Does Investor Attention Stop at the Water's Edge? The Predictability of Multinational Firms' Returns*

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Abstract

Using foreign geographic exposure extracted from 10-Ks, I find that stock prices do not promptly incorporate information regarding changes in foreign market conditions. This generates return predictability in the cross-section of firms with foreign operations. A simple trading strategy that exploits geographic information yields a risk-adjusted return of 45 basis points per month. The predictability cannot be explained by firms' momentum, industry momentum, post-earnings-announcement drift, being a conglomerate, or exposure to emerging market risk. Consistent with the investor inattention hypothesis, smaller firms, and firms with less analyst coverage, fewer institutional holdings, or more complex foreign exposure compositions exhibit stronger return predictability.

Keywords: Foreign exposure, inattention, textual analysis.
JEL Classification: G11, G12, G14

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Many multinational companies headquartered in the United States generate increasingly greater revenue in and have significant exposure to foreign markets. For example, in 2010, Walmart earned 24.6% of its total sales abroad, Intel earned 9.6% of its sales in Japan, Avon earned 41% of its sales in Latin America, and 8.6% of total sales of Sealy Corporation went to Europe. It is therefore natural to expect that shocks to foreign market demand should affect firms with foreign operations. In particular, the future profitability outlook and stock value of U.S. firms with offshore sales and operations should respond instantaneously to unexpected changes in international market conditions. However, do investors pay attention to this link between multinational firms and their international markets?

In this paper, I investigate this relationship. I analyze the impact of changes in foreign market conditions, measured by changes in foreign stock market indices, on the performance of U.S. firms having operations in those markets, and examine how shocks to foreign markets are incorporated into stock returns.

As a motivating example, consider the case of the Las Vegas Sands Corporation (NYSE: LVS) and its recent expansion into the Asian market. Las Vegas Sands (LVS) is a casino resort company that owns the iconic Venetian Resort-Hotel-Casino in Las Vegas. In August 2007, LVS launched The Venetian Macao Resort Hotel, a similar property in Macao modeled on its sister resort in Las Vegas. The Venetian Macao was a large investment and a major expansion of LVS into the Asian market. The new structure costs $2.4 billion and is the largest single-structure hotel in Asia and the fifth largest building in the world by area.

One would naturally presume that, following the opening of The Venetian Macao, the sales and revenue of LVS would have been greatly influenced by the Asian market environment. In addition, one would expect that news regarding the performance of the Asian market should instantaneously be incorporated into the firm's stock market valuation in the U.S. We should therefore expect to see no predictability between the Asia stock market index returns and LVS's future stock returns; however, this is not the case.

Figure 1 shows scatterplots of monthly LVS stock returns with respect to the lagged monthly Asia index returns, both before and after launching The Venetian Macao casino resort in August 2007. I superimpose least-squares lines on each scatterplot. The slope is close to zero before and increases significantly after the resort opened. Before the opening, the correlation between LVS stock returns and lagged Asian index returns is 0.049, which is not significantly different from zero. After August 2007, the correlation increases to 0.454 and is significantly different from zero at the 1% confidence level. In other words, since the opening of the resort, lagged Asian stock returns strongly predict the firm's subsequent stock returns in the U.S., even though the firm's exposure to Asia had been publicly available for quite some time.

[Insert Figure 1 about here]

This predictability extends beyond this particular example. In more general tests, I find that there is significant predictability of returns on stocks with foreign operations. A portfolio strategy that buys firms with exposure to countries that had the highest returns in the previous month and selling firms with exposure to countries that had the lowest returns yields risk-adjusted abnormal returns of 45 basis points over the next month (or an annualized return of 5.4%). In other words, by knowing the broad stock market performance of the geographic areas where a firm has business operations, one can predict the firm's future stock market returns. I refer to this returns predictability as "geographic momentum". Returns on this geographic momentum strategy yield strong results for the first month after portfolio formation, with zero predictability thereafter. Moreover, returns on the geographic momentum strategy have no exposure to standard traded risk factors. The results are not driven by a firm's own momentum, industry momentum, post-earnings-announcement drift, being a conglomerate, or exposure to emerging market risk.

I present additional evidence consistent with investors having limited attention. If their limited attention is driving the geographic momentum effect, varying the degree of investor inattention should vary the magnitude and significance of the result. Reconcilable with the investor inattention hypothesis, returns predictability is strongest for firms that generally receive less investor attention: stocks with less analyst coverage, small- and medium-sized stocks, and stocks that have fewer institutional holdings. Furthermore, predictability is also strongest for firms that are geographically more complex (firms with exposure to more countries) and thus may require more time to process changes in fundamentals.

There are a number of alternative explanations for the geographic momentum effect. First, the results may be driven by risk factors, not investor inattention. One might argue that firms that have sales and operations in emerging markets, such as China, Brazil, India, or Russia, are more exposed to emerging market risks and hence should logically have higher expected returns. Sorting firms based on their past geographic-based returns may just be grouping firms based on their degree of exposure to emerging markets risks. However, the evidence shows that the geographic momentum effect is essentially unchanged after controlling for the percentage of a firm's foreign exposure that come from a particular country.

Cohen and Lou (2012) document that conglomerates exhibit substantial stock-returns predictability from the weighted-average returns of an equivalent group of stand-alone firms that have business operations similar to the conglomerate. A valid concern is that the geographic momentum effect is simply a noisy proxy for their "complicated firm" effect. A conglomerate may have a chocolate business segment in Switzerland while at the same time having a coffee business segment in Italy. Hence, the stock indices in both countries are just proxies for the conditions of distinct business segments. The findings show that geographic momentum is not the same as the complicated firm effect. Indeed, geographic momentum and the complicated firm effect seem to be totally orthogonal to each other as the returns on each strategy is unchanged after controlling for the other strategy. Further, I find that even after controlling for a firm's stock return in the last quarter, following market conditions in the regions where it does business yields incremental predictive power not only for future firm stock returns, but also for a firm's operating performance (such as sales and operating income). The results concerning operating performance are important as they justify the returns results: lagged geographic returns predict stronger sales and income for a firm in the next quarter and substantiate a higher stock price.

Merton (1987), Hong and Stein (1999), and Hirshleifer and Teoh (2003) provide theoretical foundations for asset pricing in an economy where investors have limited cognitive resources. Their models imply that slow information processing can generate expected returns that are not fully explained by traditional asset pricing models. Empirically, Huberman and Regev (2001) provide evidence that investors pay more attention to news that is more readily available and more appealing. DellaVigna and Pollet (2007) show that investors disregard information beyond a four-to-eight-year horizon and find that demographic information predicts stock returns across industries. DellaVigna and Pollet (2009) show that investors respond more slowly to Friday earnings announcements. My paper is the first to document the predictability link between country-level indices returns and firm-level stock returns. My paper also contributes to the growing literature on the role of investor inattention and firm complexity in price formation.

My findings relate to the literature on information diffusion and lead-lag effects in stock returns as well. Lo and MacKinlay (1990) show that large stocks lead small stocks. Hong, Torous, and Valkanov (2007) find that industries lead stock markets.

This paper is also related to, but is distinct from, recent papers by Cohen and Frazzini (2008), Menzly and Ozbas (2010), Shahrur, Becker, and Rosenfeld (2010), and Cohen and Lou (2012). These authors find similar supply chain momentum at the firm and industry levels. They also present evidence that return predictability is consistent with gradual information diffusion. Cohen and Frazzini (2008) find, in particular, that the stock returns of the largest customer can predict the stock returns of the supplier firm. Using an international sample, Menzly and Ozbas (2010) show that there is strong predictability between upstream and downstream industries. Shahrur, Becker, and Rosenfeld (2010) provide evidence that the stock returns of customer industries predict the stock returns of supplier industries.

The remainder of the paper is organized as follows. In Section 1, I characterize the data on geographic exposures and the test strategies. Section 2 presents evidence pertaining to the geographic momentum effect and robustness tests. Section 3 presents results consistent with the explanation that geographic momentum is driven by investor inattention. Section 4 discusses the Fama and MacBeth (1973) regression tests while controlling for other explanatory variables and provides evidence that rules out alternative hypotheses. Section 5 shows the geographic momentum effect on a firm's real operations. The last section concludes.

1 Data

The analysis of stock market reactions to changes in foreign market conditions requires that information on U.S. firms' foreign exposure be publicly available at the time when the changes in foreign markets conditions are measured. Similar to how Garcia and Norli (2012) measure state-level exposure in the U.S., I measure firms' international exposure by extracting country name counts from annual reports filed with the Securities and Exchange Commission (SEC) on Form 10-K. More specifically, using textual processing techniques, I extract the number of times a country or a region is mentioned in a firm's 10-K report to measure the degree of exposure of the firm to that country or region.

I download all complete 10-K, 10-K405, and 10-KSB filings from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) from 1994 to 2013. All complete 10-K filings are in HTML text format and aggregate of all information that is submitted with each firm's file, such as exhibits, graphics, XBRL files, PDF files, and Excel files. I extract the main 10-K texts in each document and remove all tables (if their numeric character content is greater than 15%), HTML tags, XBRL tables, exhibits, ASCII-encoded PDFs, graphics, XLS, and other binary files. I count the occurrence of country and regional names in sections "Item 1: Business," "Item 2: Properties," "Item 6: Consolidated Financial Data," and "Item 7: Management's Discussion and Analysis." Table 2 reports the complete list of geographic regions and the summary statistics on the number of times each region is mentioned in Form 10-K and Figure 2 shows the distribution of the number of distinct geographic regions reported in firms' 10-Ks. Only about 20% of firms do not report any foreign exposures.

[Insert Table 2 about here]

[Insert Figure 2 about here]

It is noteworthy that this measure of U.S. firms' international exposure is novel and has many advantages over traditional measures in the existing literature. Most other studies base their measures of international exposure on information reported in Exhibit 21 of the 10-K statements, where firms break down financial variables by business and geographic segments (Huang 2015; Lee, Naranjo, and Sirmans 2016).[1] However, the biggest drawback in and criticism of the use of geographic segment data is the lax threshold for mandatory reporting. More specifically, firms have to report disaggregated information only about their operating

[1] An earlier version of the paper uses geographic segment data to measure international exposure and yields similar results.

segments that comprise more than 10% of their total consolidated annual sales, and therefore a smaller percentage of sales may not be reported, biasing the data towards larger exposures. Furthermore, geographic segment data goes back only to 1998, as the Statement of Financial Accounting Standards (SFAS) No.131 that requires firms to report disaggregated information about their operating segments was issued in June 1997 and became effective for the fiscal year beginning after December 15, 1997. On the other hand, Form 10-Ks have been available on EDGAR since 1994.

Most importantly, there is no clear SEC guideline that defines what constitutes a "geographic region", and hence a majority of the time firms report only segment sales using very broadly defined geographic segments such as "Europe", "Asia Pacific", "North America" etc. In contrast, firms are much more comprehensive when they describe their offshore exposures in 10-K reports and are much more specific when they discuss the location of their offshore operations. Another problem that arises with the current literature's use of geographic segment data to measure international exposure is that firms report only the volume of foreign sales and hence many other types of exposure are not captured. On the other hand, 10-K filings contain richer informative descriptions of firms' foreign operations abroad, such as imports, offshore sale, offshore purchase, and offshore ownership of assets.

Market conditions in the various geographic segments are measured using returns data on a large sample of countries and regions. Index returns data are from the Morgan Stanley Capital International (MSCI) Global Equity Index. The sample consists of 4 regional indices and 74 country indices, for a total of 78 "geographic regions". Table 2 reports the complete list of countries and regions considered in this study and the summary statistics on the number of times that each country or region is mentioned in a firm's 10-K report. Indices are value-weighted and include the largest and most liquid stocks in each market. All indices are denominated in U.S. dollars. In order to ensure the results are not driven by movements in exchange rates, the entire analysis is repeated using indices denominated in local currency as well. The results remain largely unchanged.

[Insert Table 2 about here]

The returns data from the indices are merged with the geographic segment files by phonetically matching geographic names extracted from firms 10-K reports to standard index names used by MSCI. I manually check to make sure geographic names are correctly matched to stock market indices.

The main variable of interest in this paper is a firm's "geographic return", which I refer to as $GeoRet$. The geographic return for each firm is the weighted average return on MSCI indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. For example, if a firm has 30% of offshore exposure to China, 50% of offshore exposure to Brazil, and 20% of offshore exposure India, the firm's geographic return is computed as:

$$GeoRet = 0.3 \times Ret(China) + 0.5 \times Ret(Brazil) + 0.2 \times Ret(India),$$

where $Ret(China)$, $Ret(Brazil)$, and $Ret(India)$ are monthly index returns for China, Brazil, and India, respectively. In accord with the previous literature, I also exclude financial firms from the analysis (SIC codes between 6001 and 6999). However, this restriction is not pivotal in any of the results. I re-incorporate financial firms later in one of the robustness tests and find that the study is not sensitive to this restriction.

I merge the Compustat sample with CRSP monthly stock return files, requiring firms to have non-missing market equity and book equity at the fiscal year end. Similar to Fama and French (1993), to ensure that the degree of international exposure and financial information is publicly known before any return predictability is measured, I impose at least a six-month gap between a firm's fiscal year end and stock returns. More specifically, returns from July in year y to June in $y+1$ are matched with the latest Compustat and Form 10-K in the fiscal year that ends on or before December 31 of year $y-1$.[2]

In addition to stock returns, I also obtain data on earnings forecasts by analysts. In particular, I extract from IBES Detail files all available analyst forecasts for annual earnings reports. The number of analysts covering a firm is used to proxy for the degree of inattention.

The final sample has 590,271 firm-month observations spanning from January 1995 through December 2013. Panel A of Table 1 reports the summary statistics on the main variables. The average firm conducts offshore activities in eight foreign countries. The *Herfindahl* index indicates that the distribution of regional exposure is diverse, from fully concentrated with *Herfindahl* index equal to 1 (conducting offshore activities in only one foreign country) to fairly widely dispersed.

[Insert Table 1 about here]

Panel B of Table 1 provides the correlations of $GeoRet_{t-1}$ with Ret_t, the return on the firm's stock for the next month, and other variables known to predict stock returns. The correlations are computed using monthly observations of all stocks. $GeoRet_{t-1}$ is positively correlated with Ret_t (0.08). $GeoRet_{t-1}$ is also highly positively correlated with Cohen and Lou (2012)'s pseudo-conglomerate return, $PseudoRet_{t-1}$ (0.39).

[2] As a robustness test, when measuring a firm's monthly stock return, I skip the first three days of the month to rule out the possibility that non-synchronous trading restrictions or potential end-of-month macroeconomics information released in foreign countries can explain the link between the lagged geographic return and a firm's returns. The results do not change.

2 Results

This section presents results on the geographic momentum effect. I perform portfolio tests that sort stocks into portfolios based on their lagged geographic returns. Robustness tests for the geographic momentum results are also discussed.

2.1 Portfolio Tests

To examine the link between geographic returns and future stock returns, I sort stocks into portfolios based on their geographic returns for the previous month. At the beginning of each calendar month t, I rank stocks into ascending order based on geographic returns in month $t-1$. Each firm's geographic returns are the foreign-exposure-weighted average of region-level index returns corresponding to the geographic exposure of the firm. A firm's 10-K and the corresponding geographic exposure information are obtained from the fiscal year ending at least six months before portfolios are formed.

I then assign stocks to five quintile portfolios and compute the value and equally weighted returns within each given quintile portfolio. The five portfolios are rebalanced every month and their time series track calendar time performance. Abnormal returns are computed by running a time series regression of portfolio excess returns on traded factors in calendar time.

Figure 3 plots the time series of the monthly excess returns from the equally weighted geographic momentum portfolio strategy that buys the top geographic return stocks and short sells the lowest geographic return stocks (where excess returns are in excess of the risk-free rate). Excess returns are shown for every month from January 1995 through December 2013. The geographic momentum strategy yields positive returns for 75% of the months and returns worse than -5% for only three months.

[Insert Figure 3 about here]

Table 3 shows the main results. This table reports excess returns and alphas in month t of the geographic momentum portfolios formed at the end of month $t-1$ from January 1996 through December 2013. Panel A presents the average raw excess returns (returns in excess of the risk-free rate) of the equally weighted geographic momentum portfolio, as well as the alphas of the portfolios with respect to the CAPM, the Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, and finally the 5-factor model that includes Pastor and Stambaugh (2003)'s liquidity factor. Panel B reports the same analysis with value-weighted returns. All numbers are in percentage points.

[Insert Table 3 about here]

Sorting firms in Table 3 based on lagged geographic returns yields large differences in subsequent monthly returns. The average monthly excess returns on the quintile portfolio sorted by geographic returns increases monotonically, from 0.46% in the lowest quintile to 0.91% in the highest quintile. Column 6 (H-L) in Table 3 shows the excess returns of a zero-cost portfolio that goes long in stocks with the top 20% geographic returns and sells short stocks with the bottom 20% geographic returns. The difference in excess returns between the highest quintile and lowest quintile portfolios is 0.45% per month, or approximately 5.4% per year, with a t-statistic of 3.09. One must keep in mind that the geographic momentum strategy yielding these large excess returns involve monthly rebalancing and thus entail non-trivial transaction costs.

In addition, adjusting returns for sensitivity with multiple risk factors has little effect on the results. After controlling for standard factors, the bottom quintile portfolio has a negative and significant alpha, while the top quintile portfolio has a positive and significant alpha. The equally weighted long-short portfolio has monthly alphas of 0.48% (*t-stat* 3.52), 0.48% (*t-stat* = 3.27), 0.41% (*t-stat* = 2.90) and 0.41% (*t-stat* = 2.90) with respect to the CAPM, the Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, and the Pastor and Stambaugh (2003) liquidity factor, respectively. All alphas are statistically significant. Therefore, the smallest and least liquid stocks in the sample do not appear to be driving the results. Using value-weighted portfolios rather than equally weighted portfolios delivers similar results. The value-weighted long-short portfolio has monthly alphas of 0.29% (*t-stat* = 2.74), 0.32% (*t-stat* = 3.12), 0.31% (*t-stat* = 3.02), 0.29% (*t-stat* = 2.88), and 0.29% (*t-stat* = 2.78) with respect to the CAPM, the Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, and the Pastor and Stambaugh (2003) liquidity factor, respectively.

Table 4 reports estimated loadings of the zero-cost long-short geographic momentum portfolio on Fama and French (1993), Carhart (1997) momentum, and the Pastor and Stambaugh (2003) liquidity factors. None of the standard factors can explain the geographic momentum returns, either individually or jointly. This indicates that the geographic momentum strategy is very robust and not sensitive to the state of the economy or the performance of other popular investment strategies.

[Insert Table 4 about here]

I next test whether geographic momentum profitability is due to investor overreaction or to slow diffusion of information. I examine returns on the strategy over a longer future horizon. Table 5 follows the average returns and alphas of the geographic momentum portfolios for each month up to six months after portfolio formation. All portfolios are formed at time

$t = 0$ and $r_{i,i+1}$ are returns over month $[i, i + 1]$. Portfolios are equally weighted in Panel A and value weighted in Panel B.

[Insert Table 5 about here]

In both weighting schemes, the geographic long-short portfolio delivers positive and significant excess returns and alphas only in the month immediately after portfolio formation and is not significant in the following months. In particular, there is no reversal of returns earned in the first month. This suggests that the returns are not driven by overreaction to news about a firm's geographic condition, but rather by slow diffusion of information. Thus, information from the geographic markets of various country exposures of a firm is incorporated into firm prices with a one-month lag and is fully incorporated into stock prices after one month.

2.2 Robustness Checks

Table 6 verifies the robustness of the geographic momentum strategy in various subsamples. For all subsamples, as in Table 3, stocks are sorted into quintiles based on lagged geographic returns. For the zero-cost portfolio (long in stocks in the top quintile of geographic returns and short in stocks in the bottom quintile), I present excess returns and alphas with respect to various risk factors. The results for the original sample are presented for comparison in Panel A.

[Insert Table 6 about here]

A natural concern is that the geographic momentum results may also be driven by micro-capitalization illiquid securities. Less liquid stocks react more slowly to news about geographic exposure due not to investor inattention but rather mechanically to infrequent trading.

Some analyses presented earlier do not support this hypothesis, as the long-short geographic momentum strategies based on value-weighted returns also earn large and significant risk-adjusted returns. Panel B of Table 6 presents a more explicit test of the liquidity hypothesis by dropping micro-cap stocks with a price of less then 5 dollars; there is very little change in the returns on the geographic momentum strategy.

The second test (Panel C in Table 6) re-incorporates financial firms (SIC codes between 6001 and 6999). The fourth test (Panel D) excludes the 2008-2009 financial crisis period. In both of these tests, the results are persistent, as well as statistically and economically significant.

3 Investor Inattention and Processing Complexity

All tests presented in the previous section point to the same conclusion: there is a strong geographic momentum effect and none of the standard risk factors can explain this result. In this section, I provide suggestive evidence that the geographic momentum effect is driven by proxies for investor inattention and information complexity.

If limited attention is driving the return predictability of the geographic momentum strategy, varying the degree of inattention should translate to changes in the magnitude and significance of the effect. I test the hypothesis that return predictability is higher for firms that attract less investor attention: smaller firms, firms with less analyst coverage, and firms with fewer institutional holdings.

Table 7 presents the mean excess returns and alphas with respect to various risk factors of the zero-cost portfolios that hold firms in the top quintile of lagged geographic returns and sell short firms in the bottom quintile of lagged geographic returns. The sample is divided further into smaller subsamples based on various proxies of investor inattention. In particular, the sample is divided into two subsamples based on *Institutional Holdings*, *Analyst Coverage*, and the *Number of countries*, where Low and High correspond to being below or above the median in each category.

[Insert Table 7 about here]

The results in Panels A and B in Table 7 suggest that all of the geographic-return predictability comes from firms that usually attract less attention from investors. In particular, firms with low institutional holdings and firms that have lower analyst coverage exhibit much stronger return predictability.

I also consider the extent to which the degree of difficulty investors face in processing information can effect return predictability. Given that investors have limited cognitive resources to take into account and evaluate multiple sources of information, increasing the complexity of firms' geographic operations can reduce investors' effective attention and potentially increase the predictability of returns. In other words, the more diversified the foreign exposure of a firm, the more difficult it may be to correctly value the firm instantaneously.

I measure the geographic complexity of a firm using the Herfindahl index:

$$Herfindahl = \sum^{N} \left(\frac{\text{geographic exposure}}{\text{total exposure}} \right)^2 ,$$

where N is the number of geographic regions in which a company operates. A low Herfindahl index means that a firm is more evenly exposed to many markets, while a high Herfindahl index means that a firm's foreign exposures are more concentrated in a few markets. Thus, a firm with a low Herfindahl index for foreign exposure is likely a firm that has higher processing complexity.

Panel C in Table 7 separates the sample into two subgroups based on the number of foreign countries to which a firm is exposed and Panel D separates the sample into two subgroups based on the foreign geographic exposure Herfindahl index (Low is below the median and High is above the median). All of the predictability comes from the subgroup of firms that likely are more complex firms to evaluate: firms that have their sales and operations in many foreign countries and firms that have their sales and operations distributed more evenly across multiple geographic regions (i.e., Low Herfindahl indexes).

Table 8 presents the mean excess returns and alphas of the zero-cost equally weighted portfolios that hold firms in the top quintile of lagged geographic returns and sell short firms in the bottom quintile of lagged geographic returns. The sample is divided into smaller quintiles based on firm size, which is also a common proxy for firm complexity and the degree of investor attention. The magnitude of excess returns and alphas increase monotonically with decreasing firm size. For firms in the lowest quintile, the geographic momentum strategy yields risk-adjusted abnormal returns of 82 basis points over the next month (or an annualized return of 9.8%, *t-stat* = 2.63). For the largest firms, the geographic momentum strategy yields risk-adjusted abnormal returns of only 32 basis points and the returns differ from zero only at the 10% significance level.

[Insert Table 8 about here]

This section has provided suggestive evidence that the return predictability of the geographic momentum strategy can be attributed largely to inattention on the part of investors coupled with the complexity of geographic information.

4 Regression Tests and Alternative Explanations

4.1 Regression Tests

The portfolio results suggest a strong link between past geographic returns and current stock returns. In this section, I test the geographic momentum effect while controlling for other explanatory variables using Fama and MacBeth (1973) regressions. I estimate the cross-sectional relationship between lagged geographic returns and current stock returns for each month and then take the average of the coefficient estimates across the entire sample period. A regression framework also allows me to control for a number of variables known to forecast the cross-section of stock returns, such as a stock's own momentum, industry momentum, and post-earnings-announcement drift.

The dependent variable is the current month's stock returns. The main independent variable is the previous month's geographic index returns. Control variables include log book-to-market ($log(BM)$) and size ($Size$). For stock returns from July of year y to June of year $y+1$, $log(BM)$ is computed using book equity at the end of the previous fiscal year ending on or before December 31 of year $y-1$ and market equity on December 31 of year $y-1$. $Size$ is log market equity at the end of June of year y.

I also include a firm's own one-month lagged stock returns (Ret_{t-1}) and 12-month lagged cumulative stock returns ($Ret_{t-12,t-2}$) to control for the Jegadeesh (1990) reversal effect and the Jegadeesh and Titman (1993) momentum effects, respectively. To control for the industry momentum effect documented by Moskowitz and Grinblatt (1999), I also include lagged industry returns ($IndRet_{t-1}$ and $IndRet_{t-12,t-2}$) for a company's primary industry.

The geographic momentum strategy could be driven by post-earnings-announcement drift. It could be the case that firms release important information regarding their foreign earnings and profitability in quarterly financial reports. In essence, the geographic momentum predictability found here may be due not to inattention to geographic returns, but rather to the well-known under-reaction to earnings announcements. In order to reject this alternative explanation, I include standardized unexpected earnings (SUE) as a control variable.

I computed SUE using the Kim and Kim (2003) methodology. The SUE of firm i in quarter q is computed as:

$$SUE_{i,q} = \frac{EPS_{i,q} - E(EPS_{i,q})}{\sigma(EPS_{i,q} - E(EPS_{i,q})},$$

where $EPS_{i,q}$ is quarterly actual earnings per share of firm i in quarter q, and $E(EPS_{i,q})$ is the estimated quarterly earnings per share of firm i in quarter q. $\sigma(\cdot)$ is the standard deviation of the forecast errors. To obtain $E(EPS_{i,q})$, I assume the following AR(1) process by using observations from the most recent 24 quarters, similar to Kim and Kim (2003):

$$EPS_{i,q} - EPS_{i,q-4} = \phi_{i,0} + \phi_{i,1} EPS_{i,q-1} - EPS_{i,q-5} + \epsilon_{i,q}$$

$$E(EPS_{i,q}) = EPS_{i,q-4} + \hat{\phi}_{i,0} + \hat{\phi}_{i,1}(EPS_{i,q-1} - EPS_{i,q-5})$$

Table 9 presents the Fama and MacBeth (1973) regression results. In Columns 1-5, I regress monthly stock returns on each variable of interest, followed by the inclusion of all previously discussed independent variables. All regression specifications deliver the same results: lagged geographic returns strongly predict subsequent stock returns. The results are large and robust and the magnitude of the effect is similar to that found in the portfolio test. For example, a one-standard-deviation increase in $GeoRet$ is associated with a 0.29 percent higher monthly return for the firm (using the coefficient on $GeoRet_{t-1}$ of 0.04 from column 5 of Table 9 and the standard deviation of 7.1%). Other predictors of stock returns have the expected sign (e.g., small firms and value firms earn higher returns, there is a one-month reversal in stock returns, there are industry momentum effects and drift following past earnings announcements). Importantly, controlling for these other predictors of stock returns does not diminish the geographic returns effect.

[Insert Table 9 about here]

4.2 Alternative Explanations

So far, I have shown that geographic momentum predictability can be explained by the investor inattention hypothesis and I have provided a battery of robustness tests for this result. I now explore two potential alternative explanations for this predictability and demonstrate that the result is robust to controlling for both possibilities.

A potential alternative explanation of the results can be found in a recent paper by Cohen and Lou (2012). The authors find that stock returns of a conglomerate can be predicted by a weighted average return of a group of stand-alone firms that have business operations similar to those of the conglomerate. One might argue that the geographic momentum effect is simply a proxy for their "complicated firm" effect. Conglomerates may have multiple business segments that perfectly coincide with multiple geographic exposures. Hence, stock indices returns could simply be proxies for the condition of each business segment.

Similar to Cohen and Lou (2012), for each conglomerate I compute the corresponding "pseudo-conglomerate" return ($PseudoRet$). A "pseudo-conglomerate" return is the weighted average of industry returns for each of the conglomerate's segments, where the industry returns are constructed using only stand-alone firms in the industry. Industry segments are defined based on SIC-2 codes. For firms with no SIC-2 industry segments, I use their primary industry returns.

Fama and MacBeth (1973) regressions are run in columns (1) and (2) of Table 10 to test how related the effects of $PseudoRet$ and $GeoRet$ are. $GeoRet_{t-1}$ is still economically and statistically significant after controlling for $PseudoRet_{t-1}$. The magnitude of either return-predictability effect is not affected by including the other, which indicates that my geographic momentum effect is entirely distinct from Cohen and Lou (2012) 's "complicated firms" effect regarding the predictability of conglomerates.

[Insert Table 10 about here]

Another possible concern regarding the observed predictability is that the findings may be driven not by an inattention story but rather by systematic differences in risks accross geographic exposures. More specifically, the geographic momentum effect may be driven largely by emerging market exposure. Firms that have sales and operations in emerging markets such as China, Brazil, India or Russia are more exposed to emerging market risks and hence should naturally have higher returns. Moreover, during my sample period most emerging markets outperform developed markets. Sorting firms based on past geographic returns may simply be grouping firms based on degree of exposure to emerging markets.

In a more direct test, I also rerun the Fama and MacBeth (1973) regression including a control variable for exposure to China, which is essentially the fraction of exposure that comes from China. Alternatively, I also include a control variable for exposure to the four largest emerging markets, which is again the fraction of exposure to Brazil, Russia, India and China (BRIC). And finally, in the most stringent test, I also include in the Fama and MacBeth (1973) regression the share of exposure coming from each of the 78 countries and regions. I present all these tests in Table 10, columns (4) through (6). All results indicate that regional controls do not change the magnitude or significance of lagged geographic returns. It is therefore clear that the finding is not driven by a firm's exposure to any particular country.

5 Predicting Operating Performance

So far we have seen that the stock returns of firms with foreign market exposure and operations are predictable. I also present results supporting the view that limited investor attention is the main reason behind the geographic momentum effect. In this section, I show that geographic returns can strongly predict firms' operating performance, i.e., sales and operating income. Effects on a firm's real operation, if found, are precisely why investors should pay close attention to foreign market conditions and would justify the return results previously documented.

A regression framework is used to test the ability of past geographic returns to predict the future operating performance of U.S. multinational firms. The dependent variables are a firm's 3-month cumulative stock returns and a firm's sales and operating income, both scaled by total assets. All dependent variables are computed at time q. The key independent variable is $GeoRet_{q-1}$, which is 3-month cumulative geographic returns in the previous quarter. Controls are also included for all geographic regions, and are denoted as *Exposure to each of the 78 countries and regions*, which are the fractions of exposure to each geographic region of a firm's total foreign exposure. The value of $geoExposure(i)/totalExposure$ is zero for firms that do not have exposure to a foreign country in a particular quarter. Note that the data are quarterly and the unit of observation is firm$\times$quarter. I also winsorize Compustat quarterly variables at the 1% level. Firm and quarter fixed effects are also included in all regression specifications.

Table 11 shows that previous quarter $GeoRet$ can strongly predict a firm's current quarterly stock returns, sales, and operating income. In other words, changes in geographic market conditions can predict not only future stock price movements, but also the profitability of multinational firms. Even after controlling for a firms' stock price information for the previous quarter, following what happens in the regions where firms conduct business has incremental predictive power not only for future firms' stock returns, as shown in prior analyses, but also for their operating performance, such as sales and operating income. The results pertaining to operating performance are important as they justify the returns results: lagged geographic returns predict stronger sales and income for firms in the next quarter, which justifies higher stock prices.

[Insert Table 11 about here]

6 Conclusion

This paper uses publicly available foreign geographic exposures disclosed in Form 10-K by U.S. multinational corporations and documents a strong link between changes in foreign market conditions and the expected stock returns of U.S. multinational firms. The previous month's geographic returns, defined as the weighted average return of a firm's corresponding geographic indices, can strongly predict the firm's future stock returns. For each firm, the weight assigned to each geographic region's index returns is defined as the fraction of exposure to that region divided by the firm's total foreign exposure. A zero-cost portfolio strategy that buys stocks with the highest geographic returns and sells short stocks with the lowest geographic returns earns risk-adjusted returns of more than 45 basis points per month, or 5.4% per year. I call this return predictability the "geographic momentum" effect.

This result is robust across multiple weighting schemes. The predictability of lagged geographic returns is also found in Fama and MacBeth (1973) regression tests. This result holds even after controlling for various firms' characteristics and standard risk factors. In particular, a firm's geographic momentum effect cannot be explained by its own momentum, industry momentum, post-earnings-announcement drift, or its being a conglomerate. The geographic return predictability also cannot be explained by systematic differences in risk exposure to emerging markets or developed markets. The return predictability is robust to various specifications, holds for multiple subsets of firms, and is strongest for the month immediately after portfolio formation, with no predictability or reversal thereafter.

The geographic momentum effect is consistent with the theory of limited investor attention. Investors have limited time and cognitive resources to process information from multiple foreign markets and hence delay incorporating this information into stock prices. I show that most of the return predictability is concentrated in stocks with less analyst coverage, smaller-sized stocks, and stocks with lower institutional ownership. The return predictability is also strongest for firms that are geographically more complex, i.e., firms with foreign exposures distributed across a wider range of countries.

Overall, this paper provides evidence that foreign geographic markets are important sources of information for price formation that investors tend to overlook. As more U.S. companies expand into the global market and their revenue sources become increasingly diverse, foreign market information will become ever more important.

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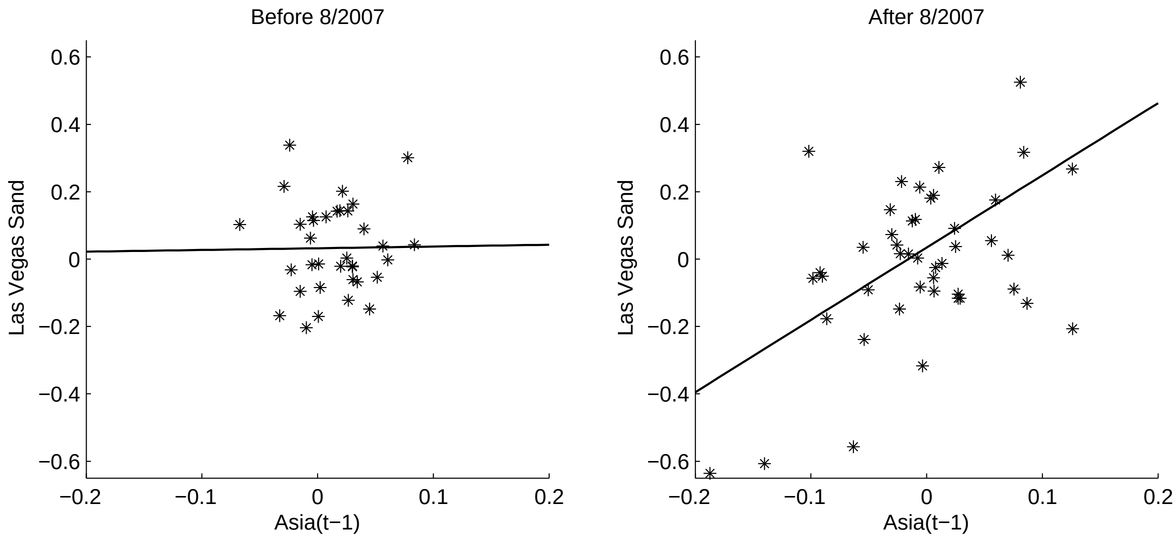
Figure 1: Las Vegas Sands Corporation and Lagged Asia Index

The figure shows scatterplots of monthly LVS raw returns and lagged Asian index returns, before and after launching The Venetian Macao Resort. Least-squares lines are added to the scatterplots. The correlation between LVS stock returns and the lagged Asia index before launching the Macao resort is 0.049, and not significantly different from zero. The correlation after the opening increases to 0.454, which is significantly different from zero at the 1% confidence level. The numbers in parentheses are standard errors. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.



	Before	After	After - Before
Correlation	0.049	0.454***	0.405**
	(0.237)	(0.063)	(0.193)

Figure 2: Distribution of Geographic Regions

The figure shows the distribution of the number of geographic regions reported in firms' 10-Ks.

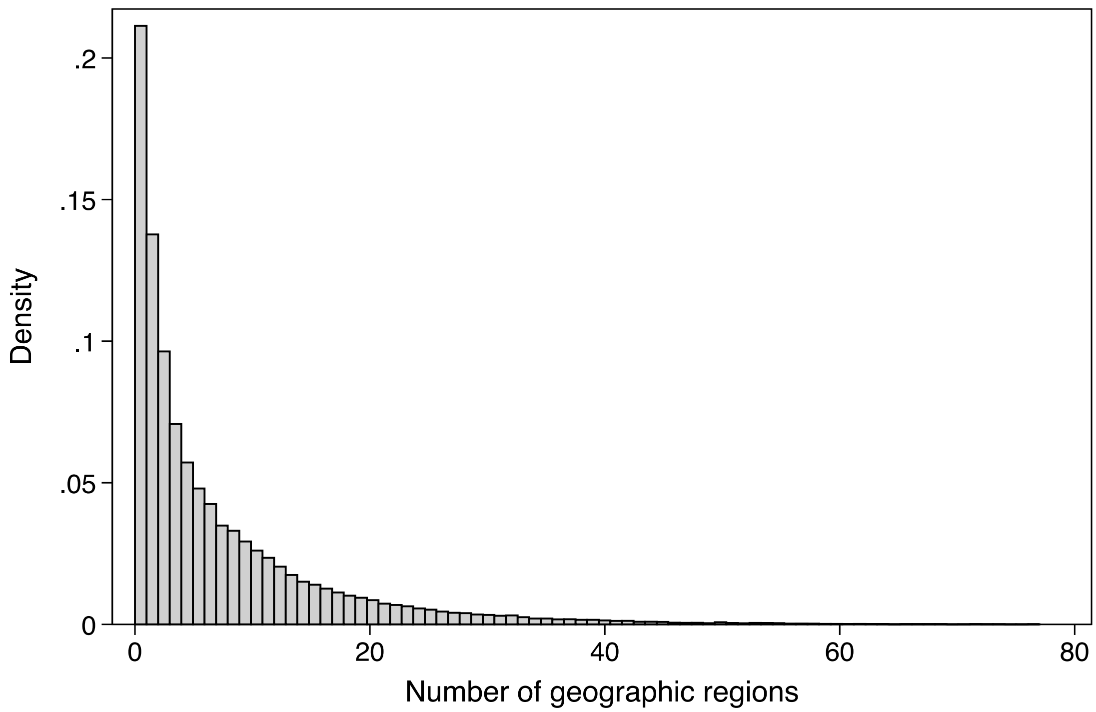


Figure 3: Returns on Geographic Momentum Strategy

The figure plots the time series of the monthly excess returns from the equal-weighted geographic momentum portfolio strategy that buys the top geographic return stocks and short sells the lowest geographic return stocks, where excess returns are in excess of the risk-free rate. Excess returns are shown for every month from January 1995 to December 2013.

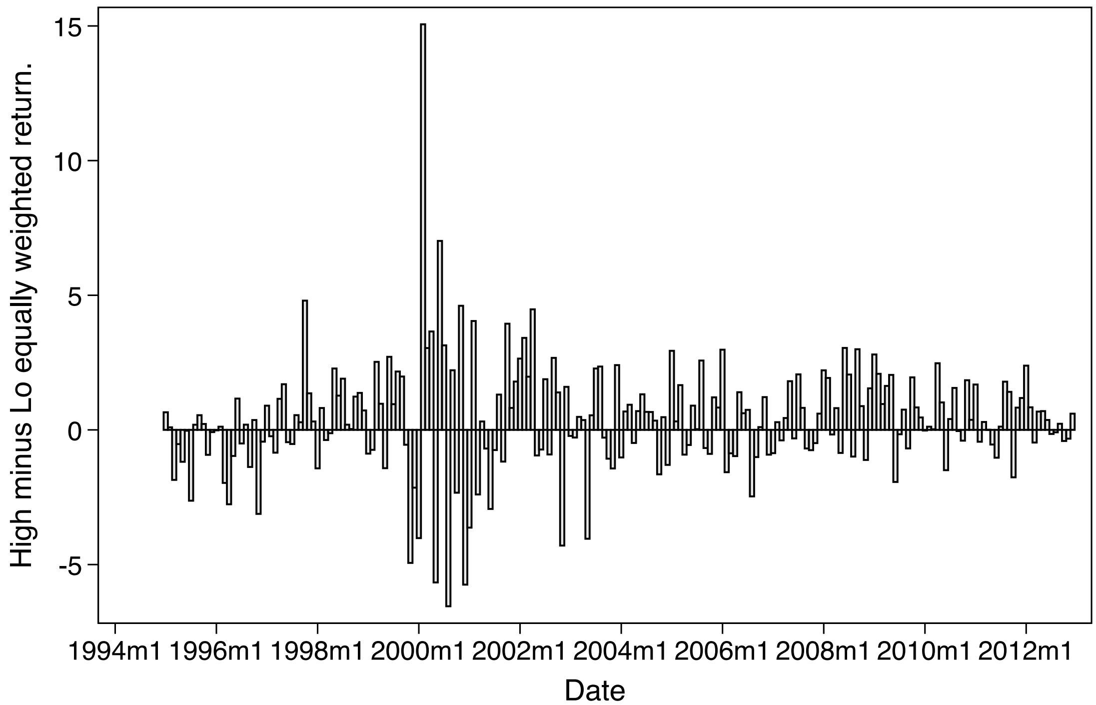


Table 1: Summary Statistics and Correlations

This table presents summary statistics on the variables of interest and the correlations between the main explanatory variables known to predict stock returns. Ret are a stock's monthly returns. $GeoRet$ are weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. $Size$ is the log of market equity. $log(BM)$ is the log of book equity over market equity. Book equity is measured at fiscal year end on or before December 31st and market equity is measured on December 31st of the previous year. *# of Countries* is the number of distinct countries mentioned in firms' 10-Ks. $Herfindahl$ measures the complexity of firms' foreign exposures and is computed as the sum of the squared fraction of exposures across various geographic regions. $Ret_{t-12,t-2}$ are the cumulative returns from month $t-12$ through month $t-2$. $IndRet_{t-12,t-2}$ are the primary industry cumulative returns from month $t-12$ through month $t-2$. SUE are the most recent standardized unexpected earnings before month t. $PseudoRet_{t-1}$ are pseudo returns computed as in Cohen and Lou (2012), which is the weighted average return on the conglomerate's industry segments (based on SIC-2) constructed using only stand-alone firms in the same industry.

Panel A: Summary Statistics

	Mean	SD	1%tile	25%tile	50%tile	75%tile	99%tile	Count
Ret	.0078	.148	-.379	-.061	.005	.071	.445	590271
GeoRet	.0055	.071	-.208	-.028	.002	.044	.183	590271
Size	20.243	1.801	16.509	18.971	20.129	21.393	24.953	590271
log(BM)	-.955	.982	-4.216	-1.449	-.840	-.332	1.175	590271
# of Countries	7.911	24.240	1	1	3	7	82	590271
Herfindahl	.226	.371	.000	.001	.0144	.25	1	590271

Panel B: Correlations

	Ret	$GeoRet_{t-1}$	$Size$	$log(BM)$	$Ret_{t-12,t-2}$	$IndRet_{t-12,t-2}$	SUE	$Herfindahl$
$GeoRet_{t-1}$	0.080							
$Size$	-0.012	0.003						
$log(BM)$	0.020	-0.015	-0.317					
$Ret_{t-12,t-2}$	0.001	-0.010	-0.019	-0.353				
$IndRet_{t-12,t-2}$	-0.002	0.021	-0.007	-0.159	0.459			
SUE	0.071	0.020	0.010	-0.043	0.118	0.093		
$Herfindahl$	0.001	0.013	-0.203	0.068	0.007	-0.006	0.001	
$PseudoRet_{t-1}$	0.073	0.395	-0.009	-0.043	0.005	0.014	0.026	-0.001

Table 2: Summary Statistics on Geographic Exposure

Geograpghic	Mean	SD	1%	25%	Median	75%	99%	Geograpghic	Mean	SD	1%	25%	Median	75%	99%
ac asia	2.409	9.234	0	0	0	1	36	kenya	0.026	0.915	0	0	0	0	0
argentina	0.574	6.073	0	0	0	0	11	korea	0.698	4.598	0	0	0	0	13
australia	1.927	9.961	0	0	0	0	34	kuwait	0.035	0.711	0	0	0	0	1
austria	0.240	2.309	0	0	0	0	5	lebanon	0.520	3.054	0	0	0	0	19
bahrain	0.024	0.451	0	0	0	0	0	lithuania	0.040	0.432	0	0	0	0	1
bangladesh	0.023	0.795	0	0	0	0	0	malaysia	1.844	9.768	0	0	0	0	60
belgium	0.452	2.707	0	0	0	0	10	mauritius	0.079	1.074	0	0	0	0	2
bosnia and herzegovina	0.005	0.153	0	0	0	0	0	mexico	3.522	26.151	0	0	0	1	54
botswana	0.014	0.583	0	0	0	0	0	morocco	0.028	0.697	0	0	0	0	0
brazil	1.051	8.278	0	0	0	0	20	netherlands	1.304	9.982	0	0	0	0	22
bulgaria	0.046	1.374	0	0	0	0	1	new zealand	0.478	4.590	0	0	0	0	9
canada	5.871	20.155	0	0	0	4	78	nigeria	0.156	2.397	0	0	0	0	2
chile	0.314	3.375	0	0	0	0	6	norway	0.227	2.346	0	0	0	0	5
china	3.937	23.922	0	0	0	1	80	oman	0.042	1.320	0	0	0	0	0
colombia	0.271	5.028	0	0	0	0	4	pakistan	0.075	2.185	0	0	0	0	1
croatia	0.029	1.341	0	0	0	0	0	peru	0.503	7.258	0	0	0	0	9
czech republic	0.216	3.984	0	0	0	0	4	philippines	0.335	3.552	0	0	0	0	7
denmark	0.227	1.715	0	0	0	0	5	poland	0.315	5.340	0	0	0	0	6
egypt	0.103	2.017	0	0	0	0	2	portugal	0.157	1.224	0	0	0	0	4
em emea	0.284	8.280	0	0	0	0	6	qatar	0.037	1.072	0	0	0	0	0
estonia	0.019	0.377	0	0	0	0	0	romania	0.094	2.118	0	0	0	0	2
europe	7.502	22.430	0	0	0	6	92	russia	0.356	5.020	0	0	0	0	6
finland	0.169	1.897	0	0	0	0	4	saudi arabia	0.136	3.594	0	0	0	0	2
fm africa	1.003	7.094	0	0	0	0	18	serbia	0.014	0.455	0	0	0	0	0
france	1.563	7.063	0	0	0	0	26	singapore	1.199	5.736	0	0	0	0	16
germany	1.737	6.686	0	0	0	0	28	slovenia	0.032	1.692	0	0	0	0	0
ghana	0.064	3.352	0	0	0	0	0	spain	0.587	3.401	0	0	0	0	12
greece	0.114	1.528	0	0	0	0	3	sri lanka	0.085	3.234	0	0	0	0	1
hong kong	1.076	6.637	0	0	0	0	20	sweden	0.375	2.580	0	0	0	0	8
hungary	0.193	2.380	0	0	0	0	4	switzerland	0.547	3.547	0	0	0	0	11
india	0.957	6.447	0	0	0	0	19	taiwan	1.212	5.637	0	0	0	0	23
indonesia	0.323	7.572	0	0	0	0	6	thailand	0.364	4.209	0	0	0	0	7
ireland	0.753	4.947	0	0	0	0	16	trinidad and tobago	0.098	6.189	0	0	0	0	1
israel	0.730	9.152	0	0	0	0	12	tunisia	0.030	1.021	0	0	0	0	0
italy	0.748	3.888	0	0	0	0	14	turkey	0.203	3.325	0	0	0	0	4
jamaica	0.075	1.332	0	0	0	0	1	ukraine	0.085	2.871	0	0	0	0	1
japan	2.248	10.191	0	0	0	1	34	united arab emirates	0.057	0.810	0	0	0	0	2
jordan	0.179	2.783	0	0	0	0	4	united kingdom	4.480	32.525	0	0	0	2	68
kazakhstan	0.092	3.228	0	0	0	0	0	zimbabwe	0.023	0.713	0	0	0	0	0

Table 3: Abnormal Returns on Geographic Momentum Strategy

This table reports abnormal returns (in %) on the portfolios of firms based on the quintile ranking of their one-month lagged monthly geographic returns. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. The first five columns report abnormal returns for firms sorted into quintiles by their lagged geographic returns. The last column reports the average monthly abnormal returns on a portfolio that longs stocks in the top quintile of geographic returns and shorts stocks in the bottom quintile of geographic returns. In addition to the raw excess returns, I also report the CAPM alpha, Fama and French (1993) 3-factor alpha, Carhart (1997) 4-factor alpha, and the Pastor and Stambaugh (2003) 5-factor alpha. The sample period is from January 1995 through December 2013. The numbers in parentheses are t-statistics. Standard errors are adjusted with 3 lags according to Newey and West (1987). *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Returns

	1 (Low)	**2**	**3**	**4**	**5 (High)**	**High−Low**
Excess Return	0.46	0.63	0.78**	0.77**	0.91**	0.45***
	(1.22)	(1.61)	(1.99)	(1.99)	(2.48)	(3.09)
CAPM $Alpha$	-0.16	-0.03	0.15	0.17	0.32*	0.48***
	(-0.92)	(-0.17)	(0.94)	(1.01)	(1.73)	(3.52)
FF-3 $Alpha$	-0.30**	-0.14	-0.01	-0.00	0.16	0.46***
	(-2.58)	(-1.61)	(-0.07)	(-0.01)	(1.49)	(3.27)
Car-4 $Alpha$	-0.27**	-0.10	0.03	0.02	0.15	0.42***
	(-2.42)	(-1.23)	(0.42)	(0.20)	(1.48)	(2.90)
PS-5 $Alpha$	-0.27**	-0.10	0.03	0.02	0.15	0.42***
	(-2.42)	(-1.23)	(0.42)	(0.20)	(1.48)	(2.90)

Panel B: Value-Weighted Returns

	1 (Low)	**2**	**3**	**4**	**5 (High)**	**High−Low**
Excess Return	0.37	0.47	0.60**	0.59**	0.65**	0.29***
	(1.35)	(1.59)	(2.02)	(2.02)	(2.53)	(2.74)
CAPM $Alpha$	-0.06	-0.01	0.12	0.13	0.26*	0.32***
	(-0.48)	(-0.06)	(0.97)	(0.98)	(1.93)	(3.12)
FF-3 $Alpha$	-0.17*	-0.11	0.01	0.02	0.13*	0.31***
	(-1.93)	(-1.51)	(0.11)	(0.20)	(1.71)	(3.02)
Car-4 $Alpha$	-0.15	-0.08	0.03	0.04	0.14*	0.29***
	(-1.65)	(-1.19)	(0.49)	(0.48)	(1.72)	(2.88)
PS-5 $Alpha$	-0.18**	-0.11	0.00	-0.00	0.10	0.29***
	(-2.08)	(-1.61)	(0.03)	(-0.06)	(1.38)	(2.78)

Table 4: Loadings from the Geographic Portfolio Strategy

This table reports factor the loadings of a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their one-month lagged geographic returns. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. The alphas displayed in the first row of Panels A and B correspond exactly to the alphas displayed in the "High−Low" columns in Panels A and B in Table 3. Loadings on the following risk factors are reported: $Mkt{-}R_f$, SMB, HML, UMD, Carhart (1997) momentum factor and LIQ, Pastor and Stambaugh (2003)'s liquidity factor. Panels C and D report results for the sample excluding 100% U.S. firms. The sample period is from January 1995 through December 2013. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Returns

	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
$Alpha$	0.45***	0.48***	0.46***	0.43***	0.42***
	(3.09)	(3.37)	(3.27)	(3.04)	(2.90)
$Mkt - R_f$		-0.06**	-0.08**	-0.06*	-0.07*
		(-1.97)	(-2.25)	(-1.84)	(-1.84)
SMB			0.13	0.13	0.13
			(1.21)	(1.22)	(1.22)
HML			0.03	0.04	0.05
			(0.48)	(0.72)	(0.72)
UMD				0.04	0.04
				(0.75)	(0.74)
LIQ					0.01
					(0.21)
R^2	0.00	0.01	0.03	0.03	0.05
N	216	216	216	216	216

Panel B: Value-Weighted Returns

	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
$Alpha$	0.29***	0.32***	0.31***	0.29***	0.29***
	(2.74)	(3.12)	(3.02)	(2.88)	(2.78)
$Mkt - R_f$		-0.06**	-0.07***	-0.06**	-0.06**
		(-2.48)	(-2.63)	(-2.26)	(-2.23)
SMB			0.09	0.08	0.08
			(1.11)	(1.11)	(1.11)
HML			0.01	0.02	0.02
			(0.30)	(0.53)	(0.51)
UMD				0.03	0.03
				(0.71)	(0.71)
LIQ					-0.00
					(-0.19)
R^2	0.00	0.01	0.02	0.03	0.04
N	216	216	216	216	216

Table 5: Geographic Momentum Strategy over Different Horizons

This table reports the abnormal returns (in %) on a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their one-month lagged geographic returns, holding over multiple horizons. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. I present results for monthly abnormal returns on portfolios formed in month zero for months one through six after portfolio formation. The alphas displayed for the first month after portfolio formation in the first row of Panels A and B correspond exactly to the alphas displayed in row one of Panels A and B of Table 3. The sample period is from January 1995 through December 2013. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Equal-Weighted Returns				
	Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
$r_{0,1}$	0.45***	0.48***	0.46***	0.43***	0.42***
	(3.09)	(3.37)	(3.27)	(3.04)	(2.90)
$r_{1,2}$	0.13	0.16	0.14	0.14	0.14
	(0.92)	(1.13)	(1.04)	(1.14)	(1.11)
$r_{2,3}$	0.04	0.03	0.06	0.05	0.09
	(0.36)	(0.26)	(0.48)	(0.41)	(0.70)
$r_{3,4}$	0.21	0.23	0.24*	0.19	0.20
	(1.44)	(1.57)	(1.69)	(1.40)	(1.41)
$r_{4,5}$	0.00	0.02	0.00	-0.05	-0.07
	(0.03)	(0.14)	(0.00)	(-0.41)	(-0.55)
$r_{5,6}$	0.03	0.07	0.05	0.08	0.04
	(0.24)	(0.54)	(0.44)	(0.66)	(0.33)

	Panel B: Value-Weighted Returns				
	Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
$r_{0,1}$	0.29***	0.32***	0.31***	0.29***	0.29***
	(2.74)	(3.12)	(3.02)	(2.88)	(2.78)
$r_{1,2}$	0.11	0.13	0.10	0.08	0.08
	(0.63)	(0.73)	(0.56)	(0.46)	(0.50)
$r_{2,3}$	0.18	0.19	0.18	0.13	0.19
	(1.24)	(1.32)	(1.25)	(0.93)	(1.38)
$r_{3,4}$	-0.01	0.00	0.02	-0.05	-0.05
	(-0.08)	(0.01)	(0.10)	(-0.33)	(-0.32)
$r_{4,5}$	0.00	0.01	-0.03	-0.10	-0.13
	(0.01)	(0.04)	(-0.17)	(-0.62)	(-0.79)
$r_{5,6}$	-0.00	0.06	0.04	0.04	-0.02
	(-0.00)	(0.39)	(0.24)	(0.23)	(-0.15)

Table 6: Subsample Robustness Checks

This table reports the abnormal returns (in %, equal-weighted) on a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their one-month lagged geographic returns for multiple subsamples. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. The various subsample of stocks are, Panel A: The base case (same as row one of Panel A in Table 3); Panel B: Excluding micro-capitalization illiquid securities (defined as firms with stock prices less than 5); Panel C: Including financial firms; and Panel D: Excluding the period 2008-2009 (the financial crisis). The sample period is from January 1995 through December 2013. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Case				
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
0.45***	0.48***	0.46***	0.43***	0.42***
(3.09)	(3.37)	(3.27)	(3.04)	(2.90)
Panel B: Including Illiquid Stocks, $prc < 5$				
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
0.35**	0.38***	0.36**	0.33**	0.32**
(2.35)	(2.64)	(2.50)	(2.32)	(2.16)
Panel C: Excluding Financial Firms				
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
0.44***	0.49***	0.47***	0.43***	0.41***
(2.87)	(3.24)	(3.16)	(2.98)	(2.74)
Panel D: Excluding 2008-2009 Financial Crisis Period				
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
0.40**	0.46***	0.46***	0.36**	0.34**
(2.57)	(3.00)	(2.89)	(2.43)	(2.25)

Table 7: The Role of Inattention and Processing Complexity

This table reports abnormal returns (in %, equal-weighted) on a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their one-month lagged geographic returns. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. I present results for various subsamples of stocks sorted by various proxies for inattention and firm complexity, including A: Institutional Holdings, B: Analyst Coverage, and C: Number of countries. In Panel D: Herfindahl, firms are sorted by their Herfindahl indexes, which measure their diversity in geographic segments. A low Herfindahl corresponds to a firm with exposure to many countries (i.e., high processing complexity). I report returns on stocks above and below the median for each of the four variables. The sample period is from January 1995 through December 2013. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at 1%, 5% and 10% levels, respectively.

	Equally-Weighted Returns, High−Low				
	Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
	Panel A: Institutional holdings				
≤ **Median (Low)**	0.46***	0.50***	0.49***	0.43***	0.43***
	(3.11)	(3.48)	(3.44)	(3.16)	(3.00)
> **Median (High)**	0.37**	0.40***	0.38***	0.35**	0.33**
	(2.59)	(2.80)	(2.68)	(2.49)	(2.31)
	Panel B: Analyst coverage				
≤ **Median (Low)**	0.41***	0.45***	0.42***	0.40***	0.41***
	(2.79)	(3.09)	(2.92)	(2.89)	(2.83)
> **Median (High)**	0.35*	0.38**	0.36**	0.30*	0.27
	(1.92)	(2.08)	(1.98)	(1.69)	(1.48)
	Panel C: Number of countries				
≤ **Median (Low)**	0.34**	0.37***	0.35**	0.32**	0.31**
	(2.42)	(2.61)	(2.51)	(2.31)	(2.14)
> **Median (High)**	0.34*	0.34*	0.31*	0.25	0.23
	(1.91)	(1.95)	(1.75)	(1.36)	(1.25)
	Panel D: Herfindale				
≤ **Median (Low)**	0.43**	0.45***	0.43***	0.34**	0.34**
	(2.59)	(2.76)	(2.64)	(2.21)	(2.11)
> **Median (High)**	0.25*	0.27*	0.26*	0.23	0.23
	(1.77)	(1.89)	(1.80)	(1.60)	(1.48)

Table 8: Double Sort on Size and Geographic Return

This table reports the abnormal returns (in %, equal-weighted) on a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their one-month lagged geographic returns, for quintiles of various sizes. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. The sample period is from January 1995 through December 2013. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Equal-Weighted Returns, High−Low				
Size	**Excess Return**	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
1 (Low)	0.89***	0.97***	0.99***	0.95***	0.82***
	(2.91)	(3.27)	(3.30)	(2.83)	(2.63)
2	0.54***	0.59***	0.56***	0.50***	0.49**
	(2.98)	(3.22)	(3.04)	(2.73)	(2.57)
3	0.35**	0.39**	0.39**	0.36**	0.37**
	(2.04)	(2.24)	(2.27)	(2.08)	(2.16)
4	0.37**	0.42***	0.41***	0.34**	0.31**
	(2.51)	(2.93)	(2.87)	(2.41)	(2.21)
5 (High)	0.32*	0.36*	0.33*	0.31*	0.32*
	(1.68)	(1.93)	(1.82)	(1.71)	(1.73)

Table 9: Fama-MacBeth Cross-Sectional Regressions

This table reports results of monthly Fama and MacBeth (1973) regressions of stock returns on lagged geographic returns. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. For the cross-sectional regression in month t, the dependent variable is stock returns in month t. $log(BM)$ is the natural log of book-to-market equity, and is the same for all observations from July of year y through June of year $y+1$. Book equity is computed from the previous fiscal year end on or before December 31 of year $y-1$ and market equity is computed on December 31 of year $y-1$. $Size$ is log market equity, and is computed at the end of June of year y, and is the same for all returns from July/y through June/$y+1$. Ret_{t-1} and $Ret_{t-12,t-2}$ are the previous month's stock return and the cumulative returns from month $t-12$ through month $t-2$, respectively. $IndRet_{t-1}$ are the industry's returns in the previous month. $IndRet_{t-12,t-2}$ are the industry's cumulative returns from month $t-12$ through month $t-2$. SUE is the most recent standardized unexpected earnings before month t. More details on the computation of SUE can be found in the data section of the text. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Monthly return, Ret_t				
	(1)	(2)	(3)	(4)	(5)
$GeoRet_{t-1}$	0.05***	0.05***	0.04***	0.04***	0.04***
	(3.80)	(3.99)	(3.88)	(3.65)	(3.78)
$log(BM)$		0.00	0.00**	0.00***	0.00**
		(1.10)	(2.34)	(2.86)	(2.26)
$Size$		0.00	0.00	0.00	-0.00
		(0.32)	(0.44)	(0.44)	(-1.05)
Ret_{t-1}			-0.02***	-0.02***	-0.02
			(-3.56)	(-5.07)	(-1.04)
$Ret_{t-12,t-2}$			0.01***	0.01***	0.00
			(2.75)	(2.79)	(1.13)
$IndRet_{t-1}$				0.11***	0.09***
				(5.09)	(3.67)
$IndRet_{t-12,t-2}$				0.01	0.01
				(1.47)	(1.12)
SUE					0.01***
					(10.50)
R^2	0.00	0.02	0.04	0.05	0.07
N	590271	587789	587789	587789	418272
N-month	216	216	216	216	200

Table 10: Fama-Macbeth Regressions and Alternative Explanations

This table reports results of monthly Fama and MacBeth (1973) regressions of stock returns on lagged geographic returns. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. For the cross-sectional regression in month t, the dependent variable is stock returns in month t. $PseudoRet_{t-1}$ is the pseudo returns computed as in Cohen and Lou (2012), which are the weighted average returns on the conglomerate's industry segments (based on SIC-2) constructed using only stand-alone firms in the same industry. *China Exposure* is the fraction of exposure to China, computed as the number of times China was mentioned divided by the number of times a foreign country or region was mentioned in firms' 10-Ks. It is zero if the firm has no exposure to China. Similarly, $BRIC$ is the fraction of exposure to Brazil, Russia, India and China. *Fraction of exposure to each of the 78 countries and regions* are the fractions of foreign exposure to each of the 78 countries and regions. *Other Controls* are same as the RHS variables in Table 9 Column 5, and include: $log(BM)$, the natural log of book-to-market equity, and is the same for all returns from July of year y through June of year $y+1$; $Size$, log market equity, and is computed at the end of June of year y, and is the same for all returns from July/y through June/$y+1$; Ret_{t-1} and $Ret_{t-12,t-2}$ are the previous month's stock returns and the cumulative returns from month $t-12$ through month $t-2$, respectively; $IndRet_{t-1}$ and $IndRet_{t-12,t-2}$ are the primary industry's previous month's return and cumulative return from month $t-12$ through month $t-2$; SUE is the most recent standardized unexpected earnings before month t. Standard errors are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Monthly return, Ret_t				
	(1)	(2)	(3)	(4)	(5)
$GeoRet_{t-1}$	0.04***	0.03***	0.04***	0.03***	0.04***
	(3.78)	(3.42)	(3.47)	(3.43)	(2.72)
$PseudoRet_{t-1}$		0.04***	0.04***	0.04***	0.03**
		(2.81)	(2.80)	(2.79)	(2.49)
$China$			-0.00		
			(-0.77)		
$BRIC$				-0.00	
				(-0.79)	
Fraction of exposure to each of the 78 regions	No	No	No	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.08	0.08	0.11
N	418272	418272	418272	418272	418272
N-month	200	200	200	200	200

Table 11: Predictability of Operating Performance by Past Geographic Returns

This table reports the regressions of firms' stock returns and operating performance on firms' past geographic returns. The independent variable is $GeoRet_{q-1}$, which is the previous quarter's geographic return. Geographic returns ($GeoRet$) are the weighted average monthly returns on a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's foreign exposure to that geographic region. *Fraction of exposure to each of the 78 countries and regions* are the fractions of foreign exposure to each of the 78 countries and regions. The dependent variables are: (1) $QtrRet$, the cumulative stock returns over a quarter (2) $Sales/Asset$, sales over total assets, and (3) $Oibdpq/Asset$, operating income before depreciation divided by total assets. All variables are quarterly and the unit of observation is firm$\times$quarter. All variables are winsorized at the 1% level. Standard errors are clustered at the firm level and are adjusted with 3 lags according to Newey and West (1987). The numbers in parentheses are t-statistics. *** , **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$QtrRet_q$ (1)	$Sales/Assets_q$ (2)	$Oibdpq/Assets_q$ (3)
$GeoRet_{q-1}$	0.07***	0.03***	0.07***
	(13.23)	(3.54)	(3.08)
Constant	0.04***	0.04***	0.07***
	(7.73)	(4.99)	(3.69)
Exposure to each of the 78 countries and regions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
R^2	0.13	0.01	0.01
N	224071	194557	160121