Geographic Momentum

(Job market paper)

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Abstract

Do investors pay attention to foreign market conditions when they evaluate multinational corporations? Using geographic segment disclosures by multinational companies headquartered in the United States, 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 135 basis points per month, or 16.2% per year. The predictability cannot be explained by a firm's own momentum, industry momentum, post-earnings-announcement drift, being a conglomerate, or exposure to emerging market risk. Consistent with the investor inattention hypothesis, I further document that smaller firms, as well as firms with less analyst coverage, fewer institutional holdings, or more complex foreign sales compositions exhibit stronger return predictability. This paper is the first to document the predictable link between foreign country-level indices returns and U.S. firm-level stock returns, and adds to the growing literature concerning the role of investor inattention and firm complexity in price formation.

Keywords: Geographic segments, Momentum, Inattention.

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Many multinational companies headquartered in the United States generate increasingly greater revenue from foreign markets. For example, in 2010, Walmart had 24.6% of total sales from abroad, Intel had 9.6% of its sales from Japan, Avon had 41% of sales from Latin America, and 8.6% of total sales of Sealy Corporation came from 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 subsequent to 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 return and future LVS's stock return; however, this is not the case.

Figure 1 shows scatter plots 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 scatter plot. The slope is close to zero before and increases significantly after the resort opened. Before the opening, the correlation between LVS stock returns and the lagged Asia 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, the lagged Asia stock returns strongly predict the firm's subsequent stock return in the U.S., even though the firm's exposure to Asia had been publicly available for quite some time.

[Insert Figure 1 here]

This predictability extends beyond this particular example. In more general tests, I find that there is significant predictability in the return of stocks with foreign operations. A portfolio strategy that buys firms whose geographic segments are located in countries that had the highest returns in the previous month and selling firms whose geographic segments are located in countries that had the lowest returns yields risk-adjusted abnormal returns of 135 basis points over the next month (or an annualized return of 16.2%). In other words, by knowing the broad stock market performance of the geographic areas where a firm has business operations (as measured by the fraction of total sales in that country), one can predict the firm's future stock market return. I refer to this return predictability as "geographic momentum". Returns to this geographic momentum strategy yield strong results for the first month after portfolio formation, with zero predictability thereafter. Further, returns to the geographic momentum strategy have no exposure to standard traded risk factors. The results are not driven by the firm's own momentum, industry momentum, post-earnings-announcement drift, being a conglomerate, or exposure to emerging market risk.

I further present 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, the return predictability is strongest among 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, the predictability is also strongest among firms that are geographically more complex (firms with sales coming from 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 sales that come from a particular country.

Cohen and Lou (2012) document that conglomerates exhibit substantial stock-return 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, and at the same time, have a coffee business segment in Italy. Hence, the stock indices in both countries are just proxies for the conditions of different business segments. The findings show that geographic momentum is not the same as the complicated firm effect. Indeed, the geographic momentum and the complicated firm effect seem to be totally orthogonal to each other as the return to each strategy is unchanged after controlling for the other strategy. Further, I find that even after controlling for the firm's stock return in the last quarter, following the market conditions in the regions where it does business gives incremental predictive power not only for the future firm stock return, but also for operating performance of the firm (such as sales and operating income). The results concerning operating performance are important as they justify the return results: the lagged geographic returns predict stronger sales and income for the firm for the next quarter and substantiates 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 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 4- to 8-year horizon and find that demographic information predicts stock returns across industries. DellaVigna and Pollet (2009) show that investors respond slower to Friday earnings announcements. My paper is the first to document the predictable 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). The authors find similar supply chain momentum at the firm and industry level. They also present evidence that return predictability is consistent with gradual information diffusion. In particular, Cohen and Frazzini (2008) find 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 stock returns of customer industries predict stock returns of supplier industries.

The remainder of the paper is organized as follows. In Section 1, I characterize the data of geographic segments and the test strategies. Section 2 presents evidence on 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 controlling for other explanatory variables and provides evidence to reject alternative hypotheses. Section 5 shows the geographic momentum effect on firm's real operations. The last section concludes.

I Data

The analysis of stock market reactions to changes in foreign market conditions requires that information on U.S. firms' foreign operations and sales be publicly available at the time when the changes in foreign markets conditions are measured. In June 1997, the Financial Accounting Standards Board (FASB) issued the Statement of Financial Accounting Standards (SFAS) No.131, which became effective for the fiscal year beginning after December 15, 1997 (FASB, 1997). It requires firms to report disaggregated information about their operating segments that comprise more than 10% of a firm's total consolidated annual sales. Firms are also required to report sales from geographic segments. Geographic segments information is therefore publicly available through 10-Ks.

Data on a firm's segment accounting and financial information are gathered from Compustat segment files. The time frame of geographic segment data release is the same as that of other standard financial variables. Hence, data on the firm-country links studied here are considered to be publicly available at the same time as other standard financial variables are released. Firm-segments that have segment sales less than 1% of the firm's total sales are excluded from the sample. Firms are also excluded if all segment sales sum up to more than 110% of the firm's total sales, as reported in Compustat annual files. The first exclusion condition is to eliminate firm-segments that account for a very trivial amount of a firm's total sales.[1] The latter condition is to exclude any firm whose sum of all geographic segments does not equal to its total sales (likely indicating a data error).

Market conditions in the different geographic segments are measured using return data on a large sample of countries and regions. Index return data are from the Morgan Stanley Capital International (MSCI) Global Equity Index. The sample consists of 13 regional indices and 34 country indices, for a total of 47 "regions".[2] Indices are value-weighted and include

[1]The results do not change without this restriction.

[2]The countries are: Argentina, Australia, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, France, Germany, Hong Kong, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Mexico, Netherlands, New Zealand, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, United Kingdom, and U.S. The regional indices are: All Countries Americas, All Countries Asia, All Countries Asia Pacific, Asia Pacific excluding Japan, Arabian markets, Arabian Markets & Africa, Emerging and Frontier

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.

The return data from the indices are merged with the geographic segment files by phonetically matching geographic names reported by firms 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*. 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 sales in that geographic region. For example, if a firm has 50% of its sales in the U.S., 30% of its sales from China, and 20% of its sales from India, the firm's geographic return is computed as:

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

where $Ret(US)$, $Ret(China)$, and $Ret(India)$ are monthly index returns for U.S., China, and India, respectively. For firms that report only one aggregate sales number to be divided across multiple geographic regions, I use the equally-weighted average of its corresponding geographic index returns (this is the case for 8% of the firm-month observations).

In accord with the previous literature, I also exclude financial firms in 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

Market Africa, Emerging and Frontier Europe & Middle East, Emerging Market Latin America, European Union, Europe, Europe excluding U.K., World excluding U.S., North America, and The Pacific 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), in order for segment and financial information to be 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 segments data in the fiscal year that ends on or before December 31 of year $y-1$.[3]

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 357,523 firm-month observations spanning from 1999 to 2010. Panel A of Table I reports the summary statistics of the main variables. There are 211,010 firm-month observations, or almost 2/3 of the total observations, where firms have sales outside of the U.S. The Herfindahl index indicates that the distribution of regional sales is diverse, from fully concentrated with Herfindahl index equal to 1 (100% U.S. only firms) to fairly dispersed. For firms that have sales outside of the U.S., the mean Herfindahl index is 0.459.

[Insert Table I here]

Panel B of Table I 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

[3]As a robustness test, when measuring a firm's monthly stock return, I skip the first 3 days of the month to rule out 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 the current firm's return. The results do not change.

correlations are computed using monthly observations of all stocks. $GeoRet_{t-1}$ is positively correlated with Ret_t (0.089). $GeoRet_{t-1}$ is also highly positively correlated with Cohen and Lou (2012)'s pseudo conglomerate return, $PseudoRet_{t-1}$ (0.521).

II 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.

A 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 $t-1$. For each firm, geographic return is the sales-weighted average of the region-level index returns corresponding to the geographic segments of the firm. A firm's geographic segments and the corresponding sales information are obtained from the fiscal year ending at least 6 months before portfolios are formed.

I then assign stocks to 5 quintile portfolios and compute the value- and equally-weighted returns within each given quintile portfolio. The quintile cutoff points are based on the distribution of unique geographic returns across firms in the previous month.[4] The 5 portfolios

[4]Only *unique* geographic returns are used to compute quintile cutoff points. As a result, the number of stocks in each quintile are not equal. This process is used because about 1/3 of the observations are U.S. only firms, and therefore, have the same geographic return. This creates a large probability mass of U.S. firms' geographic returns, which makes computing quintile cut-off points problematic. As shown below, the geographic momentum strategy results also hold when U.S.-only firms are dropped from the sample.

are rebalanced every month and their time series track calendar time performance. The abnormal returns are computed by running a time series regression of portfolio excess returns on traded factors in calendar time.

Figure 2 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 August 1999 to January 2010. The geographic momentum strategy yields positive returns for 65% of the months and returns in excess of 5% for 22% of the months, while yielding negative returns for 35% of the months, and return worse than -5% for only 7% of the months.

[Insert Figure 2 here]

Table II 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 August 1999 to December 2010. 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 II here]

Sorting firms in Table II on lagged geographic returns yields large differences in subsequent monthly returns. The average monthly excess return of the quintile portfolio sorted by geographic returns increases monotonically, from -0.29% in the lowest quintile to 1.23% in the highest quintile. Column 6 (H-L) in Table II 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 return between the highest quintile and lowest quintile portfolio is 1.52% per month, or approximately 18.24% per year, with a t-statistic of 3.23. One must keep in mind that the geographic momentum strategy yielding this large excess return involves monthly rebalancing and thus entails non-trivial transaction costs.

Further, adjusting returns for sensitivity with multiple risk factors has little effect on the results. After controlling for standard factors, the bottom quintile portfolio has negative and significant alpha, while the top quintile portfolio has positive and significant alpha. The equally-weighted long-short portfolio has a monthly alpha of 1.52%, 1.40%, 1.40% and 1.43% 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. Using value-weighted portfolios rather than equal-weighted portfolios delivers similar results. Therefore, the smallest and least liquid stocks in the sample do not appear to be driving the results.

Table III 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 and performance of other popular investment strategies.

[Insert Table III here]

As a robustness test, I exclude firms that have 100% of their sales coming from the U.S. Excluding "pure" U.S. firms addresses the critique that most of the abnormal returns come from comparing firms that only operate in the U.S. and firms that have operations in foreign countries. In other words, the observed predictability could be due to systematic differences in risks between U.S. and foreign countries. This is clearly not the case. In Table III, Panels C and D report the average excess return and alphas with respect to various risk factors of the long-short portfolio, but this time excluding 100% U.S. firms from the sample. The predictability remains strong and consistent, with the magnitude of the alphas largely unchanged.

One might argue that the performance of the U.S. market should be fully incorporated into U.S.-only firms' stock prices, thus, removing these U.S.-only firms should strengthen the results. First, U.S.-only firms appear only 19 months in the bottom quintile and only 9 months in the top quintile of the geographic momentum portfolio (out of a total of 126 months) and therefore should not significantly affect the returns of the geographic momentum long-short portfolio. Second, all of the geographic momentum excess returns are from firms that have sales in multiple regions, while there is no return predictability for firms with sales concentrated in one country like the U.S. (as will be discussed in Section 4 and displayed in Panel D of Table VII).

I next test whether the geographic momentum profitability is due to investor overreaction or to slow diffusion of information. I examine the strategy's return over a longer future horizon. Table IV follows the average returns and alphas of the geographic momentum portfolios for each month up to 6 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 IV here]

In both weighting schemes, the geographic long-short portfolio delivers positive and significant excess return and alphas only in the month immediately after portfolio formation and is not significant the following months. In particular, there is no reversal of return 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 segments of the firm is incorporated into firm prices with a one-month lag and is fully incorporated into stock prices after one month.

B Robustness Checks

Table V verifies the robustness of the geographic momentum strategy in various subsamples. For all subsamples, similar to Table II, stocks are sorted into quintiles based on the 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 V 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 segments not due to investor inattention, but rather mechanically due 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 V 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 to the geographic momentum strategy.

The second test (Panel C in Table V) 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.

So far, I use geographic stock market indices as a proxy for changes in foreign demand for goods and services exported by U.S. multinational firms. One might argue that a foreign country's GDP growth may be a more precise measure for that country's demand for U.S. goods.

Analogous to the firm's geographic return, I define the firm's geographic GDP growth as the sales-weighted average of the quarter-on-quarter GDP growth ($(GDP_{q-1} - GDP_{q-5})/GDP_{q-5}$) for the geographic regions in which the firm operates. I sort firms into quintiles based on their GDP growth for the previous quarter and compute the excess value-weighted returns and risk-adjusted alphas for the long-short portfolio. Since GDP is measured every quarter, stock portfolios are now rebalanced on a quarterly basis. Similar to the previous exercise, long-short portfolios are formed by buying stocks in the top quintile and short selling stocks in the bottom quintile. Table VI shows that differences in foreign GDP growth can also predict future stock returns for U.S. companies having operations in that country. The monthly alpha ranges from 0.65% to 0.91% after controlling for known risk factors.

[Insert Table VI here]

III Investor Inattention & 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 more severe for firms that attract less investor attention: smaller firms, firms with less analyst coverage, and firms with fewer institutional holdings.

Table VII 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 *Size*, *Analyst Coverage*, or *Institutional Holdings*, where Low and High correspond to being below or above the median in each respective category.

[Insert Table VII here]

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

I also consider the extent to which the degree of difficulty for investors to process 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 sales 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:

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

where N is the number of geographic segments in which the company operates. A low Herfindahl index means that firm's sales are widely distributed among more markets, while a high Herfindahl index means that firm's sales are more concentrated in a few markets. Thus, a firm with a low Herfindahl index for sales is likely a firm that has higher processing complexity.

Panel D in Table VII separates the sample into 2 subgroups based on their geographic sales Herfindahl index (Low is below the median and High is above the median). All of the predictability comes from the subgroup of firms that have their sales distributed more evenly among multiple geographic segments (i.e., Low Herfindahl) and likely are more complex firms to evaluate.

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

IV Regression Tests and Alternative Explanations

A 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 relation 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 return. The main independent variable is the previous month's geographic index return. 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 firm's own one-month lagged stock return (Ret_{t-1}) and 12-month lagged cumulative stock return ($Ret_{t-12,t-2}$) 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 the primary industry of the company.

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 may not be due to inattention to geographic returns, but rather due to the well-known under-reaction to earnings announcements. In order to reject this alternative explanation, I include the 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 VIII 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 of the portfolio test. For example, a one-standard-deviation increase in *GeoRet* is associated with a 1 percentage point higher monthly return for the firm (using the coefficient on $GeoRet_{t-1}$ of 0.22 from column 5 of Table VIII and the standard deviation of 4.7%). 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 return effect.

[Insert Table VIII here]

B Alternative Explanations

So far, I have shown that the geographic momentum predictability can be explained by the investor inattention hypothesis and 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 document 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 that conglomerate. One might argue that the geographic momentum effect is simply a proxy for their "complicated firm" effect. Conglomerates may have different business segments that perfectly coincide with different geographic segments. Hence, stock indices returns could just 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 return.

Fama and MacBeth (1973) regressions are run in columns (1) to (3) of Table IX 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 IX here]

Another possible concern regarding the observed predictability is that the findings may not be driven by an inattention story, but rather due to systematic differences in risks among geographic segments. More specifically, the geographic momentum effect may be largely driven by emerging market exposure. Firms that have sales and operations in emerging markets, such as China, Brazil, India or the 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, and specifically the U.S. Sorting firms based on past geographic returns may just simply be grouping firms based on the degree of exposure to emerging markets.

Table X presents the probability of a firm moving from one quintile portfolio in month t to another quintile portfolio in month $t+1$. The probability of staying in the same portfolio as the last period is only 38%. Hence, turnover is high and the composition of all quintile portfolios changes frequently, suggesting that a particular region is unlikely to account for the results.

[Insert Table X here]

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 sales that come from China. Alternatively, I also include a control variable for exposure to the four largest emerging markets, which is again the sum of sales that come from Brazil, Russia, India and China (BRIC), normalized by the firm's total sales. And finally, in the most stringent test, I also include in the Fama and MacBeth (1973) regression the share of sales coming from each of the 47 regions. I present all these tests in Table IX, columns (4) to (6). All results indicate that regional controls do not change the magnitude and significance of the lagged geographic return. Therefore, it is clear that the finding is not driven by firm's exposure to any particular country.

One possible alternative explanation is that country-level momentum can explain the geographic momentum effect. For example, the stock market for India as a whole may exhibits momentum. To the extent that there are stocks listed in the U.S. whose main business interests are in India, they may act like stocks listed on the exchange in India. Hence, the geographic momentum of a firm may just be the market momentum of the geographic region where the firm has the majority of its sales. One way to address this issue is to investigate how much the geographic return at time $t-1$ predicts the geographic return at time t. In Panel A of Table XI, I sort firms into quintiles based on their monthly geographic return in the previous month, and for each quintile, compute the average monthly geographic return in the current month, using the same weights. The geographic return in the previous month does not predict the geographic return in the current month. Panel B of Table XI reports excess returns and factor loadings of a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their geographic returns in the *current* month. Sorting stocks based on the geographic returns in the current month does not yield any significant excess returns.

[Insert Table XI here]

The systematic differences in a country's risk, country-level momentum or the complicated firms effect (i.e., conglomerate firm effect) documented by Cohen and Lou (2012) cannot explain the documented predictability of a firm's returns based on its geographic returns.

V Predicting Operating Performance

So far we have seen that the stock returns of firms with foreign market sales and operations are predictable. I also present results supporting the view that investor limited attention is the main reason behind the geographic momentum effect. In this section, I show that geographic return 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 the firm's 3-month cumulative stock return 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 the 3-month cumulative geographic return in the previous quarter. I also include in the regression $QtrRet_{q-1}$, which is the firm's actual stock return over the previous quarter. Controls are also included for all geographic regions, and are denoted as

$\{geoSales(i)/sales\}_{i=1}^{47}$, which are the fractions of sales coming from each geographic region over a firm's total sales. The value of $geoSales(i)/sales$ is zero for firms that do not have sales in a segment 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 XII shows that previous quarter *GeoRet* can strongly predict a firm's current quarter stock return, sales and operating income. In other words, changes to the different geographic market conditions can not only predict future stock price movements, but also the profitability of multinational firms. Even after controlling for firms' stock price information in 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 operating performance, such as sales and operating income. The results on operating performance are important as they justify the return results: lagged geographic returns predict stronger sales and income for firms in the next quarter, which justifies higher stock prices.

[Insert Table XII here]

VI Conclusion

This paper uses publicly available geographic segment disclosures 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 return is defined as the fraction of sales coming from that region divided by firm's total sales. 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 135 basis points per month, or 16.2% per year. I call this return predictability the "geographic momentum" effect.

This result is robust across different 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 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 different 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 investors having limited 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 among firms that are geographically more complex, i.e., firms with sales distributed among more 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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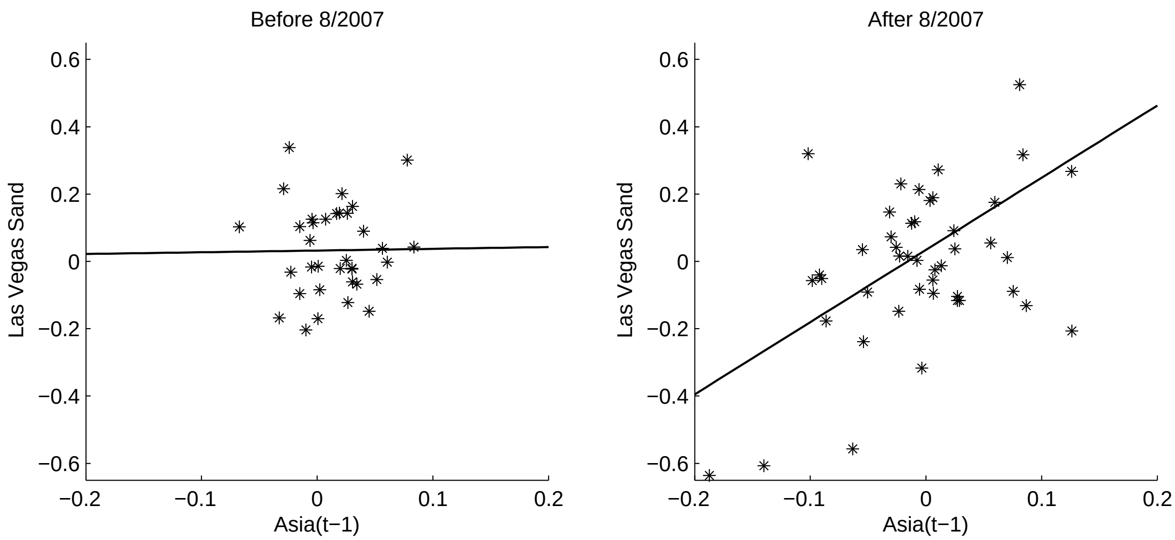
Figure 1: Las Vegas Sands Corporation and Lagged Asia Index
The figure shows the scatter plots of monthly LVS raw returns and the lagged Asia index returns, before and after launching The Venetian Macao Resort. The least-squares lines are added to the scatter plot. The correlation between LVS stock returns 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: Returns of Geographic Momentum Strategy
This figure plots the monthly times-series excess return of an equally-weighted portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their lagged one-month geographic returns. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region.

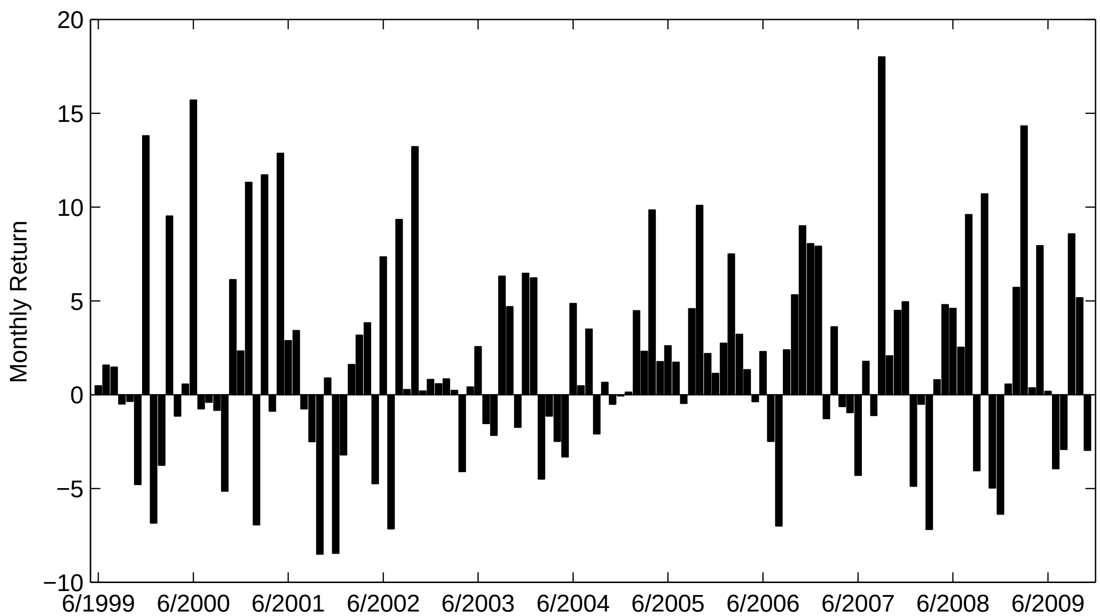


Table I: Summary Statistics and Correlations

This table presents summary statistics of the variables of interest and the correlations between the main explanatory variables known to predict stock returns. *Ret* is a stock's monthly return. *GeoRet* is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in 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. $Sales$ is firm's total sales. $Herfindahl$ measures the complexity of firms' sales distribution and is computed as the sum of squared sales fractions across various geographic regions. $Ret_{t-12,t-2}$ is the cumulative returns from month $t-12$ to month $t-2$. $IndRet_{t-12,t-2}$ is the primary industry cumulative returns from month $t-12$ to month $t-2$. SUE is the most recent standardized unexpected earnings before month t. $PseudoRet_{t-1}$ is the pseudo returns computed as in Cohen and Lou (2012), which is the weighted average return of the conglomerate's industry segments (based on SIC-2) constructed using only stand-alone firms in the same industry.

Panel A: Summary Statistics

	Mean	Std. Dev.	1%tile	25%tile	50%tile	75%tile	99%tile	Count
Ret	0.001	0.173	-0.438	-0.077	0.002	0.0813	0.581	357523
GeoRet	0.001	0.047	-0.113	-0.022	0.006	0.027	0.096	357523
Size	19.794	1.900	16.413	18.342	19.697	21.033	24.807	357491
log(BM)	-0.882	1.135	-4.597	-1.462	-0.805	-0.205	1.784	357435
Sales	2387.9	10648.3	1.01	72.3	301.8	1242.3	35214.0	357523
Herfindahl	0.680	0.340	0.001	0.309	0.790	1	1	357523
Herfindahl ($<$ 100% *US*)	0.459	0.274	0.005	0.250	0.411	0.700	0.981	211010

Panel B: Correlations

	Ret	$GeoRet_{t-1}$	$Size$	$log(BM)$	$Ret_{t-12,t-2}$	$IndRet_{t-12,t-2}$	SUE	$Herfindahl$
$GeoRet_{t-1}$	0.089							
$Size$	-0.010	0.010						
$log(BM)$	0.033	0.004	-0.441					
$Ret_{t-12,t-2}$	0.010	-0.009	-0.045	0.092				
$IndRet_{t-12,t-2}$	0.003	0.015	-0.008	0.042	0.440			
SUE	0.054	0.013	-0.008	0.034	0.097	0.044		
$Herfindahl$	-0.001	-0.010	-0.231	0.088	0.017	0.008	-0.012	
$PseudoRet_{t-1}$	0.061	0.521	-0.011	0.006	0.001	0.004	0.012	0.003

Table II: Abnormal Returns on Geographic Momentum Strategy

This table reports the abnormal returns (in %) of the portfolios of firms based on the quintile ranking of their one-month lagged monthly geographic returns. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in 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 of a portfolio that longs stocks in the top quintile geographic returns and shorts stocks in the bottom quintile geographic returns. Besides 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 August 1999 to January 2010. 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: Equally-Weighted Returns					
	1 (Low)	**2**	**3**	**4**	**5 (High)**	**High−Low**
Excess Return	-0.29	-0.01	0.13	0.09	1.23	1.52***
	(-0.38)	(-0.02)	(0.22)	(0.14)	(1.63)	(3.23)
CAPM *Alpha*	-0.28	-0.00	0.14	0.10	1.24**	1.52***
	(-0.69)	(-0.00)	(0.51)	(0.29)	(2.53)	(3.25)
FF-3 *Alpha*	-0.65*	-0.32	-0.26	-0.30	0.75*	1.40***
	(-1.80)	(-1.38)	(-1.25)	(-1.06)	(1.77)	(3.00)
Car-4 *Alpha*	-0.59*	-0.27	-0.21	-0.24	0.81**	1.40***
	(-1.67)	(-1.19)	(-1.09)	(-0.57)	(1.99)	(2.98)
PS-5 *Alpha*	-0.69*	-0.44**	-0.28	-0.37	0.74*	1.43***
	(-1.83)	(-2.07)	(-1.54)	(-1.53)	(1.72)	(2.99)
	Panel B: Value-Weighted Returns					
	1 (Low)	**2**	**3**	**4**	**5 (High)**	**High−Low**
Excess Return	-0.13	0.16	0.28	0.28	1.35*	1.48***
	(-0.17)	(0.25)	(0.47)	(0.46)	(1.81)	(3.22)
CAPM *Alpha*	-0.12	0.17	0.29	0.29	1.36***	1.48***
	(-0.30)	(0.58)	(1.08)	(0.90)	(2.84)	(3.24)
FF-3 *Alpha*	-0.48	-0.15	-0.11	-0.10	0.88**	1.36***
	(-1.39)	(-0.68)	(-0.56)	(-0.37)	(2.14)	(2.97)
Car-4 *Alpha*	-0.42	-0.10	-0.06	-0.04	0.95**	1.37***
	(-1.25)	(-0.47)	(-0.35)	(-0.17)	(2.38)	(2.97)
PS-5 *Alpha*	-0.52	-0.26	-0.13	-0.17	0.87**	1.39***
	(-1.42)	(-1.32)	(-0.77)	(-0.74)	(2.09)	(2.96)

Table III: Loadings from the Geographic Portfolio Strategy

This table reports factor 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 return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in 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" column in Panels A and B in Table II. 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 August 1999 to January 2010. P-values of F-tests for the joint significance of the factor loadings are also reported. 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: Equally-Weighted Returns

	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Alpha	1.52***	1.52***	1.40***	1.40***	1.43***
	(3.23)	(3.25)	(3.00)	(2.99)	(2.99)
$Mkt - R_f$		-0.16	-0.15	-0.15	-0.14
		(-1.45)	(-1.30)	(-1.18)	(-1.15)
SMB			0.06	0.06	0.05
			(0.43)	(0.41)	(0.40)
HML			0.17	0.17	0.16
			(1.10)	(1.10)	(1.07)
UMD				0.00	0.00
				(0.04)	(0.06)
LIQ					-0.03
					(-0.26)
p-value of F-test		0.49	0.54	0.65	0.71
R^2	0.00	0.01	0.03	0.03	0.05
N	126	126	126	126	126

Panel B: Value-Weighted Returns

	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Alpha	1.48***	1.48***	1.36***	1.37***	1.39***
	(3.22)	(3.24)	(2.97)	(2.97)	(2.96)
$Mkt - R_f$		-0.16	-0.15	-0.16	-0.15
		(-1.44)	(-1.33)	(-1.30)	(-1.27)
SMB			0.07	0.07	0.07
			(0.52)	(0.55)	(0.54)
HML			0.16	0.15	0.15
			(1.10)	(1.06)	(1.03)
UMD				-0.02	-0.01
				(-0.23)	(-0.21)
LIQ					-0.03
					(-0.25)
p-value of F-test		0.30	0.43	0.53	0.61
R^2	0.00	0.01	0.02	0.03	0.04
N	126	126	126	126	126

Panel C: Equally-Weighted Returns; Excluding 100% US firms					
	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Alpha	1.30***	1.29***	1.25***	1.26***	1.33***
	(2.85)	(2.86)	(2.70)	(2.68)	(2.74)
$Mkt - R_f$		-0.13	-0.10	-0.11	-0.10
		(-1.19)	(-0.94)	(-0.95)	(-0.87)
SMB			-0.03	-0.02	-0.03
			(-0.22)	(-0.17)	(-0.18)
HML			0.12	0.11	0.10
			(0.84)	(0.82)	(0.78)
UMD				-0.02	-0.01
				(-0.20)	(-0.15)
LIQ					-0.07
					(-0.72)
p-value of F-test		0.24	0.46	0.64	0.73
R^2	0.00	0.01	0.02	0.02	0.03
N	126	126	126	126	126

Panel D: Value-Weighted Returns; Excluding 100% US firms					
	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Alpha	1.36***	1.36***	1.30***	1.32***	1.38***
	(3.01)	(3.01)	(2.89)	(2.87)	(2.92)
$Mkt - R_f$		-0.07	-0.07	-0.11	-0.10
		(-0.72)	(-0.66)	(-0.95)	(-0.86)
SMB			0.04	0.06	0.06
			(0.25)	(0.35)	(0.34)
HML			0.08	0.06	0.06
			(0.56)	(0.45)	(0.41)
UMD				-0.06	-0.05
				(-0.54)	(-0.50)
LIQ					-0.07
					(-0.63)
p-value of F-test		0.24	0.46	0.64	0.74
R^2	0.00	0.01	0.01	0.01	0.02
N	126	126	126	126	126

Table IV: Geographic Momentum Strategy over Different Horizons

This table reports the abnormal returns (in %) 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, holding over different horizons. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region. I present results of monthly abnormal returns of portfolios formed in month zero for months one to 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 II. The sample period is from August 1999 to January 2010. 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: Equally-Weighted Returns

	Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
$r_{0,1}$	1.52***	1.52***	1.40***	1.40***	1.43***
	(3.23)	(3.25)	(3.00)	(2.99)	(2.99)
$r_{1,2}$	0.23	0.23	0.16	0.14	0.06
	(0.49)	(0.50)	(0.35)	(0.29)	(0.14)
$r_{2,3}$	0.15	0.15	0.26	0.21	-0.20
	(0.34)	(0.33)	(0.56)	(0.45)	(-0.42)
$r_{3,4}$	0.29	0.29	0.27	0.26	0.51
	(0.56)	(0.56)	(0.52)	(0.51)	(1.01)
$r_{4,5}$	-0.27	-0.27	-0.14	-0.07	-0.29
	(-0.60)	(-0.60)	(-0.31)	(-0.15)	(-0.63)
$r_{5,6}$	0.25	0.25	0.31	0.28	0.39
	(0.56)	(0.56)	(0.74)	(0.68)	(0.93)

Panel B: Value-Weighted Returns

	Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
$r_{0,1}$	1.48***	1.48***	1.36***	1.37***	1.39***
	(3.22)	(3.24)	(2.97)	(2.97)	(2.96)
$r_{1,2}$	0.20	0.20	0.15	0.13	0.05
	(0.43)	(0.44)	(0.32)	(0.27)	(0.12)
$r_{2,3}$	0.19	0.19	0.32	0.27	-0.14
	(0.42)	(0.42)	(0.70)	(0.59)	(-0.30)
$r_{3,4}$	0.30	0.30	0.27	0.27	0.49
	(0.58)	(0.58)	(0.53)	(0.53)	(0.99)
$r_{4,5}$	-0.31	-0.31	-0.18	-0.12	-0.32
	(-0.71)	(-0.71)	(-0.41)	(-0.26)	(-0.71)
$r_{5,6}$	0.29	0.29	0.36	0.33	0.42
	(0.67)	(0.66)	(0.88)	(0.81)	(1.01)

Table V: Subsample Robustness Checks

This table reports the abnormal returns (in %, equally weighted) 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 for different subsamples. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region. The various subsample of stocks are, Panel A: The base case (same as row one of Panel A in Table II), 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 (financial crisis). The sample period is from August 1999 to January 2010. 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**
1.52***	1.52***	1.40***	1.40***	1.43***
(3.23)	(3.25)	(3.00)	(2.99)	(2.99)
		Panel B: Excluding Illiquid Stocks, prc < 5		
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
1.27***	1.27***	1.19**	1.19**	1.28**
(2.71)	(2.70)	(2.38)	(2.40)	(2.49)
		Panel C: Including Financial Firms		
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
1.55***	1.55***	1.38***	1.40***	1.47***
(3.28)	(3.28)	(2.97)	(2.98)	(3.04)
		Panel D: Excluding 2008-2009 Financial Crisis Period		
Excess Return	**CAPM Alpha**	**FF-3 Alpha**	**Car-4 Alpha**	**PS-5 Alpha**
1.48***	1.51***	1.34***	1.31**	1.15**
(2.89)	(2.95)	(2.71)	(2.59)	(2.26)

Table VI: GDP Growth in Segment Regions and Future Firm Returns

This table reports the abnormal monthly returns (in %, equally weighted) of a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their lagged geographic GDP growth. Geographic GDP growth is the weighted average regional quarter-on-quarter GDP growth ($(GDP_{q-1} - GDP_{q-5})/GDP_{q-5}$) corresponding to geographic segments of the firm, where the weight assigned to each region is the fraction of a firm's sales in that geographic region. Portfolios are rebalanced every quarter. Besides 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 August 1999 to January 2010. P-values of F-tests for the joint significance of the factor loadings are also reported. 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.

	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Alpha	0.65*	0.65*	0.85*	0.89**	0.91**
	(1.70)	(1.69)	(1.96)	(2.05)	(1.99)
$Mkt - R_f$		0.01	0.06	-0.03	-0.03
		(0.07)	(0.53)	(-0.31)	(-0.27)
SMB			-0.28	-0.24	-0.24
			(-1.30)	(-1.53)	(-1.53)
HML			-0.08	-0.12	-0.13
			(-0.64)	(-1.04)	(-1.05)
UMD				-0.13*	-0.13
				(-1.71)	(-1.50)
LIQ					-0.02
					(-0.17)
p-value of F-test		0.16	0.25	0.39	0.53
R^2	0.00	0.00	0.05	0.07	0.07
N	126	126	126	126	126

Table VII: The Roll of Inattention and Processing Complexity

This table reports abnormal returns (in %, equally weighted) 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 return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region. I present results for various subsamples of stocks sorted by different proxies of inattention, including *A: Size*, *B: Analyst Coverage*, and *C: Institutional Holdings*. In Panel *D: Herfindahl*, firms are sorted by their Herfindahl index that measures a firm's diversity in geographic segments (i.e., the sum of squared sales fractions across geographic regions). A low Herfindahl corresponds to a firm with sales in many countries (i.e., high processing complexity). I report returns for stocks above and below the median for each of the four variables. The sample period is from August 1999 to January 2010. 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: Size						*Panel B: Analyst Coverage*				
	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**		**Ex. Ret**	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Small	2.12***	2.12***	2.10***	2.10***	2.21***	Low	2.65***	2.65***	2.54***	2.52***	2.74***
	(3.06)	(3.07)	(2.97)	(2.94)	(3.05)		(3.30)	(3.30)	(3.00)	(2.92)	(3.14)
Large	0.35	0.35	0.12	0.19	0.28	High	0.63	0.61	0.73	0.76	0.50
	(0.47)	(0.47)	(0.02)	(0.12)	(0.17)		(0.89)	(0.87)	(1.07)	(1.09)	(0.71)
Small−Large	1.82*	1.82*	2.09**	2.03**	2.10**	Low−High	2.02*	2.04*	1.81*	1.76	2.24**
	(1.93)	(1.93)	(2.22)	(2.14)	(2.16)		(1.90)	(1.92)	(1.66)	(1.59)	(2.00)
	Panel C: Institutional Holdings						*Panel D: Herfindahl*				
	Ex. Ret	**CAPM**	**FF-3**	**Car-4**	**PS-5**		**Ex. Ret**	**CAPM**	**FF-3**	**Car-4**	**PS-5**
Low	1.62***	1.62***	1.55***	1.56***	1.68***	Low	2.23***	2.23***	2.11***	2.19***	2.30***
	(3.04)	(3.04)	(2.88)	(2.83)	(3.00)		(2.84)	(2.82)	(2.63)	(2.70)	(2.75)
High	0.85	0.89	0.70	0.83	0.76	High	0.60	0.60	0.52	0.52	0.58
	(0.83)	(0.88)	(0.72)	(0.84)	(0.77)		(1.10)	(1.11)	(0.93)	(0.91)	(0.96)
Low−High	0.76	0.72	0.85	0.72	0.92	Low−High	1.63*	1.63*	1.58	1.67*	1.72*
	(0.66)	(0.63)	(0.77)	(0.64)	(0.81)		(1.70)	(1.71)	(1.61)	(1.69)	(1.66)

Table VIII: Fama-MacBeth Cross-Sectional Regressions

This table reports results of monthly Fama and MacBeth (1973) regressions of stock returns on lagged geographic returns. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region. For the cross-sectional regression in month t, the dependent variable is the stock return 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 to 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 to 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 $t-12$ to month $t-2$, respectively. $IndRet_{t-1}$ is the industry's return in the previous month. $IndRet_{t-12,t-2}$ is the industry's cumulative return from month $t-12$ to 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)
$GeoRet_{t-1}$	0.17***	0.19***	0.18***	0.17***	0.22***
	(2.62)	(2.76)	(2.62)	(2.63)	(2.81)
$log(BM)$		0.36**	0.36**	0.36***	0.27**
		(2.04)	(2.57)	(3.09)	(2.53)
$Size$		-0.21**	-0.22**	-0.21**	-0.22***
		(-2.19)	(-2.39)	(-2.48)	(-2.88)
Ret_{t-1}			-0.01*	-0.02***	-0.03***
			(-1.75)	(-3.10)	(-4.45)
$Ret_{t-12,t-2}$			0.00	0.00	0.00
			(1.34)	(1.10)	(0.10)
$IndRet_{t-1}$				0.15***	0.12***
				(5.13)	(4.73)
$IndRet_{t-12,t-2}$				0.01*	0.01
				(1.75)	(1.25)
SUE					0.01***
					(20.30)
R^2	0.00	0.02	0.04	0.05	0.06
N	357522	357434	357434	357434	277339
N-month	126	126	126	126	126

Table IX: 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 return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region divided by firm's total sales. For the cross-sectional regression in month t, the dependent variable is the stock return in month t. $PseudoRet_{t-1}$ is the pseudo return computed as in Cohen and Lou (2012), which is the weighted average return of the conglomerate's industry segments (based on SIC-2) constructed using only stand-alone firms in the same industry. $ChinaSales/Sales$ is the fraction of sales from China, computed as sales from China over total sales. It is zero if the firm has no sales from China. Similarly, $BRICSales/Sales$ is the sales that come from Brazil, Russia, India and China, divided by total sales. *Share of Sales in each of the 47 Regions* are the fractions of geographic sales from each of the 47 regions over total sales. *Other Controls* are the same as the RHS variables in Table VIII Column 5, and include: $log(BM)$, the natural log of book to market equity, is the same for all returns from July of year y to June of year $y+1$; $Size$, log market equity, is computed at the end of June of year y, and is the same for all returns from July/y to 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 $t-12$ to month $t-2$, respectively; $IndRet_{t-1}$ and $IndRet_{t-12,t-2}$ are the primary industry previous month's return and cumulative return from month $t-12$ to month $t-2$, respectively; 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)	(6)
$GeoRet_{t-1}$	0.22***		0.22***	0.22***	0.22***	0.24***
	(2.81)		(2.85)	(2.79)	(2.79)	(2.71)
$PseudoRet_{t-1}$		0.14***	0.14***	0.14***	0.14***	0.14***
		(3.23)	(3.21)	(3.21)	(3.21)	(2.81)
$ChinaSales/Sales$				0.98*		
				(1.77)		
$BRICSales/Sales$					0.41	
					(0.72)	
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Share of Sales in each of the 47 Regions	No	No	No	No	No	Yes
R^2	0.06	0.06	0.06	0.06	0.06	0.07
N	277339	277339	277339	277339	277339	277339
N-month	126	126	126	126	126	126

Table X: Switching Probability Between Quintile Portfolios

This table reports the probability of a firm moving from quintile i in month t to quintile j in the next month $t+1$, where quintiles are formed based on firms' geographic returns. Geographic return (*GeoRet*) is the weighted average monthly return of a firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region.

		Month $t+1$						
		1 (Low)	**2**	**3**	**4**	**5 (High)**	$P(\mathrm{q}_{t+1} = \mathrm{q}_t)$	$P(\mathrm{q}_{t+1} \neq \mathrm{q}_t)$
	1 (Low)	0.33	0.20	0.18	0.15	0.13	0.33	0.67
	2	0.28	0.38	0.16	0.16	0.03	0.38	0.62
Month t	**3**	0.17	0.24	0.31	0.22	0.06	0.31	0.69
	4	0.01	0.21	0.22	0.29	0.27	0.29	0.71
	5 (High)	0.01	0.12	0.26	0.27	0.34	0.34	0.66

Table XI: Country-Level Momentum

This table shows that country-level momentum cannot explain the geographic momentum results. Panel A sorts firms into quintile based on their monthly geographic return in the previous month, and for each quintile, reports the average monthly geographic return for the current month, using the same weights. Geographic return (*GeoRet*) is the weighted average monthly return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region. Panel B reports the average geographic return in the current month of a portfolio that longs stocks in the top quintile and shorts stocks in the bottom quintile according to their geographic return in the previous month, controlling for various risk factors. Risk factors included are: $Mkt - R_f$, SMB, HML, UMD, Carhart (1997) momentum factor and LIQ, and the Pastor and Stambaugh (2003) liquidity factor. Panel C reports monthly Fama and MacBeth (1973) regressions of geographic returns in the current month on geographic returns in the previous month. $log(BM)$ is the natural log of book to market equity and is the same for all returns from July of year y to June of year $y+1$; *Size* is the log market equity and is computed at the end of June of year y, and is the same for all returns from July/y to June/$y+1$. *Share of Sales in each of the 47 Regions* are the fractions of geographic sales from each of the 47 regions over total sales. The sample period is from August 1999 to January 2010. 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: Portfolio Test

	$GeoRet_{t-1}$					
	1 (Low)	**2**	**3**	**4**	**5 (High)**	**High−Low**
$GeoRet_t$	0.27	0.26	0.22	0.54	0.72	0.46
	(0.54)	(0.57)	(0.53)	(0.90)	(1.51)	(1.59)

Panel B: Portfolio Test with Risk Factors

	High - Low				
Constant	0.46	0.46	0.37	0.38	0.42
	(1.60)	(1.60)	(1.18)	(1.22)	(1.26)
$Mkt - R_f$		-0.06	-0.09	-0.12	-0.12
		(-0.94)	(-1.31)	(-1.58)	(-1.59)
SMB			0.15*	0.17**	0.17**
			(1.95)	(2.10)	(2.07)
HML			0.03	0.01	0.01
			(0.34)	(0.16)	(0.11)
UMD				-0.05	-0.04
				(-1.00)	(-0.96)
LIQ					-0.04
					(-0.62)
R^2	0.00	0.01	0.04	0.05	0.05
N	126	126	126	126	126

Panel C: Fama-MacBeth

	$GeoLag_t$
$GeoLag_{t-1}$	0.08
	(0.38)
$log(BM)$	0.00
	(-0.51)
Size	0.00
	(0.37)
Share of Sales in each of the 47 Regions	Yes
Constant	-0.01
	(-0.76)
R^2	0.83
N	357522

Table XII: 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 geographic return. Geographic return (*GeoRet*) is the weighted average return of firm's corresponding geographic indices, where the weight assigned to each index return is the fraction of a firm's sales in that geographic region divided by firm's total sales. *Share of Sales in each of the 47 Regions* are the fractions of geographic sales from each of the 47 regions over total sales. The dependent variables are: (1) *QtrRet*, the cumulative stock returns over the 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×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)
$GeoRet_{q-1}$	0.10***	0.03***	0.01***
	(9.13)	(2.71)	(4.45)
$QtrRet_{q-1}$	-0.02***	0.04***	0.02***
	(-4.29)	(11.69)	(15.80)
Share of Sales in each of the 47 Regions	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
R^2	0.01	0.00	0.01
N	112091	103223	109106