kaustia and Knupfer (2008), Malmendier and Nagel (2011),Malmendier and Tate (2005), Malmendier, Tate, and Yan (2011)

in more different industries. Specifically, experience in one industry influences the purchases in a similar industry by a smaller amount, and has almost no effect on the purchases in a dissimilar industry.

While these results are consistent with the view that past experience influences stock selection, there are four alternative mechanisms that may also drive the correlations between the past experiences and the future purchases in the same industry. First, momentum traders (Hong and Stein, 1999; DeLong, Shleifer, Summers, and Waldmann, 1990; Barberis and Shleifer, 2003) may be more likely to purchase new stocks in an industry that performed well in the past, regardless of their personal investment experience in that industry. To control for this momentum effect, I include past industry average returns in the regressions and show that my results are robust. A second alternative story is a wealth effect: a high experienced return may increase wealth, generating new purchases in all industries. The results mentioned above - that the experience effect spills overs only slightly to other-industry purchases - do not support this story. I also show that my results are robust to controls measuring the change in the investor's portfolio value. Third, an investor with a high investment ability is more likely to gain high returns and in the meantime may also be more active, which could drive the positive relation between experienced outcomes and future purchases. I measure investment ability by three trading characteristics variables and also test how the correlation varies with different degrees of sophistication. The evidence does not support this story either. A fourth relevant story is portfolio rebalancing. But because households should decrease their holdings in the industry that earns relatively higher returns in the past to rebalance their portfolio, this story actually leads in the direction opposite to the prediction of the experience hypothesis.

After controlling for industry momentum and time-varying investor heterogeneity, the results show that investors with positive market-adjusted returns in one industry have 1.86 pp higher propensity to buy new stocks in the same industry as opposed to those who earn negative market-adjusted returns. This magnitude corresponds to 16.60 percent of the average probability of 11.18 pp for purchasing new stocks in an industry. However, this effect that results from the experience of positive excess returns drops significantly with regard to the purchase of new stocks outside of the industry in which the investor has experience. The magnitude of this effect on the purchase of new stocks in an industry that is the most similar to the experienced industry is only one third of that for the purchase of new stocks in the original industry, whereas the effect on purchasing new stocks in an industry that differ significantly from the experienced industry is negligible.

I also test for the long-term effect of lagged experience outcomes. Because the sample only extends from 1991 to 1996, the longest horizon is chosen to be half of that sample period, i.e., three years. The results indicate that more recent experience has a stronger influence on purchase of new stocks. The effect of experience outcomes drops dramatically if the experience happens more than one year before the month of purchase. Gallagher (2012) finds a similar effect in the context of flood insurance; after a flood, the take-up rate steadily decreases in the flooded communities.

If the experience hypothesis is driving the relation between experienced outcomes and future purchases, the magnitude and significance of the results should vary with investor sophistication and portfolio diversification. As investors become more sophisticated, their past experiences may cancel each other, with the result that more recent experiences have less influence. I divide the households in the sample into four subgroups according to their self-reported investment sophistication as provided in the dataset and test the effects of experienced outcomes separately for each subgroup. The results indicate that the effect is most pronounced for the group with no experience or knowledge in investing, but insignificant for the group with extensive investment experiences, which provides further evidence in support of the experience hypothesis.

Furthermore, investors with more diversified portfolios may care less about the individual performance of each component; consequently, the experienced outcome on the industry level would have less effect. I also explore the variation in portfolio diversification by adding an interaction term between the experience variables and measures for portfolio diversification in the regression. As predicted above, the results indicate that influence of past experiences declines with the diversification of the household portfolio.

The evidence that past investment experiences have an impact on future purchases at the industry level suggests that investors may apply categorical thinking in their stock investments. To gain additional insight into the operation of categorical thinking in conjunction with the experience effect, I investigate how the latter experience effect varies with the refinement of categories. I create a proxy to measure the ability of the experienced stocks to represent other stocks in the same industry. The results indicate that the experience effect is stronger when the experienced stocks are more representative. I also test within the same industry to determine whether the effect of experience in a given subindustry would spill over to another subindustry. The results do not suggest that investors have finer categorical thinking than Fama-French 10-industry classification.

This paper is related to several strands of literature. First, it contributes to the growing literature on investor behavior; specifically, I address how investors choose which stocks to purchase. Some papers focus on investors' cross sectional preferences of stocks,[3] while others discuss investors' stock purchase in a time series that connects buying decisions with past investment experience.[4] This paper exploits the latter approach and emphasizes the affects of past experience on future purchase of new stocks at different levels of categorization.

The literature also indicates that experience affects a number of other financial decisions, including IPO subscriptions (Kaustia and Knupfer, 2008), 401(k) accounts portfolios (Choi et al., 2009), stock market participation (Malmendier and Nagel, 2011), the investment style of fund managers (Chan et al., 2002), corporate external financing (Malmendier and Tate, 2005; Malmendier et al., 2011), etc. Even though the tests employed in this study are based on the idiosyncratic personal experiences of investors, an examination of the variation in experiences across cohorts (as in Malmendier and Nagel (2011)) may lead to similar results. Specifically, assume investors begin investing in the stock market in their mid twenties. For households whose members are between the ages of 30 and 40, I compute experiences as the average of industry returns during the preceding 10 years. Likewise, for the households whose members between the ages of 50 and 60, experiences are measured by the average of industry returns during the preceding 30 years. Figure 1.1 plots the difference in the fraction of households investing in an industry between above age cohorts against the difference of the experience in the same two groups. The figure suggests that more investors hold the stocks of an industry when their experience in that industry is better, which is consistent with the experience hypothesis.

This paper also contributes to the literature's examination of investors' categorical thinking or category learning behavior. Barberis and Shleifer (2003) assume that investors categorize risky assets into different styles and trade among styles depending on their relative performance, which derives excessive comovement of assets in the same style, but little comovement of assets in different styles and other asset pricing predictions. Peng and Xiong (2006) provide justification of category-learning behavior when attention is a scarce cognitive resource; they also generates features in return comovement and other predictions. The present paper provides empirical evidence that investors extrapolate their experience of stocks in one industry to their

[3]For example, Barber and Odean (2007) study the attention-grabbing stocks and find that individual investors are net buyers of attention-grabbing stocks. French and Poterba (1991) and a lot of other papers document the home bias puzzle that individuals and institutions in most countries hold modest amounts of foreign equity even though observed returns on national equity portfolios suggest substantial benefits from international diversification.

[4]For example, recent researches find that investors tend to buy stocks with strong recent performance (Odean, 1999; Barber, Odean, and Zhu, 2009; Jackson, 2003). Barber et al. (2010) establish the trading patterns in more details about how investors' repurchase of stocks previously sold is affected by their investment experience in those stocks.

decision about similar stocks in that industry, and these results provide microfoundation for the effect of experience under categorical thinking or learning.

Section 1.2 describes the datasets used in the paper as well as the methodology, and presents summary statistics. Section 1.3 details the results for the examination of the influence of experience on the future purchase of new stocks. Section 1.4 explores the underlying mechanisms through an examination of how this experience effect varies with investor sophistication, portfolio diversification and categorization. Section 1.5 summarizes this chapter.

## 1.2 Datasets and Methodology

### 1.2.1 Data Description

The dataset used in this paper includes the trading records of 78,000 households at a large discount brokerage house over the period 1991-1996. This dataset is used by Barber and Odean (2000) and others. Each household has at least one account, but some have many. I combine the trades of accounts within the same household and build observations at the household level. This paper only focus on investors' direct investments on common stock, so I exclude their investments in mutual funds, American depository receipts(ADRs), warrants, and options. The sample is further refined by removing observations with errors in trading records, short selling trades, etc. The number of households in the final sample is 47,993. More details about the restrictions I impose to select the sample for analysis are listed in the appendix. I use the Center for Research in Security Prices (CRSP) database to obtain information on stock prices for calculating investor experienced return or portfolio related variables.

One feature of this paper is to discuss investors' stock selection choices among a manageable number of categories, more specifically, industries. The Standard Industrial Classifications (SIC) codes are obtained from two resources: CRSP and Compustat.[5] For most of the tests, stocks are classified into 10 industry groupings based on their SIC code according to a algorithm devised by Fama and French (1997). The 10 industry groupings include (1) consumer nondurables, (2) consumer durables, (3) manufacturing, (4) oil, gas, and coal extraction and products, (5) high technology, (6) telephone and television transmission, (7) wholesale, retail, and some services, (8) healthcare, medical equipment, and drugs, (9) utilities, and (10) others. I also exploit the Fama-French 48-industry classification in robustness tests and to define subindustries in further analysis.

[5]The first step is to match the Cusip of the stocks invested by the households with corresponding SIC code in CRSP. If a corresponding SIC code can not be matched in CRSP, a second round match is proceeded in Compustat.

### 1.2.2 Investors' Investment Experiences and Purchase Decisions

I construct investors' experienced returns in each industry by their trading records. I select a fixed window to measure experienced returns. For example, the experience window spans from the beginning to the end of each year. Note that the returns in a fixed window could be either realized or not. I do not use realized returns to measure experiences, because I want to avoid introducing any potential endogeneity.

The measures of experienced outcomes build on the market-adjusted experienced returns. For every household $h$, I denote by $r_{hjt}$ the annualized return (either realized or not) of the stock $j$ during the experience window $t$. The experienced returns of industry $I$, $r_{hIt}$, is defined as value-weighted average returns of stocks belonging to the industry ($j \in I$):

$$r_{hIt} = \frac{\sum_{j \in I} x_{hjt} r_{hjt}}{\sum_{j \in I} x_{hjt}} \tag{1.1}$$

where $x_{hjt}$ is the dollar value allocated on stock $j$ at the date of purchase, or at the beginning of the window if the date of purchase is before the window starts. The market-adjusted experienced return in industry $I$, $er^m_{hIt}$, is the difference between $r_{hIt}$ and the market return of period $t$, $R_{mt}$:[6]

$$er^m_{hIt} = r_{hIt} - R_{mt} \tag{1.2}$$

I consider three measures of investors' past experienced outcome, which are three indicator variables denoting good, top and bottom experiences. The dummy for good experience, $Goodexp_{hIt}$, equals to one if household $h$ earns a positive market-adjusted return in industry $I$ during period $t$, i.e. $er^m_{hIt} > 0$. The dummy for top (bottom) experience, $Topexp_{hIt}$ ($Bottomexp_{hIt}$), equals one if $er^m_{hIt}$ is above the 90th (below the 10th) percentile of market-adjusted experienced returns by all households during period $t$. While these indicator variables are all based on market-adjusted experienced returns which are relative measures of experience, the results are robust to other measures, such as those based on the raw level of experienced returns.

Investors' purchase decisions are measured by an indicator variable $B^{new}_{hI,t+1}$, which takes a value of one if household $h$ purchases new stocks (those not previously owned in the experience window) in industry $I$ in decision period $t+1$ following the experience period $t$. Note that the purchase decisions only focus on new stocks, but not on previously owned stocks. If I do not exclude the previously owned stocks, the effect of past experiences on the industry level may be confounded with the effect on

[6] I will use lowercase letters to denote the experienced returns of households, such as $r_{hIt}$, $er^m_{hIt}$; and uppercase letters to denote market and industry average returns, such as $R_{mt}$, $R_{It}$.

the experienced stocks themselves. Barber et al. (2010) find that investors are more likely to repurchase the stocks which have been previously sold for a gain; they also find investors prefer to purchase additional shares of stocks that have lost value since being purchased. Since the experienced return (previously defined) could be either realized or not, the effect on previously owned stocks can push the results either way. Therefore, to separately identify the effect on the industry level, I will only consider purchases of new stocks in the following tests.

### 1.2.3 Summary Statistics

Table 1.1 represents the summary statistics. Panel A reports the frequencies of the trades of buying new stocks and repurchasing previously owned stocks through the years of the decision periods (1992-1996). The purchases of new stocks account for a large portion (about 85%) of investors' overall purchase decisions.

Panel B and Panel C summarize statistics related to past experiences. Panel B reports the distribution of households' experience across industries for each year of experience window. First, there are relatively more households trading in some of the industries, such as (3) manufacturing, (5) high technology, (7) wholesale, and (8) health care, which attract households over 10%. But overall, households' participation in each industry is roughly balanced, which could help rule out the possibility that the results are driven by a concentration of trades in some particular industry. Second, this table could also show the distribution of households' experience among the industries is stable across years.

Panel C provides a first look at the distribution of experience outcomes within each industry for each year of experience window. We can observe both the cross sectional and the time series variations. For example, during 1991, a great portion of the households (81.2%) had bad experiences in the energy industry, while over half of the households had good experiences in other industries such as wholesale, health care and utilities. However, households in the energy industry do not always have bad experiences. In 1993, over half of the households investing in energy had good experiences.

## 1.3 Industry Investment Experience and Stock Selection

In this section, I will study the effects of experienced returns in one industry on the decision to purchase new stocks in the same industry. I estimate a baseline specification using a probit model, and then present graphical evidence, followed by several robustness tests, such as using different measures of experienced outcomes, different industry classifications, addressing alternative explanations, etc. Finally, I examines the long term effect of prior experience outcomes on stock selection.

### 1.3.1 Graphical Evidence

The monotone increasing relationship between prior experienced outcomes and future purchases can be also illustrated as in Figure 1.2. I divide all the industry experienced outcomes into five bins, ordered by market-adjusted returns in each industry of each period. The right-most bars (group 5) correspond to the top 20% experienced returns, while the left-most bars (group 1) correspond to the bottom 20% experienced returns. The black bars in both figures represent the probability of buying new stocks in the experienced industry. Figure 1.2(a) employs the original data. It shows a roughly monotone increasing relationship: as experienced returns go up from quintile 1 though 5, investors are more likely to buy new stocks in the experienced industry, especially so in the upper tail of the experienced return. Figure 1.2(b) plots the average of generalized residuals within each quintile. The residuals are obtained from a probit model of regressing purchases of new stocks in one industry on control variables. The details about control variables will be discussed later. After removing the effects of controls (industry average, wealth effect and etc), the monotone increasing relationship becomes more striking.

### 1.3.2 Baseline Model

I start by modelling the probability of purchasing new stocks in one industry with a probit model. The dependent variable ($B^{new}_{hI,t+1}$) indicates the purchases of new stocks (those not previously owned in period $t$) in industry $I$ of period $t+1$. The specification is written as follows:

$$P(B^{New}_{hI,t+1} = 1) = \Phi(\beta_0 + \beta_1 Exp_{hIt} + \beta_2 Goodexp_{hIt} + \beta_3 Topexp_{hIt} + \beta_4 Bottomexp_{hIt} + \Gamma' X_{hIt}) \tag{1.3}$$

where $\Phi(\cdot)$ denotes the cumulative standard normal distribution function. $Exp_{hIt}$ is a dummy variable equal to one if household $h$ has investment in industry $I$ in period $t$. In the model, each observation corresponds to a household/industry/year pair. Because I use the Fama-French 10-industry classification, each household/year pair corresponds to 10 observations. The primary coefficients of interest are on the variables of experienced outcomes, which are measured by three dummy variables, $Goodexp_{hIt}$, $Topexp_{hIt}$, $Bottomexp_{hIt}$, equal to one if household $h$ earns positive, above the 90th percentile, below the 10th percentile market-adjusted returns in industry $I$ of period $t$. The experience hypothesis that investors overweight their experienced outcomes predicts a monotone positive relationship between experienced outcomes and future purchases, i.e. $\beta_2 > 0$, $\beta_3 > 0$, $\beta_4 < 0$.

#### 1.3.2.A Control Variables

These predications may be consistent with other explanations as well, such as (1) industry momentum trading, (2) wealth effects, and (3) investors' heterogeneity. I include a vector of controls ($X_{hIt}$) to address these issues:

**Industry Momentum Trading.** Moskowitz and Grinblatt (1999a) find a strong and prevalent momentum effect in the industry component of stock returns, which provides a way for investors to conduct momentum trading on industry level. Industry-level momentum trading could also lead to a positive relationship between prior experienced outcome and subsequent purchases. To control for this confounding effect, I include three industry average variables. They are all based on market-adjusted industry average return, $ER_{It} = R_{It} - R_{mt}$, where $R_{It}$ denotes the value-weighted average return of industry $I$ during period $t$. Corresponding to the dummy variables measuring experienced outcomes, the three industry average variables are created as: (1) $Goodind_{It}$: an indicator of industries with positive market-adjusted industry average returns during the experience window, i.e. $ER_{It} > 0$; (2) $Topind_{It}$: an indicator of the industry with the highest market-adjusted industry average return; (3) $Bottomind_{It}$: an indicator of the industry with the lowest market-adjusted industry average return.

**Wealth Effect.** Investors with good experiences in some industries are more likely to have increases in their overall stock portfolios. If investors tend to purchase new stocks in all the industries when their overall portfolios earn profits, the positive correlation between good experiences and future purchases in a specific industry may hence show up. To address this explanation, I include a dummy variable indicating the overall value of the household's portfolio on common stocks increases during the experience window.

**Investors' Heterogeneity.** Investors differ in their investment ability and level of expertise. Some investors with superior ability may be better at picking misvalued securities or predicting economic prospects. These investors are more likely to gain high returns and have good experiences. Even though the new purchases are made randomly across industries, we may observe the positive correlation between good past experiences and future purchases. To ensure that investment ability is not driving the relation, I create three variables measuring trading characteristics as a proxy of investor's investment ability. An investor with higher investment ability may trade more frequently, own a larger portfolio or hold a greater number of stocks in the portfolio. The three variables calculated by using the beginning-of-month position data from the experience window are: (1) Average number of stocks in the beginning-of-month portfolios; (2) A logarithm of the average size of beginning-of-month portfolios; (3) A logarithm of the average of monthly turnover rate calculated following Barber and Odean (2000).[7]

#### 1.3.2.B Basic Results

Table 1.2 presents the results. In addition the controls mentioned above, all specifications include year effects and industry effects. The standard errors are clustered by industry-year level. I report the marginal effect of each variable in the table.

The results for experience-related variables are consistent across all specifications. I find a significant and monotone increasing relationship between households' experienced outcomes and their future purchases within the same industry. Columns (1)-(4) include all three experienced-related variables and divide investors' experienced outcomes into four categories: (1) bottom; (2) bad but not bottom (base category); (3) good but not top; (4) top. According to Column (1), the propensity of buying new stocks in an industry is significantly 1.15 percentage points (pp) higher when the investor enjoys a good but not top experience relative to bad but not bottom. The propensity increases by 1.93 pp more when the investor earns a top experience. In addition, having a bottom experience makes the investor even more reluctant to purchase again in the same industry, the propensity drops by 1.29 pp compared to the base category. These results are consistent with the experience hypothesis that investors have higher propensity to purchase new stocks in the same industry if they experience higher returns in their past investment.

To better understand the economic magnitude, I only include the dummy indicating good experience in Column (5). Relative to having a bad experience, the investor with a good experience has a 1.86 pp higher probability to buy new stocks in that industry. This magnitude corresponds to 16.60 percent increase (= 1.86 pp/11.18 pp) of the probability if we normalize it by the average probability of buying new stocks in an industry within a single period (11.18 pp).[8]

[7] In each month during the sample period, I identify the common stocks held by each household at the beginning of month $t$ from their position statements. To calculate monthly sales turnover, I match these positions to sales during month $t$. The monthly sales turnover is calculated as the shares sold times the beginning-of-month price per share divided by the total beginning-of-month market value of the household's portfolio. To calculate monthly purchase turnover, I match these positions to purchases during month $t-1$. The monthly purchase turnover is calculated as the shares purchased times the beginning-of-month price per share divided by the total beginning-of-month market value of the portfolio. Finally, monthly turnover is calculated by averaging monthly sales turnover and monthly purchase turnover.

[8] In addition, I want to point out that the setting of baseline model is actually estimating a lower bound of the effect. If the investors are sorted into some industry they think they have information advantage or they are more familiar with, their experienced outcomes may have less influence. And as more and more experience the investors get in some industry, the effect of new experience tends to decrease. Ideally, I would like identify the industries that investors are not sorted into (for example, the investors are attracted by some exogenous events and then start to

As a comparison with the effect of personal experiences, the effect of industry average returns is quite different and exhibits a U-shaped relationship. The non-extreme industry average variable does not have a significant influence. but the industries with the highest and lowest market-adjusted return both have positive impacts on households' future purchases. This evidence is consistent with the "attention grabbing" effect found in Barber and Odean (2007). Individual investors tend to purchase stocks in the industries which exhibit big price moves, because the stocks in those industries catch their attention. The results of the wealth effect and trading characteristics controls are reported in Column (4). Consistent with our expectations, investors have a higher probability of buying new stocks when they earned money in the past year, trade more frequently and have a larger portfolio invested in the stock market.

As a side note, the marginal effect of the experience dummy is also significantly positive. It implies a significantly positive unconditional effect of prior investment experience. In other words, regardless of outcomes, personal involvement, on average, has a positive effect on the probability of future purchases in that industry. Several explanations could explain this effect. For example, the involvement catches investors' attention, therefore, the stocks in this industry are more likely to enter the choice set for future purchase; or investors are sorted into certain industries because they may have worked in those industries, have information advantages and tend to buy stocks in those industries. The experience dummy is not the focus of this paper, but it is important to put it as a control in the regression.

### 1.3.3 Robustness Tests

These results are robust to alternative experience measures, subsample, explanations and industry classification. Table 1.3 presents a series of robustness tests.

Instead of using dummy variables to measure experienced outcomes and industry average returns, Panel A directly applies the level of market-adjusted experienced returns and industry average returns. The coefficient on the experienced return is significant and positive, confirming that investors have higher propensity to buy new stocks in an industry if they earned higher returns in the same industry in the past. Different from the effect of past experience, the effect of industry average return is nonlinear and represents a U shape, which is also consistent with the evidence found in Table 1.2.

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invest in some industry) and be able to observe investors' trading records since the first time they enter that industry. Therefore, given the setting of current dataset, the estimated magnitude of experience effect may be dampened due to sorting or diminishing influence as investors cumulate more and more experience in a certain industry.

In Panel B, I drop the industry-year observations if the household does not have investment in the industry during the past period. Then I run specification (1.3) without the experience dummy. As Panel B of Table 1.3 shows, the results remain the same, indicating a monotone increasing relationship between experienced outcomes and future purchases within the same industry.

Panel C considers an alternative story of mental accounting. If investors apply mental accounting (Thaler (1999)) and regard each industry as an account, they may rebalance portfolios only within an industry but not across industries. Such investors purchase stocks in an industry with the money from recent sales in that industry. Because sales are more likely to happen following good experiences due to disposition effect (Odean (1998)), purchases following the sales are more likely to happen as well. To address this issue, I exclude the purchases that happen within 30 days after the most recent sales in the same industry. In other words, the dependent variable is a dummy variable which indicates purchases of new stocks without recent sales. The results are virtually unchanged, though the magnitude does drop slightly. According to Column (5), good experience increases the propensity of buying new stocks without recent sales by 0.92 pp relative to bad experience, which corresponds to an increase of 11.35 percent (= 0.92 pp/8.08 pp) if normalized by the average probability of buying new stocks without recent sales in an industry.

I also exploit the Fama-French 48 industry classification as a robustness check. To make the definition of the top and bottom industries match with the definition of the top and bottom experiences, I define the top (bottom) industries as those with the top 5 (bottom 5) industry average returns. The results are reported in Panel D. The results are consistent with those using Fama-French 10 industry classification. Moreover, Column (5) implies that the economic magnitude of the experience effect on Fama-French 48 industry level is also close to that on Fama-French 10 industry level shown in Table 1.2: the effect of a good experience in Fama-French 48 industry corresponds to an increase of 14.08 percent (= 0.27 pp/1.96 pp) in the probability of future purchases in that industry if normalized by the average probability of buying new stocks in an industry. This evidence may suggest that the effect of good experiences within a category do not become stronger when the category switches from 10 industry to a much finer category - 48 industry. I will further analyze how the experience effect varies with different levels of categorization in Section 1.4.

### 1.3.4 Dynamic Effects

I have so far investigated the influence of prior stock investment experience on a one year horizon. In this section, I will further explore whether the effect lasts for a longer time, and how the significance and magnitude change for lagged experience of different time horizons.

To exhibit more details about the dynamic effects, I switch to use a monthly window in this section. Given using rolling window regression, the larger size of the experience window reduces the sample size. I will investigate the effects of investment experience in the last 36 months and hence start the decision window from January 1994. This choice represents a compromise between having a reasonable length of history of experience and having enough households in the sample. Since some households open the account or stop trading during the sample period, their trading records do not cover the whole sample period and may not be applicable for the test of the long term effects of experience. Therefore, in this section, I restrict the sample to the households who have already opened accounts since 1991 and still actively trade in 1996.

For each household, I use the data of 36 months before the decision month to create the lagged monthly experience related variables and corresponding control variables. The dependent variable indicates the investment decision within a month ($t$+1) after January 1994, which is a dummy variable equal to one when the household purchase new stocks (never bought in the past 36 months) in one industry during that month. The specification is written as a probit model as follows:

$$P(B^{New}_{hI,t+1} = 1) = \Phi(\beta_0 + \sum_{m=1}^{36} \beta_{1m} Exp_{hI,t+1-m} + \sum_{m=1}^{36} \beta_{2m} Goodexp_{hI,t+1-m} + \Gamma' X) \tag{1.4}$$

The coefficients on lagged good experience, $\beta_{1m}$, are plotted in Figure 1.3. The figure shows that the effect of experience decreases as the experience happened during earlier periods. The coefficients are significantly positive for the experience in the recent 17 months (except the most recent one), but statistically insignificant when it goes further than 17 months. The effects of monthly experiences within the past year are on average 0.40 pp. This magnitude is lower than that in the baseline model because of the change of window frequency to a monthly level. However, when normalized by the average probability of buying new stocks in an industry in the decision month 2.36 pp, the magnitude still maintains in the same level that good experience increases the propensity of buying new stocks in the same industry by about 16.95 percent (= 0.40 pp/2.36 pp).

### 1.3.5 Summary

Investors' future purchases are influenced by their past experienced returns. If they experience a higher return in an industry, their propensity of purchasing new stocks in that industry increases. This effect is robust after controlling for industry momentum trading, wealth effect, investor heterogeneity and mental accounting.

The results remain the same when using different measures of experience, subsample, industry classification. The influence of experienced outcomes becomes weaker when the experiences go further in the past; the experience from 16 months ago or earlier has insignificant effect.

## 1.4 Underlying Mechanisms

The results of the baseline model show a significantly positive relationship between good experience and probability of buying new stocks in the same industry. This section further examines the underlying mechanisms: does the relationship vary with the degrees of investor sophistication, portfolio diversification and categorization?

### 1.4.1 Investor Sophistication

The influence of experienced outcomes may vary with investor sophistication. If the experience hypothesis is true, the influence of experienced outcomes on future stock purchase decisions is more likely to be stronger for the less sophisticated investors, because given longer history of more sophisticated investors, the recent good or bad experienced outcomes may be canceled by previous ones and have less influence. However, it can also go in the opposite direction if the alternative story of investment ability is true. If the positive relation between past experienced return and future purchases is created by the better performance and more frequent trading of investors with higher investment ability, this relation should be stronger for the investors with higher sophistication.

I use self-reported experience/knowledge in the dataset as a proxy of investor sophistication. When the household opened an account, they would be asked to fill out a form to report their perception of their experience or knowledge in investment. The four levels they could be used to classify themselves are: extensive, high, limited and none knowledge about investing.[9]

I conduct the regressions of specification (1.3) separately for each group of investors and see how the coefficients change among the subgroups. The results are presented in Table 1.4. As the table shows, the marginal effect of good experience becomes weaker as investors become more sophisticated. For the most sophisticated subgroup with extensive knowledge about investing, the coefficient is insignificant.[10]

[9] Because of the missing self-reported data, the sample used in this part is much smaller than the whole sample, but in unreported tables, I show that the main summary statistics of distribution of trades among industries and distribution of experience across industries and years don't change much.

[10] I also run one regression including the observations of all the groups, and interact the sophistication group with past experience. The results show that the difference of the marginal effect

This evidence is more consistent with the experience hypothesis. The most sophisticated investors have a long history of experiences, and may obtain specialized skills in investing certain industries through their historical experienced outcomes. They are more likely to make new purchases in these specialized industries but are not affected much by their recent experience outcomes. In contrast, the least sophisticated ones are new to the stock investment and do not have a long history of experience to cancel out recent experienced outcomes, therefore are more likely to switch across industries depending on whether their experienced outcomes in that industry are good or bad.

### 1.4.2 Portfolio Diversification

I next explore the variation in portfolio diversification. Investors with different diversification in their portfolio may take different approach to invest. The investors with more concentrated portfolios may devote themselves to seeking stocks with extraordinary alpha, while some others attempt to diversify their portfolio to reduce idiosyncratic risk. I hypothesize that past investment experience matters more to those alpha seekers relative to diversification oriented investors. People who put all their eggs in one basket have to pick the best basket and their past experience could play a role in their decision making. In contrast, people who put their eggs in multiple baskets would care less about which baskets they choose. Therefore, I expect to see that the relationship between past experienced outcome and future new purchases in the same industry is more significant for the investors with more concentrated portfolios.

I test this hypothesis by adding an interaction term between experience-related variable and a diversification measure into the baseline model, the specification is as follows:

$$\begin{aligned} P(B^{New}_{hI,t+1} = 1) = \Phi(&\beta_0 + \beta_1 Exp_{hIt} + \beta_2 Goodexp_{hIt} + \beta_3 Exp_{hIt} \cdot Diversified_{ht} \\ &+ \beta_4 Goodexp_{hIt} \cdot Diversified_{ht} + \beta_5 Diversified_{ht} + \Gamma' X_{hIt}) \quad (1.5) \end{aligned}$$

I use two measures for portfolio diversification following Ivkovic, Sialm, and Weisbenner (2008). The first measure is a portfolio Herfindahl Index ($HI$), which is defined as the sum of the squared weights of each stock $k$ in the household stock portfolio ($w_k$), i.e. $HI = \sum_k w_k^2$. The more diversified the portfolio is, the Herfindahl index is smaller. If a household owns only one common stock, the Herfinndahl Index reaches its maximum and equals to one. Therefore, I define the dummy variable $Diversified_{it}$ equal to one when the Herfindahl index of investor $i$'s portfolio

of good experience is statistically significant between the none knowledge group and the extensive knowledge group.

is less than the median in the sample. The second measure is the number of stocks held in the portfolio. A portfolio with more stocks is considered as more diversified. Similarly, I define the $Diversified_{it}$ variable as equal to one when the number of stocks held is greater than 5, which is the median of the sample.

According to results in Table 1.5, the influence of experienced outcomes is stronger among the investors who hold more concentrated portfolios, since the coefficient on the interaction term between good experience and diversified portfolio is negative and statistically significant. As for investors with concentrated portfolios, good experience in an industry increases their probability of buying new stocks in the same industry by 1.32 pp. This effect is dampened by about 2/3 when the portfolio is more diversified.

### 1.4.3 Categorization

Up to this point, I have been using Fama-French 10 industry as the classification of industries. To shed more light on to what extent investors categorize stocks, I will explore how the impact of past experiences varies if I apply a broader categorization or a finer categorization.

#### 1.4.3.A Spill-over Effect across Industry

I start by testing whether past experiences of Fama-French 10 industries have spill-over effects on the purchases of other industries. The light blue and white bars in Figure 1.2 display the probability of purchasing new stocks in other industries by sorting households' experienced market-adjusted returns in the past year. The right-most bars (group 5) correspond to the top 20% experienced returns, while the left-most bars (group 1) correspond to the bottom 20% experienced returns. I create a distance measure among industries to select, among other industries, the one most similar to the experienced industry and the one most different from the experienced industry. For each year, the distance is calculated by averaging daily absolute difference between the stock returns of two industries. Suppose there are $N$ trading days in one year, the distance between industry $I$ and industry $J$ (both defined by Fama-French 10-industry) is described as $D_{IJ} = \frac{1}{N}\sum_{t=1}^{N}|R_{It} - R_{Jt}|$.[11] The matches are intuitive as well. For example, for most of the years, the most similar industry to the industry of oil, gas, and coal extraction and products is the utility industry, while the most different industry is the high technology industry.

Figure 1.2(a) plots the original probability of purchasing new stocks. The probability in the most similar industry slightly increases as the experienced return goes

[11] I also experimente with another distance measure $D_{IJ} = \frac{1}{N}\sqrt{\sum_{t=1}^{N}(R_{It} - R_{Jt})^2}$, and the results remain the same.

up, while the probability in the most different industry almost maintains itself at the same level across different levels of experienced returns. In a word, the effect of past experienced returns becomes increasingly weaker when the industry becomes more different from the experienced industry. Using the residuals from regressing the purchase decision on the controls, Figure 1.2(b) confirms this evidence.

Table 1.6 uses a regression framework to test whether spill-over effect on other industries is significant while controlling for the wealth effect, investor heterogeneity, year and industry effects. As in Figure 1.2, I consider the effect on two other industries: the most similar to the experienced industry and the most different. According to Table 1.6, compared to the effect of good experience on the purchases in the same industry, the effect in the most similar industry is only marginally significant, and the magnitude is far smaller than that in the same industry; the effect in the most different industry is even smaller and insignificant. If we also take a look at all the control variables, the significance and magnitude do not change much no matter if it is for the experienced industry or for other industries. This result is consistent with our intuition that wealth effect and investor characteristics should have the same effect on each industry.

The evidence in Figure 1.2 and Table 1.6 suggests that the impact of past experience does not spill over, or if it does only in a tiny amount, to other industries.

#### 1.4.3.B Categorical Thinking within Industry

In this section, I further investigate whether investors categorize stocks more finely than Fama-French 10 Industry. Specifically, I will consider finer categorization in two dimensions. In the first dimension, the investor may have a finer categorization through the representativeness of the stocks in which the investor has experience. If investors purchased stocks that are representative of the industry, is the impact of experienced outcomes larger compared to if investors invested in unrepresentative stocks? I construct a measure for the representativeness of each stock. The measure for an experienced stock $j$ in industry $I$ is computed as the correlation between the stock return $r_{jt}$ and the equal-weighted industry return $R_{It}$.[12] A higher correlation indicates that the experienced stock is more representative of the stocks in the same industry. The representative stocks identified by this measure are intuitive as well. For example, the representative stocks in the industry of wholesale, retail and some services include May Department Store, Target, Home Depot, etc., while the non-representative stocks in this industry include Perfumania, Skyline Chili Inc., etc.

I divide the experiences into two groups according to the representativeness of the experienced stocks. After removing the effects of controls, Figure 1.4 displays

[12] I use equal-weighted industry return to address the concern that the measure would be biased toward large firms if I use value-weighted industry return.

the probability of purchasing new stocks for experiences on representative stocks and non-representative stocks, respectively. According to the figure, the probability of purchasing new stocks increases with experienced returns for both groups, and the probability increases by a larger amount for the more representative group. It means that investors are influenced more by experiencing more representative stocks. If they profit from investing in Target, they may have higher probability to buy other stocks in the wholesale, retail and services industry again. In contrast, a good experience from investing in Perfumania may not have as much impact.

The representativeness captures one dimension of finer categorization based on the statistical feature of stock returns, and individual investors may perceive finer categorization in a more intuitive way. They may further divide stocks into subcategories beyond Fama-French 10-industry classification, such as Fama-French 48-industry. If the investors consider stocks under Fama-French 48-industry classification, it should be true that the influence of past experience within the same subindustry (Fama-French 48 Industry) is stronger than that on another subindustry, even though these two subindustries belong to the same Fama-French 10 industry.

The industries under Fama-French 48-industry classification may correspond to multiple industries under Fama-French 10-industry classification. To keep the test clean, I only consider one specific industry by Fama-French 10-industry classification in the test. Table 1.7 reports the results using the data from the Manufacturing industry according to Fama-French 10-industry classification. As Column (1) shows, good experience in a subindustry is significantly positive related to subsequent purchases of new stocks in the same subindustry. Column (2) presents the impact on another random subindustry in the Manufacturing industry. The coefficient on the good experience variable is also significantly positive and very close to the impact on the experienced subindustry (Column (1)). If an investor gains a good experience in one subindustry, she may buy new stocks in another subindustry within the same industry with the same probability as she may buy in the experienced subindustry. This evidence may suggest that investors do not think as finer as Fama-French 48-industry classification. To complement the test, I also report the impact on a random subindustry outside Manufacturing (Column (3)). The coefficient is insignificant, which is consistent with Table 1.6: the impact does not spill over beyond Fama-French 10 industry.

Overall, I find that, within Fama-French 10 industry, experiences on more representative stocks have a stronger impact on future purchases in the same industry; but the impact does not seem to become stronger if we further segment Fama-French 10 industry to Fama-French 48 industry.

### 1.4.4 Discussion

This experience effect is consistent with two possible mechanisms.[13] The first mechanism is that investors may put more weight on their experience outcomes than on other available historical information when undertaking a Bayesian updating their beliefs about stocks in the same industry. This is a natural explanation for why experience outcomes affect purchase decisions. Good experiences drive posterior expected returns upward, and consequently investors are more likely to buy new stocks in that industry. Another explanation is that investors may construe their experienced outcomes as indications of their ability to invest in a particular industry. Therefore, an investor may (correctly or falsely) learn that she has an advantage in investment in the energy industry when her energy stocks outperform the market; she then buys more stocks in the energy industry to take advantage of this perceived ability. Table 1.8 provides suggestive evidence for this mechanism. I run a Tobit regression of the number of trades in one industry (including both buys and sales) on the previous year's experience-related variables pertinent to that industry, controlling for industry average and individual characteristics. The results show that investors will trade more frequently in an industry after they have had good experience in that industry. This evidence is consistent with the hypothesis that investors may perceive that they are better at picking stocks in the industries in which they had good experiences.

These two mechanisms are not mutually exclusive, and both of them could have implications on investors' welfare. Under the first mechanism, investors' past experiences may bias their belief and lead them to miss good investment opportunities. As one practitioner notes, "the problem is that in accumulating experience, he also acquires prejudices against industries and stocks because he has lost money in them. It is easy to ... become an investment bigot with a closed mind on many subjects."[14] Does this behavior hurt investors' performances? Figure 1.5 compares the returns of actual purchases by the investors with the returns of two hypothetical strategies: (1) the index of industries in which the investors have picked stocks; and (2) the index of industries which investors could pick but choose not to. I form calendar-time portfolios corresponding to these strategies. For each day, the calendar-time portfolio of actual purchases is constructed to include all stocks bought by households within the

[13] Experience could also influence investors' behavior through other channels. For example, in the context of Barber et al. (2010), experienced buying or selling price could affect investors' reference point and further influence investors' action since investors tend to avoid anticipated regret. Because my research focuses on the decision of buying stocks not previously owned, the role of affecting reference point may not apply.

[14] See http://dailyreckoning.com/the-worst-possible-investing-mistake/

prior 21 trading days; and the portfolio of (not) invested industry is formed by investing in indices of the industries in which households have (not) bought stocks during the prior 21 trading days.[15] The weight is equally allocated to each stock-household (industry-household) pair. Figure 1.6a displays the monthly abnormal returns of these three portfolios controlling for Fama-French three factors (Fama and French, 1993). According to the figure, past experiences do not seem matter much for each portfolio, and in general returns of actual purchases are negative, while the returns of industry averages are positive. For comparison, Figure 1.6b plots the difference of the monthly abnormal returns between actual purchases and the industries invested by households. As the figure shows, the stocks picked by investors earn a much lower return compared to the average returns of corresponding industries. The industry-adjusted returns of picked stocks are statistically significant and negative, indicating that on average individual investors have inferior stock-picking ability. Additionally, Figure 1.6c plots the difference of the monthly abnormal returns between industries that are invested and not invested by households. According to the figure, these two returns are quite close to each other and the difference between the two is statistically insignificant regardless of whether investors bought in the industries with good, bad, or no experiences. In other words, even though investors tend to purchase more in industries regarding which they have had good experience, they are not missing much as a result of bias towards good experience industries. Individual investors would not systematically pick the wrong industries for investment. What may actually hurt their performance is that they appear to systematically pick the wrong stocks for investment.

Considering the evidence that on average individual investors appear to have inferior stock-picking ability as shown in Figure 1.5, it is more likely that investors incorrectly assess their ability as high because of experienced positive outcomes. As a result, investors are more likely to trade in industries in which they have had good experiences as well as to increase their trading frequency after good experiences. Their performance will then decline, both as a consequence of their inept stock picking ability and the increased transaction costs of their more frequent trades. Odean and Gervais (2001) point out that investors become overconfident because they tend to overestimate their trading ability based on their successes and downplay their failures. The evidence in this paper raises another mechanism of building up overconfidence. Investors categorize their portfolio and infer their ability to trade

[15] I exclude the stocks bought on the day of forming the portfolio. It is to address the concern that if investors tend to buy stocks after observing good returns of the industry average of that day, then including the stocks bought on the day of forming the portfolio may mechanically observe the returns of actual purchases lower than the industry average returns by the way constructing the portfolio.

in each category from their past performances. This categorization increases the chances that they will find good performances among categories they invested in and mistakenly attribute their success to talent for investing in those categories. This, in turn, causes the inertia which decreases the likelihood of giving up a stock picking strategy before diversifying their portfolio or exiting stock market.

## 1.5 Summary Remarks

This paper investigates the influence of personal investment experience on subsequent stock selection decisions. Using trading records data for households from a large discount broker collected over the period between 1991 and 1996, I demonstrate that investors have a higher propensity to purchase new stocks in an industry if during the past in that same industry they earned positive excess returns. I also provide evidence that the significance and magnitude of the influence of prior experienced outcomes varies over different time horizons, categorizations, degrees of investors' sophistication and investors' portfolio diversification.

The influence of past investment experience may result from investors overweighing their own experience relative to other available historical information when updating their beliefs about stocks in a category (e.g. the industry examined in this paper). The results may also be explained by investors learning about their ability of picking stocks in a certain category from their experiences. I provide evidence that investors may not systematically miss good opportunities as a consequence of this biased belief updating. Nevertheless, the good experience by inept investors in a given category may lead them to assume that they possess insight regarding decisions in this category. In this case, finer categorization will delay the exit of such inferior investors and cause welfare loss. Furthermore, the aggregation of the influences of investors' personal investment experiences may have a systematic effect on asset pricing; for example, this experience effect may provide a source of industry momentum effect that is different from the existing explanations in the literature. Finally, if past experience outcomes influence investors' decisions by affecting information acquisition or the constitution of their information set, we may be able to make richer predictions about the information incorporation in the market.

Figure 1.1: Motivating Example: Difference in Stock Holdings by Industry of Young and Old Groups vs Difference in Their Experienced Industry Returns

The stock holdings of an age group in industry $i$ are measured by the fraction of households investing in industry $i$ in a certain year within the age group. The young group is defined as the households with age between 30 and 40, while the old group is defined as the households with age between 50 and 60. The vertical axis denotes the difference in the stock holdings by industry of these two groups. The horizontal denotes the difference in their experienced industry returns. The experience of the young group in industry $i$ is measured as the average of industry $i$ returns over the prior 10 years, while the experience of the old group is measured over the prior 30 years. Each observation corresponds to a year-industry pair. Industry is classified according to Fama-French 10 industry classification. "High Tech" industry is excluded in this analysis.

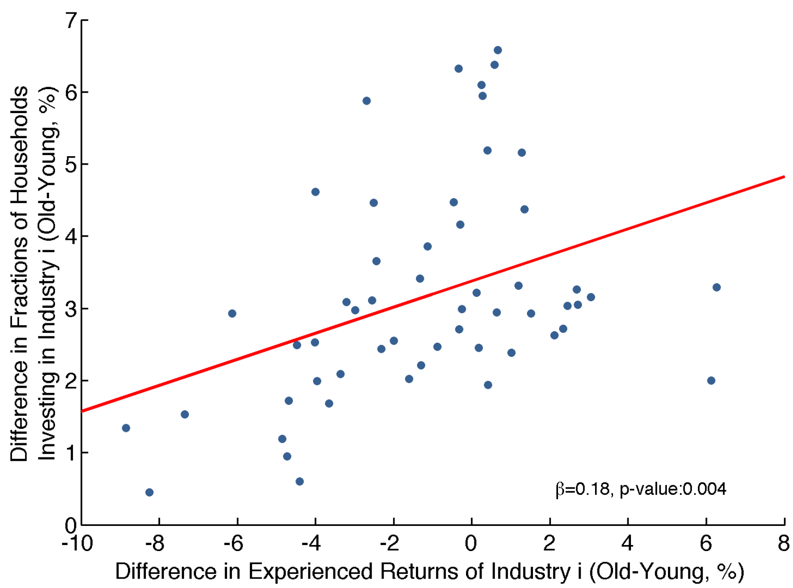
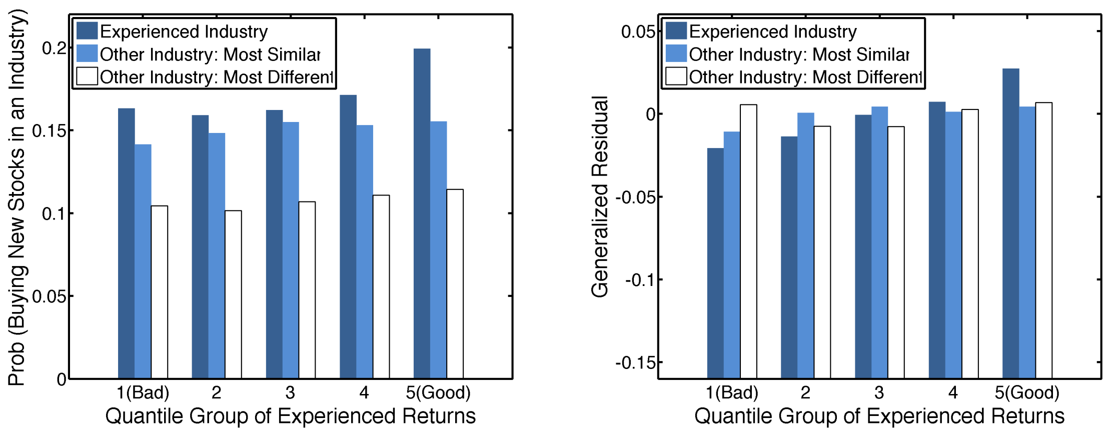


Figure 1.2: The Impact of Personal Investment Experience in an Industry on Subsequent Investment in Experienced Industry vs Other Industry

The observations are sorted by the value weighted average annualized excess return on the investment in an industry and divided into five groups. Group 1 has the lowest experienced return while group 5 has the highest. Figure (a) plots the original probability of buying new stocks, i.e. the percent of households buying new stocks in an industry. Figure (b) plots the generalized residuals from a probit model of regressing purchasing new stocks in an industry on controls of the baseline model.[16] The dark blue bars correspond to the experienced industry. The light blue and white bars correspond to the industry that is the most similar to or the most different from the experienced industry, respectively. The most similar and the most different industries are selected by measuring the distance between the stock returns in that industry and those in the experienced industry. The distance is measured by averaging daily absolute difference between the stock returns of two industries.




(a) Original

(b) Removing Effects of Control Variables

[16]The generalized residual of the probit model $Pr(Y_i = 1) = \Phi(X_i'\beta)$ is computed as:

$$\frac{Y_i - \Phi(X_i'\beta)}{\Phi(X_i'\beta)(1 - \Phi(X_i'\beta))}\phi(X_i'\beta)$$

where $\phi(\cdot)$ is the density function of the normal distribution and $\Phi(\cdot)$ is the cumulative distribution.

Figure 1.3: Dynamic Effects of Monthly Lagged Industry Experienced Outcomes

This figure shows the dynamic effects of experienced outcomes in the past 36 months on subsequent purchases of new stocks. The sample includes all the investors who already have investment from 1991 and still trade in 1996 in the dataset. The solid line connects the estimated coefficients of a rolling-window probit regression of purchasing new stocks on monthly experienced outcomes during the past 36 months. Time 0 corresponds to the decision window during which the decisions whether purchasing new stocks are made. The decision window starts from January 1994 through December 1996. The regressions are controlled for industry momentum. The broken lines show the 5% and 95% confidence intervals.

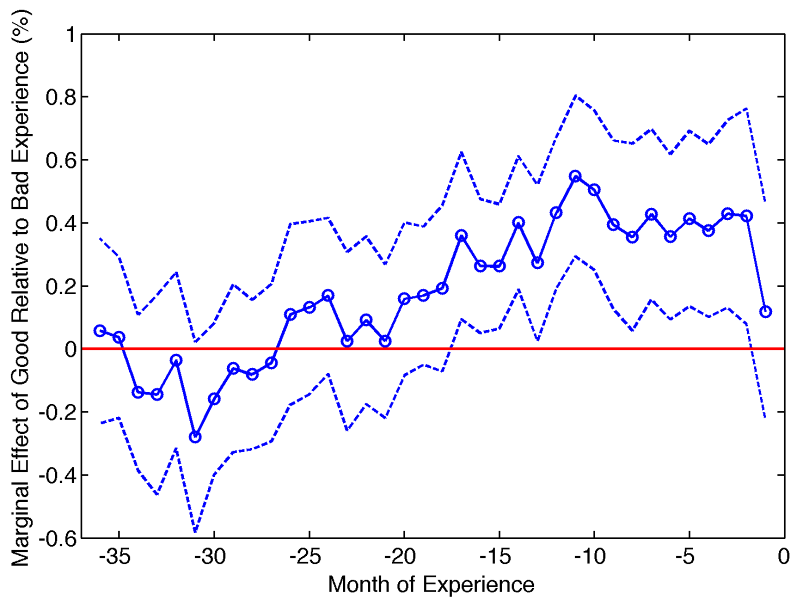
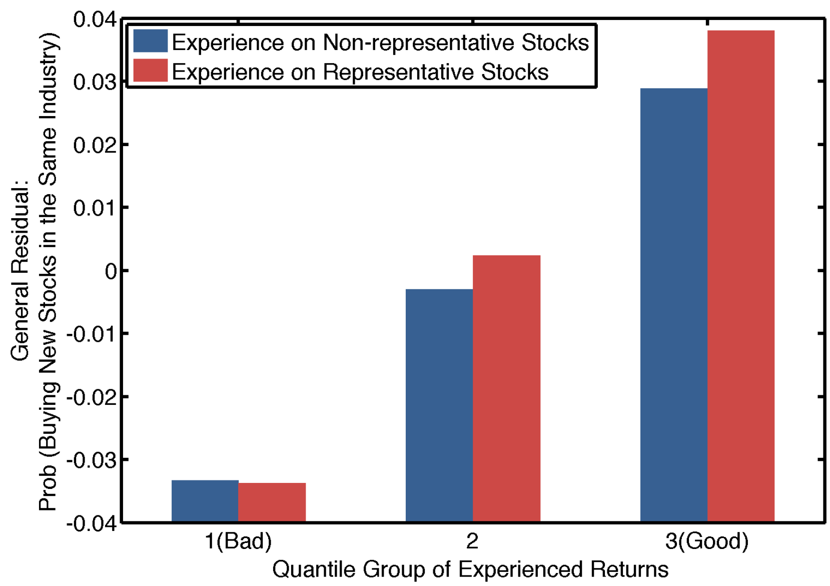


Figure 1.4: The Impact of Investment Experience: Variation in Representativeness of Experienced Stocks

The observations are sorted by the value weighted average annualized excess return on the investment in an industry and divided into three groups. Group 1 has the lowest experienced return while group 3 has the highest. The figure plots the generalized residuals from a probit model of regressing purchasing new stocks in an industry on controls of the baseline model.[17] The blue bar corresponds to the observations with experiences in the non-representative stocks, while the red bar corresponds to those with experiences in the representative stocks. The sample only includes the observations whose representativeness measures are available. The representativeness measure for one experienced stock $j$ in industry $I$ is computed as the correlation between the stock return $r_{jt}$ and the equal-weighted industry return $R_{It}$. The representative stocks are defined as stocks with representativeness measures greater than the median.



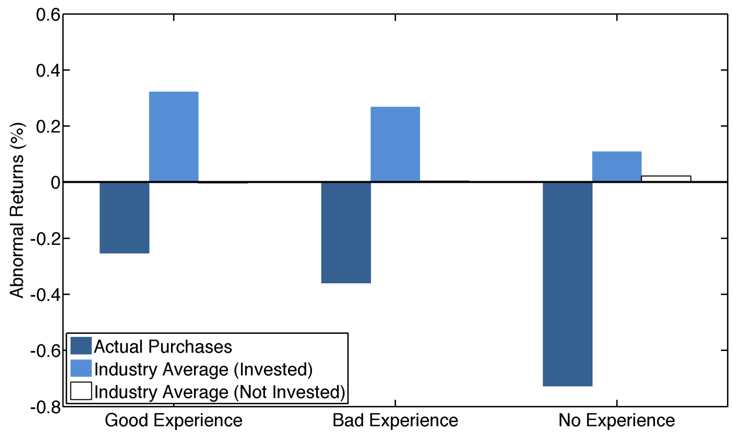

[17]The generalized residual of the probit model $Pr(Y_i = 1) = \Phi(X_i'\beta)$ is computed as:

$$\frac{Y_i - \Phi(X_i'\beta)}{\Phi(X_i'\beta)(1 - \Phi(X_i'\beta))}\phi(X_i'\beta)$$

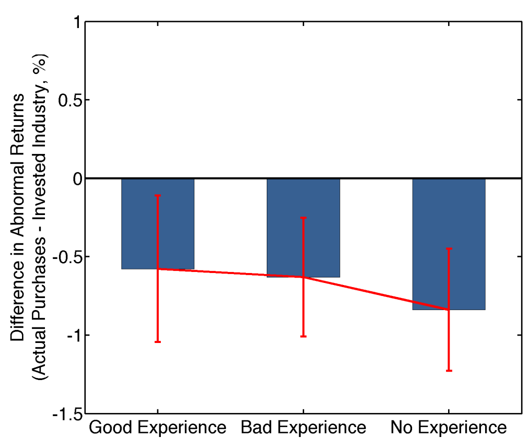
where $\phi(\cdot)$ is the density function of the normal distribution and $\Phi(\cdot)$ is the cumulative distribution.

Figure 1.5: Performance Analysis (Calendar Time Portfolio)

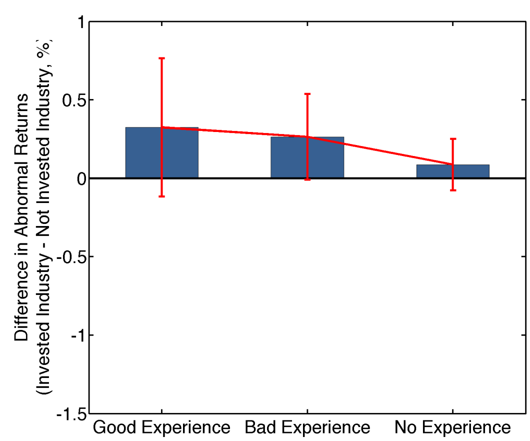
Figure (a) plots the monthly abnormal returns of calendar time portfolios controlling for Fama-French three factors (Fama and French, 1993). At each day, the calendar-time portfolio of actual purchases is formed to include all stocks bought by households within prior 21 trading days; the portfolio of (not) invested industry is formed to include all industries within which households have (not) bought stocks during prior 21 trading days. The returns of the portfolio are then accumulated within each month to obtain monthly returns. Figure (b) plots the monthly abnormal returns of going long the calendar time portfolio of actual purchases and short the portfolio of invested industries; Figure (c) plots the monthly abnormal returns of going long the portfolio of invested industries and short the portfolio of not invested industries.




(a) Portfolio Performances




(b) Actual Purchases - Invested Industry




(c) Invested Industry - Not Invested Industry

Table 1.1: Summary Statistics

Panel A reports the number and percentage of trades purchasing other stocks not previously owned and trades repurchasing the stocks previously owned. The sample period includes all the years which are used as decision windows in the baseline model (1992-1996). Panel B reports the percentage of households investing in each industry groupings from 1991-1995 for the full sample. Panel C reports the percentage of household's good(bad) experience in each industry groupings from 1991-1995 for the full sample. Good(bad) Experience is measured as the experienced market-adjusted return in the industry is greater than(smaller than or equal to) zero. The sample period includes all the years which are used as experience windows in the baseline model.

**Panel A: Distribution of Household Stock Purchases, 1992-1996**

| | 1992 | 1993 | 1994 | 1995 | 1996 | Total |
|---|---|---|---|---|---|---|
| Purchase Other Stocks | 77,057 | 70,912 | 57,626 | 68,519 | 72,727 | 346,841 |
| Repurchase Previously Owned Stocks | 10,455 | 12,013 | 12,200 | 10,946 | 13,839 | 59,453 |
| Total | 87,512 | 82,925 | 69,826 | 79,465 | 86,566 | 406,294 |
| Purchase Other Stocks | 88.1% | 85.5% | 82.5% | 86.2% | 84.0% | 85.4% |
| Repurchase Previously Owned Stocks | 11.9% | 14.5% | 17.5% | 13.8% | 16.0% | 14.6% |
| Total | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |

**Panel B: Distribution of Household Stock Investment Experience Across Industry, 1991-1995**

| | 1991 | 1992 | 1993 | 1994 | 1995 | Total |
|---|---|---|---|---|---|---|
| (1) Consumer nondurables (%) | 8.7 | 8.7 | 9.5 | 9.3 | 8.8 | 9.0 |
| (2) Consumer durables (%) | 4.6 | 5.0 | 4.4 | 4.6 | 4.9 | 4.7 |
| (3) Manufacturing (%) | 11.9 | 11.0 | 10.5 | 10.1 | 10.6 | 10.7 |
| (4) Oil, gas, and coal extraction and products (%) | 4.5 | 4.8 | 4.5 | 4.2 | 4.2 | 4.4 |
| (5) High technology (%) | 17.4 | 17.1 | 16.6 | 16.3 | 17.0 | 16.8 |
| (6) Telephone and television transmission (%) | 4.8 | 5.0 | 5.6 | 6.5 | 6.9 | 5.9 |
| (7) Wholesale, retail, and some services (%) | 10.3 | 10.7 | 11.3 | 11.7 | 12.0 | 11.3 |
| (8) Health care, medical equipment, and drugs (%) | 12.5 | 14.7 | 15.3 | 14.4 | 13.3 | 14.1 |
| (9) Utilities (%) | 5.1 | 5.8 | 5.8 | 6.4 | 6.1 | 5.9 |
| (10) Others (%) | 20.2 | 17.2 | 16.6 | 16.5 | 16.2 | 17.0 |
| N | 58,392 | 86,513 | 101,525 | 107,534 | 116,928 | 470,892 |

**Panel C: Household Stock Investment Outcomes, 1991-1995**

| | (1) Consumer non-durables | (2) Consumer durables | (3) Manufacturing | (4) Oil, gas, and coal extraction and products | (5) High technology | (6) Telephone and television transmission | (7) Wholesale, retail, and some services | (8) Health care, medical equipment, and drugs | (9) Utilities | (10) Others | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Year = 1991* | | | | | | | | | | | |
| Bad (< 0) (%) | 50.8 | 65.3 | 57.6 | 81.2 | 60.6 | 52.9 | 44.8 | 40.2 | 44.0 | 61.2 | 55.3 |
| Good (> 0) (%) | 49.2 | 34.7 | 42.4 | 18.8 | 39.4 | 47.1 | 55.2 | 59.8 | 56.0 | 38.8 | 44.7 |
| N | 5,058 | 2,715 | 6,927 | 2,633 | 10,177 | 2,793 | 6,012 | 7,297 | 2,959 | 11,821 | 58,392 |
| *Year = 1992* | | | | | | | | | | | |
| Bad (< 0) (%) | 55.1 | 34.9 | 53.3 | 63.9 | 53.6 | 33.7 | 45.2 | 74.4 | 57.2 | 43.4 | 52.9 |
| Good (> 0) (%) | 44.9 | 65.1 | 46.7 | 36.1 | 46.4 | 66.3 | 54.8 | 25.6 | 42.8 | 56.6 | 47.1 |
| N | 7,567 | 4,334 | 9,510 | 4,188 | 14,773 | 4,312 | 9,214 | 12,725 | 5,035 | 14,855 | 86,513 |
| *Year = 1993* | | | | | | | | | | | |
| Bad (< 0) (%) | 68.8 | 28.7 | 44.2 | 41.4 | 45.6 | 47.1 | 60.1 | 74.8 | 58.3 | 38.4 | 52.5 |
| Good (> 0) (%) | 31.2 | 71.3 | 55.8 | 58.6 | 54.4 | 52.9 | 39.9 | 25.2 | 41.7 | 61.6 | 47.5 |
| N | 9,633 | 4,429 | 10,621 | 4,579 | 16,871 | 5,691 | 11,447 | 15,575 | 5,870 | 16,809 | 101,525 |
| *Year = 1994* | | | | | | | | | | | |
| Bad (< 0) (%) | 53.1 | 67.3 | 45.9 | 49.3 | 37.9 | 69.2 | 64.2 | 39.7 | 78.6 | 62.4 | 54.0 |
| Good (> 0) (%) | 46.9 | 32.7 | 54.1 | 50.7 | 62.1 | 30.8 | 35.8 | 60.3 | 21.4 | 37.6 | 46.0 |
| N | 9,981 | 4,910 | 10,908 | 4,537 | 17,558 | 6,960 | 12,600 | 15,438 | 6,893 | 17,749 | 107,534 |
| *Year = 1995* | | | | | | | | | | | |
| Bad (< 0) (%) | 50.4 | 80.4 | 61.9 | 64.9 | 62.6 | 49.7 | 70.2 | 34.0 | 80.5 | 53.3 | 58.2 |
| Good (> 0) (%) | 49.6 | 19.6 | 38.1 | 35.1 | 37.4 | 50.3 | 29.8 | 66.0 | 19.5 | 46.7 | 41.8 |
| N | 10,302 | 5,706 | 12,415 | 4,961 | 19,928 | 8,019 | 14,038 | 15,547 | 7,111 | 18,901 | 116,928 |

Table 1.2: Investment Experience and the Propensity to Purchase New Stocks in the Same Industry (Fama-French 10-industry Classification)

This table reports maximum likelihood regression results for probit regressions. The results are reported as marginal effects of independent variables. Each observation corresponds to one household and one industry, regardless whether the household previously owned stocks in the industry or not. The dependent variable is based on a dummy variable coded one when a household purchases stocks not previously owned in the industry. "Experience dummy" is coded one if the household owns stocks in the industry in the past year. Other independent variables are dummy variables related to personal experience, industry average, portfolio size and individual characteristics variables. Both personal experience variables and industry average variables are based on the value of market-adjusted (experienced or industry average) return. "Good experience"("Good industry") is coded one when the market-adjusted experienced (industry average) return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above (below) the 90th percentile (10th percentile) of the sample. "Top 1 industry"("Bottom 1 industry") is coded one when the industry average return is the highest(lowest) among the 10 industries. "Increase of portfolio size" equals to one if the size of household's portfolio increases in the past year. The three individual characteristics variables are created from the beginning-of-month position data. They denote the average monthly number of stocks, the average monthly size and the average monthly turnover rate in the past year. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | | | | |
| Experience Dummy | 0.07982*** | 0.08760*** | 0.09239*** | 0.06858*** | 0.06571*** |
| | (0.00559) | (0.00640) | (0.00810) | (0.00943) | (0.00937) |
| Good Experience (> 0) | 0.01148*** | 0.01069*** | 0.01271*** | 0.01260*** | 0.01856*** |
| | (0.00266) | (0.00246) | (0.00283) | (0.00298) | (0.00312) |
| Top Experience (over the 90th percentile) | 0.01925*** | 0.01879*** | 0.02011*** | 0.01459*** | |
| | (0.00492) | (0.00488) | (0.00472) | (0.00415) | |
| Bottom Experience (below the 10th percentile) | -0.01288*** | -0.01263*** | -0.01468*** | -0.01185*** | |
| | (0.00211) | (0.00204) | (0.00251) | (0.00333) | |
| Good Industry (> 0) | 0.00396 | 0.00575 | 0.00653 | 0.00621 | 0.00618 |
| | (0.00580) | (0.00444) | (0.00525) | (0.00688) | (0.00689) |
| Top 1 Industry | | 0.02282** | 0.02914** | 0.03682** | 0.03703** |
| | | (0.01128) | (0.01276) | (0.01433) | (0.01446) |
| Bottom 1 Industry | | 0.02667** | 0.02845** | 0.03109** | 0.03132** |
| | | (0.01164) | (0.01312) | (0.01490) | (0.01499) |
| Increase of Portfolio Size | | | 0.01833*** | 0.01489*** | 0.01482*** |
| | | | (0.00202) | (0.00168) | (0.00168) |
| Average Num of Stocks > 5 | | | | 0.05680*** | 0.05685*** |
| | | | | (0.00204) | (0.00205) |
| log(Average Portfolio Size) | | | | 0.01528*** | 0.01539*** |
| | | | | (0.00071) | (0.00072) |
| log(Average Turnover Rate) | | | | 0.00832*** | 0.00851*** |
| | | | | (0.00076) | (0.00078) |
| Industry Effect | Yes | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes | Yes |
| Avg Prob (Buying New Stocks in an Industry) | 0.0846 | 0.0846 | 0.0930 | 0.1118 | 0.1118 |
| Observations | 1,550,980 | 1,550,980 | 1,094,860 | 777,630 | 777,630 |

Table 1.3: Robustness Tests

This table reports maximum likelihood regression results for probit regressions. The results are reported as marginal effects of independent variables. Panel A exploits the level of market-adjusted experienced and industry average returns as the experience variable and industry average variables, instead of dummy variables. Panel B only includes the observations with experiences in the industry in the past year. In Panel C, the dependent variable is defined as one if the household purchases stocks not previously owned in the industry and does not have sales in that industry within 30 days before the purchases. Panel D creates investment experiences based on Fama-French 48 industry classification. Without special specification, each observation corresponds to a household/industry/year pair, regardless whether the household previously owned stocks in the industry or not. The dependent variable is based on a dummy variable coded one when a household purchases stocks not previously owned in the industry. "Experience dummy" is coded one if the household owns stocks in the industry in the past year. Other independent variables are dummy variables related to personal experience, industry average, portfolio size and individual characteristics variables. Both personal experience variables and industry average variables are based on the value of market-adjusted (experienced or industry average) return. "Good experience"("Good industry") is coded one when the market-adjusted experienced (industry average) return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above (below) the 90th percentile (10th percentile) of the sample. "Top 1 industry"("Bottom 1 industry") is coded one when the industry average return is the highest(lowest) among the 10 industries. The wealth effect and individual characteristics controls are defined as in Table 1.2. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

**Panel A: Measure Experienced Outcomes by the Level of Market-adjusted Returns**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | | | |
| Expereience Dummy | 0.08553*** | 0.08912*** | 0.09281*** | 0.07058*** |
| | (0.00356) | (0.00453) | (0.00474) | (0.00495) |
| Experienced Excess Return | 0.00119*** | 0.00119*** | 0.00121*** | 0.00124*** |
| | (0.00030) | (0.00029) | (0.00040) | (0.00042) |
| Industry Average Excess Return | 0.02065 | -0.01171 | -0.00949 | -0.00855 |
| | (0.02785) | (0.02553) | (0.02769) | (0.03034) |
| Square of Industry Average Excess Return | | 0.48734*** | 0.50777*** | 0.57314*** |
| | | (0.16751) | (0.18348) | (0.21884) |
| Wealth Effect Control | No | No | Yes | Yes |
| Individual Characteristics Control | No | No | No | Yes |
| Industry Effect | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes |
| Observations | 1,550,980 | 1,550,980 | 1,094,860 | 777,630 |

**Panel B: Only Industry-Year Observations with Past Experience**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | | | |
| Good Experience (> 0) | 0.01385*** | 0.01256*** | 0.01494*** | 0.01412*** |
| | (0.00449) | (0.00437) | (0.00470) | (0.00458) |
| Top Experience (over the 90th percentile) | 0.01125* | 0.01006* | 0.00979* | 0.00375 |
| | (0.00613) | (0.00598) | (0.00578) | (0.00415) |
| Bottom Experience (below the 10th percentile) | -0.01182** | -0.01156** | -0.01486*** | -0.01350*** |
| | (0.00500) | (0.00494) | (0.00425) | (0.00451) |
| Good Industry (> 0) | 0.00437 | 0.00207 | 0.00045 | -0.00068 |
| | (0.01134) | (0.00955) | (0.01019) | (0.01083) |
| Top 1 Industry | | 0.05638*** | 0.07273*** | 0.08898*** |
| | | (0.02056) | (0.02073) | (0.02073) |
| Bottom 1 Industry | | 0.03172 | 0.03165 | 0.03378 |
| | | (0.02477) | (0.02615) | (0.02684) |
| Wealth Effect Control | No | No | Yes | Yes |
| Individual Characteristics Control | No | No | No | Yes |
| Industry Effect | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes |
| Observations | 385,552 | 385,552 | 278,427 | 225,142 |

**Panel C: Robustness Check for Mental Accounting**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks in One Industry without Recent Sales | | | | |
| Experience Dummy | 0.07781*** | 0.08581*** | 0.09048*** | 0.06635*** | 0.06466*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.009) |
| Good Experience (> 0) | 0.00562** | 0.00478* | 0.00669** | 0.00687** | 0.00917*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Top Experience (over the 90th percentile) | 0.00642* | 0.00580 | 0.00536 | 0.00306 | |
| | (0.004) | (0.004) | (0.003) | (0.003) | |
| Bottom Experience (below the 10th percentile) | -0.00683** | -0.00658** | -0.00834*** | -0.00783*** | |
| | (0.003) | (0.003) | (0.003) | (0.003) | |
| Good Industry (> 0) | 0.00405 | 0.00574 | 0.00654 | 0.00625 | 0.00628 |
| | (0.006) | (0.004) | (0.005) | (0.007) | (0.007) |
| Top 1 Industry | | 0.02289** | 0.02922** | 0.03681** | 0.03691** |
| | | (0.011) | (0.013) | (0.014) | (0.014) |
| Bottom 1 Industry | | 0.02660** | 0.02850** | 0.03106** | 0.03118** |
| | | (0.012) | (0.013) | (0.015) | (0.015) |
| Wealth Effect Control | No | No | Yes | Yes | Yes |
| Individual Characteristics Control | No | No | No | Yes | Yes |
| Industry Effect | Yes | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes | Yes |
| Avg Prob (Buying New Stocks in an Industry) | 0.0831 | 0.0831 | 0.0913 | 0.0808 | 0.0808 |
| Observations | 1,550,980 | 1,550,980 | 1,094,860 | 777,630 | 777,630 |

**Panel D: Fama-French 48 Industry Classification**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | | | | |
| Experience Dummy | 0.02205*** | 0.02349*** | 0.02404*** | 0.01583*** | 0.01550*** |
| | (0.00217) | (0.00232) | (0.00297) | (0.00252) | (0.00251) |
| Good Experience (> 0) | 0.00163** | 0.00154** | 0.00190*** | 0.00175** | 0.00276*** |
| | (0.00072) | (0.00061) | (0.00073) | (0.00076) | (0.00077) |
| Top Experience (over the 90th percentile) | 0.00385*** | 0.00370*** | 0.00408*** | 0.00304*** | |
| | (0.00080) | (0.00073) | (0.00078) | (0.00068) | |
| Bottom Experience (below the 10th percentile) | -0.00120** | -0.00121** | -0.00142** | -0.00121 | |
| | (0.00054) | (0.00051) | (0.00062) | (0.00075) | |
| Good Industry (> 0) | 0.00159* | 0.00095 | 0.00143 | 0.00189 | 0.00189 |
| | (0.00096) | (0.00116) | (0.00141) | (0.00160) | (0.00160) |
| Top 5 Industries | | 0.00313** | 0.00341*** | 0.00400*** | 0.00400*** |
| | | (0.00125) | (0.00132) | (0.00147) | (0.00147) |
| Bottom 5 Industries | | 0.00094 | 0.00109 | 0.00115 | 0.00116 |
| | | (0.00181) | (0.00216) | (0.00244) | (0.00244) |
| Wealth Effect Control | No | No | Yes | Yes | Yes |
| Individual Characteristics Control | No | No | No | Yes | Yes |
| Industry Effect | Yes | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes | Yes |
| Avg Prob (Buying New Stocks in an Industry) | 0.0262 | 0.0262 | 0.0216 | 0.0196 | 0.0196 |
| Observations | 6,990,528 | 6,990,528 | 4,961,136 | 3,490,752 | 3,490,752 |

Table 1.4: Variation in Investor Sophistication

This table reports maximum likelihood regression results for probit regressions for subgroup sample. The sample is divided into four groups by self-reported experience(knowledge): Extensive, Good, Limited and None. The results are reported as marginal effects of independent variables. Each observation corresponds to a household/industry/year pair, regardless whether the household previously owned stocks in the industry or not. The dependent variable is based on a dummy variable coded one when a household purchases stocks not previously owned in the industry. "Experience dummy" is coded one if the household owns stocks in the industry in the past year. Other independent variables are dummy variables related to personal experience, industry average, portfolio size and individual characteristics variables. Both personal experience variables and industry average variables are based on the value of market-adjusted (experienced or industry average) return. "Good experience"("Good industry") is coded one when the market-adjusted experienced (industry average) return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above (below) the 90th percentile (10th percentile) of the sample. "Top 1 industry"("Bottom 1 industry") is coded one when the industry average return is the highest(lowest) among the 10 industries. "Increase of Portfolio Size" is 1 denoting the size of household's portfolio increases in the past year. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | | | |
| Sophistication Group: | None | Limited | Good | Extensive |
| Experience Dummy | 0.07743*** | 0.07533*** | 0.08738*** | 0.11594*** |
| | (0.01099) | (0.00491) | (0.00460) | (0.00830) |
| Good Experience (> 0) | 0.01935* | 0.01128** | 0.01249*** | 0.00563 |
| | (0.01113) | (0.00469) | (0.00378) | (0.00721) |
| Top Experience (over the 90th percentile) | -0.01203 | 0.00257 | 0.00867 | 0.00118 |
| | (0.01390) | (0.00664) | (0.00626) | (0.00804) |
| Bottom Experience (below the 10th percentile) | -0.02573** | -0.00688 | -0.00763 | -0.00677 |
| | (0.01307) | (0.00463) | (0.00548) | (0.00952) |
| Good Industry (> 0) | -0.01277 | 0.00522 | 0.00473 | -0.00526 |
| | (0.01210) | (0.00489) | (0.00634) | (0.00859) |
| Top 1 Industry | 0.02227 | 0.03381*** | 0.04296*** | 0.06025** |
| | (0.02009) | (0.01094) | (0.01500) | (0.02479) |
| Bottom 1 Industry | -0.00019 | 0.01045 | 0.02446 | 0.02722 |
| | (0.01730) | (0.01063) | (0.01557) | (0.02082) |
| Increase of Portfolio Size | 0.01895*** | 0.01352*** | 0.02015*** | 0.00978*** |
| | (0.00566) | (0.00310) | (0.00281) | (0.00346) |
| Industry Effect | Yes | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes | Yes |
| Observations | 43,580 | 143,570 | 97,440 | 10,080 |

Table 1.5: Variation in Portfolio Diversification

This table reports maximum likelihood regression results for probit regressions. The results are reported as marginal effects of independent variables. Each observation corresponds to a household/industry/year pair, regardless whether the household previously owned stocks in the industry or not. The dependent variable is based on a dummy variable coded one when a household purchases stocks not previously owned in the industry. "Experience dummy" is coded one if the household owns stocks in the industry in the past year. Other independent variables are dummy variables related to personal experience, industry average, portfolio size and individual characteristics variables. Both personal experience variables and industry average variables are based on the value of market-adjusted (experienced or industry average) return. "Good experience" is coded one when the market-adjusted experienced return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above (below) the 90th percentile (10th percentile) of the sample. The independent variables also include the interaction terms between experience-related variables and portfolio diversification variables. The "Diversified" variable equals one when: either (1) the Herfindahl index is smaller than the median, where the Herfindahl index of the portfolio is defined as $\sum_k w_k^2$, where $w_k$ denotes the portfolio weight allocated in stock $k$ and $\sum_k w_k = 1$; or (2) the number of stocks in the portfolio is greater than 5, which is the median of the number of stocks owned by the households in the sample. The industry average return variables, wealth effect and individual characteristics controls are also included. The definition of these variables are noted in Table 1.2. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) |
|---|---|---|
| Dependent Variable: | Buy New Stocks (not Owned in the Past Year) in One Industry | |
| Diversified Portfolio Measured by: | Herfindahl < Median | Num of Stocks > 5 |
| Experience Dummy | 0.06365*** | 0.06163*** |
| | (0.00972) | (0.00960) |
| Good Experience (> 0) | 0.01392*** | 0.01324*** |
| | (0.00429) | (0.00360) |
| Top Experience (over the 90th percentile) | 0.00240 | 0.00256 |
| | (0.00527) | (0.00387) |
| Bottom Experience (below the 10th percentile) | -0.01052*** | -0.00927*** |
| | (0.00371) | (0.00281) |
| Experience × Diversified | 0.00997*** | 0.01362*** |
| | (0.00226) | (0.00204) |
| Good Experience × Diversified | -0.00756** | -0.00853*** |
| | (0.00306) | (0.00265) |
| Top Experience × Diversified | 0.00229 | 0.00254 |
| | (0.00546) | (0.00412) |
| Bottom Experience × Diversified | 0.00458 | 0.00301 |
| | (0.00522) | (0.00363) |
| Diversified | 0.04277*** | 0.05231*** |
| | (0.00181) | (0.00198) |
| Industry Return Control Variable | Yes | Yes |
| Wealth Effect Control | Yes | Yes |
| Individual Characteristics Control | Yes | Yes |
| Industry Effect | Yes | Yes |
| Year Effect | Yes | Yes |
| Observations | 777,630 | 777,630 |

Table 1.6: The Impact of Personal Investment Experience on Future Purchases in the Experienced Industry vs Other Industries

This table reports maximum likelihood regression results for one probit regression. The results are reported as marginal effects of independent variables. Each observation corresponds to one household and one industry, regardless whether the household previously owned stocks in the industry or not. The dependent variable is based on a dummy variable coded one when a household purchases stocks not previously owned in the industry. Column 1 corresponds to purchase in the experienced industry, while Column 2 and 3 correspond to two other industries one of which is the most similar to the experienced industry while the other one of which is the most different. The most similar and the most different industries are selected by measuring the distance between the stock returns in that industry and those in the experienced industry. The distance is measured by averaging daily absolute difference between the stock returns of two industries. "Experience dummy" is coded one if the household owns stocks in the industry in the past year. Other independent variables are dummy variables related to personal experience, industry average, portfolio size and individual characteristics variables. The personal experience variables variables are based on the value of market-adjusted experienced returns. "Good experience" is coded one when the market-adjusted experienced return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above (below) the 90th percentile (10th percentile) of the sample. The industry average return variables, wealth effect and individual characteristics controls are also included. The definition of these variables are noted in Table 1.2. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable: | Buy New Stocks (Not Owned in the Past Year) in | | |
| | the Same Industry | Most Similar Industry | Most Different Industry |
| Experience Dummy | 0.06571*** | 0.03103*** | 0.01257*** |
| | (0.00937) | (0.00190) | (0.00105) |
| Good Experience (> 0) | 0.01856*** | 0.00249* | 0.00188 |
| | (0.00312) | (0.00129) | (0.00137) |
| Increase of Portfolio Size | 0.01482*** | 0.01535*** | 0.01226*** |
| | (0.00168) | (0.00214) | (0.00254) |
| Average Num of Stocks > 5 | 0.05685*** | 0.06603*** | 0.03713*** |
| | (0.00205) | (0.00280) | (0.00157) |
| log(Average Portfolio Size) | 0.01539*** | 0.01560*** | 0.01166*** |
| | (0.00072) | (0.00108) | (0.00146) |
| log(Average Turnover Rate) | 0.00851*** | 0.00752*** | 0.00721*** |
| | (0.00078) | (0.00157) | (0.00144) |
| Experience Variable Corresponding to the Industry in the Dependent Variable | - | Yes | Yes |
| Industry Average Return Corresponding to the Industry in the Dependent Variable | - | Yes | Yes |
| Industry Effect | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes |
| Observations | 777,630 | 777,630 | 777,630 |

Table 1.7: The Impact of Personal Investment Experience: Variation in Categorization

This table reports maximum likelihood regression results for one probit regression. The results are reported as marginal effects of independent variables. The sample are the observations corresponding to the subindustries within the Manufacture industry (defined as Industry 3 in Fama-French 10 Industry). Each observation corresponds to a household/subindustry/year pair. The subindustry is classified by Fama-French 48 Industry. The dependent variable is based on a dummy variables coded one when the household purchases stocks not previously owned in one subindustry. Column 1 corresponds to the purchase in the experienced subindustry. Column 2 corresponds to a random subindustry (other than the experienced one) in the Manufacture industry. Column 3 corresponds to a random subindustry outside the Manufacture industry. "Experience dummy" is coded one if the household owns stocks in the subindustry in the past year. "Good experience" is coded one when the market-adjusted experienced return is greater than 0. "Increase of Portfolio Size" is 1 denoting the size of household's portfolio increases in the past year. The three individual variables are created from the beginning-of-month position data. They denote average monthly number of stocks, average monthly size and average monthly turnover rate in the past year. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable: | Buy New Stocks (Not Owned in the Past Year) in | | |
| | the Same Subindustry | A Random Subindustry in Manufacture Industry | A Random Subindustry Outside Manufacture Industry |
| Experience Dummy | 0.01256*** | 0.00572*** | 0.00486*** |
| | (0.00094) | (0.00083) | (0.00054) |
| Good Experience (> 0) | 0.00148** | 0.00158* | 0.00010 |
| | (0.00067) | (0.00094) | (0.00075) |
| Increase of Portfolio Size | 0.00263*** | 0.00476*** | 0.00349*** |
| | (0.00022) | (0.00032) | (0.00025) |
| Average Num of Stocks > 5 | 0.00945*** | 0.01513*** | 0.01111*** |
| | (0.00039) | (0.00039) | (0.00035) |
| log(Average Portfolio Size) | 0.00246*** | 0.00365*** | 0.00306*** |
| | (0.00012) | (0.00013) | (0.00011) |
| log(Average Turnover Rate) | 0.00181*** | 0.00189*** | 0.00181*** |
| | (0.00010) | (0.00014) | (0.00010) |
| Experience Variable Corresponding to the Subindustry in the Dependent Variable | - | Yes | Yes |
| Industry Average Return Corresponding to the Subindustry in the Dependent Variable | Yes | Yes | Yes |
| Industry Effect | Yes | Yes | Yes |
| Year Effect | Yes | Yes | Yes |
| Observations | 1,309,032 | 1,309,032 | 1,309,032 |

Table 1.8: The Impact of Personal Investment Outcomes on Subsequent Trade Frequencies in an Industry

This table reports the results of Tobit regression of the number of trades in a industry during the subsequent year on the investor's investment outcomes in that industry. Each observation corresponds to a household/industry/year pair. The observation is only included if the household previously owned stocks in that industry. The dependent variable is the number of trades the investors execute in one industry, including both buys and sells. The personal experience outcome variables are based on the value of market-adjusted experienced return. "Good experience" is coded one when the market-adjusted experienced return is greater than 0. "Top experience"("Bottom experience") is coded one when the market-adjusted experienced return is above(below) the 90th percentile (10th percentile) of the sample. The control variables include industry average variables, portfolio size, and individual characteristics variables. The definitions of these variables are noted in Table 1.2. Standard errors, shown in parentheses, are clustered by industry-year level. *10%, **5%, ***1% significance.

| | (1) | (2) |
|---|---|---|
| Dependent Variable: | Number of Trades in the Same Industry in the Subsequent Year | |
| Good Experience (> 0) | 0.62076*** | 0.45660*** |
| | (0.09937) | (0.08877) |
| Extremely Good Experience (over the 90th percentile) | 1.86391*** | 1.25045*** |
| | (0.21580) | (0.13850) |
| Extremely Bad Experience (below the 10th percentile) | -0.05677 | 0.10375 |
| | (0.09374) | (0.13370) |
| Good Industry (> 0) | -0.08504 | -0.08349 |
| | (0.19169) | (0.18384) |
| Best Industry | 1.03377*** | 1.44166*** |
| | (0.37715) | (0.30588) |
| Worst Industry | 0.64351 | 0.59849 |
| | (0.42882) | (0.38981) |
| Wealth Effect Control | No | Yes |
| Individual Characteristics Control | No | Yes |
| Industry Effect | Yes | Yes |
| Year Effect | Yes | Yes |
| Observations | 385,552 | 225,142 |

# Chapter 2

# Thinking Outside the Borders (1): Market Underreaction to Foreign Information

## 2.1 Introduction

Firms are increasingly operating globally in order to take advantage of opportunities for global diversification of their operations, as well as access to lower cost of capital. Does this tendency have any effect on the market efficiency of stock prices? If investors collect information about foreign operations less promptly, due to, e.g., limited attention or processing capacity, they may not adequately adjusts their portfolio to such information. Because both gradual information diffusion (Hong and Stein (2007)) and slow-moving capital (Duffie (2010)) may impede information incorporation into stock prices, especially given potential barriers and the high transaction costs of trading international assets, the market may not be efficient enough to rapidly reflect the foreign operations information of multinational firms.

I hypothesize that, if foreign operations information is diffused gradually as a result of investors' inattention and limited processing capacity, or due to slow-moving capital, this information will be only slowly incorporated into stock prices. In other words, a proxy measuring current operations abroad of a multinational firm should have predictive power for future stock returns.

A growing literature finds that this phenomenon is prevalent for various other information types, for instance, distant forecastable demand changes related to demographics (DellaVigna and Pollet (2007)); the economic link between customers and suppliers (Cohen and Frazzini (2008)); complicated industry information for conglomerates (Cohen and Lou (2011)); and predictable innovation ability (Cohen, Diether, and Malloy (2011), Hirshleifer, Hsu, and Li (2012)).

The specific context considered here, the slow incorporation of foreign operations information, is important in the following ways. First, the evidence of return predictability by foreign information has asset-pricing implications from an international perspective. Because multinational firms account for a nonnegligible portion of the U.S. economy,[1] U.S. multinational firms can serve as channels connecting the U.S. market and the global market. I find that a trading strategy using a proxy based on foreign industry return creates a roughly 0.8 percentage point monthly abnormal return. Through the channel of multinational firms, the predictability by foreign industry return may also apply to other firms in the industry, which further leads to potential industry momentum across country borders. The variation in the incorporation speed of information from different countries may imply the dynamic feature of the momentum. Hence, this study potentially contributes to understanding the global market within a unified framework. Furthermore, even though investors may choose to hold a home-biased portfolio because of the lack of information advan-

[1] As Denis, Denis, and Yost (2002) document, global diversification is increasing in the U.S.; in 1997, the fraction of multinational firms reaches 45%.

tage, the shareholders of multinational firms may by default hold an underdiversified pseudo-international portfolio. Hence, this context provides a setting to test how language, culture and geographic factors influence investors' information acquisition. In addition, I also test several other hypotheses about the underlying mechanism of the incorporation of foreign operations information. The next chapter will analyze the underlying mechanism in detail. To better understand the underlying mechanism could help facilitate information processing and reduce market inefficiency. A more efficient market for multinational firms will play a better role in monitoring managers' decisions, especially on global diversification, and in providing a fair price for firms to obtain financing.

In the empirical analysis, I proxy for foreign operations information using a sales-weighted sum of industry returns in the relevant foreign countries. For example, if a U.S. automobile firm has 30% sales from U.S. operations, 20% sales from the German market, and 50% from the Canadian market, I compute its foreign information proxy as 20%×Automobile industry return in Germany + 50%×Automobile industry return in Canada. I show that the proxy actually contains information about firms' future real activities by showing that it predicts firms' future sales. Therefore, if investors have limited attention to firms' foreign operations information which is hence slowly incorporated into the stock prices, the aforementioned foreign information proxy should have predictive power for firms' stock returns.

I begin by testing the predictive power of the foreign information proxy by forming a trading strategy. At the beginning of each month, I sort on the computed foreign information proxies of multinational firms in the previous month and divide the sample into five quintile groups. The strategy is to form a zero-cost portfolio by going long the quintile group with the highest foreign information proxies and short the quintile group with the lowest foreign information proxies. After controlling for Carhart (1997) four risk factors, I obtain 0.80 ($t$ = 3.13) percentage point abnormal return from an equal-weighted Long/Short portfolio. The abnormal return is 0.76 ($t$ = 2.39) percentage point if I form a value-weighted portfolio.

I also implement regressions as an alternative approach to control for other explanations. I consider, among others, U.S. industry momentum, global industry momentum and foreign country-specific industry momentum. Moskowitz and Grinblatt (1999b) show the existence of industry momentum in the U.S. stock market. Given the comovement among international stock markets, the foreign information proxy, which is a weighted sum of international industry returns, may be correlated with the U.S. industry return; therefore, the proxy may predict stock returns as a result of the autocoreelation of U.S. industry returns. Similarly, if industry momentum also exists in foreign countries, it could also lead to the predictive power of the foreign information proxy. Or, as shown in Appendix A, because international business is interdependent, there may exist a momentum effect in the global industry component, which could be a source of return predictability by the foreign information proxy as well. Therefore, in the regression, I exploit various approaches to address these issues. These include controlling for, among others, past U.S. industry and global industry returns; controlling for contemporaneous U.S. industry and foreign industry returns; and subtracting contemporaneous U.S. and foreign industry returns from stock returns in the dependent variable. For all these specifications, the predictive power of the foreign information proxy remains significant.

In addition, this paper differentiates the predictive power of the foreign information proxy from that of an analogously computed domestic information proxy. It achieves this by showing that, while the predictive power of the foreign information proxy survives, the predictive power of the domestic information proxy vanishes after controlling for global industry momentum.

While the predictive power of the foreign information proxy is consistent with the view that foreign operations information is incorporated into stock prices with delay, it is possible that the phenomenon is driven by overreaction of the stock market to previous information.[2] Looking at the cumulative average return over a long horizon up to 36 months after formation, I find that the return of a Long/Short portfolio based on sorting the previous month's foreign information proxy does not show a reversal in the long term, which provides more support for the slow incorporation of foreign operation information. In contrast, I show that the return of a strategy based on sorting the previous month's domestic information proxy does reverse eventually.

This paper contributes to the literature on information diffusion in the stock market due to investors' limited attention[3] and limited information processing capacity[4]. The findings suggest that investors react slowly to multinational firms' foreign operations information, especially when the information comes from a segment distant from the U.S. in the sense of language, culture or geography. This evidence sheds light on gradual diffusion of information across geographic segments, which differs from any previous evidence about information diffusion across firms (Cohen and Frazzini (2008); Cohen and Lou (2011); Hou (2007)) or across time horizons (DellaVigna and Pollet (2007)). The evidence in my paper that investors neglect the foreign operations information of multinational firms is related to the evidence on the stock markets underreaction to news about trading partners in Rizova (2010). Rizova (2010) shows that the stock market return of a country can be predicted by

[2]Investors' overreaction to news content in the media is documented by Da, Engelberg, and Gao (2011), Dougal, Engelberg, Garcia, and Parsons (2011), Tetlock (2007), and Tetlock (2011).

[3]Barber and Odean (2008), Cohen and Frazzini (2008), DellaVigna and Pollet (2009), Hirshleifer and Teoh (2003), Hirshleifer, Lim, and Teoh (2009), and Hong, Lim, and Stein (2000).

[4]Cohen et al. (2011), Cohen and Lou (2011), and DellaVigna and Pollet (2007).

the stock market return of that countrys major partners. In contrast, I focus on how the stock market returns of individual US companies are affected by the industry average return in the foreign countries where they operate. A related contemporaneous paper by Nguyen (2011) also investigates investors' limited attention to firms' geographic information, and finds evidence of return predictability. Compared to that paper, I use a longer sample (1990-2010 compared to 1998-2010 in Nguyen (2011)) and a more detailed measure of performance in foreign countries (country-industry returns compared to country-level returns in Nguyen (2011)). Interestingly, I find that country-level information has no predictive power without splitting up by industry. At the same time, including country-level returns does not diminish the significant effect of the foreign information proxy (constructed by industry average returns in foreign countries): investors underreact to industry-country-specific information in foreign countries even after controlling for aggregate country-level news.[5] I also present additional evidence on how earnings announcements and geographic segments (distance in terms of language, culture or geography) influence the speed of information incorporation.

My paper also relates to the literature on the economic significance of geography and its influence on information acquisition. Bae, Stulz, and Tan (2008) find there is a local advantage for financial analysts: analysts resident in a country make more precise earnings forecasts for firms in that country than do non-resident analysts. Coval and Moskowitz (1999) suggest that asymmetric information between local and nonlocal investors may drive the preference for geographically proximate investments. In this paper, the shareholders of multinational firms by default hold a pseudo-international portfolio. Under such a relatively exogenous setting, I test how the market reacts to information from different segments of the world, and find that the market is less efficient at reflecting information that is more distant.

The remainder of this chapter is organized as follows. Section 2.2 describes the data, methods and summary statistics. Section 2.3 provides the evidence of return predictability by the foreign information proxy through employing both a portfolio test and regression test. Besides controlling for other alternative explanations, I also compare the predictive power between foreign information proxy and domestic information proxy. Section 2.4 summarizes this chapter. I will continue to explore a variety of underlying mechanisms in the next chapter.

[5] Nguyen (2011) finds, instead, the return predictability by the sales-weighted average of country average returns. When I set my sample to start from 1998, country-level information is marginally predictive. Other factors may lead to the different results as well, for example, different sample coverage. The sample in Nguyen (2011) also includes U.S. firms which only operate in the domestic market.

## 2.2 Data and Methods

### 2.2.1 Data

The main data used to construct the global segment information proxy is financial data for multinational firms' operations in each country and the stock market return for the respective industry in the operating countries. I obtain firms' geographic segment financial information from Compustat Segment files. FASB (Financial Accounting Standards Board) 14 and FASB 131 require public business enterprises to report financial information and descriptive information about their operating segments. These also establish standards for related disclosures about, among others, geographic areas. Compustat collects and reports this information in its Geographic Segment File. The accounting data that is available by segment includes sales, operating profits, capital expenditures, etc. I use segment sales as weight to compute the global segment information proxy. The sample covers the period of 1990 to 2010.[6]

Global industry monthly returns are computed from Datastream Global Equity Sector Indices. Datastream classifies industries according to Industrial Classification Benchmark (ICB). I obtain indices on ICB Supersector Level/Datastream Level 3, which includes 20 industries.[7] I remove utility and financial firms (i.e. firms in Utilities, Banks, Insurance, Financial Services, and Equity/Non-Equity Investment Instruments). All the indices are converted into dollars. Because the segment data in Compustat employs a different framework (Global Industry Classification Standard, GICS) to define industries, I exploit the concordance table between ICB categories and GICS categories constructed by Bekaert, Harvey, Lundblad, and Siegel (2011) to combine these two datasets.

The data on monthly stock information, such as end-of-month closing price and shares outstanding, comes from the CRSP monthly stock file. To mitigate the influence of penny stocks, I follow other studies to remove those stocks with a price below five dollars a share at the beginning of each holding period. The sample requires firms

[6]As documented by Denis et al. (2002), before 1997, Compustat limited the number of global geographic segments to four. But after FASB 131, Compustat started collecting the geographic information as reported by the company in the required report, which means there is no limit to the number of geographic segments collected since 1997. Some companies have more than 10 geographic segments collected for a given year after 1997. Given the tradeoff between sample size and preciseness of segment data, I choose our sample of period 1990-2010. I replicated our analysis below using only data after 1997 and found qualitatively similar results.

[7]ICB Supersector Level classifies industries as the following: Oil & Gas, Chemicals, Basic Resources, Construction & Materials, Industrial Goods & Services, Automobiles & Parts, Food & Beverage, Personal & Household Goods, Health Care, Retail, Media, Travel & Leisure, Telecommnications, Utilities, Banks, Insurance, Real Estate, Financial Services, Equity/Non-Equity Investment Instruments, Technology.

to have both non-missing stock returns and non-missing segment information. I also obtain a variety of accounting variables from Compustat, such as market equity and book equity.

To examine the mechanism of gradual diffusion of foreign operation information, I also combine the sample with analyst coverage, institutional ownership, news coverage, etc. The data on analyst coverage comes from the Institutional Brokers Estimates System (IBES) Database; the data on institutional ownership is obtained from Thomson-Reuters Institutional Holdings (13F) Database; and the data on news coverage is based on the news count of the articles on the New York Times.

### 2.2.2 Global Segment Information Proxy

To test whether foreign operations information is slowly incorporated into stock prices, I need to first have a measure to proxy foreign operations information. A variety of shocks could affect foreign operations, for example, demand shock, macroeconomic shock, policy shock, etc., but it is hard to find measures of high frequency for each of these shocks. However, because stock market is a system to aggregate information, if I assume local shocks are relatively promptly incorporated into the market, then I can use corresponding foreign market stock returns to proxy U.S. firms' foreign business/operations.

More specifically, I create a foreign information proxy for each multinational firm as a sales-weighted sum of corresponding industry returns in operating foreign countries:

$$InfoProxy_{i,j,t-1}(Foreign) = \sum_{c \neq U.S.} f^c_{i,t-1} R^c_{j,t-1} \tag{2.1}$$

where $InfoProxy_{i,j,t-1}(Foreign)$ denotes the foreign information proxy for firm $i$ in industry $j$ during period $t-1$, $f^c_{i,t-1}$ denotes the fraction of sales from foreign country $c$,[8] and $R^c_{j,t-1}$ denotes industry $j$'s return in country $c$ during period $t-1$. For example, a U.S. automobile firm UCG has 30% sales from U.S. operations, 20% sales from the German market, and 50% from the Canadian market. Hence, I compute UCG's Foreign Information Proxy as:

$$InfoProxy_{\ UCG,Auto,t-1}(Foreign) = 20\% \times R^{Canada}_{Auto,t-1} + 50\% \times R^{Germany}_{Auto,t-1} \tag{2.2}$$

The fraction of sales from foreign operations is obtained from the Compustat Segment. If a firm reports multiple countries together, I assign equal weights among these countries. To make sure the sales fraction can be publicly accessible by investors as of the time they form the portfolio according to the past foreign information proxy,

[8] $\sum_c f^c_{i,t-1} = 1$

I impose at least a 6-month gap between fiscal year end and formation time,[9] which means that the sales fraction from a fiscal year $y-1$ is used for the information proxy from June of year $y$ to May of year $y+1$. This in turn is used to predict returns from July of year $y$ to June of year $y+1$. I exclude firm-year observations with a total foreign sales fraction less than 10%, because the variation in the influences of foreign operations on these firms is only modest due to the small fraction of foreign sales.[10]

Similarly, I compute the information proxy for another geographic segment definition, which will be used to compare information incorporation speed across different geographic segments. The information proxy for segment $\Omega$ is:

$$InfoProxy_{i,j,t-1}(\Omega) = \sum_{c\in\Omega} f^c_{i,t-1} R^c_{j,t-1} \tag{2.3}$$

For example, if I want to proxy UCG's domestic information or to summarize the information about UCG's operations only in English-speaking foreign countries (i.e. $\Omega_{Eng} = \{Canada, U.K.\}$), I compute these proxies as:

$$InfoProxy\ _{UCG,Auto,t-1}(\Omega_{U.S.}) = 30\% \times R^{U.S.}_{Auto,t-1} \tag{2.4}$$

$$InfoProxy\ _{UCG,Auto,t-1}(\Omega_{Eng}) = 20\% \times R^{Canada}_{Auto,t-1} \tag{2.5}$$

### 2.2.3 Summary Statistics

Table 2.1 shows the summary statistics of all firm-month observations. As reported in Panel A, there are on average 1287 multinational firms for one month in the sample, which may go as low as 895 firms and as high as 1929 firms. The sample covers about 16% of the CRSP universe in terms of total number of firms and around 32% of the CRSP universe if I consider market capitalization. The U.S. multinational firms in the sample have on average 44.27% sales from foreign operations. If I take this average foreign sale fraction and multiply it by the average monthly industry return of 1.37%, I get roughly the mean of foreign information proxy in the table.

[ Insert Table 2.1 ]

To understand the composition of foreign operations by countries/geographic segments, I plot the across-firms average fraction of foreign sales by countries from $1990-2009$ in Figure 2.1. Through the whole sample period, Canada and the U.K. are always among the top countries where U.S. firms have operations, although the

[9] Other papers in the literature also impose such a 6-month lag, including Cohen and Frazzini (2008), Cohen and Lou (2011), and Cohen et al. (2011)

[10] I also experimented with keeping all the sample or using other cutoffs, and the results do not change.

fraction of sales from these two countries drops gradually. The foreign sales fractions from two Asian countries, Japan and China, have climbed since the late 1990s, and China has been the country with the highest average sales fractions since 2006. There are also some European countries, such as Germany and France, where U.S. firms maintain a fair amount of operations. Among these main foreign countries where U.S. firms operate, I classify them into three segments according to language and geographic factors: (1) an English-speaking segment that includes Canada and the U.K.; (2) an European segment that includes Germany and France; (3) an Asian segment that includes Japan and China. I will explore the different speed at which information about these segments is incorporated into stock prices.

[ Insert Figure 2.1 ]

## 2.3 Return Predictability

The hypothesis that foreign operations information is slowly incorporated into stock prices predicts that the foreign information proxy can predict future stock returns. In this section, I implement two approaches to examine the predictive power of the foreign information proxy that measures the information about foreign operations of a multinational firm.

### 2.3.1 Portfolio Test

I begin by creating a trading strategy to test the predictive power of the foreign information proxy, which is a sales-weighted sum of industry returns in corresponding foreign countries, as described in Section 2.2. At the beginning of each month, I sort the stocks of multinational firms on their computed foreign information proxies in the previous month and divide the sample into five quintile groups.[11] The strategy is to form a zero-cost portfolio by going long the quintile group with the highest foreign information proxies and short the quintile group with the lowest foreign information proxies. The portfolio is rebalanced every month. To rule out the possibility that the predictability could be explained by well-known risk factors, I run time-series regressions of the excess returns of formed portfolio on market excess return, the Fama-French three factors (Fama and French (1993)) and the Carhart four factors (Carhart (1997)).[12] Table 2.2 reports the alphas (intercepts) of the five quintile

[11] As the foreign information proxy only accounts for the operations abroad, the weights may not add up to 1. Actually, the sum of the weights affects the variation of the proxy. The larger the total fraction of foreign operation sales (i.e. the sum of the weights), the more likely the stock will be sorted in the top and bottom quintile. As Figure 2.2(c) shows, the average fraction of foreign operations is slightly higher for the top and bottom quintiles relative to the middle three quintiles.

[12] The data on risk factors is obtained from Ken French's website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`)

portfolios and the Long/Short portfolio. The results for both equal-weighted and value-weighted portfolios are reported.

[ Insert Table 2.2 ]

As shown in Table 2.2 and also in Figure 2.2(a), the abnormal return in the following month increases monotonically as the foreign information proxy goes up, indicating the return predictability by foreign information proxy. The results also highlight the robustness of return predictability; the Long/Short portfolio earns a significantly positive abnormal return adjusted for various combinations of risk factors.[13] Specifically, after controlling for Carhart (1997) four risk factors, I obtain 0.80 ($t = 3.13$) percentage point monthly abnormal return from an equal-weighted Long/Short portfolio. The abnormal return is 0.76 ($t = 2.39$) percentage point monthly if I form a value-weighted one. Generally speaking, the value-weighted Long/Short portfolio produces a slightly lower profit relative to the equal-weighted portfolio, which suggests that size may play a role in information incorporation. Because large firms may have higher market making power, and because investors may allocate more efforts to acquire information about large firms given that they can trade larger positions, the predictability should be less significant for larger firms. This hypothesis will be further tested in Chapter 3.

[ Insert Figure 2.2 ]

I also report the factor loadings using the Carhart (1997) four factor model in Table 2.3. The five quintile portfolios have positive loadings around 1 on market excess return, indicating that the portfolios are well-diversified. The equal-weighted portfolios load on size factor (SML) around 0.5, which indicates that the sample on average features medium firms. The load on size factor is smaller for value-weighted portfolios because they weigh more on large-capitalization stocks. More importantly, the Long/Short strategy is neutral with respect to any of the four risk factors, as none of the loadings on these four factors for the Long/Short strategy is statistically significant.

[ Insert Table 2.3 ]

Figure 2.3 provides additional perspective on the profits of the Long/Short portfolio sorting on the foreign information proxy by presenting yearly raw returns. The yearly return is computed as if the investor, at the beginning of the first month of each year, provides $1 going long the top quintile and uses it as collateral to short the bottom quintile, and rolls the portfolio monthly by using the funds collected from last month as the portfolio size. This Long/Short strategy earns 13.04% on

[13] Usually, if the sample covers all the stocks in the market universe, the abnormal returns of quantile portfolios using a market model should add up to approximately zero. The abnormal returns of five quintile portfolios using a market model do not add up to zero, because this sample covers only multinational firms.

average through the sample periods. Among the sample periods from 1990 to 2010, the return is above 15% in 8 out of 21 years. The returns in 1999 and 2000 are even more than 45%.

[ Insert Figure 2.3 ]

### 2.3.2 Fama-MacBeth Regression

The above results provide evidence of return predictability and supports the hypothesis that stock prices react sluggishly to foreign operations information. However, this return predictability is also consistent with other explanations, such as (1) U.S. industry momentum; (2) global industry momentum; (3) foreign country specific industry momentum; etc. Therefore, I will implement Fama-MacBeth regressions to control and address these issues. For each month, I estimate a separate cross-sectional regression specification as follows:

$$Ret_{ijt} = \alpha + \beta_1 ForInfo_{ij,t-1} + \beta_2 DomInfo_{ij,t-1} + X'_{ij,t-1}\gamma + \epsilon_{ijt} \tag{2.6}$$

where $ForInfo_{ij,t-1}$ denotes the foreign information proxy in month $t-1$ for firm $i$ in industry $j$, $DomInfo_{ij,t-1}$ denotes its domestic information proxy in month $t-1$,[14] and $X'_{ij,t-1}$ are control variables. The hypothesis that foreign operation information is incorporated slowly into stock price predicts that the foreign information proxy has predictive power, i.e. the coefficient $\beta_1$ is positive. I also include the domestic information proxy in the regression, because I want to compare the market reactions to these two types of information. I then compute the time-series average of the estimated coefficients. Because the regression is estimated separately for each period, this approach addresses time effects. The standard errors are computed with a Newey-West correction with 12 lags.

For robustness, I also use the quintile rank of the information proxy to account for the potential nonlinearity between returns and the lagged foreign information proxy. Figure 2.2(b) plots the return of a quintile portfolio against the average foreign information proxy of the corresponding portfolio. As the figure shows, the return becomes highly nonlinear as the foreign information proxy increases above zero. In contrast, the relationship between returns and quintile ranks is relatively closer to a linear specification. Therefore, I conduct the regression using the following specification as well:[15]

$$Ret_{ijt} = \alpha + \beta_1 QFI_{ij,t-1} + \beta_2 QDI_{ij,t-1} + X'_{ij,t-1}\gamma + \epsilon_{ijt} \tag{2.7}$$

[14] Domestic information proxy is computed as the product of U.S. industry return and fraction of sales from U.S. operations

[15] This specification using quantile ranks is also employed in other research, such as DellaVigna and Pollet (2009), and Hirshleifer et al. (2009).

where $QFI_{ij,t-1}$ denotes the quintile group of the foreign information proxy in month $t-1$ for firm $i$ in industry $j$, and $QDI_{ij,t-1}$ denotes the quintile group of domestic information proxy in month $t-1$. The quintile group equals 1 for the group with the lowest proxy and equals 5 for the group with the highest proxy. Regression results using levels are reported in Panel A of Table 2.4 while results using quintile groups are shown in Panel B.

The basic set of control variables includes: (1) the predetermined firm characteristics, size ($lnMktVal_{ij,t-1}$) and log of book-to-market ratio ($lnB/M_{ij,t-1}$) controlling for the size (Banz (1981)) and value effect (Fama and French (1992));[16] (2) the previous month stock return ($Ret_{ij,t-1}$) for short-term reversal due to the microstructure effect (Jegadeesh (1990)); and (3) the lagged cumulative return from $t-12$ to $t-2$ ($Ret_{ij,(t-12,t-2)}$) for the stock-level momentum effect (Jegadeesh and Titman (1993)). More importantly, I also control for some alternative explanations which can potentially lead to the correlation between the foreign information proxy and the stock return in the following month. I will elaborate them one by one.

### 2.3.2.A U.S. and Global Industry Momentum

I include the previous month U.S. industry return ($USIndRet_{j,t-1}$) and the previous month global excluding U.S. industry return ($WUIndRet_{j,t-1}$) to control for the U.S. industry momentum and the global industry momentum respectively.[17] As Moskowitz and Grinblatt (1999b) show, industry portfolios exhibit significant momentum in the U.S. market, and the momentum is strongest at the one-month horizon. Given the comovement of the international stock market, the foreign information proxy may be correlated with the U.S. industry return. Through its correlation to the U.S. industry return and the existence of U.S. industry momentum, the foreign information proxy may be correlated with the future stock return. In addition, because the international business is interdependent, momentum effect may exist in the global industry component as well (shown in Appendix A). Because the foreign information proxy is created as the weighted sum of industry returns of multiple

[16] Following Hou (2007), I match book equity for fiscal year ending in year $y-1$ with stock returns from July of year $y$ to June of year $y+1$. The book-to-market ratio is computed as book equity divided by market capitalization at the end of December of year $y-1$. The market capitalization is measured at the end of June of year $y$.

[17] The global excluding U.S. industry return ($WUIndRet$) is computed based on the Global excluding U.S. industry index from Datastream. The constituent countries contain Argentina, Australia, Austria, Bahrain, Belgium, Brazil, Canada, Chile, China, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Kuwait, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Oman, Pakistan, Philippines, Poland, Portugal, Qatar, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UAE, United Kingdom, Vietnam.

countries, it may be correlated with the global industry return and hence predict returns of multinational firms given the global industry momentum.

Table 2.4 presents the regression results. Column (1) only includes the basic set of controls, while Column (2) adds the lagged U.S. industry return and global excluding U.S. industry return. From both Panel (A) and Panel (B), I find that the coefficient on the lagged foreign information proxy is positive and statistically significant at the 1% level, which is consistent with the hypothesis. Specifically, after controlling for size, value, short-term reversal, stock level momentum, U.S. and global industry momentum, the coefficient on $ForInfo_{t-1}$ in Column (2) of Panel A is 0.065 with a t-statistics of 3.57, indicating that a one-standard-deviation increase in the lagged foreign information proxy creates 29.3 basis point increase in the current return of the multinational firm. Column (2) of Panel B shows that the coefficient on $QFI_{ij,t-1}$ is 0.2 with a t-statistics of 3.91. This magnitude indicates that the difference between the highest quintile group ($QFI = 5$) and the lowest quintile group ($QFI = 1$) is roughly 0.8, which is in accordance with the results of the portfolio test shown in Table 2.2.

Furthermore, the U.S. and global industry momentum indeed play some role in the return predictability, because the coefficient on the lagged U.S. and global excluding U.S. industry returns are both significantly positive, and the magnitude of the coefficient on the foreign information proxy decreases to some extent in Column (2). In contrast, the coefficient on the domestic information proxy becomes insignificant after controlling for the U.S. and global industry momentum.

#### 2.3.2.B Country Information vs Country Industry Specific Information

I further pin down the source of the predictive power of the foreign information proxy. The foreign information proxy is based on industry average returns in foreign countries, which could be decomposed into two components: country-level component and country-industry-specific component. Therefore, the predictive power of the foreign information proxy could be due either to underreaction to country-level information or to slow incorporation of country-industry-specific information or both. If the effect of the foreign information proxy is mainly driven by country-level information, and if country-industry-specific information does not add more predictive power, the effect of country-level returns should be significant and the effect of the foreign information proxy should become weaker or even insignificant after controlling for country-level information.

Hence, I construct an alternative information proxy by country average returns. Define $ForInfo_{ijt}^{Country}$ as a sales-weighted sum of country average returns in foreign countries with operations. As Column (3) shows, the coefficient on $ForInfo_{ij,t-1}^{Country}$ is not significant, meaning the proxies constructed by country average returns do not predict stock returns.[18] More importantly, controlling for the country-level proxy (Columns (3)-(8)), the original foreign information proxy (constructed by country industry average returns) remains statistically significant. This suggests that investors may be able to react quickly to country-level information from abroad, but it is more difficult for the stock market to immediately incorporate industry-level information in foreign countries. Therefore, compared to the alternative proxy (constructed by country average returns), the original one (constructed by country industry average returns) could be considered as a better proxy, measuring more specific information about foreign operations and creating a more pronounced return effect.

### 2.3.2.C Foreign Country Specific Industry Momentum

Next I will consider a more subtle alternative interpretation, foreign country specific industry momentum. Even though the multinational firms in the sample are based on the U.S., we can consider them as combined entities of separated parts from multiple countries. If there exists industry momentum in each individual foreign country as in the U.S. (autocorrelation of country-specific industry returns), we would expect to find the predictive power of the foreign information proxy as well.

To address this alternative explanation, I first subtract the contemporaneous foreign industry information ($ForIndRet_{ijt}$) from stock returns ($Ret_{ijt}$) in the dependent variable. $ForIndRet_{ijt}$ is constructed as the weighted average of industry average returns across all operating foreign countries, which is essentially to normalize $ForInfo_{ijt}$ by the total sales fractions from foreign operations, i.e.

$$ForIndRet_{ijt} = \sum_{c \neq US} \frac{f^c_{ijt}}{\sum_{c \neq US} f^c_{ijt}} R^c_{jt} = \frac{ForInfo_{ijt}}{\sum_{c \neq US} f^c_{ijt}} \tag{2.8}$$

This adjusted stock return ($Ret_{ijt} - ForIndRet_{ijt}$) picks out the component which is not relevant to the autocorrelation of foreign industry returns. The coefficients on $ForInfo_{ij,t-1}$ in Columns (5) and (6) in both Panel A and Panel B of Table 2.4 remain positive and statistically significant. It indicates that the lagged foreign information proxy can predict future multinational firm returns over and beyond the autocorrelation of foreign industry returns. Similarly, I could adjust for both U.S. and foreign country specific industry momentum at the same time by using $Ret_{ijt} - GlobalInfo_{ijt}$ as the dependent variable, where $GlobalInfo_{ijt}$ is the sum of

[18] A related paper by Nguyen (2011) using a sample from 1998 to 2010 and MSCI country index finds, instead, the return predictability by the sales-weighted average of country average returns ($GlobalInfo^{Country}_{ij,t-1}$). The difference may be attributed to a combination of factors, such as different sample period, or different sample coverage. The sample in Nguyen (2011) also includes the U.S. firms which only operate in the domestic market.

$ForInfo_{ijt}$ and $DomInfo_{ijt}$ and measures the contemporaneous relevant global industry information. Columns (7) and (8) show that the predictive power of $ForInfo_{ij,t-1}$ remains. Also note that, when using the adjusted return as the dependent variable, the coefficients on $USIndRet_{j,t-1}$ and $WUIndRet_{j,t-1}$ become insignificant, because the predictive power of these variables may mainly depend on the autocorrelations between average industry returns.

An alternative method is to directly control for the contemporaneous information on the right hand side, as shown in Column (4). I include domestic information and foreign information separately to allow for different response ratios. Consistent with the hypothesis and with my other results, the coefficient on $ForInfo_{ij,t-1}$ is still significantly positive. In addition, controlling for current information can also help reduce estimation errors of the coefficient on $ForInfo_{ij,t-1}$.[19] Therefore, I also include controls for current information in the following analysis in this paper.

[ Insert Table 2.4 ]

### 2.3.3 Long-horizon Return Pattern

While the predictive power of the foreign information proxy is consistent with the view that there is delay in incorporating foreign operations information into stock prices, it is possible that the result is driven by overreaction of the stock market to previous information. To further separate these two stories, I investigate the long-term reaction of stock prices after information comes out. An underreaction story predicts that stock return does not reverse in the long term, while an overreaction story predicts the opposite. For example, Da et al. (2011) find that a higher Search Volume Index measuring the search frequency in Google predicts higher stock prices in the next two weeks but that prices eventually reverse within the year.[20]

I plot the average holding period return of a Long/Short portfolio over a long horizon in Figure 2.4. At the beginning of month $t$, I form the Long/Short portfolio based on sorting stocks' foreign information proxies in month $t-1$ and then compute

[19] Conceptually, let us think of a case when there are only two periods($t = 1, 2$). A dividend $w_f F_1 + (1 - w_f)D_1 + \varepsilon_2$ will be paid out at $t = 2$, where $F_1$, $D_1$, $\varepsilon_2$ are independent and all have expectation zero. $\varepsilon_2$ will be revealed at $t = 2$, which also can decomposed into foreign and domestic components, i.e. $\varepsilon_2 = w_f \varepsilon_2^f + (1 - w_f)\varepsilon_2^d$. At $t = 1$, investors receive signals about $F_1$ (foreign component) and $D_1$ (domestic component). However, suppose only $\theta_f$ of investors pay attention to signals of $F_1$, and only $\theta_d$ of investors pay attention to signals of $D_1$; then the price at $t = 1$ is $P_1 = \theta_f w_f F_1 + \theta_d(1 - w_f)D_1$. The price at $t = 2$ will be equal to the dividend, i.e. $P_2 = w_f F_1 + (1 - w_f)D_1 + \varepsilon_2$. Following that, the dollar return at $t = 2$ is $(1 - \theta_f)w_f F_1 + (1 - \theta_d)(1 - w_f)D_1 + \varepsilon_2$. The goal is to proxy for $w_f F_1$ and identify $\theta_f$. The current innovation $\varepsilon_2$ adds errors on the estimation which could be reduced by controlling for the current innovation.

[20] Similar return reversals can be found in Dougal et al. (2011), Tetlock (2007), and Tetlock (2011).

the returns of this portfolio for different holding periods. Let $R^{L/S}_{t,t-1+k}(k = 1, ..., 38)$ denote the return of a Long/Short portfolio formed at the beginning of month $t$ and held until the end of month $t-1+k$. The average holding period return for horizon $k$ is then computed as the average of the $k$-period holding returns ($R^{L/S}_{t,t-1+k}$, $k = 1, ..., 38$) of portfolios formed in all the months of the sample ($t = 1, ..., T$):

$$HPR_k = \frac{1}{T}\sum_{t=1}^{T} R^{L/S}_{t,t-1+k} \tag{2.9}$$

As Figure 2.4 shows, the Long/Short (value-weighted) portfolio produces around 1% return in the first month. The holding return keeps climbing after the first month, though with a lower monthly rate, reaches the peak value of roughly 3% around 2 years after the formation date and then fluctuates around that level thereafter. In a word, the profit of a Long/Short portfolio does not reverse in the long term, at least not until 38 months after the formation date, as shown in Figure 2.4. This evidence supports the underreaction of the stock market to multinational firms' foreign operation information.

[ Insert Figure 2.4 ]

As a comparison, I also plot an analogous figure for domestic information proxy in Figure 2.5. The return of the Long/Short portfolio sorting on domestic information proxy behaves differently in the long run. The return of the portfolio slowly climbs up with fluctuations, reaching the peak value at 13 months or so. Then it starts reversing back and finally reverses back to zero. This pattern of long term reversal provides additional evidence to differentiate the market reaction to the domestic information proxy from the reaction to the foreign information proxy.

[ Insert Figure 2.5 ]

### 2.3.4 Real Effects

To complete the argument that the predictive power of the foreign information proxy suggests investors' sluggish reaction to foreign operations information, we should confirm whether this proxy actually measures the information about the real activities of multinational firms. I use a regression framework in Table 2.5 to regress firms' real operations on information proxies, controlling for industry and/or time effects. The real operations are measured by firms' sales scaled by assets.

Table 2.5 shows the results. In columns (1)-(2), I consider the global information proxy which is the weighted sum of industry average returns in all operating countries, including the U.S. as well as foreign countries, and the weights add up to one. The results show that the global information proxy can predict the firms' future real activities, meaning that the proxy contains information about firms' future real operations. In columns (5)-(6), I split the global information proxy into two parts, the foreign information proxy and the domestic proxy. In general, these two proxies have predictive power for firms' future real activities. I also add an alternative proxy created by country average returns in the regression (shown in columns (3)-(4) and columns (7)-(8)). The coefficients on the original proxies constructed by country industry-specific returns remain statistically significant, while coefficients on the alternative proxies are statistically insignificant, indicating that country industry-specific returns contain less noisy signals for measuring innovations about firms' foreign operations than do country average returns. The real effect tests emphasize that, for multinational firms, the geographic shares of firms' operations around the world and the industry returns in those operating countries contain information about firms' real quantities. If investors do not give enough attention to any part of the information, the corresponding proxy shows predictive power for future stock returns.

[ Insert Table 2.5 ]

## 2.4 Summary Remarks

In this chapter, I find that foreign operations information for multinational firms diffuses gradually and is slowly incorporated into stock prices. A proxy based on the corresponding industry return of foreign country operations predicts future stock returns. A closer investigation also shows that the diffusion of foreign operations information differs from that of domestic operations information. Investors can respond relatively more promptly to domestic information relative to foreign information.

Figure 2.1: The National Composition of Foreign Sales From 1990 to 2009

This figure provides the average fraction of total sales from foreign operations by countries. For each year, the fraction from operations in a foreign country is averaged across all the multinational firms in the sample for that year. The countries with average fractions never greater than 0.02 is not plotted.

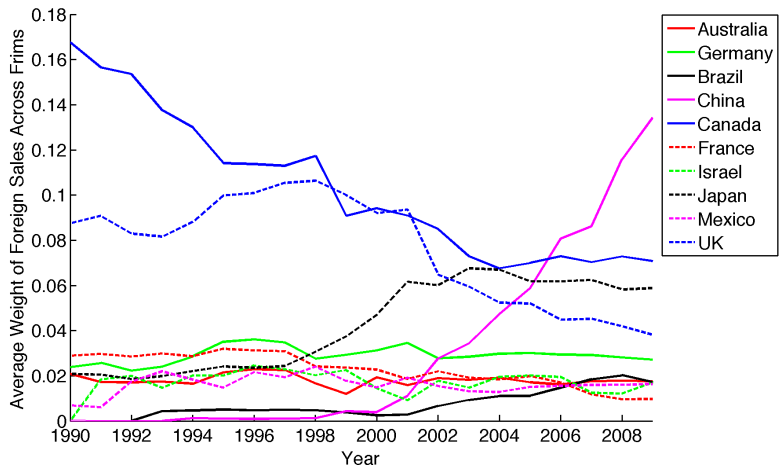


Figure 2.2: Abnormal Returns of Calendar Time Portfolio

At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxy of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The portfolios are rebalanced every month. The abnormal return is the intercept on a regression of monthly excess return from the rolling strategy on Carhart four factor (Carhart (1997)). Figure (a) plots the abnormal return of equal-weighted quintile portfolio against the quintile group. Figure (b) plots the abnormal return against the average lag foreign information proxy for each quintile group. Figure (c) plots the average fraction of foreign operation sales for each quintile group.

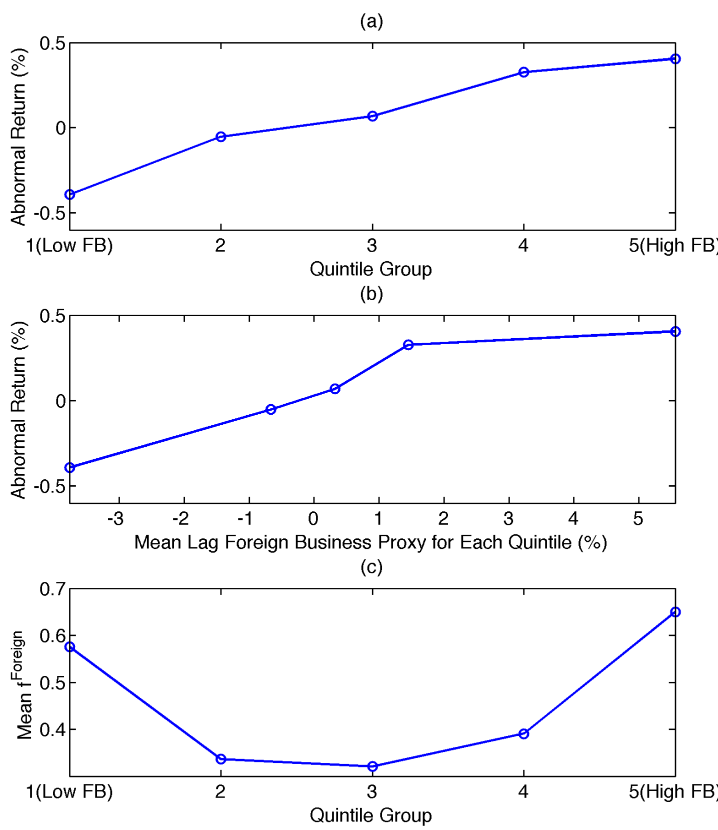


Figure 2.3: Annual Raw Return of L/S Portfolio

The figure shows annual raw returns of the Long/Short portfolio from 1990 to 2010. The Y axis corresponds to the percent of annual return. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxy of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The L/S portfolio is a zero-cost portfolio to go long the top quintile stocks and short the bottom quintile stocks. The annual raw return is calculated as the end-of-year profit/loss of investing $1 in the long side at the beginning of each year and rolling the portfolio monthly.

**Sort on the 1-month Lagged Foreign Information Proxy**

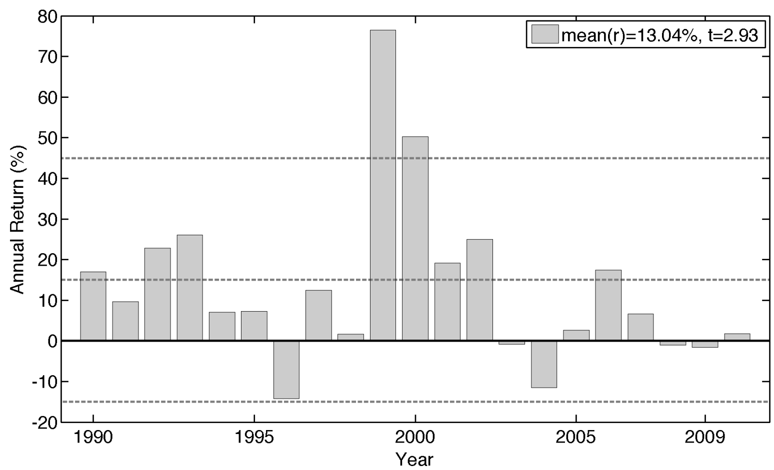


Figure 2.4: Average Holding Period Returns to the Long/Short Portfolio Sorted by Foreign Information Proxy

This figure shows the average holding period returns to the Long/Short portfolio in the 36 months after forming the portfolio. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxies of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The figure shows the average holding period returns (in %) over time of a zero-cost portfolio going long the stocks in the top quintile and short the stocks in the bottom quintile.

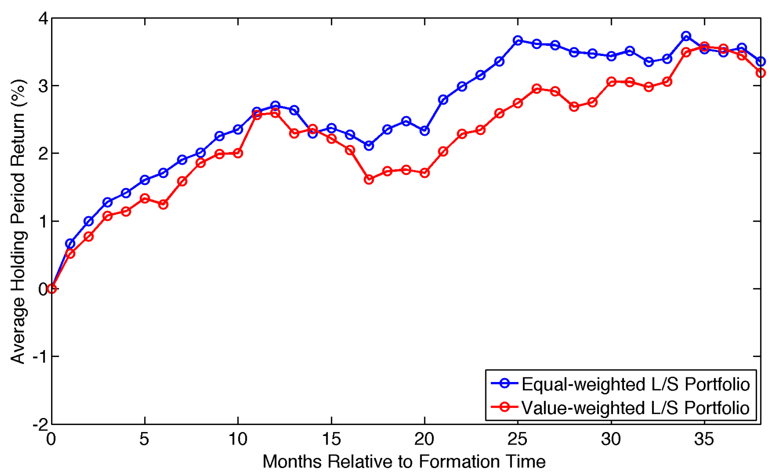


Figure 2.5: Average Holding Period Returns to the Long/Short Portfolio Sorted by Domestic Information Proxy

This figure shows the average holding period returns to the Long/Short portfolio in the 36 months after forming the portfolio. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of domestic information proxies of the previous month. The domestic information proxy is the product of the fraction of sales from U.S. operations and corresponding U.S. industry return. The figure shows the average holding period returns (in %) over time of a zero-cost portfolio going long the stocks in the top quintile and short the stocks in the bottom quintile.

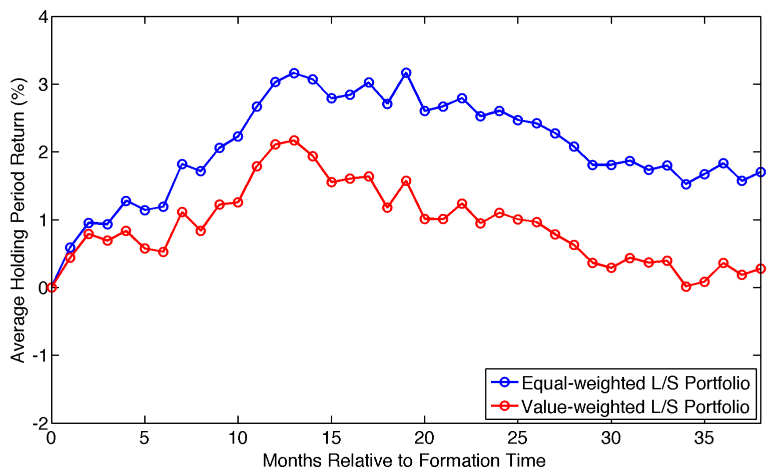


Table 2.1: Summary Statistics

This table shows summary statistics of firm-month observations. Multinational firm coverage of CRSP stock universe (EW) is the ratio of the number of multinational firms in the sample to the total number of CRSP stocks. Multinational firm coverage of CRSP stock universe (VW) is the ratio of the sum of market capitalization of multinational firms in the sample to the total market value of the CRSP stock universe. Total Fraction of Sales from Foreign Operations is the ratio of sales to all the foreign countries with business to total sales of the firm. Foreign Information Proxy is computed as the weighted sum of monthly industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. B/M Ratio is book equity divided by market capitalization at the end of December of the fiscal year. Market Capitalization is measured at the end of June and in millions.

| | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|
| Panel A: Sample Coverage | | | | | |
| Number of Multinational Firms | 1287 | 259 | 895 | 1183 | 1929 |
| Sample Coverage of CRSP Stock Universe(EW) | 15.84% | 1.59% | 12.40% | 15.78% | 19.97% |
| Sample Coverage of CRSP Stock Universe(VW) | 31.50% | 7.50% | 18.90% | 30.91% | 47.08% |
| Panel B: Foreign Characteristics | | | | | |
| Total Fraction of Sales from Foreign Operations | 44.27% | 29.09% | 10.00% | 36.02% | 100.00% |
| Foreign Information Proxy (%) | 0.56 | 4.14 | -17.31 | 0.38 | 19.96 |
| B/M Ratio | 1.24 | 1.84 | 0.11 | 0.51 | 6.24 |
| Market Capitalization (in millions) | 1852.92 | 3231.04 | 22.56 | 474.33 | 12651.26 |

Table 2.2: Predictability by Foreign Information Proxy (1990 – 2010)

This table shows abnormal returns of calendar time portfolio. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxies of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The portfolios are rebalanced every month as equally weighted or value weighted. The abnormal return is the intercept on a regression of monthly excess return from the rolling strategy on market excess return, Fama-French three factors (Fama and French (1993)) and Carhart four factor (Carhart (1997)). L/S is the abnormal return of a zero-cost portfolio that goes long the stocks in the top quintile and short the stocks in the bottom quintile. Returns are in monthly percent, t-statistics are shown below the coefficient estimates. *10%, **5%, ***1% significance.

| Panel A: Equally Weighted | Q1 (Low ForInfo) | Q2 | Q3 | Q4 | Q5 (High ForInfo) | L/S |
|---|---|---|---|---|---|---|
| Market | -0.430** | -0.00889 | 0.153 | 0.448** | 0.451** | 0.882*** |
| | (-2.04) | (-0.05) | (0.99) | (2.54) | (2.01) | (3.42) |
| Fama-French 3 Factor | -0.494** | -0.160 | -0.00901 | 0.284** | 0.394** | 0.888*** |
| | (-2.58) | (-1.17) | (-0.08) | (2.14) | (2.14) | (3.51) |
| Carhart 4 Factor | -0.392** | -0.0516 | 0.0684 | 0.326** | 0.405** | 0.796*** |
| | (-2.03) | (-0.39) | (0.61) | (2.49) | (2.15) | (3.13) |
| **Panel B: Value Weighted** | **Q1 (Low ForInfo)** | **Q2** | **Q3** | **Q4** | **Q5 (High ForInfo)** | **L/S** |
| Market | -0.222 | -0.0936 | 0.224 | 0.414** | 0.605*** | 0.827** |
| | (-1.07) | (-0.54) | (1.50) | (2.53) | (2.63) | (2.53) |
| Fama-French 3 Factor | -0.230 | -0.104 | 0.160 | 0.399** | 0.653*** | 0.883*** |
| | (-1.10) | (-0.63) | (1.07) | (2.46) | (3.07) | (2.79) |
| Carhart 4 Factor | -0.186 | -0.106 | 0.165 | 0.351** | 0.570*** | 0.756** |
| | (-0.86) | (-0.63) | (1.14) | (2.23) | (2.68) | (2.39) |

Table 2.3: Calendar Time Portfolio Factor Loadings (1990 – 2010)

This table shows factor loadings of calendar time portfolio using Carhart four factor model. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxies of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The portfolios are rebalanced every month as equally weighted. The monthly excess return is regressed on Carhart four factors (Carhart (1997)), which includes Fama-French three factors (Fama and French (1993)) plus momentum factor. L/S is a zero-cost portfolio that goes long the stocks in the top quintile and short the stocks in the bottom quintile. t-statistics are shown below the coefficient estimates. *10%, **5%, ***1% significance.

| Panel A: Equally Weighted | Q1 (Low ForInfo) | Q2 | Q3 | Q4 | Q5 (High ForInfo) | L/S |
|---|---|---|---|---|---|---|
| $\beta_{R_m-R_f}$ | 1.112*** | 1.053*** | 1.056*** | 1.060*** | 1.074*** | -0.0383 |
| | (20.52) | (27.59) | (37.82) | (33.62) | (22.58) | (-0.58) |
| $\beta_{SMB}$ | 0.469*** | 0.573*** | 0.535*** | 0.606*** | 0.631*** | 0.162 |
| | (5.97) | (10.11) | (12.91) | (11.17) | (8.81) | (1.31) |
| $\beta_{HML}$ | -0.0289 | 0.161* | 0.213*** | 0.206*** | -0.0683 | -0.0395 |
| | (-0.33) | (2.33) | (4.88) | (3.37) | (-0.96) | (-0.30) |
| $\beta_{Mom}$ | -0.119 | -0.126*** | -0.0897*** | -0.0491 | -0.0128 | 0.106 |
| | (-1.94) | (-3.51) | (-3.52) | (-1.32) | (-0.26) | (1.20) |
| **Panel B: Value Weighted** | **Q1 (Low ForInfo)** | **Q2** | **Q3** | **Q4** | **Q5 (High ForInfo)** | **L/S** |
| $\beta_{R_m-R_f}$ | 1.091*** | 1.102*** | 1.034*** | 1.030*** | 1.007*** | -0.0843 |
| | (16.83) | (20.60) | (24.45) | (26.99) | (18.26) | (-0.96) |
| $\beta_{SMB}$ | 0.127 | 0.205*** | 0.145** | 0.159* | 0.309** | 0.182 |
| | (1.64) | (3.78) | (2.74) | (2.53) | (3.33) | (1.23) |
| $\beta_{HML}$ | -0.0389 | -0.0410 | 0.116* | 0.000680 | -0.202* | -0.163 |
| | (-0.36) | (-0.44) | (2.04) | (0.01) | (-2.19) | (-0.94) |
| $\beta_{Mom}$ | -0.0507 | 0.00217 | -0.00611 | 0.0565 | 0.0961 | 0.147 |
| | (-0.69) | (0.05) | (-0.17) | (1.23) | (1.72) | (1.35) |

Table 2.4: Fama-MacBeth Regression of Return Predictability by Foreign Information Proxy

This table reports the results for Fama-MacBeth regressions of stock monthly returns for the period $1990-2010$. The main explanatory variables include the lagged foreign information proxy ($ForInfo_{t-1}$) and the lagged domestic proxy ($DomInfo_{t-1}$). The foreign information proxy ($ForInfo_{t-1}$)is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The domestic information proxy ($DomInfo_{t-1}$)is the product of the fraction of sales from U.S. operations and corresponding U.S. industry return. Three forms of dependent variables are used: (1) the monthly return of multinational firms ($Ret_t$); (2) the excess monthly return over its current foreign country specific industry return ($Ret_t - ForIndRet_t$); (3) the excess monthly return over its current global information proxy ($Ret_t - GlobalInfo_t$). $ForIndRet_t$ is defined as the weighted average of industry average returns across operating foreign countries and can also specified as $ForIndRet_t = ForInfo_t / \sum_{c \neq US} f^c$. $GlobalInfo_t$ is the sum of contemporary foreign information proxy and domestic information proxy, i.e. $GlobalInfo_t = ForInfo_t + DomInfo_t$. The control variables include the lagged U.S. industry return ($USIndRet_{t-1}$), the lagged world industry return (excluding U.S. market) ($WUIndRet_{t-1}$), the sales-weighted sum of country average returns of the corresponding foreign countries with operations ($ForInfo_t^{Country}$), the contemporaneous foreign country specific industry return ($ForIndRet_t$), the contemporaneous U.S. industry return ($USIndRet_t$). Other controls that are included in each specification but not reported are: the firm's lagged stock monthly return ($Ret_{t-1}$), the firm's lagged cumulative return from $t-12$ to $t-2$ ($Ret_{(t-12,t-2)}$), the size of the firm measured by the log of market value, the log of book-to-market ratio and the total sales fraction from foreign operations. The standard errors are computed with a Newey-west correction with 12 lags. Fama-MacBeth standard errors are reported within parentheses. $^{*}$10%, $^{**}$5%, $^{***}$1% significance.

**Panel A - Information Proxy Measured by Levels**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable (%) | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t -$ $ForInd_t$ | $Ret_t -$ $ForInd_t$ | $Ret_t -$ $GlobalInfo_t$ | $Ret_t -$ $GlobalInfo_t$ |
| $ForInfo_{t-1}$ | 0.0973*** | 0.0650*** | 0.0397** | 0.0354** | 0.0603** | 0.0372* | 0.0665*** | 0.0458*** |
| | (0.0216) | (0.0182) | (0.0191) | (0.0165) | (0.0235) | (0.0205) | (0.0204) | (0.0171) |
| $DomInfo_{t-1}$ | 0.129*** | -0.0285 | -0.0265 | -0.00351 | -0.0699 | -0.0761 | 0.0259 | 0.0183 |
| | (0.0342) | (0.0465) | (0.0510) | (0.0476) | (0.0493) | (0.0544) | (0.0521) | (0.0566) |
| $USIndRet_{t-1}$ | | 0.0995*** | 0.0949** | 0.0655* | 0.0517 | 0.0558 | 0.0453 | 0.0475 |
| | | (0.0380) | (0.0412) | (0.0389) | (0.0374) | (0.0385) | (0.0369) | (0.0389) |
| $WUIndRet_{t-1}$ | | 0.104* | 0.131** | 0.0677 | - 0.0000811 | 0.0138 | -0.00177 | 0.0153 |
| | | (0.0566) | (0.0518) | (0.0424) | (0.0458) | (0.0461) | (0.0439) | (0.0442) |
| $ForInfo_{t-1}^{Country}$ | | | 0.0142 | 0.0191 | | -0.00580 | | -0.0120 |
| | | | (0.0358) | (0.0297) | | (0.0476) | | (0.0388) |
| $USIndRet_t$ | | | | 0.276*** | | | | |
| | | | | (0.0258) | | | | |
| $WUIndRet_t$ | | | | 0.210*** | | | | |
| | | | | (0.0447) | | | | |
| $ForIndRet_t$ | | | | 0.219*** | | | | |
| | | | | (0.0112) | | | | |
| Basic Set of Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| R-sq | 0.046 | 0.052 | 0.054 | 0.070 | 0.040 | 0.043 | 0.037 | 0.039 |

**Panel B: Information Proxy Measured by Quantile Groups**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable (%) | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t -$ $ForInd_t$ | $Ret_t -$ $ForInd_t$ | $Ret_t -$ $GlobalInfo_t$ | $Ret_t -$ $GlobalInfo_t$ |
| Quintile Group of $ForInfo_{t-1}$ | 0.275*** | 0.200*** | 0.166*** | 0.0968** | 0.112** | 0.0787* | 0.120*** | 0.0805* |
| | (0.0844) | (0.0511) | (0.0564) | (0.0439) | (0.0462) | (0.0443) | (0.0361) | (0.0416) |
| Quintile Group of $DomInfo_{t-1}$ | 0.171*** | 0.0242 | 0.0265 | 0.0528 | -0.0333 | -0.0314 | 0.0858 | 0.0795 |
| | (0.0509) | (0.0773) | (0.0716) | (0.0585) | (0.0733) | (0.0702) | (0.0744) | (0.0719) |
| Quintile Group of $USIndRet_{t-1}$ | | 0.187 | 0.177 | 0.128 | 0.0569 | 0.0405 | 0.135 | 0.129 |
| | | (0.156) | (0.148) | (0.151) | (0.152) | (0.142) | (0.116) | (0.113) |
| Quintile Group of $WUIndRet_{t-1}$ | | 0.458** | 0.469** | 0.0606 | 0.0328 | 0.0451 | 0.0689 | 0.0847 |
| | | (0.185) | (0.182) | (0.141) | (0.0964) | (0.105) | (0.101) | (0.106) |
| Quintile Group of $ForInfo_{t-1}^{Country}$ | | | 0.00819 | 0.0307 | | -0.0133 | | -0.0107 |
| | | | (0.0639) | (0.0528) | | (0.0594) | | (0.0466) |
| Quintile Group of $USIndRet_t$ | | | | 1.153*** | | | | |
| | | | | (0.0878) | | | | |
| Quintile Group of $WUIndRet_t$ | | | | 0.680*** | | | | |
| | | | | (0.160) | | | | |
| Quintile Group of $ForIndRet_t$ | | | | 1.332*** | | | | |
| | | | | (0.147) | | | | |
| Basic Set of Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| R-sq | 0.045 | 0.050 | 0.053 | 0.065 | 0.040 | 0.044 | 0.036 | 0.038 |

Table 2.5: Real Effects of Global, Foreign and Domestic Information Proxies

This table reports the results of OLS predictive regressions of the real quantities of firm sales on constructed 1-year lagged global, foreign and domestic information proxies for the period 1990 − 2010. The dependent variable is the annual sales normalized by firm assets ($Sales_t/Asset_t$). The main independent variables are various lagged information proxies. The foreign information proxy ($ForInfo_{t-1}$) is computed as the weighted sum of industry average returns in the foreign countries with operations within the corresponding segment. The domestic information proxy ($DomInfo_{t-1}$) is the product of the fraction of sales from U.S. operations and corresponding U.S. industry return. The global information proxy ($GlobalInfo_{t-1}$) is the sum of the foreign information proxy and the domestic information proxy. $ForInfo_{t-1}^{Country}$, $DomInfo_{t-1}^{Country}$, $GlobalInfo_{t-1}^{Country}$ are constructed as the sales-weighted sum of country average returns. All proxies are annualized by averaging across months during the corresponding year. The control variables include the combinations of year effect and industry effect or industry-year effect. Robust standard errors are clustered by year. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable | | | | $Sales_t/Asset_t$ | | | | |
| $GlobalInfo_{t-1}$ | 0.0306*** | 0.0325*** | 0.0275*** | 0.0288*** | | | | |
| | (0.00640) | (0.00694) | (0.00802) | (0.00907) | | | | |
| $GlobalInfo_{t-1}^{Country}$ | | | 0.00591 | 0.00526 | | | | |
| | | | (0.00770) | (0.00799) | | | | |
| $ForInfo_{t-1}$ | | | | | 0.0283*** | 0.0287*** | 0.0207** | 0.0183** |
| | | | | | (0.00628) | (0.00530) | (0.00805) | (0.00764) |
| $DomInfo_{t-1}$ | | | | | 0.0146*** | 0.0125** | 0.0156* | 0.0103 |
| | | | | | (0.00483) | (0.00450) | (0.00857) | (0.00640) |
| $ForInfo_{t-1}^{Country}$ | | | | | | | 0.0148 | 0.0172 |
| | | | | | | | (0.0104) | (0.0105) |
| $DomInfo_{t-1}^{Country}$ | | | | | | | -0.00448 | 0.000671 |
| | | | | | | | (0.0156) | (0.0106) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Effect | Yes | No | Yes | No | Yes | No | Yes | No |
| Year Effect | Yes | No | Yes | No | Yes | No | Yes | No |
| Industry×Year Effect | No | Yes | No | Yes | No | Yes | No | Yes |
| Number of Observations | 14062 | 14062 | 14062 | 14062 | 14062 | 14062 | 14062 | 14062 |
| R-sq | 0.222 | 0.258 | 0.222 | 0.258 | 0.224 | 0.259 | 0.225 | 0.260 |

# Chapter 3

# Thinking Outside the Borders (2): Underlying Mechanisms of Investors' Inattention

## 3.1 Introduction

Having established the return predictability by the foreign information proxy, I strive to understand more about the mechanisms affecting the information incorporation process. In this chapter, I explore what factors affect the incorporation speed of foreign operation information through testing the magnitude of return predictability of the foreign information proxy.

I first explore the following types of effects on the magnitude of predictability in a regression framework: firm size, analyst coverage, institutional ownership, foreign (institutional) investors, the fraction of sales from foreign operations, and the complexity of international operation structure.

Firm size potentially plays an important role in the gradual diffusion of foreign operations information. Previous literature suggests that firm-specific information about small firms may emerge slowly, because investors devote less effort to these firms, in which they can only take small positions. The delay may be amplified in small-capitalization stocks because of less market making or arbitrage capacity (Merton (1987); Grossman and Miller (1988)). My finding is consistent with other papers (Hong et al. (2000); Cohen and Lou (2011)) and supports the conclusion that return predictability is stronger for small firms.

I also investigate the effect of analyst coverage on the incorporation of foreign operation information. Analyst coverage directly proxies for the amount of attention or processed information, given that financial analysts synthesize complex information into a more easily understandable form for less sophisticated investors, and may also circulate information that is sometimes not widely known. The results show that analyst coverage reduces the magnitude of return predictability by foreign information proxy.

The return effects vary with firms' institutional ownership as well. Given the sophistication and advantage of acquiring and trading on information, institutional investors may speed the price adjustment to foreign innovations, and hence lead to a less strong return effect. This hypothesis is also supported by the data.

Among all the institutional investors, foreign institutional investors may play a special role. As foreign investors, they may pay more attention to foreign information; at the same time, they also have better access to foreign assets to trade on foreign information. Consistently, the results show that the return effect of firms with high foreign institutional ownership is less pronounced.

Given a cost-benefit model of attention allocation,[1] I argue that investors are more

[1] Gabaix and Laibson (2005) derive a general cost-benefit model of endogenous attention allocation, which is supported by the experimental evidence provided by Gabaix, Laibson, Moloche, and Weinberg (2006).

likely to allocate more attention to foreign operations information when the foreign fraction of a firm's total operation is larger. Through a regression test, I confirm this hypothesis: the magnitude of predictability of foreign information proxy decreases when the total fraction of the firm's sales from foreign operations increases.

I directly proxy the complexity of firms' operation structure and look into whether the more complicated the firms' operations are, the more slowly firms' foreign information is reflected by stock prices. I use the Herfindahl index and the number of country segments to proxy for firms' operation complexity. The results show that the return predictability is more pronounced among firms with more complicated operation structures.

Next, in a more precise way, I examine the role of quarterly earnings announcements in facilitating the incorporation of firms' foreign operations information. Because an earnings announcement is an important source of information that aggregates segmented complex information for investors, I expect that stock prices would react more to firms' foreign operations information during the month when quarterly earnings announcements come out. Specifically, I find that, for foreign information in month $t-1$, an earnings announcement in month $t-1$ increases the initial month response and decreases the subsequent month $t$ response, while an earnings announcement in month $t$ has no effect on the initial month response but increases the magnitude of the delayed month $t$ response.

The context also allows me to explore the speed of U.S. market incorporation of information from different geographic segments (i.e. English-speaking countries, European countries or Asian countries). As expected, I find that foreign operations information is incorporated relatively faster if the language is more similar or the geographic distance is closer. More specifically, sorting on the information of month $t-1$, the predictability of the English-speaking countries' information proxy for the following month's stock return ($Ret_t$) is less pronounced than that of European countries' information proxy. The incorporation of information about operations in Asian countries is delayed even more; the predictability does not show up until two months (month $t+1$) after the time of innovations. The evidence of this mechanism relates to the literature on the economic significance of geography and its influence on information acquisition. Bae et al. (2008) find there is a local advantage for financial analysts: analysts resident in a country make more precise earnings forecasts for firms in that country than do non-resident analysts. Coval and Moskowitz (1999) suggest that asymmetric information between local and nonlocal investors may drive the preference for geographically proximate investments. Here, the shareholders of multinational firms by default hold a pseudo-international portfolio. Under such a relatively exogenous setting, I test how the market reacts to information from different segments of the world, and find that the market is less efficient at reflecting information that is more distant.

Interestingly, I also find suggestive evidence that media coverage, which can serve as a direct measure of attention, influences the market reaction to foreign information. Specifically, the time series dynamics of annual returns of the trading strategy closely relates to the relative news coverage of domestic events and foreign events. The strategy creates more profit when there are more news articles covering domestic events relative to foreign events. For instance, the annual returns of the strategy surged during 1999 and 2000 when the media was highly concentrated on the U.S. "dot-com" boom, while the return slumped in 1996 as the focus was on the miracle growth in Asia right before the 1997 Asian financial crisis. It suggests that attention is a crucial and relevant channel for delaying the incorporation of foreign operations information.

This chapter provides a better understanding of the underlying mechanism, which could help facilitate information processing and reduce market inefficiency. A more efficient market for multinational firms will play a better role in monitoring managers' decisions, especially on global diversification, and in providing a fair price for firms to obtain financing.

## 3.2 Regression Framework

The speed of foreign information incorporation could be affected by many factors, such as investors' attention to the information, investor's capacity to process the information, the complexity of firms' operations, the salience of firms' foreign operations, etc. To analyze these mechanisms, I first characterize mechanism-related variables ($Mechanism_{ij,t-1}$), including firm size, analyst coverage, institutional holdings, foreign sale fractions, and complexity; and then implement Fama-MacBeth regressions by adding an interaction term between the foreign information proxy ($ForInfo_{ij,t-1}$) and the mechanism variable ($Mechanism_{ij,t-1}$):

$$\begin{aligned} Ret_{ijt} =& \alpha + \beta_1 ForInfo_{ij,t-1} + \beta_2 Mechanism_{ij,t-1} + \beta_3 ForInfo_{ij,t-1} \times Mechanism_{ij,t-1} \\ &+ X'_{ij,t-1}\gamma + \epsilon_{ijt} \end{aligned} \tag{3.1}$$

For robustness, I also substitute the quintile group of $ForInfo_{ij,t-1}$ for its level in equation (3.1) and run the following equation:

$$\begin{aligned} Ret_{ijt} =& \alpha + \beta_1 QFI_{ij,t-1} + \beta_2 Mechanism_{ij,t-1} + \beta_3 QFI_{ij,t-1} \times Mechanism_{ij,t-1} \\ &+ X'_{ij,t-1}\gamma + \epsilon_{ijt} \end{aligned} \tag{3.2}$$

The results are reported in Table 3.1, where Panel A shows the results using levels of foreign information proxy, while Panel B presents the results using quantile groups.

For brevity, I only report the main effect of the foreign information proxy and the interaction term; the coefficient on $Mechanism_{ij,t-1}$ itself and other controls are not reported.

### 3.2.1 Firm Size

Previous literature suggests firm size plays an important role in the rate of diffusion. For example, Hong et al. (2000) argues that firm-specific information about small firms gets out slowly because investors devote less effort to these firms, in which they can only take small positions. Hou (2007) finds that industry information is incorporated first into firms with large market share before it spreads to other firms in the industry, which is a leading cause of the intra-industry lead-lag effect. These pieces of evidence suggest that information is more likely to be incorporated into large firms first and the incorporation into small firms' prices is delayed. Besides, the delay may be further amplified in small-capitalization stocks because of less market making or arbitrage capacity (Merton (1987); Grossman and Miller (1988)).

Using Fama-MacBeth regressions, I interact the foreign information proxy with a size dummy to examine how firm size affects the speed of market reaction to the foreign operation information. The "large firm" dummy equals one for firms with size over the median of the sample.[2] The regression estimation is shown in Column (1) of Panel A and B in Table 3.1. I find that the coefficient on the interaction term is negative and statistically significant, which is consistent with the hypothesis that prices of large firms adjust more quickly to foreign operation information. In addition, using levels and quantile groups of the foreign information proxy gives virtually the same results.

### 3.2.2 Analyst Coverage

Analyst coverage also influences the rate of information flow (Brennan, Jegadeesh, and Swaminathan (1993); Hong et al. (2000)). Because financial analysts synthesize complex information into a more easily understandable form for less sophisticated investors, and sometimes circulate information that is not widely known, information travels faster across the investing public for the stocks with higher analyst coverage.

I add into the regression an interaction term between foreign information and a dummy which equals to one when the analyst coverage is greater than the sample median. Analyst coverage is measured by $ln(1 + NumEst)$, where $NumEst$ denotes the number of analyst earnings forecasts recorded by the I/B/E/S database.[3] If there

[2] The size, measured by the market capitalization at the end of June of year $y$, is matched with stock returns from July of year $y$ to June of year $y + 1$.

[3] The analyst coverage, which is averaged through the period from July of year $y - 1$ to June of year $y$, is matched with stock returns from July of year $y$ to June of year $y + 1$.

is no record in I/B/E/S, *NumEst* is set to be zero. Following the literature, I use the log form of the number of forecasts to characterize analyst coverage because this captures the marginally decreasing contribution of analyst forecasts as the number of analyst forecasts increases. I add one to the number to make the log form equal to zero when there is no analyst coverage.

The estimations are shown in Column (2) of Panel A and B in Table 3.1. The coefficient on the interaction term is significantly positive, indicating that return effects are less strong for firms with higher analyst coverage. This evidence is consistent with the previous literature as well. However, there may be some counfounding factors. Analyst coverage is correlated with other firm characteristics, such as size (Bhushan (1989)); and, as shown in Section 3.2.1, larger size also reduces the return effects. To factor out the confounding effect of firm size, I first regress analyst coverage on firm size and then use the residuals to create the dummy. Column (3) reports the estimations. In both Panel A and Panel B, the coefficient on the interaction term is still significant and negative, with the magnitude slightly reduced after the influence of firm size is removed.

### 3.2.3 Institutional Holdings

Because the information is incorporated into stock prices through investors' trading, we may expect that the sophistication of investors or their advantages in information acquisition could affect the amount of incorporation as well. Badrinath, Kale, and Noe (1995) argue that the returns on stocks held by informed institutional investors lead the returns on stocks owned by uninformed individual investors. Institutional investors may be generally more sophisticated and informed; furthermore, given that they may have more exposure to international assets, they may not only be more attentive to foreign information but also have less constraints on trading on the information. Therefore, the hypothesis is that the predictability is less pronounced if more shares of a firm are owned by institutional investors.

I examine the role of institutional investors using the interaction term between foreign information and a dummy denoting that institutional ownership is greater than the sample median.[4] The institutional ownership is obtained from Thomson-Reuters Institutional Holdings (13F) Database, which provides Institutional Common Stock Holdings and Transactions, as reported on Form 13F filed with the SEC.[5]

[4] Institutional ownership, measured at the end of December of year $y-1$, is matched with stock returns from July of year $y$ to June of year $y+1$.

[5] This database contains ownership information by institutional managers with 100 million or more in Assets Under Management. The ownership is set to be zero if there is no institution in the database reporting its ownership of the stock.

According to Column (4) of Panel A and B in Table 3.1, the magnitude of return predictability is smaller when the firm is owned largely by institutional investors; the coefficient on the interaction term is significantly negative. As above, this effect could be confounded with firm size. Therefore I control for the effect of firm size by using the institutional ownership orthogonalized with firm size instead of the original measure of institutional ownership. As Column (5) shows, the magnitude of the coefficient on the interaction term decreases but remains significant when I use the foreign information proxy. When using the quantile groups of the foreign information proxy, the coefficient becomes insignificant, possibly because using quantile groups here introduces more noise. Generally speaking, the results support the hypothesis that institutional investors facilitate processing and the incorporation of foreign information.

### 3.2.4 Foreign Institutional Ownership

Among all institutional investors, foreign institutions may play a special role in the context of multinational firms. Compared to domestic institutional investors, foreign institutional investors could be less attention-constrained to foreign information and have advantages to process foreign information. In addition, since foreign institutional investors are relatively more accessible to foreign market, they would have advantages to trade on the arbitrage opportunity as well. I then explore whether the return effect becomes less strong when foreign institutional investors hold higher fractions of firms' stocks.

The data of foreign institutional ownership is also obtained from Thomson-Reuters Institutional Holdings (13F) Database. A variable about the owner/manager's country origin was added into the database from 1999. Since the ownership of institutions from each individual foreign country is fairly small, I aggregate the ownership from all the foreign countries into the foreign institutional ownership.[6] On average, 74.47% of the firms in the sample have positive foreign institutional ownerships. Among these firms, the average ownership by foreign institutional investors is 6.14%.

Since the data of the foreign institutional ownership is only available for half of the sample, I report the results separately in Panel C of Table 3.1. Columns (1)-(3) use the level of foreign information proxy, while Columns (4)-(6) uses the quantile group. As the hypothesis predicts, Column (1) shows that the return effect for firms with high foreign institutional ownership is significantly less pronounced than those with low foreign institutional ownership. This means that the prices

[6]Foreign institutional ownership, measured at the end of December of year $y-1$, is matched with stock returns from July of year $y$ to June of year $y+1$. Since the country variable is available starting from 1999, the foreign institutional ownership will be used for regressions of returns starting from July 2000.

of firms with higher foreign institutional ownership react more promptly to foreign information. Foreign institutional investors are foreign investors and at the same time institutional investors. Since I've shown above that institutional ownership could speed the incorporation of foreign information, it is still not clear whether the influence identified in Column (1) comes only from the role as institutional investors, or also from the role as foreign investors. In Column (2), I further separate the influence contributed to the role of foreign investors by controlling for the mechanism of institutional ownership. It shows that the channel as foreign investors still has significant effects after I parse out the effect of institutional investors. The results using the quantile group of foreign information proxy are similar.

### 3.2.5 Total Fraction of Sales from Foreign Operations

If investors allocate attention according to a cost-benefit model, then investors are likely to allocate more attention to foreign operations information when the foreign fraction of a firm's total operation is larger, because the benefit of paying attention to foreign operations information increases when foreign operations play a more important role. Therefore, I expect that foreign operations information is incorporated into stock prices relatively faster for firms with more foreign operations and hence the return predictability is less pronounced. For example, consider two firms, A and B. Firm A has 20% operations in the U.K., 20% operations in China, and 60% operations in the U.S., while firm B has 60% operations in the U.K., 20% operations in China, and 20% operations in the U.S. These two firms have same complexity in the sense of the Herfindahl index or the number of segments, but firm B has a larger amount of operations outside the U.S. compared to firm A. The hypothesis predicts that return predictability by foreign information proxy would be less pronounced for firm B, because investors are more likely to allocate more efforts to collect information for its foreign operations.

I construct a dummy variable that equals one if a firm's foreign sales fraction ($f^{Foreign}$) is above the median of the sample. The group with the low foreign sales fraction ($f^{Foreign} < Median$) has around 22% sales from foreign operations on average, while the group with the high foreign sales fraction ($f^{Foreign} > Median$) has on average about 71% of its operations abroad. Note that the group with the low foreign sales fraction does not include the firms with extremely low sales from abroad, because the observations with total foreign sales fraction less than 10% are removed from the sample. I then implement Fama-MacBeth regressions by adding an interaction term between foreign information proxy and this dummy.

Column (6) in Table 3.1 reports the estimations. Both the interaction term and the level of foreign sales fraction dummy are also added in the regression, but are not reported for brevity. The negative coefficient on the interaction term is statistically significant, which confirms that stock prices react to foreign operation information faster when the total fraction of foreign sales is larger.

### 3.2.6 Complexity

In this subsection, I directly examine the influence of complexity on the processing of foreign operations information. Cohen and Lou (2011) document that the complexity of firms' industry and operation structure impedes information processing. Specifically, they find that information about conglomerates that operate in multiple industries is more slowly incorporated into stock prices compared to information about stand-alone firms. Similarly, in the context of multinational firms, I expect that the more complicated geographic operations structures the firms have, the more their foreign operations information is likely to be delayed.

I use two measures to proxy for firms' complexity of geographic operations: the Herfindahl index[7] and the number of country segments. If a firm has operations in more countries, and more dispersed operations across these countries, it may be more complicated for investors to analyze and incorporate a single piece of information into prices, resulting in more pronounced predictability of the foreign information measure.

Column (7) shows that the coefficient of the interaction term between foreign information proxy and high Herfindahl index is negative and statistically significant. It is consistent with my prediction: a firm with a higher Herfindahl index has more concentrated operations and thus is easier to analyze, so that the return effect is less strong. The result for the other measure of complexity, the number of country segments, is reported in Column (8). The coefficient on the interaction term with a dummy denoting the number of segments greater than the sample median is positive. It is significant in Panel B while barely lacking significance in Panel A. Generally speaking, the results show that the more countries the firm operates in, the more complicated analysis is required, and thus the more delayed is information revelation.

[ Insert Table 3.1 ]

### 3.2.7 Summary

Because the aforementioned mechanisms generally have influence on the return predictability, I include all of them in one regression to control for each other's influence, for a robustness check. The results are shown in the last two columns in

[7]Because there is not a consensus format for firms reporting geographic segment data, sales may be reported for different combinations of countries. If sales from multiple countries are combined in a report, I equally distribute them among the countries. For example, if firm A reports that it has 50% operations in Germany and France, I compute the Herfindahl index assuming firm A has 25% in each of the two countries.

Panel A and B of Table 3.1, and Columns (3) and (6) in Panel C. The results are consistent with those when I put them separately into the regression. In summary, Table 3.1 shows that the price adjustment to foreign information is faster when firms are larger, have higher analyst coverage, have larger shares owned by institutional investors, especially foreign institutional investors, and higher percentage of operations abroad, and have a less complex international operation structure.

## 3.3 More Mechanisms

### 3.3.1 Quarterly Earnings Announcement

Earnings announcements may play a role in the return dynamics as well. There are two possible stories to explain the influence of earnings announcements: (1) salience hypothesis: earnings announcement is a salient event which could gather investor's attention around the announcement date. More attention leads to more information incorporation.(2) information-content hypothesis: a quarterly earnings report provides a summary measure of a firm's business and aggregates the segmented complex information for investors, so it may facilitate incorporation of foreign operations information and hence affect the return dynamics. These two stories, which may not be mutually exclusive, both suggest that earnings announcements can affect the speed of the incorporation of firms' foreign information. This evidence can also further imply whether limited attention and processing capacity matters for the sluggish information incorporation examined in this paper.

I will first exploit the variation in earnings announcements across monthly calendar time. The hypothesis is that the price in the month with an earnings announcement responds at a greater magnitude to current and previous information relative to the price does in the month without. If, instead, an earnings report adds no value to an investors' information processing, or the information channel does not matter for the return effect, the price response would be no different between the month with an earnings announcement and the month without.

To test this hypothesis, I take a different approach, which can capture more details about time series pattern of stock price response to foreign information. For each month $t-1$, I sort stocks by their month $t-1$ foreign information proxy into three portfolios (bottom 30%, middle 30%, and top 30%), and form a zero-cost Long/Short portfolio by going long the top 30% and short the bottom 30% portfolio. I consider a one-year holding period return from month $t-1$ and month $t+11$ ($HPR^{L/S}_{t-1,t+11}$) as a proxy for the total response of prices to month $t-1$ foreign information. Figure 2.4 shows that the long term response of prices fluctuates and increases only marginally after one year following the sorting month. Therefore, choosing one-year holding period returns as a proxy for total responses represents a compromise between capturing a large amount of total responses for normalization and not bringing in too much noise. The ratio of monthly returns ($Ret_{t-1}^{L/S}$ or $Ret_t^{L/S}$) to $HPR_{t-1,t+11}^{L/S}$ measures the fraction of the total response that occurs within that month. I call it a response ratio ($RR$), and

$$RR_{t-1}^{L/S} = \frac{Ret_{t-1}^{L/S}}{HPR_{t-1,t+11}^{L/S}} \quad (3.3)$$

$$RR_{t}^{L/S} = \frac{Ret_{t}^{L/S}}{HPR_{t-1,t+11}^{L/S}} \quad (3.4)$$

I now compare the initial month response ($RR_{t-1}^{L/S}$) and subsequent month response ($RR_t^{L/S}$) among three cases:
(1) $Announcement_{t-1} = 1$, $Announcement_t = 0$: Earnings announcement in the sorting month ($t-1$);
(2) $Announcement_{t-1} = 0$, $Announcement_t = 1$: Earnings announcement in the subsequent month ($t$);
(3) $Announcement_{t-1} = 0$, $Announcement_t = 0$: No earnings announcement in either month.

As Table 3.2 shows, if quarterly earnings are reported in month $t-1$, stock prices respond to 79.25% of month $t-1$ foreign information within that month, and the response ratio is not significantly different from 1. In other words, with the information provided by an earnings report, investors are able to process most of the foreign information in the current month, and hence price underreaction is not significant. As a result, in the subsequent month, the response ratio is very small and not significantly different from zero. In contrast, without an announcement in month $t-1$, price underreacts to month $t-1$ foreign information; the initial response ratio (around 63%) is much lower and significantly different from 1.

An earnings announcement also speeds up investors' delayed processing of previous information. If an earnings report is announced during month $t$, stock price in month $t$ reacts 15.52% of total response to month $t-1$ foreign information, which is higher than the month $t$ response ratio 9.52% that occurs when there is no announcement in either of the months. These results are consistent with the hypothesis that stock prices response more to both current and previous month foreign information when earnings reports are present.

[ Insert Table 3.2 ]

Next I turn to an analysis using daily event time. Using this way, I could more precisely identify the influence of earnings reports around the announcement dates.

If earnings announcements speed the incorporation of foreign information, the differences of cumulative abnormal returns should widen around the announcements between the firms with high lagged foreign information proxy and those with low lagged foreign information proxy.

I construct cumulative abnormal returns for the [-3, 3] window around the announcement date, which is obtained from two sources: Compustat and I/B/E/S. Because the date recorded in the database may be the date from a newswire source or the date of the publication in the *Wall Street Journal*, I assign the earlier date from the two sources as the announcement date.[8] The abnormal return is computed using the market model. First, for any stock $i$, I use the data from 300 days to 46 days before the announcement date to estimate the coefficients $(\hat{\alpha}_i,\ \hat{\beta}_i)$ from the regression:

$$R_{i,u} = \alpha_i + \beta_i R_{m,u} + \epsilon_{i,u},\ u \in [-300,\ -46] \tag{3.5}$$

where $R_{i,u}$ denotes the stock return of company $i$ on day $u$ and $R_{m,u}$ denotes the market return on day $u$. Then, I compute the abnormal return in the event window [-3, 3] as:

$$AR_{i,h} = R_{i,h} - \hat{\alpha}_i - \hat{\beta}_i R_{m,h},\ h \in [-3,\ 3] \tag{3.6}$$

The cumulative abnormal return $CAR_{i,h}$ is the cumulative sum of abnormal returns from day -3 to day $h$. For the announcement dates in month $t$,[9] I sort firms on their foreign information proxy of month $t-1$ into three groups (bottom 30%, middle 30%, and top 30%). Figure 3.1(a) displays the average cumulative abnormal returns for the top 30% group and the bottom 30% group; and Figure 3.1(b) displays the differences. The figure shows that the differences become larger around the announcement date. During the event window from day -3 to day 3, the difference of the cumulative abnormal return reaches about 1%, which is statistically significantly different from zero. A closer look of the figure shows that the largest difference of the abnormal returns between the top and bottom group is on one day preceding the announcement, but not on the date of the announcement. This evidence is more consistent with the

[8] According to DellaVigna and Pollet (2009), if I/B/E/S and Compustat announcement dates agree, after January 1990, the announcement date is usually from a newswire source. Since the sample in this paper starts from 1990, the announcement date is assigned as the I/B/E/S and Compustat date, not the previous trading date.

[9] I only include the announcement dates between the 4th and 18th in month $t$. New information also comes in every day during month $t$. As it goes to the later of month $t$, the previous month foreign information proxy may become less informative about the information to be incorporated into the prices. As a compromise between having a more informative proxy and not having a too small sample, I keep the announcement dates in the first half of the month.

salience hypothesis. It is possible that earnings announcement, as a salient event, brings attention of institutional investors. They process the information and trade on it right before the announcement. This explanation could be supported by the evidence documented in Frazzini and Lamont (2006) that institutional investors' trading volume surges one day preceding the announcement. Having said that, I can not fully rule out the information content hypothesis. Even though I try to increase the accuracy of announcement date by using two data sources, it is still possible that the date is mismeasured by -1 or +1 day. Nevertheless, the evidence using daily event time strongly supports the earnings announcement has influence on the incorporation of firms' foreign information. The pattern of the timing shows that a large amount of information is incorporated around the earnings announcement date.

[ Insert Figure 3.1 ]

### 3.3.2 Geographic Segments

The previous tests based on the foreign information proxy capture the average reaction to information across all foreign countries; I now divide foreign countries into regional segments, and explore the speed of U.S. market incorporation of information from different geographic segments. In the literature about home bias, researchers suggest that one reason that investors prefer to invest in domestic securities is that they prefer geographically proximate investments because of information advantages (Coval and Moskowitz (1999)). In the context of multinational firms, the combination of information from different geographic segments is close to exogenous, and provides a good setting for me to directly test whether distance affects investors' information procession.

As Figure 2.1 shows, Canada, the U.K., Germany, France, Japan and China are the main countries where U.S. firms operate businesses. Taking into account various factors, such as physical distance, language and culture, I naturally classify these countries into three groups: (1) English-speaking countries: Canada and the U.K.; (2) European countries: Germany and France; (3) Asian countries: Japan and China. We can roughly consider the ranking of "economic distance" between these groups and the U.S. as (from close to distant): English-speaking<European<Asian.

I then implement a portfolio test and sort the firms by decomposed information proxies which are computed separately for different segments. For example, for a U.S. automobile firm which has 30% sales from U.S. operations, 20% sales from Germany, and 50% from Canada, I compute its information proxy from English-speaking countries as 50%×Automobile industry return in Canada, and its information proxy from European countries as 20%×Automobile industry return in Germany. I first conduct the portfolio test and then exploit the response ratio method as in the analysis for earnings announcement. Directly comparing the magnitudes of abnormal returns of the Long/Short portfolio across segments may be problematic, because the returns across segments capture reactions to different ranges of information due to different sales percentages and market volatility. Normalizing the returns by long-term responses could address the problem so that the normalized returns (i.e. the response ratios) are comparable. I compute response ratios from the sorting month (month $t-1$) to month $t+1$ for each geographic segment (Table 3.3). In the initial month, stock prices respond more to information from English-speaking countries (71.09%) than that from European countries (60.45%). These two response ratios are both higher than that from Asian countries (58.21%), though the difference between European countries and Asian countries is only marginal. If I look at the delayed response, prices still react by a statistically significant amount to information from English-speaking and European countries during month $t$, while the price reaction to information from Asian countries becomes statistically significant only from month $t+1$. This result is also robust when I use a regression framework and control for the potential confounding effect of sales fraction in Appendix C.1.

[ Insert Table 3.3 ]

To better capture and visualize the dynamics of information incorporation across segments, I plot the response ratios from $t-1$ to $t+4$ for these three segments in Figure 3.2. The figure shows that for the information from English-speaking countries, stock prices respond in a large amount initially and have a relatively flat slope afterwards. The incorporation of the information from European countries has a smaller initial response but almost catches up with the response to English-speaking country information at month $t+4$. The adjustment to the information from Asian countries is even more sluggish. The cumulative response ratio for Asian information is still lower than that of the other two segments up to month $t+4$. The evidence could be consistent with a scenario as follows. Assume there are two groups of investors (sophisticated and naive) holding multinational firms' stocks and that it is not easy for sophisticated investors to fully arbitrage away predictable returns. The geographic or cultural distance may affect sophisticated investors marginally, but may add more difficulties for naive investors. It takes much longer for naive investors to process the information if the geographic or cultural distance is larger.

[ Insert Figure 3.2 ]

The evidence in this section may also be related to the post-2000 decreasing annual return of the Long/Short portfolio shown in Figure 2.3. As Figure 2.1 shows, the U.S. multinational firms largely increased their operations in Asian countries after 2000. Since the reaction to Asian information becomes significant only in the second month following the sorting month, if only sorting on the previous month foreign information proxy, the magnitude of the profit of the Long/Short portfolio will be dampened by the sluggish reaction to Asian information. But if sorting on the past 2-month foreign information proxy, we should expect a larger magnitude of the profit of the Long/Short portfolio after 2000. This hypothesis is confirmed in Figure 3.3.

[ Insert Figure 3.3 ]

### 3.3.3 Time-Varying Media Coverage

Media coverage may play a role in the transmission of foreign information as well.[10] Mass media outlets, such as newspapers, regularly cover topics about foreign affairs, politics and economics, and disseminate information to a broad audience, especially individual investors. A larger amount of foreign news coverage may give investors a better understanding of the economic, political and cultural environment in foreign countries and increase the salience and availability of news events. Therefore, investors of multinational firms can react more quickly to foreign information. In this section, I explore whether foreign news coverage relates to the profit of a trading strategy that exploits investors' inattention to foreign information. The hypothesis is that the trading strategy produces a lower profit when the foreign news coverage is higher.

I first create a news ratio of domestic news coverage over foreign news coverage to measure the relative salience of domestic news. I measure the foreign news coverage using an annual count of the number of news stories from the New York Times that contain the name of the country or its adjective form of that name, in the title or descriptions. The domestic news coverage is an annual count of words such as U.S., United States, America, Dow Jones Industrial Average, S&P, and Nasdaq.

Figure 3.4 plots the detrended time series of the news ratio of domestic over foreign news coverage. As the figure suggests, the media focus shifted back to the domestic market after the first Gulf War ended in early 1991, and maintained a high level of domestic coverage through the 1992 election period. It moved outwards again following the miracle growth of East Asian countries. The ratio of domestic over foreign news coverage reached the lowest point right before the Asian financial crisis started in 1997. After that, the media focus switched back to the U.S. market once again and peaked during the "dot-com" boom period (1999-2000). The relative salience of foreign news coverage started rising once more after 2001. The context focused more on the foreign economy after the collapse of the tech bubble in 2001 as

[10] Earlier papers provide related evidence. For example, Fang and Peress (2009) document that mass media can alleviate informational frictions and affect stock prices in the sense that the stocks with no media coverage earn higher returns given higher frictions. Klibanoff, Lamont, and Wizman (1998) show that prices of closed-end funds react more to their fundamentals when country specific news is reported on the front page of the New York Times.

well as on international relations and politics after the shift into the American war on terrorism after the tragedy on September 11, 2001.

To test whether the relative salience of foreign news affects the magnitude of investors' reactions to foreign information of multinational firms, we relate the news ratio of domestic over foreign news coverage to annual raw returns of the Long/Short portfolio in Figure 3.4. Because the Long/Short portfolio can produce higher profits when investors process foreign information more slowly, the hypothesis predicts that higher news ratio of domestic over foreign news relates to higher profit for the Long/Short portfolio. Figure 3.4 provides supportive evidence for this hypothesis. The return of the trading strategy comoves with the news ratio line. In particular, the peaks of annual return during 1999 and 2000 match well with the substantial amount of media coverage domestically on the soaring tech industry. Similarly, the big fall of annual returns during 1996 corresponds to the fact that the center of news attention was in Asian preceding the 1997 Asian financial crisis.

## 3.4 Summary Remarks

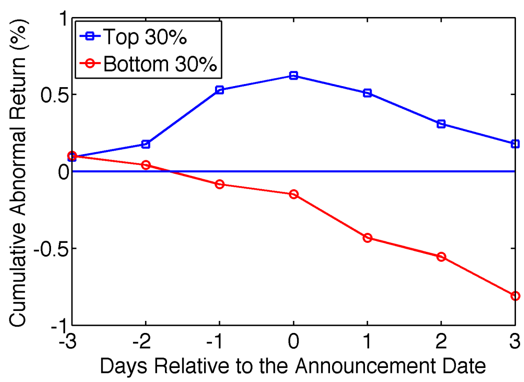
In this chapter, I examine the underlying mechanism of information processing. The evidence emphasizes that investors' limited attention and information complexity plays an important role in explaining the return predictability shown in Chapter 2. I find that investors' limited attention, the complexity of the information, and the geographic or cultural distance of the information impede the diffusion of foreign operation information, while analyst coverage and earnings reports facilitate information incorporation.

Even though investors may choose to hold a home-biased portfolio, the shareholders of multinational firms by default hold an underdiversified pseudo-international portfolio. As shown in this paper, their limited capacity and resources create difficulties in processing foreign operation information promptly. Further studies on the effect of analyst reports about global industry may identify more specific ways to facilitate information processing for these investors.

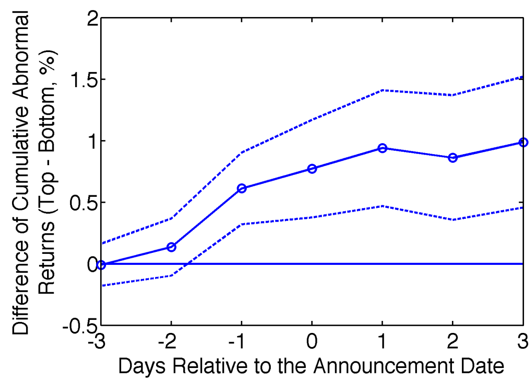
The evidence may also provide some asset pricing implications. For example, the gradual information diffusion of multinational firms' foreign operations could be a channel to create cross-country industry momentum. Integrated consideration of the share of multinational firms in the industry and the distance of the foreign countries from the U.S. may provide predictions about the magnitude of the momentum effect.

Figure 3.1: Difference between Cumulative Abnormal Returns of the Top 30% Group and Bottom 30% Group

Figure (a) plots the cumulative abnormal returns of the top and bottom quintile stocks around the announcement date. Figure (b) plots the difference between abnormal returns of the top 30% and bottom 30% stocks (solid line). In Figure (b), the dash line represents the lower and upper bounds of the 95% confidence interval. Stocks are sorted into three groups (bottome 30%, middle 40%, and top 30%) based on the level of foreign information proxy of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. In event time, day 0 is the day of the announcement. The announcement date is obtained from both Compustat and I/B/E/S databases. When the two databases disagree, the earlier date is chosen. The abnormal return for each stock is the return adjusted using the estimated beta from market model. The sample only includes the firms with the announcement is between the 4th and the 18th of each month.




(a) Cumulative Abnormal Return




(b) Difference of Cumulative Abnormal Returns

Figure 3.2: Cumulative Response Ratios: Partition on Geographic Segments

This figure shows the cumulative response ratio of the Long/Short portfolio sorted on the information of month $t-1$. For each month $t-1$, stocks are sorted into three portfolios (bottom 30%, middle 40%, and top 30%) based on the level of foreign information measures (of month $t-1$) corresponding to a specific geographical segment. The stocks are equal-weighted within portfolios. The segment information proxy is computed as the weighted sum of industry average returns in the foreign countries with operations within the corresponding segment. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The response ratio for month $\tau$ is defined as: $RR_\tau = \frac{Ret_\tau}{HPR_{t-1,t+11}}$, where $\tau = t-1,\ \ldots,\ t+5$, $Ret_\tau$ and $HPR_{t-1,t+11}$ are the month $\tau$ return and one-year holding period return from month $t-1$ to month $t+11$ of a zero-cost L/S portfolio that goes long the stocks in the top 30% and short the stocks in the bottom 30%. The figure plots the cumulative response ratio of month $\tau$ which sums up the response ratios from month $t-1$ to month $\tau$. It measures the fraction of total reaction from month $t-1$ to month $t+11$ that occurs until month $\tau$.

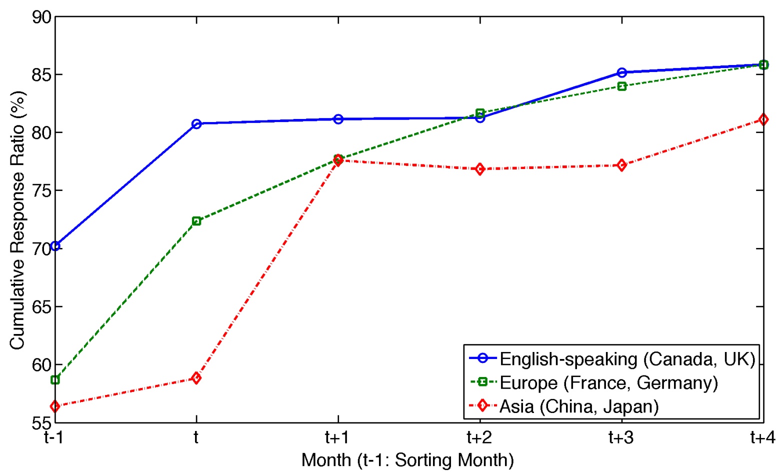


Figure 3.3: Annual Raw Return of L/S Portfolio (Sort on the 2-month Lagged Foreign Information Proxy)

The figure shows annual raw returns of the Long/Short portfolio from 1990 to 2009. The left Y axis corresponds to the percent of annual return. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxy of the previous 2 months. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The L/S portfolio is a zero-cost portfolio to go long the top quintile stocks and short the bottom quintile stocks. The annual raw return is calculated as the end-of-year profit/loss of investing $1 in the long side at the beginning of each year and rolling the portfolio monthly.

**Sort on the 2-month Lagged Foreign Information Proxy**

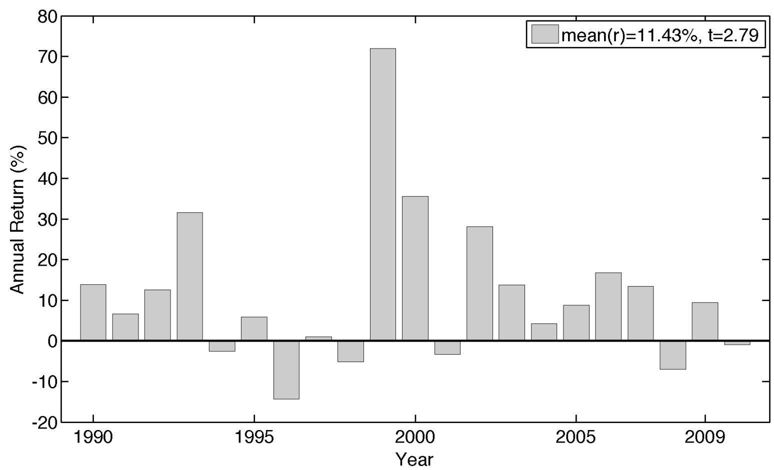


Figure 3.4: Annual Raw Return of L/S Portfolio and Domestic/Foreign News Coverage Ratio by Year

The figure shows annual raw returns of the Long/Short portfolio (gray bar) and domestic/foreign news coverage ratio (blue line) from 1990 to 2010. The left Y axis corresponds to the percent of annual return. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxy of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The L/S portfolio is a zero-cost portfolio to go long the top quintile stocks and short the bottom quintile stocks. The annual raw return is calculated as the end-of-year profit/loss of investing $1 in the long side at the beginning of each year and rolling the portfolio monthly.

The right Y axis corresponds to the news measure, which is a filtered ratio of the domestic news coverage to the foreign news coverage. The domestic news coverage is an annual count of the number of news stories from the New York Times that contain U.S., United States, America, Dow Jones Industrial Average, S&P, Nasdaq, in the title or descriptions; the foreign news coverage is a similar count of the number of news stories which contain the name of a foreign country or its adjective form. The detrended ratio is calculated by subtracting the Hodrick-Prescott filtered trend from the original domestic/foreign news coverage ratio.

**Sort on the 1-month Lagged Foreign Information Proxy**

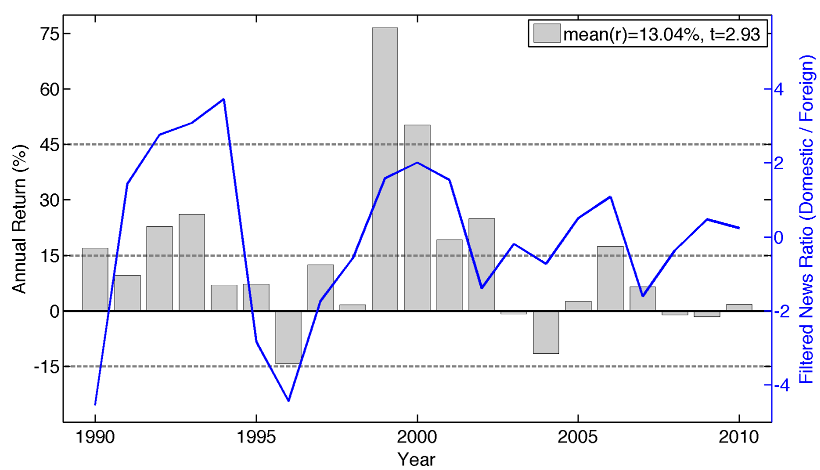


Table 3.1: Fama-MacBeth Regression of Underlying Mechanisms

This table reports the results for Fama-MacBeth regressions of stock monthly returns for the period $1990 - 2010$. Independent variables include the lagged foreign information proxy ($ForInfo_{t-1}$) and a number of interaction terms. The foreign information proxy ($ForInfo_{t-1}$) is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The interacted variables are dummies which equal to 1 when the following variables are greater than the medians: (1) *Size*: market capitalization at the end of June; (2) $f^{Foreign}$: the total foreign sales fraction; (3) *Herfindahl*: the Herfindahl index of segment sales; (4) *NumSeg*: the number of segments; (5) *AnnCov*: the analyst coverage measure which is defined as $ln(1 + NumEst)$, where *NumEst* is the number of earnings forecasts are reported by analysts and recorded in I/B/E/S; (6) $AnnCov^{Res}$: the analyst coverage measure orthogonalized with regard to firm size; (7) *InstiOwn*: the institutional ownership which are obtained from Thomson-Reuters Institutional Holdings (13F) Database; (8) $InstiOwn^{Res}$: the institutional ownership orthogonalized with regard to firm size; *ForeignInstiHold*: the foreign institutional ownership, which are also obtained from Thomson-Reuters Institutional Holdings (13F) Database. All specifications also include the dummy itself and other control variables, the lagged U.S. industry return ($USIndRet_{t-1}$), the lagged world industry return (excluding U.S. market) ($WUIndRet_{t-1}$), the contemporaneous foreign country specific industry return ($ForIndRet_t$), the contemporaneous U.S. industry return ($USIndRet_t$), the firm's lagged stock monthly return ($Ret_{t-1}$), the firm's lagged cumulative return from $t - 12$ to $t - 2$ ($Ret_{(t-12,t-2)}$), the size of the firm measured by the log of market value, the log of book-to-market ratio and the total sales fraction from foreign operations. The standard errors are computed with a Newey-west correction with 12 lags. Fama-MacBeth t-statistics are reported within parentheses. $^{*}$10%, $^{**}$5%, $^{***}$1% significance.

**Panel A - Information Proxy Measured by Levels**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: | | | | | | $Ret_t(\%)$ | | | | |
| *Mech Dummy* Based On: | Original | Original | Residual | Original | Residual | Original | Original | Original | Original | Original |
| $ForInfo_{t-1}$ | 0.0808*** | 0.0796*** | 0.0738*** | 0.0923*** | 0.0764*** | 0.212*** | 0.114** | 0.0211 | 0.354*** | 0.290*** |
| | (0.0273) | (0.0245) | (0.0204) | (0.0263) | (0.0216) | (0.0526) | (0.0541) | (0.0176) | (0.0733) | (0.0694) |
| $ForInfo_{t-1}$ $\times(Size > Median)$ | -0.0662** | | | | | | | | -0.0801** | -0.0803** |
| | (0.0321) | | | | | | | | (0.0368) | (0.0368) |
| $ForInfo_{t-1}$ $\times(AnnCov > Median)$ | | -0.0589*** | -0.0550** | | | | | | -0.0712*** | -0.0679** |
| | | (0.0220) | (0.0245) | | | | | | (0.0273) | (0.0271) |
| $ForInfo_{t-1}$ $\times(InstiHold > Median)$ | | | | -0.0945*** | -0.0603* | | | | -0.0501** | -0.0510** |
| | | | | (0.0288) | (0.0330) | | | | (0.0230) | (0.0236) |
| $ForInfo_{t-1}$ $\times(f^{Foreign} > Median)$ | | | | | | -0.148** | | | -0.177*** | -0.189*** |
| | | | | | | (0.0571) | | | (0.0576) | (0.0588) |
| $ForInfo_{t-1}$ $\times(Herfindahl > Median)$ | | | | | | | -0.0947* | | -0.0899** | |
| | | | | | | | (0.0536) | | (0.0396) | |
| $ForInfo_{t-1}$ $\times(NumSeg > Median)$ | | | | | | | | 0.0467 | | 0.0780*** |
| | | | | | | | | (0.0350) | | (0.0289) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| R-sq | 0.069 | 0.069 | 0.067 | 0.068 | 0.068 | 0.070 | 0.063 | 0.065 | 0.072 | 0.072 |

**Panel B - Information Proxy Measured by Quantile groups**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: | $Ret_t(\%)$ | | | | | | | | | |
| *Mech Dummy* Based On: | Original | Original | Residual | Original | Residual | Original | Original | Original | Original | Original |
| Quintile Group of $ForInfo_{t-1}$ | 0.204*** | 0.217*** | 0.189*** | 0.195*** | 0.168*** | 0.249*** | 0.189*** | 0.0547 | 0.485*** | 0.373*** |
| | (0.0554) | (0.0559) | (0.0434) | (0.0424) | (0.0395) | (0.0642) | (0.0703) | (0.0391) | (0.0956) | (0.0986) |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(Size > Median)$ | -0.120* | | | | | | | | -0.161* | -0.165* |
| | (0.0611) | | | | | | | | (0.0966) | (0.0977) |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(AnnCov > Median)$ | | -0.159*** | -0.130** | | | | | | -0.108* | -0.102* |
| | | (0.0552) | (0.0623) | | | | | | (0.0606) | (0.0605) |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(InstiHold > Median)$ | | | | -0.105** | -0.0658 | | | | -0.0863* | -0.0793* |
| | | | | (0.0413) | (0.0581) | | | | (0.0457) | (0.0457) |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(f^{Foreign} > Median)$ | | | | | | -0.149* | | | -0.128* | -0.140* |
| | | | | | | (0.0760) | | | (0.0694) | (0.0729) |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(Herfindahl > Median)$ | | | | | | | -0.143** | | -0.130* | |
| | | | | | | | (0.0711) | | (0.0700) | |
| Quintile Group of $ForInfo_{t-1}$ $\times$ $(NumSeg > Median)$ | | | | | | | | 0.114* | | 0.139* |
| | | | | | | | | (0.0644) | | (0.0804) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 | 252 |
| R-sq | 0.064 | 0.064 | 0.062 | 0.063 | 0.062 | 0.064 | 0.062 | 0.064 | 0.067 | 0.066 |

**Panel C: Variation in Foreign Institutional Ownership (2000-2010)**[11]

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: | | | $Ret_t(\%)$ | | | |
| Foreign Information Proxy Measured by: | Level | Level | Level | Quantile | Quantile | Quantile |
| $ForInfo_{t-1}$ | 0.0749** | 0.101*** | 0.247*** | 0.197** | 0.280** | 0.426* |
| | (0.0330) | (0.0350) | (0.0875) | (0.0900) | (0.114) | (0.244) |
| $ForInfo_{t-1} \times (ForeignInstiHold > Median)$ | -0.0825*** | -0.0599*** | -0.0658** | -0.198** | -0.148* | -0.171* |
| | (0.0216) | (0.0225) | (0.0261) | (0.0827) | (0.0862) | (0.0985) |
| $ForInfo_{t-1} \times (InstiHold > Median)$ | | -0.0682** | -0.0871** | | -0.174** | -0.195** |
| | | (0.0281) | (0.0417) | | (0.0775) | (0.0833) |
| Interaction Terms with Other Mechanisms | No | No | Yes | No | No | Yes |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Months | 126 | 126 | 126 | 126 | 126 | 126 |
| R-sq | 0.086 | 0.088 | 0.096 | 0.080 | 0.083 | 0.090 |

[11] The sample is from July 2000 to Dec 2010. The reason is that the data of the foreign institutional ownership is available since 1999, and the data of Dec 1999 is matched with stock returns from July 2000 to June 2001.

Table 3.2: Response Ratios: Effects of Quarterly Earnings Announcement

This table shows the effects of quarterly earnings announcement on the pattern of firms' reaction to foreign information. For each month $t-1$, stocks are sorted into three portfolios (bottome 30%, middle 40%, and top 30%) based on the level of foreign information proxies of that month (month $t-1$). The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The table reports the month $t-1$ return ($Ret_{t-1}$), month $t$ return ($Ret_t$), month $t+1$ return ($Ret_{t+1}$) and one-year holding period return from month $t-1$ to month $t+11$ ($HPR_{t-1,t+11}$) of a zero-cost L/S portfolio that goes long the stocks in the top 30% and short the stocks in the bottom 30%. The stocks are equal-weighted within portfolios. The response ratios are defined as: $RR_{t-1} = \frac{Ret_{t-1}}{HPR_{t-1,t+11}}$, $RR_t = \frac{Ret_t}{HPR_{t-1,t+11}}$, $RR_{t+1} = \frac{Ret_{t+1}}{HPR_{t-1,t+11}}$, which measure the fraction of total reaction from month $t-1$ to month $t+11$ that occurs in month $t-1$, month $t$ and month $t+1$ respectively. The results are reported by three groups, depending on whether there is quarterly earnings report announced in month $t$ or month $t-1$. $Announcement_t$ equals 1 if quarterly earnings is reported in month $t$. The Returns are in monthly percent. t-statistics are shown in parentheses. The t-statistics for $RR_{t-1}$ represents the distance of the coefficient from 1, otherwise, the t-statistics represents the distance of the coefficient from 0. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) |
|---|---|---|---|
| | $Announcement_{t-1} = 1$<br>$Announcement_t = 0$ | $Announcement_{t-1} = 0$<br>$Announcement_t = 1$ | $Announcement_{t-1} = 0$<br>$Announcement_t = 0$ |
| Sorting-month Monthly Return | 3.899*** | 3.813*** | 4.956*** |
| of L/S Portfolio, $Ret_{t-1}^{L/S}$ (%) | (12.80) | (11.37) | (20.46) |
| 1-month Subsequent Monthly Return | 0.275 | 0.932*** | 0.746*** |
| of L/S Portfolio, $Ret_t^{L/S}$ (%) | (0.85) | (3.45) | (3.22) |
| 12-month Holding Period Return | 4.920*** | 6.006*** | 7.833*** |
| of L/S Portfolio, $HPR_{t-1,t+11}^{L/S}$ (%) | (4.71) | (5.57) | (8.95) |
| Initial Response Ratio [12] | 79.25% | 63.49%*** | 63.27%*** |
| of L/S Portfolio, $RR_{t-1}$ | (1.26) | (3.35) | (5.21) |
| 1-month Delayed Response Ratio | 5.59% | 15.52%*** | 9.522%*** |
| of L/S Portfolio, $RR_t$ | (0.89) | (3.35) | (3.29) |

[12] The t-stat for $RR_{t-1}$ represents the distance of the ratio from 1.

Table 3.3: Response Ratios: Partition on Geographic Segments

For each month $t-1$, stocks are sorted into three portfolios (bottom 30%, middle 40%, and top 30%) based on the level of information proxy (of month $t-1$) corresponding to a specific geographical segment. The segment information proxy is computed as the weighted sum of industry average returns in the foreign countries with operations within the corresponding segment. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The table reports the month $t-1$ return ($Ret_{t-1}$), month $t$ return ($Ret_t$), month $t+1$ return ($Ret_{t+1}$) and one-year holding period return from month $t-1$ to month $t+11$ ($HPR_{t-1,t+11}$) of a zero-cost L/S portfolio that goes long the stocks in the top 30% and short the stocks in the bottom 30%. The stocks are equal-weighted within portfolios. The response ratios are defined as: $RR_{t-1} = \frac{Ret_{t-1}}{HPR_{t-1,t+11}}$, $RR_t = \frac{Ret_t}{HPR_{t-1,t+11}}$, $RR_{t+1} = \frac{Ret_{t+1}}{HPR_{t-1,t+11}}$, which measure the fraction of total reaction from month $t-1$ to month $t+11$ that occurs in month $t-1$, month $t$ and month $t+1$ respectively. Returns are in monthly percent. t-statistics are shown in parentheses. The t-statistics for $RR_{t-1}$ represents the distance of the coefficient from 1, otherwise, the t-statistics represents the distance of the coefficient from 0. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) |
|---|---|---|---|
| | English-Speaking (Canada, UK) | Europe (France, Germany) | Asia (China, Japan) |
| Sorting-month Monthly Return of L/S Portfolio ($Ret^{L/S}_{t-1}$ (%)) | 4.513*** | 3.045*** | 3.147*** |
| | (15.51) | (8.719) | (7.701) |
| 1-month Subsequent Monthly Return of L/S Portfolio ($Ret^{L/S}_{t}$ (%)) | 0.675** | 0.710** | 0.285 |
| | (2.505) | (2.572) | (0.404) |
| 2-month Subsequent Monthly Return of L/S Portfolio ($Ret^{L/S}_{t+1}$ (%)) | 0.026 | 0.276 | 0.959** |
| | (0.125) | (0.688) | (2.522) |
| 12-month Holding Period Return ($HPR^{L/S}_{t-1,t+11}$ (%)) | 6.348*** | 5.037*** | 5.406*** |
| | (7.227) | (4.730) | (3.164) |
| Initial Response Ratio ($RR_{t-1}$) | 71.09%*** | 60.45%** | 58.21%** |
| | (3.757) | (2.323) | (2.037) |
| 1-month Delayed Response Ratio ($RR_t$) | 10.65%*** | 14.09%*** | 5.28% |
| | (2.602) | (2.662) | (0.417) |
| 2-month Delayed Response Ratio ($RR_{t+1}$) | 0.41% | 5.48% | 17.74%** |
| | (0.125) | (0.705) | (2.567) |

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# Appendix A

# Industry Investment Experience and Stock Selection

## A.1 Details on Processing Data

I implement some restrictions to select the trading records related to the empirical analysis in this paper, and during the process of combing trading records data with SIC code or price data from CRSP or Compustat, I have to eliminate some observations with missing data. This Appendix details the steps I took to get the final subsample used in this paper.

Before combining with data from other datasets, I select the trading records through three steps. First, among the trades of various investments, I only retain those related to investors' direct investments on common stock. Second, I remove the observations of households if there are inconsistent buy/sell records and quantity records for their trades. For example, the trading activity is recorded as "B(uy)" (or "S(ell)"), while the quantity of that trade is recorded as a negative number (or a positive number). Third, I eliminate the observations of households if the households have trades including short sell, more specifically, if they once had negative cumulative shares on some stocks.

The next step is to combine the trading records with SIC code from CRSP and Compustat. As I described before, I get the Cusips for the stocks invested and match them first with CRSP, and then with Compustat if I can't find a match in CRSP. Only all the investments of the household could match with a SIC code either from CRSP or Compustat, the observations of this household will be selected into the final subsample used for the baseline regression.

In other analysis (variation in sophistication, time horizon or categorization), due to missing data of specific related variables, I have to further restrict the sample.

Table A.1: Number of Households Retained after Each Refinement

| | Number of Households |
|---|---|
| With direct investments on common stocks | 66,465 |
| Without inconsistent buy/sell records and quantity records | 62,554 |
| Without short-selling trades | 54,210 |
| Without missing SIC code | 47,793 |

Through robustness check, basic summary statistics and main results remain the same with different samples.

# Appendix B

# Market Underreaction to Foreign Information

## B.1 Global Industry Momentum

Moskowitz and Grinblatt (1999b) document a strong and prevalent momentum effect in industry component of stock returns in the U.S. market. It is plausible to infer that industry momentum still exists if I extend the market globally. Since my focus multinational firms relates to the information in the international context, the potential existence of industry momentum in a more general setting may confound with the return predictability I want to test. This appendix provides some evidence that the industry momentum can be extended to the global market which is relevant to the price valuation of multinational firms, and hence it is crucial to control for the global industry momentum to check the robustness of the predictive power of the foreign information proxy.

I also include the firms that only operate in the U.S. market in the sample and report the results both for the subsample of domestic and multinational firms and for the overall sample in Table B.1. The coefficients on past U.S. industry returns and past global (excluding U.S.) returns are both significantly positive no matter using the overall sample or subsample. The magnitude of coefficients for domestic and multinational firms implies that the global industry momentum may matter more for multinational firm. I then add two interaction terms between past industry returns ($USIndRet_{t-1}$ and $WUIndRet_{t-1}$) and a multinational dummy to explore the importance of these two momentums to these two types of firms. The significantly positive coefficient on the interaction term between past global industry returns and the multinational firm dummy confirms that the global industry momentum is more pronounced among multinational firms.

[ Insert Table B.1 ]

## B.2 Robustness Test: Standalone Firms

Cohen and Lou (2011) find that the processing complexity of conglomerate firms leads to a significant delay of information impounding into asset prices. Given that multinational firms are likely to be conglomerates, it is possible that the predictability by foreign information proxy is caused by the complexity of industry diversification rather than the inattention to foreign information or the complexity of geographic diversification. To filter out the effect of processing complexity of industry diversification, I conduct the portfolio test of return predictability for a restricted sample which only includes standalone multinational firms[1], i.e. those operating only in one industry but in multiple countries. If it is actually the complexity of industry diversification that causes the predictability while the complexity of geographic diversification plays no role, the portfolio constructed solely by standalone multinational firms will not have positive abnormal returns.

According to Table B.2, the return predictability remains when the sample is restricted to the standalone firms. The abnormal return of the trading strategy based on sorting foreign information proxy is significantly positive. After controlling for Carhart (1997) four risk factors, the equal-weighted Long/Short portfolio creates 0.71 (t = 2.20) percentage point monthly abnormal return and the value-weighted Long/Short portfolio creates 0.62 (t = 1.78) percentage point monthly. To only look at this subsample isolates the influence of the complexity of geographic diversification. The magnitude of profits based on standalone firms is slightly lower than those created by the portfolios using the whole sample, which suggests the industry diversification may also contribute to the slow information incorporation for the whole sample but only in a small amount. Therefore, the evidence provides additional support that inattention to foreign information or the complexity of geographic diversification plays an important role in delaying the incorporation of foreign operations information.

[ Insert Table B.2 ]

[1] The standalone firms are identified as those with only one industry segment reported in Compustat segment files and the segment sales reported in Compustat segment files account for more than 80% of the total sales reported in Compustat annual files

## Table B.1: Fama-MacBeth Regression of Global Industry Momentum

This table reports the results for Fama-MacBeth OLS regressions of stock monthly returns for the period $1990 - 2010$. The dependent variable is the monthly return of multinational firms (Column (1)), domestic firms (Column (2)) and all CRSP universe (Column (3) and (4)). The explanatory variables include the firm's lagged stock monthly return, the lagged U.S. return of the corresponding industry ($USIndRet_t$), the lagged world return (excluding U.S. market) of the corresponding industry ($WUIndRet_t$), the size of the firm measured by the log of market value, and the log of book-to-market ratio. *Multinational* is a dummy that equals 1 if the firm has operations abroad. The standard errors are computed with a Newey-west correction with 12 lags. Fama-MacBeth t-statistics are reported within parentheses. $^{*}$10%, $^{**}$5%, $^{***}$1% significance.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | | $Ret_t(\%)$ | | |
| Sample | Multinational Firms | Domestic Firms | All Firms | All Firms |
| $USIndRet_{t-1}$ | 0.0693*** | 0.0893*** | 0.0888*** | 0.0893*** |
| | (0.0246) | (0.0218) | (0.0217) | (0.0218) |
| $WUIndRet_{t-1}$ | 0.114*** | 0.0724** | 0.0774** | 0.0689** |
| | (0.0358) | (0.0317) | (0.0316) | (0.0307) |
| $USIndRet_{t-1} \times MultiNational$ | | | | -0.0225 |
| | | | | (0.0152) |
| $WUIndRet_{t-1} \times MultiNational$ | | | | 0.0516** |
| | | | | (0.0248) |
| Control Variables | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 |
| R-sq | 0.053 | 0.052 | 0.051 | 0.052 |

Table B.2: Predictability by Foreign Information Proxy: Standalone Firms

This table shows abnormal returns of calendar time portfolio. The sample is restricted to standalone multinational firms, which operate in only one industry but multiple countries. Similar to Cohen and Lou (2011), I remove the firms if the segment sales reported in Compustat segment files account for less than 80% of the total sales reported in Compustat annual files. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxies of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the foreign countries that the firm has business with. The weight is the fraction of total sales from the operations in the corresponding foreign country in the last fiscal year. The portfolios are rebalanced every month as equally weighted or value weighted. The abnormal return is the intercept on a regression of monthly excess return from the rolling strategy on market excess return, Fama-French three factors (Fama and French (1993)) and Carhart four factor (Carhart (1997)). L/S is the abnormal return of a zero-cost portfolio that goes long the stocks in the top quintile and short the stocks in the bottom quintile. Returns are in monthly percent, t-statistics are shown below the coefficient estimates. *10%, **5%, ***1% significance.

| Panel A: Equally Weighted | Q1 (Low ForInfo) | Q2 | Q3 | Q4 | Q5 (High ForInfo) | L/S |
|---|---|---|---|---|---|---|
| Market | -0.425 | -0.334 | 0.00206 | 0.339 | 0.377 | 0.803** |
| | (-1.63) | (-1.62) | (0.01) | (1.64) | (1.48) | (2.54) |
| Fama-French 3 Factor | -0.500** | -0.457*** | -0.0321 | 0.230 | 0.336 | 0.836*** |
| | (-2.11) | (-2.79) | (-0.23) | (1.44) | (1.54) | (2.65) |
| Carhart 4 Factor | -0.367 | -0.385** | 0.0647 | 0.326** | 0.342 | 0.709** |
| | (-1.54) | (-2.31) | (0.45) | (2.05) | (1.51) | (2.20) |
| **Panel B: Value Weighted** | **Q1 (Low ForInfo)** | **Q2** | **Q3** | **Q4** | **Q5 (High ForInfo)** | **L/S** |
| Market | -0.200 | -0.417* | -0.0376 | 0.645*** | 0.455* | 0.655* |
| | (-0.76) | (-1.86) | (-0.19) | (2.82) | (1.74) | (1.93) |
| Fama-French 3 Factor | -0.257 | -0.471** | -0.0154 | 0.623*** | 0.501** | 0.758** |
| | (-1.03) | (-2.41) | (-0.10) | (3.16) | (2.17) | (2.23) |
| Carhart 4 Factor | -0.149 | -0.412** | 0.00118 | 0.657*** | 0.469* | 0.618* |
| | (-0.58) | (-2.14) | (0.01) | (3.32) | (1.94) | (1.78) |

# Appendix C

# Underlying Mechanisms of Investors' Inattention

## C.1 Regression Results of Effects of Geographic Segments

I also test in a regression framework how price adjustments to information vary across different geographic segments. In doing this, I could account for the confounding effect of sales fraction, which is shown to have effects on the return predictability in Section 3.2.5. I run the following specification for both one-month-ahead and two-month-ahead prediction: [1]

$$\begin{aligned} Ret_{ij\tau} =& \alpha + \sum_s \beta_{1s} GeoSegInfo^s_{ij,t-1} + \sum_s \beta_{2s} \frac{GeoSegInfo^s_{ij,t-1}}{ForInfo_{ij,t-1}} + \sum_s \delta_{1s} ForInfo_{ij,t-1} \times f^s_{ij,t-1} \\ &+ \sum_s \delta_{2s} f^s_{ij,t-1} + X'_{ij,\tau-1}\gamma + \epsilon_\tau \qquad \text{(C.1)} \\ &(\tau = \{t,\ t+1\};\ \text{s=\{English-speaking countries, Europe, Asia, Other\}}) \end{aligned}$$

The regression results are shown in Table C.1. As for the one-month-ahead prediction, the information from European countries and Other countries dominates the information from English-speaking to predict returns. Combined with the two-month-ahead prediction, I find that investors react to Asian information even more

[1] $GeoSegInfo^s_{t-1}$ could be regarded as the interaction between $ForInfo_{t-1}$ and $\frac{GeoSegInfo^s_{t-1}}{ForInfo_{t-1}}$, so I include the base term $\frac{GeoSegInfo^s_{t-1}}{ForInfo_{t-1}}$ in the regression. $ForInfo_{t-1}$ is not included because $\sum_s GeoSegInfo^s_{t-1} = ForInfo_{t-1}$.

sluggishly, because, for two-month-ahead returns, only Asian information has predictive power. Besides, the larger magnitude of return effects of Asian information relative to the information from Europe and English-speaking countries also indicates smaller initial reaction to Asian information. The results are not driven by the sales percentage from the corresponding segment, because the results remain unchanged when I include the interaction term with sales percentage. Therefore, the evidence in Table C.1 provides additional support to the heterogeneity of incorporation speeds of information from different geographic segments, which is not driven by the sales percentage from that segment but may relate to the geographic or culture distance.

[ Insert Table C.1 ]

Table C.1: Fama-MacBeth Regression of Return Predictability: Decomposed by Geographic Segments

This table reports the results for Fama-MacBeth regressions of stock monthly returns for the period 1990−2010. The dependent variable is monthly return one month ahead ($Ret_t$) or two months ahead ($Ret_{t+1}$). Independent variables include the lagged information proxy for geographic segments (English-speaking countries, European countries, Asian countries and others). These information proxies ($EngInfo_{t-1}$, $EuroInfo_{t-1}$, $AsiaInfo_{t-1}$, $OtherInfo_{t-1}$) are computed as the weighted sum of industry average returns in the foreign countries with operations within the corresponding geographci segment. The weight is the ratio of sales to the corresponding foreign country to the total sales of the firm in the last fiscal year. The ratio of segment information proxy to $ForInfo_{t-1}$ is also included. Other control variables include dummies which equal to 1 when the sale fraction from the corresponding segment is less than 5%, the lagged U.S. industry return ($USIndRet_{t-1}$), the lagged world industry return (excluding U.S. market) ($WUIndRet_{t-1}$), the contemporaneous foreign country specific industry return ($ForIndRet_t$), the contemporaneous U.S. industry return ($USIndRet_t$), the firm's lagged stock monthly return ($Ret_{t-1}$), the firm's lagged cumulative return from $t-12$ to $t-2$ ($Ret_{(t-12,t-2)}$), the size of the firm measured by the log of market value, the log of book-to-market ratio and the total sales fraction from foreign operations. Column (2) and (4) also control for the sales fraction of each geographic segment, by adding the interaction term between $ForInfo_{t-1}$ and the sales fraction from the corresponding segment as well as the sales fraction itself.[2] The standard errors are computed with a Newey-west correction with 12 lags. Fama-MacBeth t-statistics are reported within parentheses. *10%, **5%, ***1% significance.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: | $Ret_t$(%) | $Ret_t$(%) | $Ret_{t+1}$(%) | $Ret_{t+1}$(%) |
| $EngInfo_{t-1}$ | 0.0393 | -0.0169 | -0.0705 | -0.0696 |
| | (0.0478) | (0.0725) | (0.0539) | (0.0697) |
| $EuroInfo_{t-1}$ | 0.247** | 0.293*** | -0.0790 | -0.114 |
| | (0.113) | (0.112) | (0.167) | (0.218) |
| $AsiaInfo_{t-1}$ | -0.0426 | -0.0214 | 0.586** | 0.764** |
| | (0.328) | (0.353) | (0.266) | (0.358) |
| $OtherInfo_{t-1}$ | 0.123** | 0.155** | -0.0967 | -0.133 |
| | (0.0612) | (0.0705) | (0.0994) | (0.135) |
| $DomInfo_{t-1}$ | 0.0102 | 0.0364 | 0.0462 | 0.0430 |
| | (0.0372) | (0.0349) | (0.0474) | (0.0562) |
| Control for Sales Fraction | No | Yes | No | Yes |
| Other Controls | Yes | Yes | Yes | Yes |
| Number of Months | 252 | 252 | 252 | 252 |
| R-sq | 0.084 | 0.087 | 0.081 | 0.086 |

[2] All these lagged control variables are moved forward one month correspondingly for column (3) and (4) when the dependent variable is $Ret_{t+1}$.