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DOES FOREIGN INFORMATION PREDICT THE RETURNS OF MULTINATIONAL FIRMS WORLDWIDE?

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Keywords: Foreign information, return predictability, limited attention

JEL Classification Numbers: G12, G14, G15

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1. Introduction

The continuing globalization over the past decades has led to a liberalization of international trade, capital flows and a more integrated global economy. As a result, there is an increasing number of internationally diversified firms that sell their products and services in multiple countries. For example, Denis, Denis, and Yost (2002) report that the share of globally diversified U.S. firms has increased from 29% to 45% between 1984 and 1997. Also the fraction of total sales coming from foreign markets has increased from 21% to 29% during this time span.

A multinational firm, which generates sales in multiple geographic regions, is exposed to unexpected economic shocks from its corresponding geographic segments. Specifically, a positive (negative) shock to a foreign country's industry segment – where the firm operates – is likely to increase (decrease) the multinational corporation's future financial performance. At the same time, it is reasonable to assume that investors are challenged with investments in these firms because they are limited in their time and ability to process complicated (but value-relevant) information. Hence, these restrictions in investors' attention have the potential to induce market inefficiences in the form of slow, rather than immediate, incorporation into stock prices (Hong and Stein (2007) and Duffie (2010)). In line with this idea, Huang (2015) finds that a portfolio strategy based on foreign sales information of multinational firms in the USA generates

abnormal returns of 9.6% p.a. and that this spread is not due to conventional risk factors, firm characteristics, and industry momentum.[1]

In this paper we extend the study of Huang (2015) to a worldwide scale and use a sample of multinational firms from 22 countries in our empirical analysis. This broader international sample enables us to investigate whether the foreign information predictability effect is a specific feature of the U.S. market or extends to other markets globally. Moreover, it allows us to study the relationship between investor characteristics as well as macroeconomic variables and the strength of the predictability effect on the individual country level.

To proxy for a firm's foreign information, we use the sales-weighted average of industry-level returns in the relevant foreign countries. As an example, consider a firm that is located in the United Kingdom (UK) and operates in the pharma sector with 50% of its sales located in the UK, 30% in the USA, and 20% in Japan. The foreign info proxy (Foreign_Info) in month t is computed as 0.3 times the pharma-industry return of the USA in month t plus 0.2 times the pharma-industry return of Japan in month t.

We show that Foreign_Info has significant predictive power for multinationals' future stock returns on a global scale and across different geographical subsamples. In the pooled worldwide sample including U.S. stocks (excluding U.S. stocks) from June 2001 to December 2013, stocks with the highest Foreign_Info in month t-1 outperform stocks with the lowest

[1] Similar results are found by Nguyen (2012). He documents that – in the USA – a simple portfolio strategy exploiting foreign information yields a risk-adjusted return of 135 basis points per month or 16.2% per annum.

Foreign_Info on average by 0.85% (0.63%) in month t. This outperformance translates into a large annual return spread of 10.20% (7.56%). Furthermore, we find that the return spread due to Foreign_Info (the Foreign_Info effect) is positive across the different geographical subsamples Asia-Pacific, Europe, and North America and amounts to 9.60% p.a., 4.56% p.a., and 9.84% p.a, respectively.[2]

Is the Foreign_Info effect explained by a stock's risk exposure to traditional asset pricing factor models and/or other firm characteristics? No. Our results indicate that the returns of a worldwide portfolio strategy going long in stocks with high Foreign_Info and going short in stocks with low Foreign_Info – risk-adjusted by a global version of the Carhart (1997) four-factor model – still earns a statistically significant alpha of 0.89% per month (10.68% per annum).[3] In addition, Foreign_Info shows a robust positive and statistically significant impact on future returns in multivariate Fama-MacBeth (1973) regressions when we control for additional firm characteristics, such as market beta (Sharpe (1964) and Lintner (1965)), size (Banz (1981)), book-to-market (Basu (1983)), momentum (Jegadeesh and Titman (1993)), short term reversal (Jegadeesh (1990) and Lo and McKinley (1990)), turnover (Rouwenhorst (1999) and Ibbotson, Chen, Kim, and Hu (2013)), and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009)).

[2] The return spread is statistically significant at the 5% significance level for Asia-Pacific and North America. The spread is not statistically significant at the 10% significance level for Europe.

[3] We obtain similar results if we adjust returns by global versions of the CAPM one-factor model or the Fama-French (1993) three-factor model. However, our results are only indicative, as we not not take into account any trading costs when forming the portfolio strategy.

A potential concern is that the Foreign_Info effect is driven by industry momentum as shown in Moskowitz and Grinblatt (1999) and Nijman, Swinkels, and Verbeek (2004). We investigate the impact of foreign information on future returns when explicitly controlling for lagged domestic industry returns in portfolio double sorts. Our results indicate that the positive and statistically significant impact of Foreign_Info on future returns remains large when controlling for industry momentum. Hence, industry momentum is unable to explain the cross-sectional variation in future stock returns due to foreign information.

Having established a profound positive link between Foreign_Info and future stock returns on a global scale, we shed light on possible drivers of this effect. Our main hypothesis is that investors' inattention to foreign information slows the incorporation of news into stock prices and increases the return predictability of future returns of multinationals. Our empirical tests support this notion and reveal the following results:

(i) The Foreign_Info effect is particularly strong for small stocks with low analyst coverage, stocks with low institutional ownership, and stocks with high idiosyncratic volatility. This result is in line with Nguyen (2012) and Huang (2015) for the USA and supports the idea that predictability is strongest among firms that generally receive less investor attention and stocks that are difficult to arbitrage. Furthermore, we find that differences in common language between the multinational firm's resident country and its sales countries contribute significantly to the gradual diffusion of foreign information. This finding suggests that investors face greater

challenges in processing information from countries with a different main language as their home country.

(ii) The Foreign_Info effect is pronounced during times of business cycle recessions and periods of financial distress (as indicated by a relatively high VIX volatility index). These findings are in line with Hou, Peng, and Xiong (2009), Karlsson, Loewenstein, and Seppi (2009), Sicherman, Loewenstein, Seppi, and Utkus (2015) and Jacobs and Weber (2015) who find that stock market participants pay less attention to value-relevant pricing information during periods of market downturn.

(iii) The Foreign_Info effect is particularly strong in countries characterized by strong domestic bias, segmented equity markets, and high capital flow restrictions. Hence, diffusion of foreign information into domestic stock prices occurs particularly slowly in countries where investors under-proportionally contribute their wealth into foreign assets and where equity markets are less integrated into the global financial system.

Our study is related to a broader literature on firm-level return predictability due to gradual information diffusion across geographic segments, firms, and time. Hou (2007) argues that the slow diffusion of industry information is a leading cause of the lead-lag effect in stock returns. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) find that stock prices do not promptly incorporate news about economically related firms which in turn generates return predictability across assets. Rizzova (2010) explores the interactions between international trade and stock markets and finds that stock market returns of trading partners do forecast trade flows.

Cohen and Lou (2012) document substantial return predictability from the set of single industry firms to more complicated peers such as conglomerates and Cao, Chordia, and Lin (2015) show that stock returns of strategic alliance partners predict each other. Smajlbegovic (2014) and Addoum, Kumar, and Law (2014) find that U.S. state level economic activity measures predict fundamentals and returns of U.S. firms that are economically exposed to these states. Finally, Nguyen (2012) and Huang (2015) investigate the hypothesis that value-relevant foreign information slowly difuses into the stock prices of U.S. multinational firrms. They find that stock prices do not promptly incorporate information regarding changes in foreign market conditions and that a simple portfolio strategy that exploits geographic information yields high abnormal risk-adjusted returns. Our paper enhances the existing literature by documenting that foreign information is globally priced into stock prices with a considerable delay and limited attention of investors is likely to be the main driver of this obstacle worldwide.

We proceed as follows. In Section 2, we summarize the international stock market data and explain the methodology for the empirical analysis. Section 3 shows that stocks with high Foreign_Info earn higher future (risk-adjusted) returns than stocks with low Foreign_Info worldwide and across geographical subsamples. In Section 4, we shed light on drivers of the Foreign_Info effect and Section 5 concludes.

2. Data and Methodology

2.1 Data

Our sample covers 22 developed markets according to the MSCI classification as of December 2013. The sample period is from June 2001 to December 2013 with a total of 151 months.[4]

The dataset employed in this paper is compiled from different sources: Geographical segment data and accounting information for firms located in the United States is from Compustat. Price, volume and return data for U.S. firms are from the Center for Research in Security Prices (CRSP). We restrict our sample to common equity (share code 10 or 11 in CRSP) listed on the NYSE, AMEX or NASDAQ. Our data source for firms located outside the United States is FactSet. The FactSet Fundamentals database provides geographical segment information as well as price and accounting data for individual stocks around the world. Finally, institutional ownership data and analyst coverage for all firms in the sample are obtained from FactSet Lionshares and Thomson Reuters I/B/E/S, respectively.

The Statement of Financial Accounting Standards (SFAS) No. 131 requires public business enterprises located in the United Sates to disclose geographical segment information in their annual financial statements.[5] Similar regulations exist for international firms according to the International Financial Reporting Standard (IFRS) No. 8. According to these standards, firms

[4] We choose 2001 as our starting year because market capitalization data from FactSet for non-U.S. firms is not available before.
[5] SFAS 131 is effective for financial statements for periods beginning after December 15, 1997.

are required to report financial information for individual geographic segments, which comprise 10% or more of total sales, profit or loss, or assets. Firms are required to report measures of profit and loss, such as sales, operating income and assets for each geographic segment.[6]

We restrict our dataset to stocks classified as common equity listed on a regular stock exchange in their respective home country. If a firm has issued multiple share classes, we use the share class identified by FactSet as the primary issue.[7] As for U.S. firms, all stocks are required to be headquartered in their home country. Since we are primarily interested in stock price responses to foreign information, we exclude firms with 100% sales in the domestic market. Finally, we exclude very small firms with low price levels from our sample in order to avoid potential micro-structure effects such as bid-ask-bounce. Hence, for each country and month, we exclude stocks that fall into the 5% percentile according to their market capitalization or price level at the end of the previous month. As indicated in Ince and Porter (2006), these stocks are particularly known to be prone to potential data errors. To mitigate further concerns with respect to illiquidity and infrequent trading of stocks, we require firms to trade on every day of month t-1 to be included in our empirical analysis in month t. As common in the international asset pricing literature, all stock returns are denominated in USD (see, e.g., Griffin (2002)). As in Fama and

[6] There are potential limitations with the reported geographic segment information. In particular, firms are allowed to aggregate multiple geographic areas into one reported geographic segment. For example, a U.S. multinational firm with sales from Germany, France, and Italy, might aggregate these countries into one segment Europe.
[7] FactSet will usually choose the primary security based on a combination of factors, such as liquidity, market cap, and the availability to foreign ownership.

French (2012), we use the one-month U.S. T-bill rate for the USA and the remaining countries to calculate monthly excess returns.[8]

2.2 Foreign Information

The main variable of interest in this paper is a firm's "foreign information", which we refer to as *Foreign_Info*. To compute this measure, we first need an exposure of each multinational firm to a specific country or region. Second, we need to construct a measure of the economically relevant information from that country or region.[9]

To do so, we compute *Foreign_Info* as the sales-weighted sum of corresponding industry returns in relevant foreign countries:

$$Foreign\_Info_{i,j,t} = \sum_{c \neq Home} f_{i,t}^{c} \cdot R_{j,t}^{c}$$

where $Foreign\_Info_{i,j,t}$ denotes the foreign information proxy for firm *i* belonging to industry *j* during month *t*, $f_{i,t}^{c}$ denotes the fraction of sales from country c (note that $\sum_{c \neq Home} f_{i,t}^{c} \neq 1$), and $R_{j,t}^{c}$ denotes industry *j*'s return in country c during month *t*.[10] For example, a firm that is

[8] Our results are stable if we use local currency returns and work with raw returns instead of excess returns.

[9] A practical issue when working with geographical segment information from Compustat or Factset is that the geographical segment labels are not standardized. For example, a geographic segment can be labeled as "United Kingdom", "U.K.", "UK", "Great Britain", or "England", etc. Therefore, we manually go through all unique segment labels in the sample and assign one standardized label to each different geographic area. We come up with a total number of 59 geographic areas in the standardized geographic segments.

[10] Local industry indices for all of the 59 geographic segments are obtained from Datastream. Specifically, we use the Industry Classification Benchmark (ICB) Supersector (Level 3 sector in Datastream) classifications, which uniquely assigns a firm to one of 19 industries. In order to match U.S. stocks (which are classified according to the Global Industry Classification System, GICS) with the ICB system we utilize an updated version of the GICS - ICB

located in the UK and operates in the pharma sector with 50% of its sales located in the UK, 30% in the USA, and 20% in Japan has a foreign operation proxy of:

$$Foreign\_Info_{i,j,t} = 0.3 \cdot R^{USA}_{Pharma,t} + 0.2 \cdot R^{Japan}_{Pharma,t}.$$

Hence, *Foreign_Info* is a weighted measure of a firm's exposure (fraction of sales) to a specific country or region combined with economically relevant information (corresponding foreign industry return).[11]

2.3 Summary Statistics

Our final sample consists of 12,162 individual firms from 22 developed countries with a total of 677,896 firm-month observations. Table 1 provides summary statistics.

[Insert Table 1 about here]

Columns (1) - (2) of Table 1 report the number of firms and firm-month observations per country. The USA has the highest number of unique firms (3,314), followed by Japan (1,439) and the UK (1,370). The countries with the lowest number of unique firms are Ireland and Portugal (41 each), and New Zealand (64). Columns (3) - (5) assign each country into different

concordance table from Bekaert, Harvey, Lundblad, and Siegel (2011). We thank Campbell Harvey for providing us with the concordance table.

[11] We follow Huang (2015) and use industry returns from the respective geographic segments as measures of economic performance instead of macroeconomic indicators. The use of equity returns instead of macro variables has several advantages: equity returns are available in real-time for investors, are historical stored at a monthly frequency for all countries in CRSP and Factset, are forward-looking, and aggregate new economic information - including macroeconomic information. In contrast, data availability of macroeconomic indicators is often limited, available at most at a quarterly or annual frequency, published with a certain delay and often revised after their first publication.

geographical subsamples. When assigning each country to a geographic region, we find that our sample is quite balanced: 30% of all firm-month observations are from Asia-Pacific, 33% are from Europe, and 37% are from North America. Finally, columns (6) - (8) show the minimum, average, and maximum values of Foreign_Info across countries. We document - although there exists substantial country-within dispersion - that the average value of Foreign_Info for each country is close to zero.

3. Foreign Information and Future Stock Returns Worldwide

3.1 Univariate Portfolio Sorts

The first section of our empirical analysis conducts univariate portfolio sorts. Portfolio sorts represent an intuitive and nonparametric way to examine cross-sectional variation in expected returns with respect to a common predictor variable. They also provide an important cross-check for more formal regression tests, which we utilize in the subsequent section.

In each month *t* of our sample period, we sort stocks into five quintiles based on $Foreign\_Info_{i,j,t-1}$. Then, we report the average value-weighted US-dollar excess returns for these quintile portfolios in month *t* as well as differences in average excess returns between quintile portfolio 5 (high *Foreign_Info*) and quintile portfolio 1 (low *Foreign_Info*) with corresponding statistical significance level.[12] We focus on value-weighted portfolio tests in our base-case scenario to limit the influence of small firms; however, our results are also robust if we

[12] In order to adjust for serial correlation in monthly stock returns, we use Newey and West (1987) standard errors with 12 lags in the statistical t-tests.

base our sorts on an equal-weighted scheme instead (see Section 3.4). Portfolio sorts are conducted for five different regions: the worldwide sample (Global), the worldwide sample excluding the USA (Global ex. USA), Asia-Pacific, Europe, and North America.[13] Results are reported in Panel A of Table 2.

[Insert Table 2 about here]

Panel A documents that stocks with high *Foreign_Info* have significantly higher future returns than stocks with low *Foreign_Info*. In the pooled global sample, stocks in the quintile with lowest (highest) *Foreign_Info* earn an average future monthly excess return of 0.15% (1.00%). The return spread between quintile portfolio 5 and 1 thus amounts to 0.85% per month, which is statistically significant at the 1% significance level. This monthly return spread translates into an annual spread of 10.20%. Panel A also reports the relationship between *Foreign_Info* and future returns for different geographical areas. We find that the monthly return spread between stocks with high *Foreign_Info* and stocks with low *Foreign_Info* is positive for the global sample excluding the USA (0.63%), Asia-Pacific (0.80%), Europe (0.38%), and North America (0.82%). It is statistically significant (at least at the 5% significance level) for all geographical subsamples except from Europe.

Panel B of Table 2 reports risk-adjusted excess returns for each quintile portfolio and the 5-1 difference portfolio (the long-short return spread based on *Foreign_Info*). We employ a

[13] We impose a minimum gap of 6 months between the portfolio formation period and the fiscal year end period from which the geographic segment data is taken. The procedure ensures that the geographic segment information of each multinational firm is publicly known at the start of the portfolio formation period and could have been used by investors in real time.

regional version of the Carhart (1997) four-factor model to adjust the returns with respect to four common risk factors: the market (MKT), a porfolio going long in small stocks and going short in large stocks (SMB), a porfolio buying value stocks and selling growth stocks (HML), and a portfolio going long past winner stocks and shorting past loser stocks (UMD). The corresponding risk factors for each specific region are obtained from the webpage of Andrea Frazzini.[14]

Similar as for raw excess returns, we find that monthly spreads in Carhart (1997) alphas between quintile 5 (high *Foreign_Info*) and quintile 1 (low *Foreign_Info*) are positive and statistically significant (at least at the 10% significance level) for the worldwide sample (0.89%), the worldwide sample excluding the USA (0.65%), Asia-Pacific (0.68), and North America (0.95%). We also document a positive, but statistically insignificant spread for Europe (0.44%, t-statistic of 1.35).[15]

In order to better understand the risk characteristics of the long-short return spread based on *Foreign_Info*, we look at the factor loadings of the 5-1 difference portfolio. Our results for the global sample indicate negative exposures to the market, the SMB factor, and the UMD factor as well as a positive exposure to the HML factor. Hence, a portfolio strategy buying high

[14] Asness, Frazzini, and Pedersen (2014) study a multi-factor model in a sample of developed markets, which is very similar to the set of countries used in this paper. We thank Andrea Frazzini for making the risk factors available on his homepage http://www.econ.yale.edu/~af227/data_library.htm.

[15] We obtain similar results when risk-adjusting the raw returns for a regional version of the Fama and French (1993) three-factor model and the Sharpe (1964) one-factor CAPM model.

Foreign_Info stocks and selling low *Foreign_Info* stocks is countercyclical and tends to invest buy large stocks, value stocks, as well as stocks with low past returns.[16]

In summary, the results of Table 2 suggest that *Foreign_Info* has predictive power for future stock returns of multinational firms both worldwide as well as for different geographical subsamples and that conventional asset pricing models (such as the Carhart (1997) four-factor model) fail to explain the return spread due to *Foreign_Info*.

3.2 Multivariate Regressions

We now proceed to run Fama and MacBeth (1973) regressions to analyze the predictive power of Foreign_Info on future returns when controlling for a wide array of different firm characteristics.

The Fama and MacBeth (1973) regression procedure follows two steps. In the first step, we estimate the following cross-sectional regression in each month:

$$R_{i,t} = \beta_{0,t} + \beta_{1,c,t} + \beta_{2,t} Foreign\_Info_{i,j,t-1} + \beta'_{3,t} Z_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ denotes firm i's excess return in month *t*, $\beta_{0,t}$ denotes the intercept, $\beta_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm *i* is from country *c* and zero otherwise, and $Z_{i,t-1}$ is a vector of firm controls which are known to predict the cross-section of

[16] Please note that the negative loading on the SMB factor is mainly driven by a few stocks with very large market capitalization. Based on an equal-weighted regression analysis in Section 4.1, we find that the *Foreign_Info* effect is stronger for small caps.

expected stock returns. All control variables are constructed in a way that they are publicly known at the end of the previous month.

The second step tests the statistical significance of the coefficient estimates. Note that this procedure accounts for time fixed effects and controls for different means for firms from different countries (country fixed effects). Standard errors are computed using the Newey and West (1987) adjustment with 12 lags to account for heteroscedasticity and autocorrelation.

We include a comprehensive set of firm characteristics in our asset pricing tests: *Beta* is the firm's beta coefficient estimated in a market model regression (using domestic total return indices) over the past 60 months using rolling window regressions (Sharpe (1964)). *Size* is the firm's log market capitalization expressed in USD at the end of previous June (Banz (1981)). *BM* is the logarithm of a firm's book-to-market equity, where the book value of common equity and the market capitalization are taken from end of December of the previous year (Basu (1983)). $R_{i,t-12:t-2}$ is the cumulative medium-term return of stock *i* from month *t-12* through *t-2* in order to control for individual stock momentum (Jagadeesh and Titman (1993)). $R_{i,t-1}$ is the previous month return of stock *i* and controls for short term reversal (Jagadeesh (1990) and Lo and McKinley (1990)). *Turnover* is defined as the number of stocks traded during a given day divided by the number of stocks outstanding at the end of the day, averaged over the past 12 months (Rouwenhorst (1999) and Ibbotson, Chen, Kim, and Hu (2013)). *Idio_Vola* is the firm's idiosyncratic volatility computed from the volatility of the error term in a market model regression (Ang, Hodrick, Xing and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009)).

$Dom\_Ind\_Ret_{i,t-1}$ is the previous month return of stock *i*'s corresponding domestic industry portfolio in order to control for short-term domestic industry momentum (Grinblatt and Moskowitz (1999) and Nijman, Swinkels, and Verbeek (2004)). Similarly, $Dom\_Ind\_Ret_{i,t-12:t-2}$ is the cumulative domestic industry return from month *t-12* through *t-2* and controls for industry momentum at the intermediate horizon.

[Insert Table 3 about here]

Panel A of Table 3 presents the regression results for the pooled worldwide sample and the geographical subsamples. In line with previous research we confirm a standard set of cross-sectional return patterns: Size (-), BM (+), $R_{i,t-1}$ (-), Turnover (-), Idio_Vola (-), and $Dom\_Ind\_Ret_{i,t-1}$ (+) are significant predictors for the cross-section of future stock returns worldwide. More importantly in our context, we document that the marginal effect of $Foreign\_Info_{i,t-1}$ is positive and statistically significant at the 1% level both for the worldwide sample as well as for all geographical subsamples.17 Hence, the Foreign Info effect is different from the impact of other firm characteristics and not subsumed by stock return reversal, momentum and/or industry momentum.

Specifications (6) - (8) repeat the Fama and MacBeth (1973) regression on the global sample; however, instead of one-month ahead returns we use two-, three-, and six-month ahead

[17] Interestingly, the predictive power of *Foreign_Info* is also highly significant for European multinationals, although we did not detect predictive power in the portfolio sorts in Section 3.1. Note that these results do not contradict each other. The portfolio tests in the previous section are based on value-weighted sorts whereas each return observation receives an equal weight in the multivariate regression analysis. This finding suggests that the *Foreign_Info* effect for multinationals from Europe is stronger when we use equal-weighted portfolio sorts, which we confirm in Section 3.4 below.

returns. In all specifications we report a positive and statistically significant impact of Foreign_Info on future returns. Hence, the effect is not driven by overreaction of stock market investors; instead the effect seems to be long-lasting and permanent.

In Panel B of Table 3 we perform a horserace between two measures of foreign information recently proposed in the literature. Besides the Foreign_Info measure of Huang (2015), we evaluate the predictive power of Foreign_Info_Market – computed as the sales-weighted average of country-level (instead of industry-level) returns in relevant foreign countries. This measure is proposed by Nguyen (2012) who documents that Foreign_Info_Market significantly predicts future returns for U.S. multinational firms. Using our worldwide sample, we can provide an out-of-sample check to analyze which measure of foreign information is more important to predict multinationals' future stock returns.

Our empirical results yield a clear winner: In all regressions (based on the worldwide sample and different geographical subsamples) we find a positive and significant impact of Foreign_Info on future returns whereas the Foreign_Info_Market measure is never statistically significant. Hence, our results indicate that return predictability of multinationals comes from industry-related information instead of market-related information. Hence, we complement previous findings by Hou (2007) who documents that – in the USA – the lead-lag effect between big firms and small firms is predominantly an intra-industry phenomenon. We contribute by demonstrating that not only domestic, but also foreign industry returns are relevant for the predictability of multinational firms.

3.3 Foreign Information vs. Industry Momentum

The foreign information effect is conceptionally related to industry momentum. Grinblatt and Moskowitz (1999) document strong and prevalent momentum in U.S. industry components of stock returns which accounts for much of the individual stock momentum anomaly. In addition, Nijman, Swinkels, and Verbeek (2004) find that positive returns of momentum strategies in European stock markets are partly driven by industry momentum. The difference between *Foreign_Info* and industry momentum is that *Foreign_Info* accounts for past industry returns of a firm's foreign sales markets compared to past domestic industry returns.

This section aims to isolate the predictability effect of *Foreign_Info* from domestic industry momentum. Although our multivariate regressions in Section 3.2 demonstrate that the marginal impact of *Foreign_Info* remains statistically significant when controlling for past industry returns, we now take a closer look at the joint dynamics of both effects in portfolio double sorts.

In a first step, we first sort all stocks in the global sample into quintile portfolios based on $Dom\_Ind\_Ret_{i,t-1}$. Then, we again sort the stocks within each portfolio into five quintiles based on $Foreign\_Info_{i,j,t-1}$. This way, we can study the predictability effect of $Foreign\_Info_{i,j,t-1}$ while fixing different levels of domestic industry momentum. We report the average monthly

excess returns in month t for the 25 industry momentum × *Foreign_Info* porfolios in Panel A of Table 4.[18]

[Insert Table 4 about here]

We find – within four of five quintiles (except the one with the highest industry momentum) – that the future return of the high *Foreign_Info* portfolio is larger than the return of the small *Foreign_Info* portfolio and that return differences are economically large and statistically significant at the 1% level. The average monthly spread in future returns amounts to 0.67%; that is, it is slightly reduced as compared to the return spread of 0.85% from the univariate sorts. Hence, industry momentum is related to *Foreign_Info*, but it only accounts for a small part of the effect.

Panel B of Table 4 presents portfolio double sorts based on $Dom\_Ind\_Ret_{i,t-2:t-12}$ and $Foreign\_Info_{i,j,t-1}$. Again, we find that the future return of the high *Foreign_Info* portfolio is larger than the return of the small *Foreign_Info* portfolio in four of five quintiles (except the one with the lowest medium-term industry momentum). The return differences are economically large and statistically significant at the 1% level (in four of five quintiles) with an average monthly spread in future returns amounting to 0.50%.

[18] We obtain similar results when we reverse the sorting order or when we use geographical subsamples in the empirical analysis.

In summary, based on portfolio double sorts we provide strong evidence that the predictability effect based on *Foreign_Info* is related but clearly different from the effect of industry momentum.

3.4 Robustness

This section provides additional analyses and stability checks to provide robustness for our main empirical results. To do so, we perform equal-weighted and value-weighted portfolio sorts based on the worldwide dataset as well as geographical regions for different sample specifications. Table 5 presents the results.

[Insert Table 5 about here]

First, Panel A repeats our base-case specifications. The value-weighted portfolio results are the same as already discussed in Section 3.1. We document – for the equal-weighted portfolio sorts – that average returns are monotonically increasing from quintile one through five. Moreover, the 5-1 difference portfolio going long in stocks with high *Foreign_Info* and going short in stocks with low *Foreign_Info* yields a positive and statistically significant return spread for all geographical samples.

Panel B addresses concerns that our results might be driven by exchange rate effects as the returns in our base-case specification are converted to USD. Therefore, we repeat our portfolio sorts with all returns denominated in local currency. Our results indicate that the spread

due to *Foreign_Info* remains strong; it shows a magnitude similar to our base-case scenario. Thus, *Foreign_Info* effect is not driven by exchange rate effects.

Panel C reports the results of portfolio sorts when we skip five trading days between the measurement period of $Foreign\_Info_{i,j,t-1}$ and the start of the portfolio formation period. This procedure provides additional protection against potential biases induced by illiquidity issues. Our results remain qualitatively unchanged to the base-case scenario.

Panel D addresses concerns that the predictability effect could be driven by small firms and caused by lead-lag effects along the lines of Hou (2007). Hou (2007) finds that the returns of small firms are predictable by lagged returns of large firms in the same industry. Large firms, on the other hand, exhibit no predictability. To investigate if our results are caused by lead-lag effects related to firm size, we repeat the portfolio sorts using only the 20% largest firms in each country and month. We document that the excess returns of the long-short return spread based on *Foreign_Info* remain statistically significant for all of the equal-weighted portfolios and for four out of five value-weighted portfolios.

Finally, Panel E excludes all firms from our sample that operate in the financial sector. Financial firms are often excluded in empirical asset pricing tests as the characteristics of accounting variables can be very different from firms operating in the real economy. Our portfolio results remain robust when we exclude financial firms.

Overall, the results in Table 5 show that the predictability effect of *Foreign_Info* is robust with respect to different sample specifications.

4. Which Factors Drive the Foreign Information Effect?

4.1 Firm Characteristics

Having established a robust positive association between *Foreign_Info* and future stock returns on a global scale, we now shed light on possible drivers of this effect. We argue (in line with Nguyen (2012) and Huang (2015)) that the predictive power of *Foreign_Info* is caused by investors' lack of attention to non-domestic information. According to this explanation, *Foreign_Info* reflects information about future growth opportunities in the geographic segments in which a multinational firm operates. Because of limited attention and information processing constraints of (some) investors, the prices of multinational firms do not instantly react to new information about future economic prospects of the firms' geographic segments. Hence, the key prediction of this hypothesis is that multinational firms with higher (lower) levels of investor attention should exhibit lower (higher) predictability by *Foreign_Info*.

In this section we investigate whether limited attention is a main driver of the *Foreign_Info* effect on the firm level. Because investor attention is unobservable to the researcher, we use a broad range of variables to proxy for it. All proxies are at least available on a quarterly frequency.

Size is a firm's log market capitalization in USD at the end of previous June. It is a common proxy for attention as small firms are generally less visible and receive less attention compared to large firms (e.g. Arbel, Carvell, and Strebel (1983); Hou and Moskowitz (2005); Hou (2007)).

Res_Num_Ana is the number of equity analysts providing earnings forecasts for a firm (taken from Thomson Reuters I/B/E/S). Equity analysts are an important provider of firm-specific information and the number of analysts following a firm can be seen as a proxy for the overall amount of information produced about the firm (e.g., Brennan, Jegadeesh, and Swaminathan (1993); Hong, Lim, and Stein (2000)). As the number of analysts following a firm is highly correlated with firm size (Bushan (1989)), we follow the procedure of Hong, Lim and Stein (2000), and orthogonalize analyst coverage with respect to size.[19] Then we use the residuals of this regression as a proxy for investor attention.

Res_Ownership is defined as the residual percentage of shares outstanding held by institutional investors, orthogonalized with respect to size (taken from FactSet Lionshares). Institutional investors are generally considered to be better informed and have greater information processing capacities than individual investors (e.g., Badrinath, Kale, and Noe (1995); Boehmer and Kelley (2009)). Therefore, we expect firms with low levels of institutional ownership to respond more slowly to new information.

[19] Following Hong, Lim and Stein (2000), we regress log(1+Num_Ana) on log(Size) and use the residuals of this regression as our measure for analyst coverage. The analyst coverage of firms not covered by I/B/E/S is set to zero.

Res_Num_Investors is the number of institutional investors owning shares of a firm. Analogous to analyst coverage, the total number of institutional investors can be seen as a proxy for the amount of information produced about a firm. We also orthogonalize this measure with respect to size.

Distance is the sales-weighted geographical distance between the resident country of a multinational firm and its respective geographic segments.[20] We would expect that multinational firms with greater distance between the resident country and their respective geographic segments are prone to a greater predictability effect.

Finally, *Sales_Same_Language* is the fraction of a firm's foreign sales from countries with the same official language as the firm's resident country. Recall the previous example where a firm is located in the United Kingdom and generates 50% of its sales in the UK, 30% in the USA and 20% in Japan. *Sales_Same_Language* for this firm is 0.3 because the official language in both the UK and the USA is English. A common language in the firm's resident country and geographical segments substantially simplifies the processing of value-relevant foreign information for domestic investors. Therefore, we expect firms with a higher value of *Sales_Same_Language* to exhibit less information frictions which in turn leads to a lower predictability effect by *Foreign_Info*.

[20] Geographical distances between the capital cities of two countries are obtained from http://ec.europa.eu/programmes/erasmus-plus/tools/distance_en.htm.

Even if some investors exhibit limited attention – deterring the incorporation of foreign information into prices – less informationally constrained investors, such as professional money managers, should attempt to arbitrage away the predictive power of *Foreign_Info*. However, limits to arbitrage potentially prevent these informed investors from fully arbitraging away the predictability effect (Shleifer and Vishny (1997)). Especially stocks with high idiosyncratic volatility are associated with higher arbitrage risk, which limits arbitrage activities of informed investors (e.g., De Long, Shleifer, Summers, and Waldmann (1990); Pontiff (2006); Cohen and Lou (2012); Stambaugh, Yu, and Yuan (2015)). This line of argument predicts that stocks with high idiosyncratic volatility should experience a higher predictability by *Foreign_Info*. Therefore, we also include *Idio_Vola* in our tests.

We construct a dummy variable, $dummy_{i,t-1}$, which is equal to one if the corresponding attention proxy of multinational i in the previous month is above the cross-sectional median of all firms. Then we run Fama-MacBeth regressions including the dummy and an interaction term between the dummy and $Foreign\_Info_{i,j,t-1}$

$$R_{i,t} = \beta_0 + \beta_{1,c} + \beta_2 dummy_{i,t-1} + \beta_3 Foreign\_Info_{i,j,t-1} \quad (2)$$

$$+\beta_4 (dummy_{i,t-1} \times Foreign\_Info_{i,j,t-1}) + \beta_5' Z_{i,t-1} + \varepsilon_{i,t}.$$

A positive, statistically significant coefficient estimate for β_4 implies that the predictability effect of $Foreign\_Info_{i,j,t-1}$ is higher for firms with low investor attention and vice versa. As before, we include our standard set of firm characteristics in the regression and

also control for country fixed effects. Table 6 presents the regression estimates and t-statistics for β_3 and β_4 for the global sample. For brevity, we do not report the coefficient estimates for the control variables.

[Insert Table 6 about here]

We find that the predictive effect of $Foreign\_Info_{i,j,t-1}$ is significantly weaker for firms with high levels of investor attention as measured by firm size, residual analyst coverage, residual institutional ownership and residual number of institutional investors.[21] We also document a significantly weaker return predictability for firms with high *Sales_Same_Language*, which supports our argument that differences in language play an important role for the speed of information diffusion across international financial markets. These results are in line with the findings of Nguyen (2012) and Huang (2015) and support the gradual information diffusion explanation. Moreover, the predictive effect of *Foreign_Info* is larger for firms with high idiosyncratic volatility, supporting the argument that arbitrage risk prevents informed investors from fully exploiting the return predictability. This finding is also consistent with Cohen and Lou (2012), who show that the returns on conglomerates are predictable and that the predictability effect is stronger for firms with high idiosyncratic volatility.

[21] Surprisingly, we do not find evidence of a significant impact of *Distance*. Hence, the average distance between the country where a firm is headquartered and the corresponding geographic segment markets is not significantly related to the magnitude of return predictability.

4.2 Business Cycle Variation

In this section we investigate whether the degree of return predictability by foreign information is related to the business cycle and/or periods of economic and financial distress. In particular, we test if the return spread of the long-short portfolio strategy based on *Foreign_Info* can be (partly) explained by domestic and global recession indicators as well as the VIX volatility index.

In order to perform this empirical analyis, we first compute the excess returns generated by the long-short portfolio strategy based on *Foreign_Info* for each individual country. Due to the limited number of multinationals in some countries in our sample, we sort stocks into tercile portfolios instead of quintiles. Panel A of Table 7 reports the results of country-individual value-weighted portfolio sorts. We report the average monthly return for the low (1) *Foreign_Info* portfolio, the high (3) *Foreign_Info* portfolio, the 3-1 long-short return spread portfolio, as well as the 3-1 long-short spread in Carhart (1997) four-factor alphas.[22]

[Insert Table 7 about here]

We observe that the excess returns of the long-short return portfolio are positive for 20 out of 22 countries. However, the positive spreads in returns are not always statistically significant. In particular, we find that the long-short return spread based on *Foreign_Info* is statistically significant for 9 out of 22 countries, and the alphas are significant for 11 of the 22

[22] Carhart (1997) four-factor alphas are calculated using risk factors from Asia-Pacific, Europe, North America for each country in the corresponding region.

countries. We find the highest alphas for Ireland, followed by Denmark, Switzerland and Singapore. One interesting observation is that the excess returns and alphas are statistically significant for all three Asian countries in our sample: Hong Kong, Japan and Singapore.

To measure domestic business cycle variation, we use the recession indicator for the United States from the National Bureau of Economic Research (NBER) and recession indicators for the non-U.S. countries in our sample from the Organisation for Economic Co-operation and Development (OECD).[23] We also obtain data for the recession indicator of the total OECD area to measure global business cycle variation. Finally, we use monthly percentage changes of the VIX volatility index as an alternative measure for periods of financial and economic distress.[24]

Our tests are based on three different regression specifications: First, we regress the excess returns of the country-specific long-short portfolio strategy for country *c* (denoted by $R_{c,t}^{h-l}$) on the corresponding recession indicator for country *c* ($Recession_{c,t}$). $Recession_{c,t}$ takes a value of one when country *c* experiences a recession in month *t* and zero else. We run a pooled regression across all countries controlling for country-fixed effects:

$$R_{c,t}^{h-l} = \beta_0 + \beta_{1,c} + \beta_2 Recession_{c,t} + \varepsilon_{c,t}. \quad (3)$$

[23] We obtain recession indicators from the OECD for all non-U.S. countries in our sample except for Hong Kong and Singapore, which are not members of the OECD.

[24] The VIX is computed as a weighted average of implied option volatilities on the S&P 500 index and is frequently considered as the fear index: It represents a measure of the market's expectation of stock market volatility.

In our second and third specification, we regress the excess returns of the global long-short strategy on a global recession indicator as well as changes in the VIX volatility index, respectively. Panel B of Table 8 reports the results.

In all three specifications, we find that the *Foreign_Info* effect is significantly larger during periods of economic downturn. On average, the long-short return spread based on *Foreign_Info* in individual countries is 0.46% per month higher during recessions than during expansions. The effect is statistically significant at the 5% significance level. In a similar vein, we find that the returns of the global long-short portfolio strategy are significantly positive related to the global recession dummy and ΔVIX.

Overall, the results in Table 7 provide strong evidence that the return predictability due to *Foreign_Info* is countercyclical. One potential explanation for this result is that investors are more distracted during times of economic downturn in their home country and devote less attention to foreign information. In periods of domestic economic turmoil, investors are often flooded with news and face serious challenges in interpreting the implications of this information for their investment decisions. If attention is a limited cognitive resource (e.g., Kahneman (1979); Cohen and Frazzini (2008)), an increase in the amount of domestic information potentially limits investors' capabilities to observe foreign information, which in turn leads to a greater *Foreign_Info* predictability effect. Increased limited attention in periods of economic downturns is also consistent with empirical findings of Hou, Peng, and Xiong (2009), Karlsson, Loewenstein, and Seppi (2009), Sicherman, Loewenstein, Seppi, and Utkus (2015) and Jacobs

and Weber (2015). These studies show that investors pay more attention to their investments in rising markets, but begin to "put their heads in the sand" during bad market environments.

4.3 Country Characteristics

Section 3 indicates that *Foreign_Info* has a significant impact on future returns of multinational firms worldwide. However, the return difference between high *Foreign_Info* stocks and low *Foreign_Info* stocks strongly varies across countries (see Panel A of Table 7). Hence, we finally turn to the question of which factors drive the differenes in the magnitude of the *Foreign_Info* effect across countries. To do so, we regress the annual return of the country-specific 3-1 long-short portfolio strategy based on *Foreign_Info* for country *c* (denoted by $R_{c,t}^{h-l}$, annualized based on monthly return realizations) on time-fixed country characteristics controlling for the annual domestic market returns and market volatility (computed as the past 36 months rolling standard deviation of the market return):

$$R_{c,t}^{h-l} = \beta_0 + \beta_1 Characteristics_c + \beta_2 Market\_Ret_{c,t} + \beta_3 Market\_Vola_{c,t} + \varepsilon_{c,t}. \quad (4)$$

We use a pooled regression framework with yearly time dummies and clustered standard errors by country to estimate equation (4). We differentiate between two set of country characteristics as explanatory variables: investor characteristics and macroeconomic variables.

Investor Characteristics. We hypothesize that investors' inattention to foreign news slows the incorporation of foreign information into prices and increases the predictability of multinationals' stock returns. To proxy for investor inattention with regard to foreign information

we use a country's domestic bias level *(Domestic Bias)*. We obtain data for *Domestic Bias* for all countries in our sample from Chan, Covrig, and Ng (2005) who examine how mutual fund managers allocate their investments between domestic and foreign equity markets. In particular, the *Domestic Bias* for country *c* reflects the deviation of the share of the home country in its mutual fund holdings from the world market capitalization.[25]

Another potential explanation of the *Foreign_Info* effect is that investors lack the knowledge to understand and interpret foreign information when evaluating financial decisisions. A testable implication of this hypothesis is that the *Foreign_Info* effect should be high in countries with low (financial) literacy of domestic stock market investors. To proxy for (financial) literacy of domestic investors we use the average years of schooling *(Schooling)* of a country's resident obtained from Barro and Lee (2013).

Finally, we also investigate the relationship between a country's trust level *(Trust)* and the magnitude of the foreign information effect. It is feasible that investors from countries with low levels of trust doubt foreign information and do not include it when evaluating financial investments. This behaviour would subsequently enhance the magnitude of the foreign information effect in those countries. Data for *Trust* is obtained from Guiso, Sapienza, and Zingales (2008). Specification (1) of Table 8 reports the results.

[Insert Table 8 about here]

[25] In our regression analysis we also control for a country's *Foreign Bias*. The *Foreign Bias* reflects the extent to which investors underweight or overweight foreign markets (see Chan, Covrig, and Ng (2005).

As expected, we find that *Domestic Bias* has a positive and statistically significant impact on the magnitude of the *Foreign_Info* effect. This result is again consistent with the notion that limited attention of investors is the main driving force behind the *Foreign_Info* effect. We do not find evidence of a statistically significant impact of *Schooling* or *Trust*.

Macroeconomic Variables. The *Foreign_Info* effect is likely to be related to different macroeconomic state variables. In particular, we hypothesize that the magnitude of the *Foreign_Info* effect is higher in country's with segmented equity markets and strict capital flow restrictions. To test for these hypotheses we obtain data for a country's equity market segmentation *(Segmentation)* from Bekaert, Harvey, Lundblad, and Siegel (2011) as well as capital flow restrictions *(Capital Flow Resrictions)* from Chan, Covrig, and Ng (2005). We also control for different macroeconomic / stock market variables such as a country's credit rating obtained from Chan, Covrig, and Ng (2005) as well as stock market turnover and trading volume obained from La Porta, Lopez-De-Silanes, and Shleifer (2006).

Specification (2) of Table 8 shows that the variables significantly positive related to the magnitude of the *Foreign_Info* effect are indeed *Segmentation* and *Capital Flow Restrictions*. These results are in accordance to the idea that value-relevant foreign information particularly slowly dilutes into stock prices in countries with weakly integrated equity markets and severe capital flow constraints.

5. Conclusion

This paper analyzes whether value-relevant foreign information only gradually mitigates into stock prices of multinationals using a sample of firms from 22 developed countries worldwide.

We proxy for a firm's exposure to foreign information (Foreign_Info) using the sales-weighted average of industry-level returns in the relevant foreign countries and show that Foreign_Info has significant predictive power for future stock returns on a global scale and across different geographical subsamples. Worldwide, stocks with the highest Foreign_Info outperform stocks with the lowest Foreign_Info on average by 0.85% per month (10.20% per annum). We document that this outperformance is not explained by traditional risk factors, firm characteristics, and industry momentum.

Having established a robust link between Foreign_Info and future stock returns on a global scale, we also shed light on possible drivers of this effect. We find that the Foreign_Info effect is particularly strong for small firms with low analyst coverage, firms with low institutional ownership and high idiosyncratic volatility, and firms with the majority of sales in countries with a different main language as the home country language. Moreover, we show that the effect is pronounced during periods of economic and financial distress, and particularly strong in countries characterized by strong domestic bias, segmented equity markets, and high capital flow restrictions. Our empirical findings are consistent with the notion that investors'

inattention to non-domestic information is likely to be the main driver of the Foreign_Info effect worldwide.

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Table 1: Summary Statistics

This table presents summary statistics for the sample used in this paper. The sample consists of multinational firms from 22 developed markets from June 2001 to December 2014. Data for U.S. multinationals are from CRSP and Compustat. Data for non-U.S. multinationals are from FactSet. We assign each individual country to one of three regions: Asia-Pacific, Europe and North America. The table also provides summary statistics for our key variable of interest: *Foreign_Info*, which is used to predict returns of multinational firms. *Foreign_Info* is the geographic sales weighted average of foreign industry returns from a multinational firm's foreign segments.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country	No. of Firms	Firm-month Observations	Asia-Pacific	Europe	North America	*Foreign_Info* Min	*Foreign_Info* Average	*Foreign_Info* Max
Australia	736	24,733	x			-0.34	0.00	0.42
Austria	70	4,009		x		-0.35	0.01	0.26
Belgium	96	5,628		x		-0.28	0.01	0.30
Canada	919	39,129			x	-0.34	0.00	0.27
Denmark	110	5,988		x		-0.28	0.01	0.30
Finland	113	8,294		x		-0.29	0.01	0.46
France	641	38,760		x		-0.28	0.00	0.32
Germany	564	30,414		x		-0.31	0.00	0.26
HongKong	985	45,453	x			-0.34	0.01	0.45
Ireland	41	1,974		x		-0.22	0.01	0.24
Italy	230	15,609		x		-0.27	0.00	0.25
Japan	1,439	108,004	x			-0.22	0.00	0.28
Netherlands	132	10,193		x		-0.30	0.00	0.25
Norway	150	6,262		x		-0.29	0.01	0.33
New Zealand	64	3,044	x			-0.24	0.01	0.17
Portugal	41	2,534		x		-0.22	0.01	0.19
Singapore	568	23,198	x			-0.43	0.01	0.32
Spain	124	9,099		x		-0.24	0.00	0.27
Sweden	264	15,711		x		-0.34	0.01	0.36
Switzerland	191	14,343		x		-0.31	0.01	0.33
UK	1,370	54,574		x		-0.38	0.00	0.31
USA	3,314	210,943			x	-0.29	0.00	0.25
Total	12,162	677,896	5	15	2	-0.43	0.00	0.46

Table 2: Univariate Portfolio Sorts

This table reports the results of value-weighted univariate portfolio sorts. Panel A presents average excess returns (in USD) in month *t* of five value weighted quintile portfolios sorted on *Foreign_Info* in month *t-1*. The results are shown for five regions: Global, Global ex US, Asia-Pacific, Europe and North America. Panel A also reports the returns on a self-financing portfolio strategy (5-1) that buys (sells) the top (bottom) quintile portfolio stocks. Panel B reports risk-adjused returns for each quintile portfolio and the 5-1 difference portfolio using a regional version of the Carhart (1997) four factor model. The risk factors are obtained from Asness, Frazzini, and Pedersen (2014). We also report the factor loadings of the 5-1 difference portfolio. T-statistics are shown in parentheses and calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Portfolio Excess Returns

	(1)	(2)	(3)	(4)	(5)
	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (low)	0.15	0.32	0.20	0.49	0.18
2	0.54	0.57	0.21	0.59	0.48
3	0.57	0.74	0.61	0.83	0.39
4	0.64	0.68	0.78	0.79	0.77
5 (high)	1.00	0.95	1.00	0.87	1.00
5 – 1	0.85***	0.63**	0.80**	0.38	0.82**
	(3.22)	(2.45)	(2.28)	(1.38)	(2.22)

Panel B: Carhart (1997) Risk-Adjusted Returns

	(1)	(2)	(3)	(4)	(5)
	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (low)	-0.37	-0.17	-0.09	-0.07	-0.42
2	-0.01	-0.13	-0.47	-0.09	0.01
3	0.07	0.08	-0.02	0.06	-0.02
4	0.13	0.02	0.18	0.19	0.30
5 (high)	0.52	0.48	0.59	0.36	0.54
5 – 1	0.89***	0.65**	0.68*	0.44	0.95**
	(3.59)	(2.26)	(1.80)	(1.35)	(2.55)
MKT	-0.20***	-0.16***	-0.07	-0.18***	-0.23***
	(-2.97)	(-2.83)	(-1.15)	(-3.12)	(-2.90)
SMB	-0.33*	-0.25**	-0.37**	-0.14	-0.20
	(-1.70)	(-2.18)	(-2.28)	(-1.15)	(-0.89)
HML	0.58***	0.33**	0.39***	0.33*	0.40**
	(3.12)	(2.10)	(2.65)	(1.66)	(2.12)
UMD	-0.19*	-0.13	-0.13	-0.11	-0.14
	(-1.78)	(-1.10)	(-1.02)	(-1.23)	(-1.26)

Table 3: Fama-MacBeth Regressions

This table reports the results of Fama and MacBeth (1973) regressions where the excess return of multinational firm *i*, $R_{i,t}$, is regressed on $Foreign\_Info_{i,j,t-1}$ and a vector of control variables. All returns are denominated in USD. $Foreign\_Info_{i,j,t-1}$ is the sales-weighted foreign industry return of multinational firm *i* in month *t-1*. *Beta* is the firm's beta factor, estimated over the previous 60 months. *Size* is the log market capitalization in USD at the end of previous June. *BM* is the log book-to-market ratio in USD at the end of December (in USD). $R_{i,t-12:t-2}$ is the lagged firm return from month t-12 through month t-2. $R_{i,t-1}$ is the lagged firm return. *Turnover* is defined as the number of stocks traded during a given day divided by the number of stocks outstanding at the end of the day, averaged over the past 12 months. *Idio_Vola* is the standard deviation of the residuals of a market model regression, estimated over the previous 60 months. $Dom\_Ind\_Ret_{i,t-1}$ is the lagged domestic industry return. $Dom\_Ind\_Ret_{i,t-12:t-2}$ is the lagged domestic industry return from month t-12 through month t-2. Panel B reports the results of Fama-MacBeth regressions including $Foreign\_Info\_Market_{i,t-1}$, the sales weighted foreign market return of multinational firm *i*. T-statistics are calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 3: Continued

Panel A: Baseline Fama and MacBeth (1973) Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global	Global
k-month future return	1	1	1	1	1	2	3	6
$Foreign\_Info_{i,j,t-1}$	0.084***	0.095***	0.084***	0.075***	0.073***	0.117***	0.144***	0.169***
	(4.76)	(6.20)	(4.21)	(4.72)	(2.80)	(4.97)	(4.30)	(3.19)
Beta	0.002	0.002	0.003	0.002	0.003	0.005	0.007	0.014
	(1.07)	(0.91)	(1.16)	(0.94)	(1.45)	(1.15)	(1.18)	(1.14)
Size	-0.001*	0.000	-0.001**	0.000	-0.002***	-0.001*	-0.002*	-0.004*
	(-1.70)	(-0.89)	(-2.16)	(-0.36)	(-3.29)	(-1.74)	(-1.73)	(-1.69)
BM	0.001***	0.002***	0.003***	0.001	0.000	0.002***	0.003***	0.008***
	(2.67)	(3.37)	(3.48)	(1.36)	(-0.75)	(2.67)	(2.87)	(3.30)
$R_{i,t-12:t-2}$	0.002	0.004	0.002	0.008	0.000	0.004	0.004	0.000
	(0.45)	(0.93)	(0.42)	(1.48)	(0.04)	(0.46)	(0.33)	(-0.01)
$R_{i,t-1}$	-0.012*	-0.009	-0.006	-0.010	-0.015**	-0.011	-0.004	0.007
	(-1.96)	(-1.34)	(-0.74)	(-1.26)	(-2.25)	(-1.01)	(-0.32)	(0.25)
Turnover	-0.009***	-0.542**	-0.611***	-0.371	-0.007***	-0.017***	-0.026***	-0.051***
	(-3.35)	(-2.51)	(-3.03)	(-1.54)	(-2.75)	(-3.48)	(-3.54)	(-3.56)
Idio_Vola	-0.005***	-0.004***	-0.006***	-0.004**	-0.003	-0.009***	-0.012***	-0.023***
	(-3.22)	(-3.83)	(-4.99)	(-2.32)	(-1.19)	(-3.01)	(-3.00)	(-2.92)
$Dom\_Ind\_Ret_{i,t-1}$	0.031***	0.031***	0.058***	0.019*	0.056***	0.037**	0.054***	0.069***
	(3.33)	(3.19)	(3.89)	(1.73)	(2.61)	(2.47)	(3.90)	(3.07)
$Dom\_Ind\_Ret_{i,t-12:t-2}$	0.005	0.003	0.001	0.003	0.012*	0.011*	0.015*	0.021
	(1.47)	(0.83)	(0.21)	(1.24)	(1.88)	(1.79)	(1.80)	(1.15)
N	475981	327038	150362	151444	174175	472233	468462	457163
R2	0.107	0.129	0.136	0.102	0.066	0.111	0.110	0.104

Table 3: Continued

Panel B: Fama and MacBeth (1973) Regressions Including *Foreign_Info_Market*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global	Global
k-month future return	1	1	1	1	1	2	3	6
$Foreign\_Info_{i,j,t-1}$	0.097***	0.092***	0.077***	0.067***	0.092**	0.099***	0.130***	0.158***
	(6.89)	(6.79)	(2.74)	(3.86)	(2.16)	(4.48)	(4.65)	(3.19)
$Foreign\_Info\_Market_{i,j,t-1}$	0.006	0.029	0.047	0.013	-0.071	0.056	0.057	0.063
	(0.26)	(1.26)	(0.91)	(0.79)	(-1.25)	(1.63)	(1.38)	(0.87)
Beta	0.002	0.001	0.003	0.002	0.003	0.005	0.007	0.014
	(1.01)	(0.83)	(1.39)	(0.74)	(1.50)	(1.15)	(1.18)	(1.14)
Size	-0.001**	-0.001	-0.001***	0.000	-0.001***	-0.001*	-0.002*	-0.004*
	(-2.00)	(-1.22)	(-2.60)	(-0.38)	(-2.81)	(-1.76)	(-1.74)	(-1.69)
BM	0.001**	0.002***	0.003***	0.002	0.000	0.002***	0.003***	0.008***
	(2.51)	(3.53)	(3.82)	(1.51)	(-0.13)	(2.69)	(2.87)	(3.29)
$R_{i,t-12:t-2}$	0.001	0.004	0.000	0.008	0.000	0.004	0.004	0.000
	(0.30)	(0.70)	(-0.05)	(1.55)	(-0.04)	(0.45)	(0.33)	(-0.01)
$R_{i,t-1}$	-0.012*	-0.009	-0.005	-0.012	-0.015**	-0.011	-0.004	0.007
	(-1.90)	(-1.20)	(-0.49)	(-1.52)	(-2.21)	(-1.00)	(-0.31)	(0.26)
Turnover	-0.008***	-0.478**	-0.489**	-0.308*	-0.006**	-0.017***	-0.026***	-0.051***
	(-2.81)	(-2.35)	(-2.16)	(-1.87)	(-2.21)	(-3.46)	(-3.52)	(-3.54)
Idio_Vola	-0.005***	-0.004***	-0.007***	-0.005*	-0.004	-0.009***	-0.012***	-0.023***
	(-3.03)	(-3.28)	(-5.01)	(-1.67)	(-1.36)	(-3.03)	(-3.01)	(-2.93)
$Dom\_Ind\_Ret_{i,t-1}$	0.029***	0.028***	0.051***	0.020*	0.062***	0.039***	0.056***	0.069***
	(2.92)	(2.95)	(2.89)	(1.86)	(2.98)	(2.65)	(4.01)	(3.13)
$Dom\_Ind\_Ret_{i,t-12:t-2}$	0.004	0.001	0.002	0.002	0.007	0.011*	0.015*	0.021
	(1.13)	(0.51)	(0.44)	(0.64)	(1.11)	(1.74)	(1.78)	(1.17)
N	475981	327038	150362	151444	174175	472233	468462	457163
R2	0.111	0.135	0.139	0.109	0.064	0.111	0.111	0.104

Table 4: Foreign Information vs. Domestic Industry Momentum

Panel A presents the averages of monthly excess returns of 25 value weighted quintile portfolios sorted on $Dom\_Ind\_Ret_{i,t-1}$ and then sorted on $Foreign\_Info_{i,j,t-1}$. The quintile portfolios are constructed by pooling all stocks in the sample, i.e., covering the global region. All returns are denominated in USD. Panel A also reports the returns on a self-financing portfolio strategy (5-1) that buys (sells) the top (bottom) quintile portfolio. Panel B presents the averages of monthly excess returns of 25 value weighted quintile portfolios sorted on $Dom\_Ind\_Ret_{i,t-2:t-12}$ and then sorted on $Foreign\_Info_{i,j,t-1}$. T-statistics are shown in parentheses and calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Short-term Industry Momentum and *Foreign_Info*

		$Dom\_Ind\_Ret_{i,t-1}$					
		1 (low)	2	3	4	5 (high)	Average
$Foreign\_Info_{i,j,t-1}$	1 (low)	0.17	0.34	0.17	0.17	0.75	0.32
	2	0.18	0.61	0.74	0.52	0.65	0.54
	3	0.24	0.60	0.65	0.58	0.77	0.57
	4	0.42	0.86	0.59	0.72	0.82	0.68
	5 (high)	0.89	1.15	1.07	1.16	0.67	0.99
	5-1	0.71***	0.81***	0.91***	1.00***	-0.08	0.67
		(2.72)	(3.00)	(3.24)	(3.40)	(-0.28)	

Panel B: Medium-term Industry Momentum and *Foreign_Info*

		$Dom\_Ind\_Ret_{i,t-12:t-2}$					
		1 (low)	2	3	4	5 (high)	Average
$Foreign\_Info_{i,j,t-1}$	1 (low)	0.26	0.22	0.39	0.59	0.49	0.39
	2	0.34	0.27	0.54	0.52	0.83	0.50
	3	0.94	0.39	0.60	0.58	1.02	0.71
	4	0.65	0.55	0.57	0.77	0.87	0.68
	5 (high)	0.56	1.15	0.75	0.99	1.02	0.89
	5-1	0.30	0.93***	0.37*	0.40**	0.52*	0.50
		(1.07)	(3.19)	(1.80)	(2.02)	(1.82)	

Table 5: Robustness

This table presents the averages of monthly excess returns (in percent) of five equally weighted and value weighted quintile portfolios sorted on *Foreign_Info* in month *t-1*. The quintile portfolios are constructed by pooling all stocks that are headquartered in the corresponding region: Global, Global ex US, Asia-Pacific, Europe and North America. It also reports the returns on a self-financing portfolio strategy (5-1) that buys (sells) the top (bottom) quintile portfolio. Panel A reports average portfolio returns denominated in USD from our base case specifications using the entire sample. Panel B reports the average returns of the portfolio sorts in local currency instead of USD. Panel C reports the average returns of portfolio sorts skipping five trading days between the measurement period of $Foreign\_Info_{i,j,t-1}$ and the start of the portfolio formation period. Panel D reports the average returns of portfolio sorts when we only use the 20% largest firms in each country and month. Panel E reports the average returns of portfolio sorts excluding financial firms. T-statistics are calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Equal-Weighted and Value-Weighted Sorts

	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global ex USA	Asia-Pacific	Europe	North America
	Equal-Weighted					Value-Weighted				
1 (low)	0.47	0.44	0.61	0.51	0.55	0.15	0.32	0.20	0.49	0.18
2	0.80	0.74	0.65	0.83	0.93	0.54	0.57	0.21	0.59	0.48
3	1.00	0.95	0.88	1.00	1.10	0.57	0.74	0.61	0.83	0.39
4	1.18	1.22	1.14	1.20	1.24	0.64	0.68	0.78	0.79	0.77
5 (high)	1.42	1.44	1.41	1.35	1.32	1.00	0.95	1.00	0.87	1.00
5-1	0.95***	1.00***	0.79**	0.84***	0.77**	0.85***	0.63**	0.80**	0.38	0.82**
	(3.53)	(4.03)	(2.20)	(4.16)	(2.37)	(3.22)	(2.45)	(2.28)	(1.38)	(2.22)

Panel B: Local Currency Returns

	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global ex USA	Asia-Pacific	Europe	North America
	Equal-Weighted					Value-Weighted				
1 (low)	0.34	0.22	0.53	0.12	0.48	0.02	0.05	0.04	0.13	0.16
2	0.66	0.54	0.53	0.49	0.89	0.39	0.30	0.06	0.24	0.45
3	0.86	0.71	0.73	0.63	1.06	0.41	0.46	0.46	0.44	0.39
4	0.97	0.91	0.96	0.83	1.19	0.49	0.37	0.63	0.47	0.72
5 (high)	1.19	1.11	1.21	1.00	1.23	0.77	0.61	0.72	0.51	0.96
5-1	0.85***	0.88***	0.68*	0.87***	0.75**	0.74***	0.55**	0.68**	0.39	0.81**
	(3.20)	(3.45)	(1.89)	(4.27)	(2.32)	(2.98)	(2.24)	(2.08)	(1.52)	(2.14)

Table 5: Continued

Panel C: Five Days Skip

	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global ex USA	Asia-Pacific	Europe	North America
	Equal-Weighted					Value-Weighted				
1 (low)	0.54	0.53	0.64	0.58	0.57	0.23	0.56	0.19	0.54	0.07
2	0.80	0.73	0.63	0.89	0.96	0.53	0.52	0.27	0.59	0.55
3	1.01	0.96	0.87	0.97	1.11	0.61	0.68	0.60	0.74	0.61
4	1.09	1.08	1.17	1.11	1.17	0.57	0.65	0.83	0.74	0.61
5 (high)	1.44	1.50	1.38	1.34	1.31	0.96	0.90	0.81	0.91	0.95
5-1	0.90***	0.97***	0.74**	0.75***	0.74***	0.73***	0.34	0.62**	0.37	0.88***
	(4.65)	(4.55)	(2.17)	(4.22)	(3.10)	(3.57)	(1.33)	(2.05)	(1.19)	(3.12)

Panel D: Only 20% Largest Firms

	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global ex USA	Asia-Pacific	Europe	North America
	Equal-Weighted					Value-Weighted				
1 (low)	0.46	0.54	0.74	0.53	0.27	0.13	0.36	0.23	0.45	0.14
2	0.75	0.88	0.61	0.96	0.81	0.54	0.58	0.17	0.60	0.60
3	0.91	0.92	0.77	0.98	0.82	0.53	0.65	0.61	0.78	0.37
4	1.05	1.18	1.20	1.25	0.95	0.66	0.75	0.80	0.87	0.70
5 (high)	1.33	1.37	1.37	1.35	1.17	0.98	0.88	0.93	0.86	0.98
5-1	0.88***	0.84***	0.63**	0.81***	0.90***	0.85***	0.52**	0.70**	0.40	0.84***
	(3.42)	(3.56)	(2.19)	(3.56)	(2.82)	(3.36)	(2.22)	(2.18)	(1.49)	(2.61)

Panel E: Excluding Financials

	Global	Global ex USA	Asia-Pacific	Europe	North America	Global	Global ex USA	Asia-Pacific	Europe	North America
	Equal-Weighted					Value-Weighted				
1 (low)	0.49	0.44	0.58	0.49	0.57	0.14	0.26	0.16	0.47	0.22
2	0.84	0.77	0.66	0.88	0.97	0.55	0.65	0.14	0.67	0.46
3	1.01	0.95	0.93	0.98	1.12	0.57	0.71	0.60	0.87	0.43
4	1.20	1.26	1.21	1.18	1.25	0.75	0.81	0.80	0.93	0.87
5 (high)	1.45	1.49	1.42	1.41	1.33	1.07	0.97	0.99	0.94	1.05
5-1	0.96***	1.04***	0.83**	0.92***	0.76**	0.93***	0.71***	0.83**	0.47*	0.83**
	(3.46)	(3.79)	(2.13)	(3.95)	(2.34)	(3.26)	(2.84)	(2.34)	(1.71)	(2.03)

Table 6: Drivers of the Foreign Information Effect: Firm Characteristics

This table reports the estimated coefficients and t-statistics (in parentheses) of Fama-MacBeth (1973) regressions where the excess return of multinational firm *i*, $R_{i,t}$, is regressed on $Foreign\_Info_{i,j,t-1}$, a vector of control variables, a dummy variable which is equal to one if the attention proxy of multinational *i* in the previous month is above the cross-sectional median of all firms, and the interaction effect between $Foreign\_Info_{i,j,t-1}$ and the dummy variable. $Foreign\_Info_{i,j,t-1}$ is the sales weighted foreign industry return of multinational firm *i* in month *t-1*. *Size* is the log market capitalization in USD at the end of June. *Res_Num_Ana* is the residual number of equity analysts providing earnings forecasts for a firm, orthogonalized with respect to firm size following Hong, Lim, and Stein (2000). *Res_Ownership* is the residual percentage of shares outstanding held by institutional investors, orthogonalized with respect to firm size. *Res_Num_Investors* is the residual number of individual institutional investors owning shares of a firm, orthogonalized with respect to size. *Idio_Vola* is the firm's idiosyncratic volatility. *Distance* is the sales-weighted geographical distance between the resident country of a multinational firm and its respective foreign geographical segments. *Sales_Same_Language* is the firm's share of sales from foreign countries with the same official language as the firm's resident country. We display the coefficient estimate of $Foreign\_Info_{i,j,t-1}$ and the interaction term. All regressions also include the standard set of control variables as described in the text. T-statistics are calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign Info	0.13***	0.11***	0.11***	0.13***	0.07***	0.13***	0.12***
	(5.56)	(5.85)	(5.21)	(4.58)	(4.47)	(4.21)	(4.90)
Size > Median	-0.05**						
	(-2.36)						
Res_Num_Ana > Median		-0.04*					
		(-1.79)					
Res_Ownership > Median			-0.04*				
			(-1.78)				
Res_Num_Investors > Median				-0.06*			
				(-1.78)			
Idio_Vola > Median					0.05**		
					(2.20)		
Distance > Median						-0.03	
						(-1.08)	
Sales_Same_Language > Median							-0.05***
							(-2.64)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Drivers of the Foreign Information Effect: Business Cycle Variation

Panel A presents the averages of monthly excess returns (in percent) of value weighted top and bottom tertile portfolios sorted on *Foreign_Info* in month *t-1* for each individual country in the sample. All returns are denominated in USD. We also reports the returns on a self-financing portfolio strategy (3-1) that buys (sells) the top (bottom) tertile portfolio. The table also reports the regression results of a Carhart (1997) four factor model, where the 3-1 returns of each country are regressed on corresponding regional risk factors. The risk factors are obtained from Asness, Frazzini, and Pedersen (2014). Panel B reports the coefficient estimates and t-statistics of various time series regressions. The dependent variable is the monthly country-level / global excess return of a self-financing strategy that buys (sells) the stocks of multinational firms with the highest (lowest) *Foreign_Info* in the previous month and the independent variable is an indicator for months of economic distress. In the first column, we regress the country-level long-short portfolio returns on country-level recession indicators. In the second column, the long-short portfolio returns of the global strategy are regressed on a recession indicator for the total OECD area. In the third column, long-short portfolio returns of the global strategy are regressed on monthly changes of the VIX. T-statistics are shown in parentheses and calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Individual Country Portfolio Returns

	Excess Return				Four-Factor Alpha	
	1	3	3-1	t-stat	3-1	t-stat
Australia	1.05	1.34	0.29	(0.84)	0.36	(1.02)
Austria	1.33	1.84	0.50	(1.16)	0.76	(1.59)
Belgium	0.22	1.32	1.09**	(2.00)	1.38**	(2.23)
Canada	0.96	0.99	0.02	(0.05)	0.16	(0.35)
Denmark	0.30	1.66	1.36**	(2.17)	1.29*	(1.75)
Finland	1.27	1.07	-0.20	(-0.34)	-0.14	(-0.20)
France	0.53	0.85	0.31	(0.88)	0.23	(0.49)
Germany	0.68	0.84	0.16	(0.70)	0.13	(0.65)
Hong Kong	0.46	1.44	0.98***	(2.79)	0.65*	(1.67)
Ireland	-0.21	1.57	1.78	(1.52)	0.93	(0.91)
Italy	0.36	0.42	0.06	(0.17)	0.25	(0.95)
Japan	-0.14	0.64	0.78***	(4.07)	0.76**	(2.56)
Netherlands	0.62	1.12	0.50*	(1.84)	0.57*	(1.69)
Norway	1.11	1.47	0.36	(0.71)	0.89*	(1.77)
New Zealand	1.14	1.39	0.25	(0.53)	0.13	(0.22)
Portugal	0.42	0.40	-0.02	(-0.04)	-0.17	(-0.24)
Singapore	0.53	1.70	1.17***	(4.00)	1.20***	(3.76)
Spain	0.76	0.87	0.12	(0.45)	0.21	(0.66)
Sweden	0.97	1.16	0.19	(0.51)	0.66**	(2.28)
Switzerland	0.19	1.38	1.20***	(3.12)	1.29***	(3.83)
UK	0.30	0.84	0.54***	(2.65)	0.70**	(2.55)
USA	0.27	0.79	0.52**	(2.13)	0.56**	(2.38)

Table 7: Continued

Panel B: Business Cycle Regressions

	(1)	(2)	(3)
	Individual Country Recession Indicator	Global Recession Indicator	ΔVix
Coefficient	0.46**	1.04*	3.52**
	(2.12)	(1.69)	(2.48)
N	3000	150	150
R2	0.033	0.014	0.033

Table 8: Drivers of the Foreign Information Effect: Country Characteristics

In this table we regress the annual return of the country-specific 3-1 long-short portfolio strategy based on *Foreign_Info* for country *c* on time-fixed country characteristics controlling for the annual market return and market volatility (computed as the past 36 months rolling standard deviation of the market return). We use a pooled regression framework with yearly time dummies and clustered standard errors by country. As explanatory variables we use both investor characteristics and macroeconomic variables. As investor characteristics we include a country's *Domestic Bias*, *Foreign Bias*, the average years of schooling of a country's resident *(Schooling)*, and a country's *Trust* level. Included macroeconomic variables are a country's equity market segmentation *(Segmentation)*, capital flow resrictions *(Capital Flow Restrictions)*, a country's credit rating *(Credit Rating)* as well as stock market turnover *(Turnover)* and trading volume *(Trading)*. T-statistics are shown in parentheses and calculated using the Newey and West (1987) method with 12 lags. *,** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)
	Investor Characteristics	Macroeconomic Variables
Domestic Bias	0.0274**	
	(2.43)	
Foreign Bias	0.0344	
	(1.17)	
Schooling	0.0061	
	(0.45)	
Trust	0.0562	
	(0.23)	
Segmentation		0.0420*
		(1.94)
Capital Flow Restrictions		0.0184*
		(1.77)
Credit Rating		0.000285
		(0.11)
Turnover		-0.000337
		(-0.9)
Trading		0.000299
		(1.12)
Constant	0.194*	-0.0906
	(1.85)	(-0.33)
Stock Market Characteristics Controls	Yes	Yes
N	216	210
R2	0.131	0.135