Thinking Outside the Borders: Investors' Inattention to Foreign Operations

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Abstract

Using the corresponding industry return in the foreign countries, I show that the foreign operations information of multinational firms is slowly incorporated into stock prices. A trading strategy based on this effect generates an abnormal return of approximately 0.8% per month, or 9.6% per year, 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, nor can be explained by the future change of risks. The predictability becomes more pronounced for smaller and more opaque firms, and firms with lower fraction of foreign operations and more geographic segments. I also find that stock prices respond more to foreign operations information around quarterly earnings announcements 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.

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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

[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%.

a home-biased portfolio because of the lack of information advantage, 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. 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. Interestingly, the time series dynamics of annual returns of this 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.

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 (1999) 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.

In addition to examining the hypothesis that foreign operations information is slowly incorporated into stock prices, I seek to understand what mechanisms affect this process. I 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

[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).

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, Lim, and Stein (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,[3] I argue that investors are more 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.

Next, 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.

In a more precise way, I examine the role of quarterly earnings announcements in fa-

[3] 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).

cilitating 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.

Finally, 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.

This paper contributes to the literature on information diffusion in the stock market due to investors' limited attention[4] and limited information processing capacity[5]. 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 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

[4] 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).

[5] Cohen, Diether, and Malloy (2011), Cohen and Lou (2011), and DellaVigna and Pollet (2007).

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.[6] 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 the paper is organized as follows. Section 2 describes the data, methods and summary statistics. Section 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. I then explore a variety of underlying mechanisms in Section 4. Section 5 concludes.

2 Data and Methods

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)

[6] 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.

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.[7]

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.[8] 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 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.

[7]As documented by Denis, Denis, and Yost (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.

[8]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.

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:

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

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,[9] 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:

$$InfoProxy_{\ UCG,Auto,t-1}(Foreign) = 20\% \times R^{Canada}_{Auto,t-1} + 50\% \times R^{Germany}_{Auto,t-1} \tag{2}$$

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, I impose at least a 6-month gap between fiscal year end and formation time,[10] 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.[11]

Similarly, I compute the information proxy for another geographic segment definition, which will be used to compare information incorporation speed across different geographic

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

[10] Other papers in the literature also impose such a 6-month lag, including Cohen and Frazzini (2008), Cohen and Lou (2011), and Cohen, Diether, and Malloy (2011)

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

segments. The information proxy for segment Ω is:

$$InfoProxy_{i,j,t-1}(\Omega) = \sum_{c\in\Omega} f^c_{i,t-1} R^c_{j,t-1} \tag{3}$$

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:

$$InfoProxy_{\ UCG,Auto,t-1}(\Omega_{U.S.}) = 30\% \times R^{U.S.}_{Auto,t-1} \tag{4}$$

$$InfoProxy_{\ UCG,Auto,t-1}(\Omega_{Eng}) = 20\% \times R^{Canada}_{Auto,t-1} \tag{5}$$

2.3 Summary Statistics

Table 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 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 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 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 1]

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.

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. 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.[12] 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)).[13] Table 2 reports the alphas (intercepts) of the five quintile portfolios and the Long/Short portfolio. The results for both equal-weighted and value-weighted portfolios are reported.

[Insert Table 2]

As shown in Table 2 and also in Figure 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.[14] Specifically, after controlling for Carhart (1997) four risk factors, I obtain 0.80 ($t = 3.13$) percentage point monthly abnormal return

[12] 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(c) shows, the average fraction of foreign operations is slightly higher for the top and bottom quintiles relative to the middle three quintiles.

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

[14] 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.

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. The results remain the same if I control for global risk factors instead of U.S. risk factors (Appendix Table A.1). The magnitude of abnormal returns becomes even larger. Besides, we could also notice that 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 Section 4.

[Insert Figure 2]

I also report the factor loadings using the Carhart (1997) four factor model in Table 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 3]

Figure 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 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 3]

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:

$$Ret_{ijt} = \alpha + \beta_1 ForInfo_{ij,t-1} + \beta_2 DomInfo_{ij,t-1} + X'_{ij,t-1}\gamma + \epsilon_{ijt} \tag{6}$$

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 $t-1$,[15] 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 β_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(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:[16]

$$Ret_{ijt} = \alpha + \beta_1 QFI_{ij,t-1} + \beta_2 QDI_{ij,t-1} + X'_{ij,t-1}\gamma + \epsilon_{ijt} \tag{7}$$

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 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));[17] (2) the previous month stock

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

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

[17] 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.

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.

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.[18] As Moskowitz and Grinblatt (1999) 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 countries, it may be correlated with the global industry return and hence predict returns of multinational firms given the global industry momentum.

Table 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

[18] 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.

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.

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.

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.[19] 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.

[19] 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 ($GlobalInfo_{ij,t-1}^{Country}$). 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.

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.

$$ForIndRet_{ijt} = \sum_{c \neq US} \frac{f_{ijt}^c}{\sum_{c \neq US} f_{ijt}^c} R_{jt}^c = \frac{ForInfo_{ijt}}{\sum_{c \neq US} f_{ijt}^c} \tag{8}$$

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 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 $ForInfo_{ijt}$ 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 $ForInfo_{ij,t-1}$.[20] Therefore, I also include controls for current information in the

[20]Conceptually, let us think of a case when there are only two periods($t = 1, 2$). A dividend $w_f F_1 +$

following analysis in this paper.

[Insert Table 4]

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, Engelberg, and Gao (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.[21]

I plot the cumulative abnormal return (Carhart alpha) of a Long/Short portfolio over a long horizon in Figure 4. At the beginning of month t, I form the Long/Short portfolio based on sorting stocks' foreign information proxies (Figure 4(a)) or domestic information proxy (Figure 4(b)) in month $t-1$. For each event time τ, I regress the returns of the Long/Short portfolios on the Carhart (1997) four factors:

$$R^{L/S}_{t-1+\tau} = \alpha_\tau + \beta_\tau(R_{m,t-1+\tau} - R_f) + s_\tau SMB_{t-1+\tau} + h_\tau HML_{t-1+\tau} + m_\tau MOM_{t-1+\tau} + \varepsilon_{t-1+\tau} \quad (9)$$

where $R^{L/S}_{t-1+\tau}$ denotes the month $t-1+\tau$ return of a Long/Short portfolio sorted on the information proxy of month $t-1$. The cumulative abnormal return for each month k is the sum of the alphas from 1 month after the formation time to k months after the formation time:

$$\sum_{\tau=1}^{k} \alpha_\tau, \quad k = 1, ..., 36 \quad (10)$$

The 90% confidence intervals are also plotted.

As Figure 4(a) shows, the Long/Short (value-weighted) portfolio produces around 0.8%

$(1-w_f)D_1 + \varepsilon_2$ will be paid out at $t=2$, where F_1, D_1, ε_2 are independent and all have expectation zero. ε_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 θ_f of investors pay attention to signals of F_1, and only θ_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 θ_f. The current innovation ε_2 adds errors on the estimation which could be reduced by controlling for the current innovation.

[21] Similar return reversals can be found in Dougal, Engelberg, Garcia, and Parsons (2011), Tetlock (2007), and Tetlock (2011).

return in the first month. The cumulative abnormal return keeps climbing after the first month, though with a lower monthly rate, reaches the peak value of roughly 3% around 1 year 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 36 months after the formation date. The cumulative alpha is significantly positive even in the long run. This evidence supports the underreaction of the stock market to multinational firms' foreign operation information.

As a comparison, in Figure 4(b), 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 around 13 months after the formation time. 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 4]

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 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 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 5]

3.5 Risk Explanation

In this subsection, I study the possibility of a risk explanation - foreign information proxy predicts the future change of risk, which leads to the change of expected returns. In this case, the pattern in returns reflects compensation for risk rather than an underreaction to foreign information.

I start from examining the event time variation in stock risks with regards to the Carhart (1997) four factors, over 6 months prior to the sorting month to 36 months after. If time-varying loadings on the four factors is to explain the return patterns, we would expect the risk exposures to increase after the sorting month for firms with higher foreign information proxy. For each of the event months, we construct a Long/Short portfolio by going long the stocks in the top quintile and short the stocks in the bottom quintile of foreign information proxy measured in the sorting month. Then I estimate the factor loadings for each event time.

Figure 5 shows the estimated factor loadings in event time. The loadings on these four factors are quite small through the 42 months around the sorting month. The magnitudes of the loadings are generally smaller than 0.2 for all four factors and are not statistically significantly different from zero. I find no evidence of significant time variation in these loadings, which suggests that the higher returns for firms with higher previous foreign information proxy do not come from compensation for the risks with regard to the market, size, value or momentum factors.

Another possibility of a risk explanation is that foreign information proxy predicts the future change of other potential risks rather than these four systematic factors. For example, higher foreign industry returns may indicate an increase of competitiveness of the domestic firms in the foreign countries. Stronger competitors in the local economy may bring more uncertainty to the local business operated by the U.S. multinational firms. The increase of risk would also require a higher expected return. To examine whether the future change of returns could be explained by the future change of risks, we could look at the contemporaneous change of returns. If the return predictability comes from any risk explanation, we would expect the contemporaneous returns decrease for the firms with higher foreign information proxy. However, this is not supported by the data - the coefficient on contemporaneous foreign information proxy is significantly positive as shown in Column (4) of Table 4.

4 Underlying Mechanisms

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 section, I explore what factors affect the incorporation speed of foreign operation information through testing the magnitude of return predictability of the foreign information proxy.

4.1 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 ($Mechanism_{ij,t-1}$):

$$\begin{aligned} Ret_{ijt} =& \alpha + \beta_1 ForInfo_{ij,t-1} + \beta_2 Mechanism_{ij,t-1} + \beta_3 ForInfo_{ij,t-1} \times Mechanism_{ij,t-1} \\ &+ X'_{ij,t-1}\gamma + \epsilon_{ijt} \end{aligned} \tag{11}$$

For robustness, I also substitute the quintile group of $ForInfo_{ij,t-1}$ for its level in equation (11) and run the following equation:

$$\begin{aligned} Ret_{ijt} =& \alpha + \beta_1 QFI_{ij,t-1} + \beta_2 Mechanism_{ij,t-1} + \beta_3 QFI_{ij,t-1} \times Mechanism_{ij,t-1} \\ &+ X'_{ij,t-1}\gamma + \epsilon_{ijt} \end{aligned} \tag{12}$$

The results are reported in Table 6, 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.

4.1.A Firm Size

Previous literature suggests firm size plays an important role in the rate of diffusion. For example, Hong, Lim, and Stein (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.[22] The regression estimation is shown in Column (1) of Panel A and B in Table 6. 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.

4.1.B Analyst Coverage

Analyst coverage also influences the rate of information flow (Brennan, Jegadeesh, and Swaminathan (1993); Hong, Lim, and Stein (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.[23] If there 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 6. 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

[22]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 $y + 1$.

[23]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 $y + 1$.

4.1.A, 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.

4.1.C 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.[24] 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.[25]

According to Column (4) of Panel A and B in Table 6, 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.

[24]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 $y+1$.

[25]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.

4.1.D 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.[26] 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 6. 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 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.

4.1.E 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

[26] 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.

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 6 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.

4.1.F 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[27] 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 6]

4.1.G 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 Panel A and B of Table 6, 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 6 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.

4.2 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

[27] 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.

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 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 ($Ret^{L/S}_{t-1}$ or $Ret^{L/S}_{t}$) to $HPR^{L/S}_{t-1,t+11}$ measures the fraction of the total response that occurs within that month. I call it a response ratio (RR), and

$$RR^{L/S}_{t-1} = \frac{Ret^{L/S}_{t-1}}{HPR^{L/S}_{t-1,t+11}} \tag{13}$$

$$RR^{L/S}_{t} = \frac{Ret^{L/S}_{t}}{HPR^{L/S}_{t-1,t+11}} \tag{14}$$

I now compare the initial month response ($RR^{L/S}_{t-1}$) and subsequent month response ($RR^{L/S}_{t}$) 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 7 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 7]

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.[28] 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:

$$R_{i,u} = \alpha_i + \beta_i R_{m,u} + \epsilon_{i,u},\ \ u \in [-300,\ -46] \tag{15}$$

where $R_{i,u}$ denotes the stock return of company i on day u and $R_{m,u}$ denotes the market

[28] 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.

return on day u. Then, I compute the abnormal return in the event window [-3, 3] as:

$$AR_{i,h} = R_{i,h} - \hat{\alpha}_i - \hat{\beta}_i R_{m,h}, \ h \in [-3, \ 3] \tag{16}$$

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,[29] I sort firms on their foreign information proxy of month $t-1$ into three groups (bottom 30%, middle 30%, and top 30%). Figure 6(a) displays the average cumulative abnormal returns for the top 30% group and the bottom 30% group; and Figure 6(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 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 6]

4.3 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

[29] 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.

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 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 8). 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 A.4.

[Insert Table 8]

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 7. 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 7]

The evidence in this section may also be related to the post-2000 decreasing annual return of the Long/Short portfolio shown in Figure 3. As Figure 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 8.

[Insert Figure 8]

4.4 Time-Varying Media Coverage

Media coverage may play a role in the transmission of foreign information as well.[30] 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

[30] 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.

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 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 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. 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 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.

5 Conclusion

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. Moreover, I examine the underlying mechanism of information processing and 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 or foreign institutional holdings 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.

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Figure 1: Breakdown of Foreign Sales for U.S. Firms by Country (1990-2009)
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 plot excludes those countries whose average foreign sales have never greater than 2%.

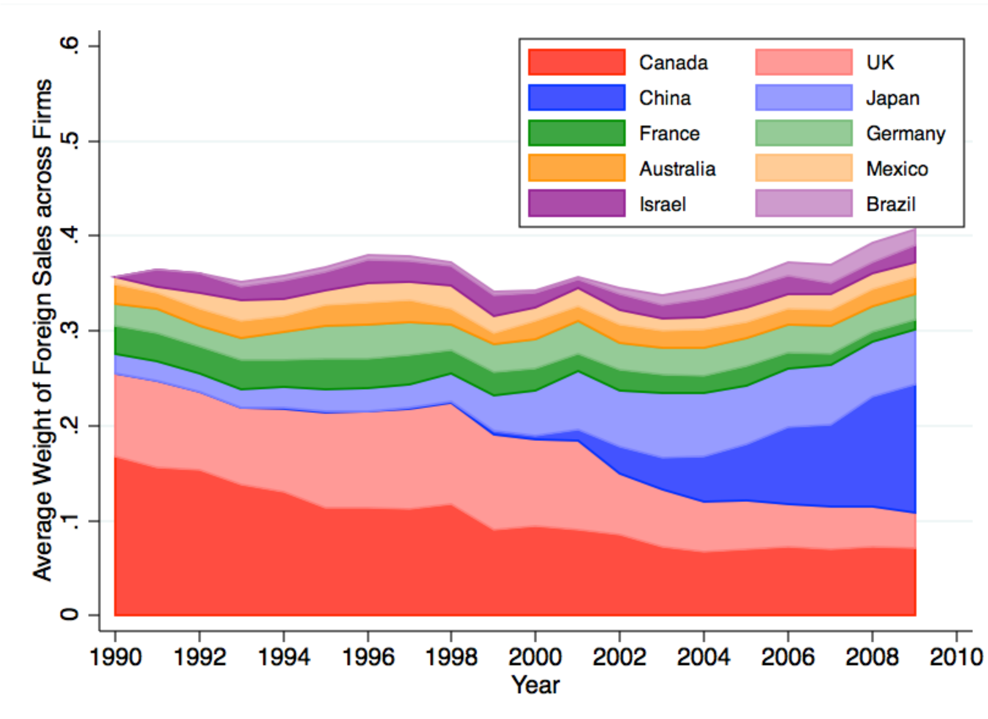

Figure 2: Abnormal Returns of Calendar Time Portfolio
At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxy of the previous month. The foreign information proxy is computed as the weighted sum of industry average returns in the 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.

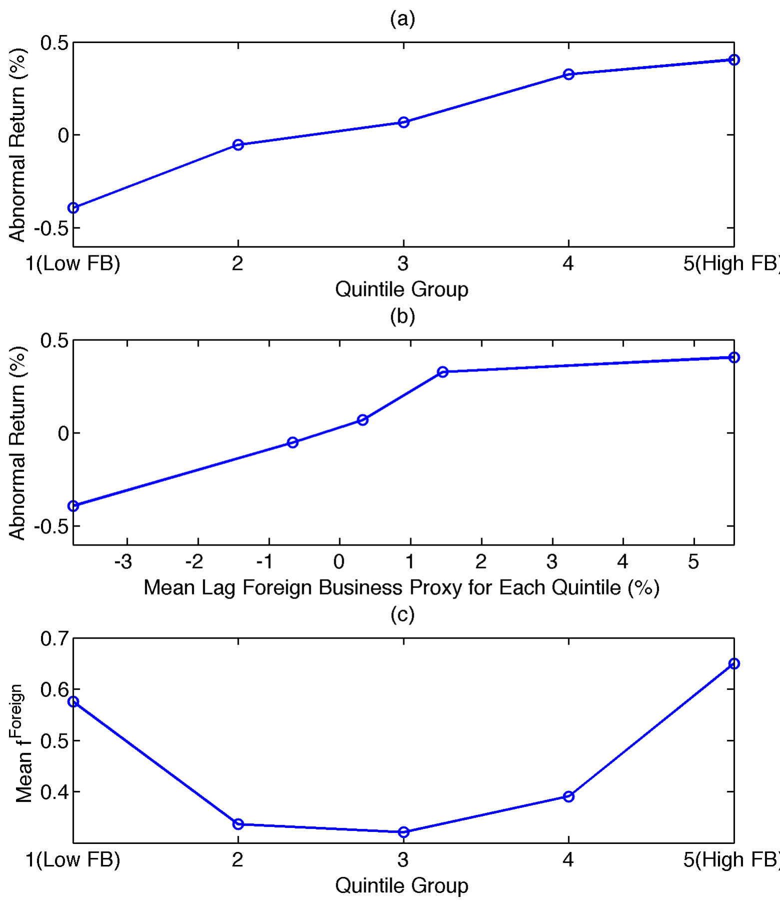

Figure 3: Annual Raw Return of L/S Portfolio and Domestic/Foreign News Coverage Ratio by Year

The figure shows annual raw returns of the Long/Short portfolio (gray bar) and domestic/foreign news coverage ratio (blue line) from 1990 to 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 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.

Sorted on the 1-month Lagged Foreign Information Proxy

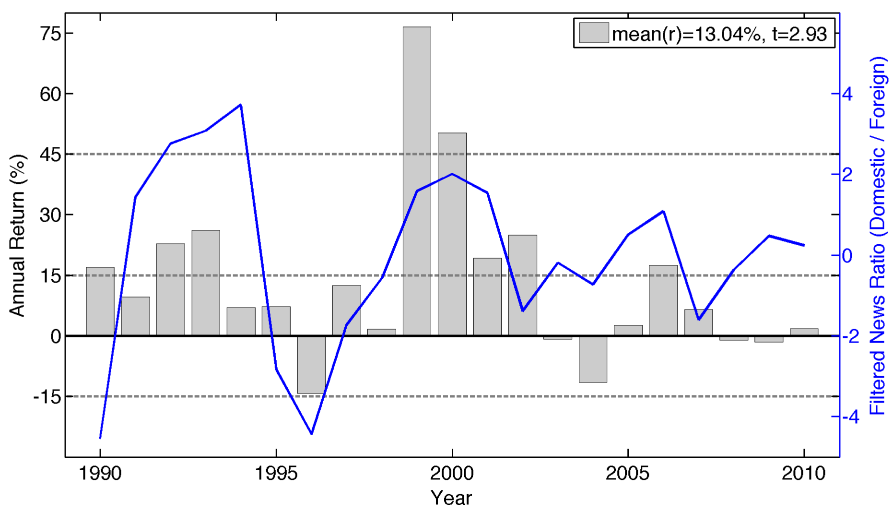

Figure 4: Cumulative Abnormal Return to the Long/Short Portfolio Sorted on Foreign Information Proxy vs Sorted on Domestic Information Proxy

This figure shows the cumulative abnormatl return (Carhart alpha) 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 (Figure (a)) or domestic information proxies (Figure (b)) 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 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 cumulative Carhart alpha (solid line) over time of a zero-cost portfolio going long the stocks in the top quintile and short the stocks in the bottom quintile. The figures also includes the associated 90% confidence interval (dashed line).

(a) Sorted on Foreign Information Proxy

(b) Sorted on Domestic Information Proxy

Figure 5: Event Time Variation in Factor Loadings of the Long/Short Portfolio

This figure plots the loadings with the Carhart (1997) four factors in event time. 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. For each event time, I run a 4-factor model on the Long/Short portfolio going long the stocks in the top quintile and short the stocks in the bottom quintile. This solid line shows these factor loadings in event time. The 90% confidence interval is the area enclosed by the dashed line.

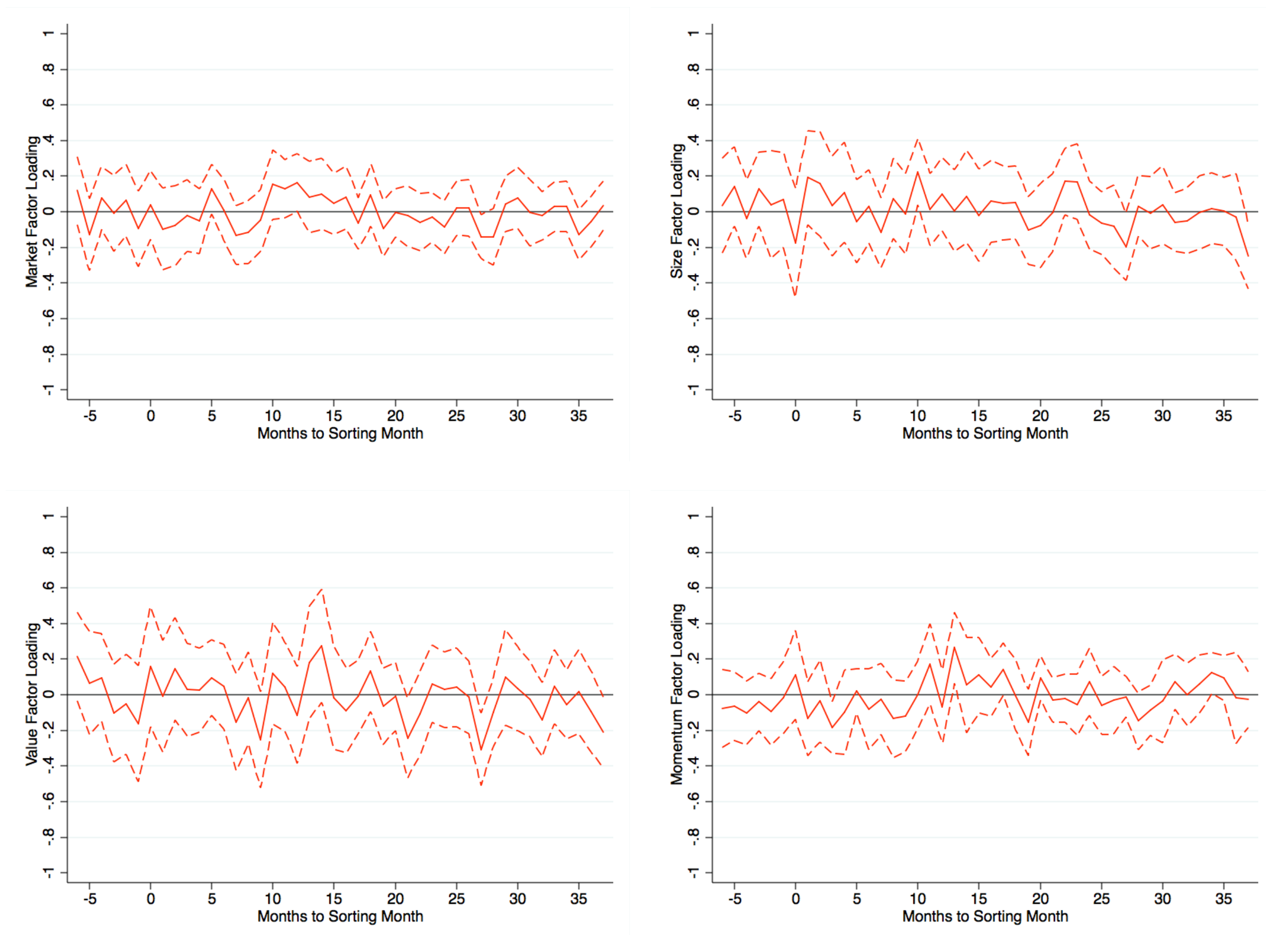

Figure 6: Difference between Cumulative Abnormal Returns of the Top 30% Group and Bottom 30% Group

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

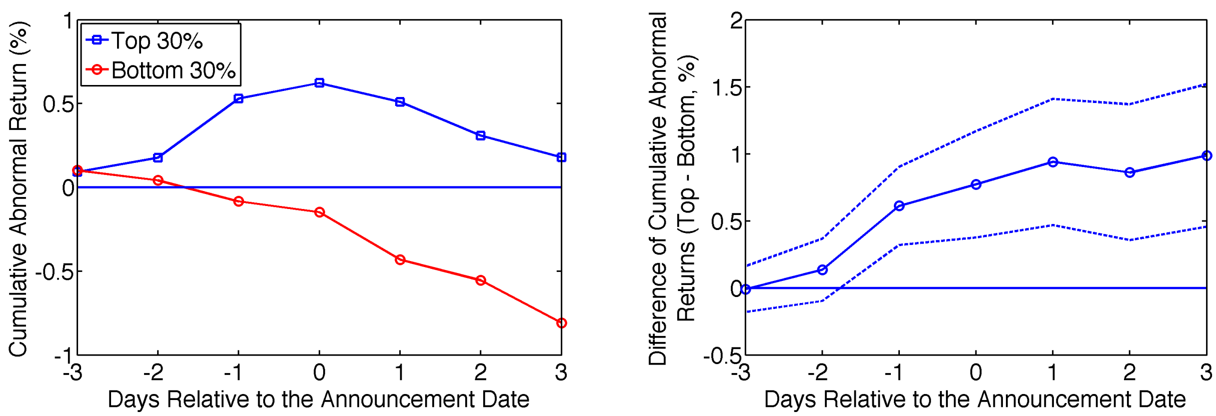

Figure 7: Cumulative Response Ratios: Partition on Geographic Segments

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 τ is defined as: $RR_\tau = \frac{Ret_\tau}{HPR_{t-1,t+11}}$, where $\tau = t-1, \ ..., \ t+5$, Ret_τ and $HPR_{t-1,t+11}$ are the month τ 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 τ which sums up the response ratios from month $t-1$ to month τ. It measures the fraction of total reaction from month $t-1$ to month $t+11$ that occurs until month τ.

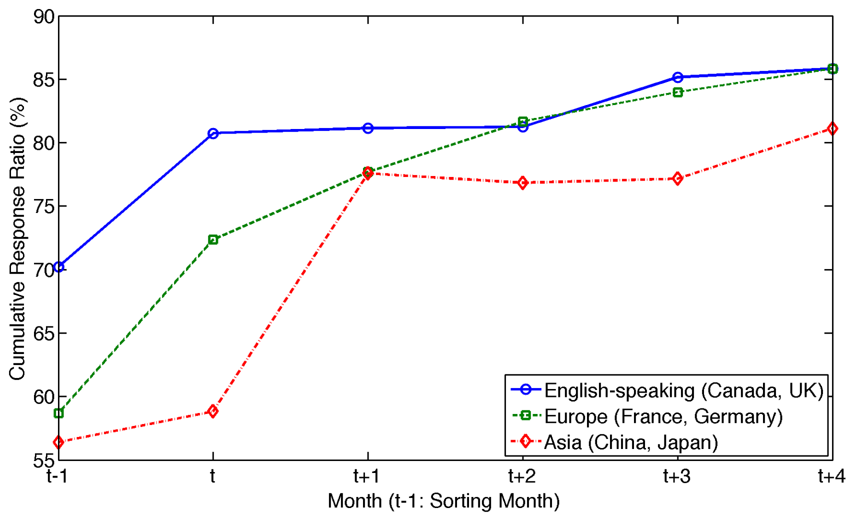

Figure 8: Annual Raw Return of L/S Portfolio (Sorted on the 2-month Lagged Foreign Information Proxy)

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

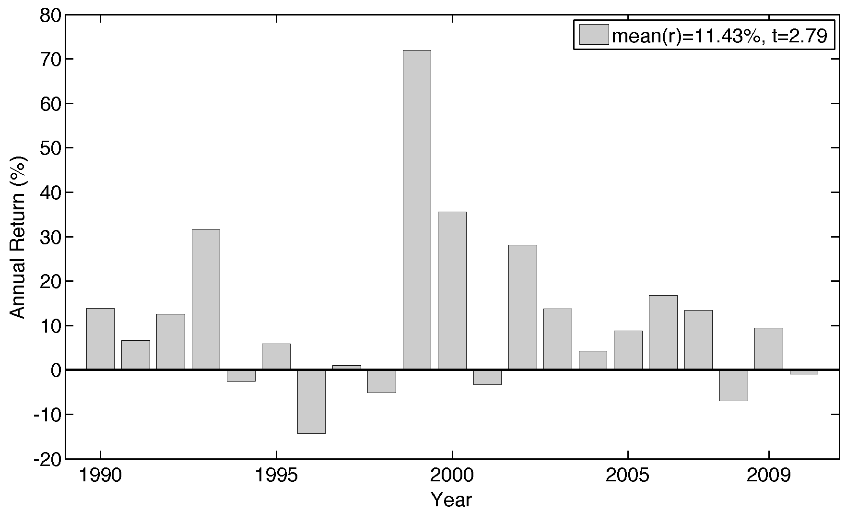

Table 1: Summary Statistics

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
Multinational Firm Coverage of CRSP Stock Universe(EW)	15.84%	1.59%	12.40%	15.78%	19.97%
Multinational Firm 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: 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 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)
β_{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)
β_{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)
β_{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)
β_{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)
β_{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)
β_{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 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 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

Table 6: 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:					$Ret_t(\%)$					
Mechanism 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:					$Ret_t(\%)$					
Mechanism 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)[31]

	(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

[31] 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 7: 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)
	$Announcement_{t-1} = 1$ $Announcement_t = 0$	$Announcement_{t-1} = 0$ $Announcement_t = 1$	$Announcement_{t-1} = 0$ $Announcement_t = 0$
Sorting-month Monthly Return of L/S Portfolio, $Ret_{t-1}^{L/S}$ (%)	3.899***	3.813***	4.956***
	(12.80)	(11.37)	(20.46)
1-month Subsequent Monthly Return of L/S Portfolio, $Ret_t^{L/S}$ (%)	0.275	0.932***	0.746***
	(0.85)	(3.45)	(3.22)
12-month Holding Period Return of L/S Portfolio, $HPR_{t-1,t+11}^{L/S}$ (%)	4.920***	6.006***	7.833***
	(4.71)	(5.57)	(8.95)
Initial Response Ratio of L/S Portfolio, RR_{t-1} [32]	79.25%	63.49%***	63.27%***
	(1.26)	(3.35)	(5.21)
1-month Delayed Response Ratio of L/S Portfolio, RR_t	5.59%	15.52%***	9.522%***
	(0.89)	(3.35)	(3.29)

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

Table 8: 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 ($Ret_{t-1}^{L/S}$ (%))	4.513***	3.045***	3.147***
	(15.51)	(8.719)	(7.701)
1-month Subsequent Monthly Return of L/S Portfolio ($Ret_{t}^{L/S}$ (%))	0.675**	0.710**	0.285
	(2.505)	(2.572)	(0.404)
2-month Subsequent Monthly Return of L/S Portfolio ($Ret_{t+1}^{L/S}$ (%))	0.026	0.276	0.959**
	(0.125)	(0.688)	(2.522)
12-month Holding Period Return ($HPR_{t-1,t+11}^{L/S}$ (%))	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)

Appendix

A.1 Size Distribution

Figure A.1 plots the size distribution of my sample. The firms are classified into 10 groups by NYSE decile breakpoints. As the figure shows, the sample is concentrated relatively more towards small size firms. However, the feature that the coverage is higher in terms of market capitalization than of total number of firms may suggest that multinational firms account for more weight within each decile, especially within large firm deciles.

[Insert Figure A.1]

A.2 Global Industry Momentum

Moskowitz and Grinblatt (1999) 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 A.2. 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 A.2]

A.3 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[33], 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 A.3, 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 A.3]

A.4 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 4.1.E. I run the following specification for both one-month-ahead and two-month-ahead prediction: [34]

[33] 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

[34] $GeoSegInfo^s_{t-1}$ 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 $\sum_s GeoSegInfo^s_{t-1} = ForInfo_{t-1}$.

$$
\begin{aligned}
Ret_{ij\tau} =& \alpha + \sum_s \beta_{1s} GeoSegInfo^s_{ij,t-1} + \sum_s \beta_{2s} \frac{GeoSegInfo^s_{ij,t-1}}{ForInfo_{ij,t-1}} + \sum_s \delta_{1s} ForInfo_{ij,t-1} \times f^s_{ij,t-1} \\
&+ \sum_s \delta_{2s} f^s_{ij,t-1} + X'_{ij,\tau-1}\gamma + \epsilon_\tau \qquad (17) \\
&(\tau = \{t,\ t+1\};\ \text{s=\{English-speaking countries, Europe, Asia, Other\}})
\end{aligned}
$$

The regression results are shown in Table A.4. 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 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 A.4 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 A.4]

Figure A.1: Size Distribution, 1990-2009

This figure plots the size distribution of multinational firms. The firms are divided by NYSE market capitalization decile breakpoints. Group 1 corresponds to small firms while Group 10 corresponds to large firms.

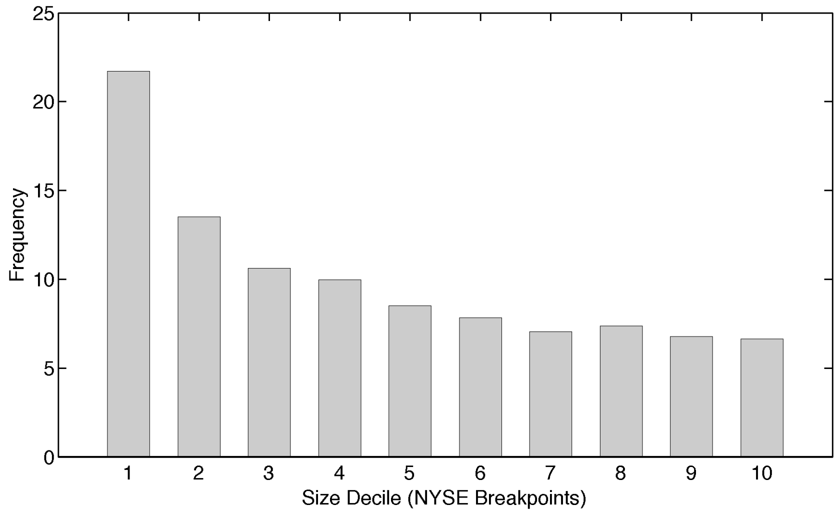

Table A.1: Predictability by Foreign Information Proxy: Control for Global Risk Factors
This table shows abnormal returns of calendar time portfolio. At the beginning of each month, stocks are sorted into five quintile portfolios based on the level of foreign information proxies of the previous month. 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 global market excess return, global Fama-French three factors (Fama and French (1993)) and global Carhart four factor (Carhart (1997)).[35] 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 Info)	L/S
Global Market	-0.189	0.208	0.394*	0.653***	0.675***	0.864***
	(-0.81)	(0.94)	(1.92)	(3.08)	(2.67)	(3.28)
Global Fama-French 3 Factor	-0.171	0.110	0.317*	0.596***	0.749***	0.920***
	(-0.82)	(0.59)	(1.71)	(2.95)	(3.26)	(3.31)
Global Carhart 4 Factor	-0.171	0.120	0.332*	0.626***	0.769***	0.940***
	(-0.83)	(0.66)	(1.83)	(3.17)	(3.45)	(3.35)
Panel B: Value Weighted	**Q1 (Low ForInfo)**	**Q2**	**Q3**	**Q4**	**Q5 (High Info)**	**L/S**
Global Market	-0.0169	0.119	0.405**	0.617***	0.762***	0.779**
	(-0.07)	(0.56)	(2.14)	(3.10)	(2.97)	(2.44)
Global Fama-French 3 Factor	0.0306	0.142	0.399**	0.684***	0.916***	0.885***
	(0.13)	(0.71)	(2.04)	(3.35)	(3.78)	(2.71)
Global Carhart 4 Factor	0.0346	0.166	0.411**	0.717***	0.944***	0.909***
	(0.15)	(0.84)	(2.12)	(3.58)	(4.01)	(2.76)

[35] The global factors are obtained from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The global factors and portfolios include all 23 countries in the four regions: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, Sweden, United Kingdom, United States.

Table A.2: 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 A.3: 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)

Table A.4: 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.[36] 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

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