Foreign Sentiment*

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This Draft: November 2019

Abstract

We construct a direct measure of U.S. based foreign sentiment using flow shifts between U.S. and international mutual funds. Foreign sentiment predicts return reversals in international markets, while local sentiments predict reversals in local markets. Exploring this segmentation, we find that foreign sentiment predictability is driven by overreaction to non-U.S. local negative news, which increases with the foreignness of a country to U.S. investors. In contrast, non-U.S. local sentiment predictability is not driven by overreaction to the same news. A complementary analysis of the U.S. provides consistent results, suggesting that the U.S. is also not immune to foreign sentiment from international markets. Our findings shed light on a new behavioral explanation for how foreign sentiment is generated, in the spirit of Dumas et al. (2017) "foreign sentiment" concept.

Keywords: Sentiment, foreign sentiment, news, flow shifts, international markets
JEL Codes: G10; G11; G15; G40

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1. Introduction

The literature on investor sentiment is fast growing. Sentiment is found to affect the cross section of stock returns, the aggregate stock market, and various asset classes (e.g., Baker and Wurgler, 2006; Ben-Rephael, Kandel and Wohl, 2012; and Huang, Lehkonen, Pukthuanthong, and Zhou, 2018).[1] Recent evidence suggests that sentiment can also play an important role in international markets (Hwang, 2011; Baker, Wurgler and Yuan, 2012; Gao, Ren and Zhang, 2018). Despite this evidence, our understanding on the effect of foreign investors' sentiment on local assets, namely "foreign sentiment," is still limited. This question is of paramount importance in light of the increasingly integrated financial markets and the growing importance of international markets, which necessitates the understanding of the effects of foreign investors on asset prices.

In their influential paper, Baker, Wurgler and Yuan (2012) (hereafter, BWY) find that both local and global sentiment measures are contrarian predictors of local markets.[2] Sentiment contagion is suggested as one channel by which sentiment can spreads across markets. However, without differentiating foreign and local sentiments, it is impossible to clearly understand the cross-country effects of sentiment, be it through contagion or other channels.

In this paper, we construct direct measures of foreign and local investor sentiment and use them to shed light on the following questions: Is foreign sentiment generated by investors in country A toward country B a mere reflection of general optimism (or pessimism) in county A, country B, or both? Do public signals in country B affect the generation process of foreign

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[1] Zhou (2018) provides a recent survey of the literature. A few examples are, Lee, Shleifer, and Thaler (1991), Goetzmann, and Massa (2003), Brown and Cliff (2005), Lemmon and Portniaguina (2006), Baker and Wurgler (2006, 2007), Qiu and Welch (2006), Tetlock (2007), Frazzini and Lamont (2008), Stambaugh, Yu and Yuan (2012), Da, Engelberg and Gao (2015), Huang, Jiang, Tu and Zhou (2015), Soo (2018), and Cassella and Gulen (2019).

[2] Following Baker and Wurgler (2006), BWY construct investor sentiment indices for the U.S. and five other major stock markets. The global sentiment measure is defined as the first principal component of the six indices. The *local* indices are defined as the residual from a regression of each country's sentiment on the global sentiment measure.

sentiment from country A and local sentiment in country B differently? Can country/culture/social differences between foreign and local investors lead to different foreign and local sentiments in response to the same public signals?

These questions are critical for understanding the differential roles played by foreign and local sentiments in affecting asset prices across markets. They are also highly relevant as inherent informational as well as other differences between local and foreign investors may lead to difference in opinions, which can result in mis-reaction to market information. Building on this point, in a recent theoretical paper, Dumas, Lewis, and Osambela (2017) advance the existence of a "foreign sentiment" concept, where foreign investors misinterpret the same publicly available information.[3]

To study the differential sentiment effects, we use Ben-Rephael et al. (2012) (hereafter, BKW) local U.S. sentiment measure based on U.S. flows shifts; and introduce a new and *direct* U.S. based foreign investor sentiment measure by applying BKW approach in the international setting. The foreign measure termed "*FNEIO*" is based on flow shifts of *pre-existing investments* held in mutual fund families toward international markets. When U.S. investors shift their *pre-existing* investments from (to) the U.S. market to (from) the foreign market, it directly signals that U.S. investors are optimistic (pessimistic) about the foreign market rather than generally optimistic (pessimistic) about both the foreign and the local markets. As such, this measure differs from the global and local sentiment measures in existing studies such as BWY and Gao et al. (2018), which cannot directly tease out the foreign sentiment concept. For completeness, we also construct similar flow-based non-U.S. foreign sentiment proxies for each non-U.S. country, which are based

[3] Brennan and Cao (1997) also model informational differences between local and foreign investors. However, in their both foreign and domestic investors are rational, therefore, behavioral errors and, as a result, mispricing, do not arise.

on *total* net flows instead of flow shifts. [4] Finally, to analyze the relation between foreign sentiment and countries' public signals, we use Calomiris and Mamaysky (2019; hereafter, CM) newly-developed country specific news tone measures. Importantly, these measures do not rely on market returns to measure the tone of the news.

We first establish that foreign sentiment generated by U.S. investors has distinct price effects from those of local U.S. sentiment and local sentiment in international markets. We find that *FNEIO* predicts return reversals in international markets, but has no predictive power in the U.S. market. Put differently, when U.S. investors shift their pre-existing investments between the U.S. and international markets, international market prices move in the direction of U.S. flows contemporaneously, but then reverse in subsequent months. Thus, it appears that such money shifting is sentimental in that it tends to "mis-react" when U.S. investors reallocate their assets between the U.S. and international markets. A one standard deviation increase in *FNEIO* is associated with -1% (-2.7%) MSCI foreign country index return in the next month (12 months). *FNEIO* also has significant out-of-sample predictability on international market returns, achieving up to 4% out-of-sample R-squared for one-month ahead returns. In contrast, U.S. local sentiment has no predictive power in international markets. Thus, our local and foreign investor sentiment measures seem to capture different aspects of U.S. investor behavior other than sentiment contagion.

To identify the channel driving the foreign sentiment effect (i.e., the *FNEIO*-return relation), we then turn to explore the relation between sentiment and public news, which are important source of public signals. We first analyze the monthly lead-lag relation between non-U.S. local news tone

[4] Flow shifts data (i.e., transfers of existing money) are not available for non-U.S. countries. Consequently, for each non-U.S. country we construct a local sentiment proxy as the difference between percentage *total net flows* into equity and bond mutual funds. We also construct a non-U.S. foreign sentiment proxy as the differences between percentage flows into U.S. equity and non-U.S. equity funds in international markets.

and *FNEIO* in a VAR setting. We find that non-U.S. local news tone leads *FNEIO* and not vice versa, where the first three lags of news tone are positive and significant. In contrast, we do not find any predictability between local non-U.S. sentiment (*LEBD*) and news tone.

Next, we analyze the relation between *FNEIO*, news tone and returns. Strikingly, we find that the ability of *FNEIO* to predict subsequent returns is driven by its interaction with non-U.S. local public news tone. Specifically, including *FNEIO* * *NewsTone* in the regression, we find that *FNEIO* becomes insignificant while its interaction with *NewsTone* is economically and statistically significant. Consistent with the lead-lag analysis, we find that non-U.S. investors' local sentiment interaction with *NewsTone* is neither economically nor statistically significant. These results suggest that non-U.S. local public news, drives the foreign sentiment effect, whereas non-U.S. local sentiment is not driven by mis-reaction to the same local public signals. Finally, we do not find the same results when we interact *FNEIO* with non-U.S. local market returns. Thus, news tone is not a mere proxy of market returns.

We also find that *FNEIO* has a stronger effect for countries with larger U.S. active participation, proxied by U.S. AUM-based weight of a country relative to the country's market cap-based weight. The result supports that the foreign-sentiment effect is related to U.S. investors' active action. Furthermore, splitting *FNEIO* into positive and negative flow shift components and exploring their interaction with *NewsTone*, we find that *FNEIO* predictability is driven by overreaction to negative non-U.S. local public news. Specifically, when news from foreign markets are bad, and U.S. investors shift their foreign investments back to the U.S. market, international market returns will reverse in future periods.

We relate our finding - that foreign sentiment appears to overreact towards bad news in foreign countries while local sentiment is not driven by its local news tone - to a couple of potential explanations from the psychology literature. They include "*attribution bias*" and "*outgroup negativity,*" where investors perceive more negatively events that occur outside their group. To explore these explanations, we use six measures that reflects the degree that U.S. investors may view an international country as outgroup, i.e., "foreign." These are, Hofstede's cultural distance measure based on six dimensions of national culture (i.e., individualism, power distance, masculinity, uncertainty avoidance, long-term orientation and indulgence), physical distance, ancestral distance (the fraction of US citizens with ancestors from the country), religious distance, language, and a composite distance measure that combines the information from all the above five measures. Interacting these six measures with our negative news-induced foreign sentiment effect generally indicates that the overreaction to negative news signals is stronger for countries, which are presumably more likely to be perceived as outgroup. Thus, U.S. investors' reaction to negative public signals seem to be more pronounced when the signals are from countries that are more foreign. In sum, our collective results provide first hand evidence of a new and important behavioral mechanism that explains how foreign sentiment can be generated in the spirit of Dumas et al. (2017).

Our main analysis is based on monthly panel data of developed market countries from 1992 to 2017. To construct our U.S. based local and foreign sentiment measures we obtain monthly data on intra-family flow shifts from the Investment Company Institute (ICI). Specifically, the ICI categorizes investor flows into exchanges in, exchanges out, sales, and redemptions, which aggregate to total net fund flows. Ben-Rephael et al. (2012, 2017) discuss the advantages of using net-exchanges (i.e., intra-family flow shifts) over net sales and redemptions.[5]

[5] In particular, net exchanges are a clean measure of investors' asset allocation decisions, where net sales and redemptions are driven mainly by investors' long-term saving decisions and reflect trends in amounts injected into retirement accounts and asset management.

In all our regressions, we make sure to control for contemporaneous and lagged market returns. This reassures that our findings are not driven by investors' feedback response. As in BKW, we also control for net sales and redemptions. As expected, sales and redemptions of international mutual funds (*FNSR*) exhibit a different price pattern than *FNEIO*. In particular, *FNSR* seems to reflect the growth in international market investment, which results in short-term momentum (Lou, 2012). Thus, using total net flows, as usually employed in the literature masks these differences.

For completeness, we also provide a complimentary analysis on non-U.S. investors' sentiment in the U.S. market, namely their foreign sentiment. Our non-U.S. foreign sentiment proxy is based on a single time series of aggregate differences between percentage flows into U.S. equity and non-U.S. local equity funds in international markets. We find results that are overall consistent with our international markets main findings. A one standard deviation increase in non-U.S. investor foreign sentiment is associated with a reversal of -4.06% of the U.S. market index return in the next 12 months. Similar to the international markets analysis, we also find that the predictive power of the non-U.S. foreign sentiment measure stems from negative local U.S. *NewsTone*, while the interaction between *local U.S. sentiment* and local U.S. news tone is not significant. Thus, we can conclude that in both – international and U.S. - markets local investors do not overreact to negative public news, while foreign investors do.

A natural question to ask is why foreign investors overreact to negative public signals. One explanation is that without access to soft information, foreign investors might observe the public signal as the tip of the iceberg. Another explanation is that foreign investors may choose not to become informed about the public signals, since it is costly to acquire information and requires effort. Thus, they may particularly overreact to foreign negative news if they are overly pessimistic about foreign fundamentals due to outgroup negativity. These explanations are consistent with the fact that our flow shifts measures are based on retail investors' asset allocation decisions, which represent the set of investors that are likely to be less sophisticated, or choose not to become informed.[6] Consequently, arbitrage activity is not riskless and prices are not corrected right away.[7]

We address several alternative explanations including changes in risk, risk aversion, or fundamentals, changes in market liquidity or volatility or by hedging demand (i.e., liquidity shocks). First, we validate that *FNEIO* is positively associated with contemporaneous returns and difference in ADR prices, consistent with price dislocations, which subsequently revert. Since ADRs and their foreign counterparts have similar return dynamic on a monthly basis and are driven by the same fundamentals, the ADR test also helps alleviating the concerns of time varying risk or time varying risk aversion. Second, we replace returns with market volatility and find no relation between *FNEIO* and subsequent market volatility in both U.S. and non-U.S. markets. Third, it is difficult for risk or risk aversion to explain the large and rapid nature of our findings.[8] Fourth, we control for Pastor and Stambaugh (2003) systematic liquidity measure and changes in the VIX, and find that *FNEIO* coefficient estimates remain similar. Fifth, we take advantage of our panel data and sort countries based on their market cap. The idea is that smaller countries, which presumably have less efficient market, are more subject to liquidity and risk concerns. Our findings are not concentrated in smaller countries, which provides an additional support that liquidity or risk do not drive our findings. Relatedly, if the return reversal effect of *FNEIO* is due to the temporary price pressure of flows, *FNSR* should have generated much stronger reversals than

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[6] According to ICI 2019 Fact Book, in 2018 households (institutional investors) held 89% (11%) of mutual funds total net assets.
[7] De Long, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997) show that irrational investors can induce price noises that do not quickly vanish if they cannot be corrected by riskless arbitrage.
[8] Note that the magnitude of the change in returns over the short period is too large to be justified by such explanations. Brunnermeier and Nagel (2008) find little evidence that risk aversion change rapidly. Campbell and Cochrane (1999) and Kyle and Xiong (2001) show that time varying risk or risk aversion does not generate a predictable reversal in prices.

FNEIO as *FNEIO* is fairly small – only 1/6 of the size of *FNSR* in terms dollar terms. Moreover, the analysis of the U.S. market provides consistent results, where the U.S. market is considered to be fairly liquid. Sixth, we contrast our measure with BWY (2012) global sentiment measure and Hwang (2011) country popularity score and find that our results are robust and distinct from these measures. Finally, we also verify that our findings are not driven by the 2007-8 financial crisis.

Our paper directly contributes several strands of literature. First, we contribute to the literature on investor sentiment. Sentiment is hard to quantify and has many facets. Different measures capture different sentiment dimensions. Prior literature focused on identifying a "global" sentiment component and found convincing evidence of sentiment contagion (e.g., BWY 2012 and Gao et al. 2018). In this paper, we use a direct measure to tease out the "foreign" sentiment component. We reveal a new and important channel, which is about investors' interpretation of publicly available information. Prior literature has also found that global sentiment is more important than local sentiment in predicting the aggregate market. Interestingly, we find that the reversal patterns associated with our foreign and local sentiment measures are equally important. Our results also indicate that *FNEIO* is distinct from Hwang's (2011) annual Gallup based country popularity. First, *FNEIO* predicts return reversals in international markets while it has no effect on the U.S. market. This is distinct from predicting price difference between similar assets traded across markets. Second, we link this patterns to investors' reaction to local public news, which suggest a new behavioral channel.

Second, our paper also contributes to the literature on international finance. It is of recent interest to investigate the role of foreign investors in international asset pricing. Their effects are likely to be complicated, thus requiring in-depth understanding. On the one hand, foreign investors may be less informed (e.g., Van Nieuwerburgh and Veldkamp, 2009); on the other hand, they are not subject to the same biases that local investors have (e.g., home bias). For example, Kacperczyk, Sundaresan, Wang (2018) find that foreign institutional investors contribute to market efficiency in the long term. We complement their study by showing another side of foreign investors. That is, their sentiment is related to mispricing and therefore market inefficiency, potentially because they are subject to different behavior bias from the local investors. Separately, Rapach, Strauss and Zhou (2013) argue that U.S. fundamentals (reflected in U.S. market returns) are a *momentum predictor* of foreign returns, while non-U.S. fundamentals display limited predictive ability with respect to the U.S. In contrast, we find that non-U.S. foreign sentiment is also a *contrarian predictor* of U.S. returns. Thus, the effect of foreign sentiment in more symmetric for both the U.S. and international markets. This suggests that behavioral effects seem to play a symmetric role across markets, while U.S. fundamentals dominate in affecting global markets.

Third, our paper also contributes to the literature on news and investor behavior. Tetlock (2007) finds that negative news content predicts returns at the daily level. Garcia (2013) finds that negative news are more pronounced during recessions. We find that investors respond to foreign countries' negative news. Separately, Golez and Karapandza (2018) show that medias are overly positive to home-country companies in a particular industry (automotive). Complementing their study, our results suggest that investors are too negative to foreign bad news at the entire market level. Therefore, instead of examining the bias of journalists in writing news, we focus on the potential bias of investors in reacting to the news in a general setting. [9] Finally, while studies use news tone

[9] CM construct their local news tone measures based on English written articles disseminated by Tomson Reuters (TR). While the news tone of articles written in local language may differ from the new tone measured by English articles (i.e., a coverage bias), the following reduces the concern that our findings are driven by a potential coverage bias. First, the overreaction of non-U.S. investors to U.S. local tone measures is comparable. Second, conversations with Thomson Reuters (TR), the vendor who provides the news wire data, suggest that TR is an international news conglomerate that provides newswire services to its subscribers (similar to Bloomberg). Newswire journalists generate news almost in real time as news is released. This is materially different than the media coverage of local and national newspapers, which include journalists' in-depth analysis, thus more reflecting journalists' opinions and biases.

itself as sentiment, we reveal an important link between news tone and investor sentiment. In particular, news tone leads *FNEIO* and their interaction matters for return predictability,

The remainder of the paper is organized as follows. In Section 2, we describe our panel data of international markets, our sentiment measures and provide summary statistics. In Section 3, we analyze our foreign sentiment measure and its interaction with local news. In Section 4, we provide additional analysis and a few robustness tests. Section 5 concludes.

2. Data and Sentiment Measures

2.1 Returns, flows, and news

We obtain data from several sources. Aggregate monthly U.S.-based open-end mutual fund flow data are from Investment Company Institute (ICI). In terms of fund investment objectives, ICI classifies U.S.-based mutual fund into 42 categories.[10] The ICI provides fund flows into four components: exchanges in, exchanges out, sales and redemptions. The summation of all four components equals to the total fund flows. Following BKW, we decompose the flows into two different parts: net exchanges (exchanges in – exchanges out), which capture intra-family mutual fund money shifts across different fund categories; and net sales (sales – redemptions), which captures the cash that enters or exists the fund family. BKW argue that net sales are likely to capture long term savings and withdraws, while net exchanges are likely to capture short-term allocation decisions.

To construct non-U.S. based mutual fund flows, we obtain data from the global open-end fund section of the Morningstar Direct mutual fund database. We focus on equity and bond funds which

[10] ICI used to have 33 distinct investment categories. ICI did the reclassification in 2014. After reclassification, there are 7 major categories (level 3), 13 categories (level 4) and 42 sub-categories (level 5).

are domiciled in all developed countries except the U.S.[11] Following Chuprinin, Massa, Schumacher (2015), we exclude funds with TNA less than 5 million USD. We further exclude first 2 years return data for all funds to alleviate the concern of the incubation bias (Evans 2010). The final sample includes 16905 funds. Using the Morningstar style category, we mainly consider three groups of fund: (1) non-U.S. local equity funds, which are defined as non-U.S. based mutual funds investing in their respective local equity markets (e.g., Germany-based funds investing in Germany equity); (2) non-U.S. local bond funds, which are defined as non-U.S. based mutual funds investing in their respective bond markets (e.g., Germany-based funds investing in Germany bonds); (3) non-U.S. based U.S. equity funds, which are defined as non-U.S. domiciled mutual funds investing in the U.S. equity market (e.g., Germany-based funds investing in U.S. equity). There are 9146 non-U.S. local equity funds, 6278 non-U.S. local bond funds, and 1481 non-U.S. based U.S. equity funds.

International county-level equity returns are the monthly returns of Morgan Stanly International Capital (MSCI) country indices obtained from Datastream.[12] MSCI country index normally covers approximately 85% of equity universe, which represents a major part of a country's equity market. Due to issues that are particularly relevant for shorter term return predictability tests such as tradability and illiquidity, we consider the 21 international developed

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[11] Morgan Stanly International Capital (MSCI) defined 22 Non-US countries (or regions) as developed markets, including: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom.
[12] Monthly returns of foreign indices are adjusted for changes in the value of the foreign local currency relative to U.S. dollar.

countries as defined by MSCI in our analyses.[13] To be consistent with Calomiris and Mamaysky (2019) developed countries classification, we remove Hong Kong and end up with 21 countries.[14]

The total market cap of developed markets as whole represent more than 70% of the world market cap. There are also liquid ETFs tracking each of the MSCI developed country index. Therefore, these market indices represent the most economically important as well as liquid and tradable international financial market indices.

Country level news tone are obtained from CM, which investigates the content and context of *local* news article in each country (based on the entire database of English news articles by Thomson Reuters) and then constructs country-level topic-specific news tone from 1996-2015. We focus on the news about the financial market.[15] News tone is an aggregation of word tone difference of each news article in a specific topic within a country.[16] Market topic news tone are used in our paper to proxy for the news tone of a given country's market.

2.2 Sentiment measures

U.S. investors' sentiment measures are based on ICI aggregate mutual fund flow data. U.S. investors' foreign sentiment *FNEIO* is defined as intra-family net exchanges into and out of

[13] We concentrate on developed countries because the majority of international funds available to U.S. investors are funds tracking non-emerging markets. Within our sample period, the average U.S. investors' allocation to emerging equity market funds accounts for only 12% of their total allocation to international mutual funds. As of Dec 2017, total assets held by U.S. funds tracking emerging markets is 396 billion, while total assets held by all U.S. international funds are 3 trillion.
[14] Our findings are virtually the same if we include Hong Kong in the analysis (see Appendix A for country list).
[15] CM considers five topics for developed countries: Market, Commodity, Governments, Corporate governance and structure, and the extension of credit.
[16] According to CM, article-level tone is defined as the number of positive words minus the number of negative words, scaled by the total number of words. Article-level topic specific tone is aggregated at the daily level. Monthly topic specific tone is a simple average of that month's daily tone.

international funds, normalized by previous-month total asset.[17] The normalization takes into account the natural asset growth in mutual fund industry. In a similar manner, *FNSR* is the normalized net sales of U.S.-based international funds. *FNEIO* measures how U.S. investors allocate assets between the U.S. local market and international market. When U.S. investors are optimistic (pessimistic) about international market relative to the U.S. market, they shift their pre-existing investment in the U.S. (international) market towards international (the U.S.) market, resulting in a positive (negative) *FNEIO*. Therefore, in contrast to existing sentiment measures, the measure teases out a foreign sentiment concept that is harder to be linked to equal optimism (or pessimism) about both the U.S. local market and the international market. Following BKW, we also construct U.S. investors' local sentiment measure *LNEIO* (i.e., sentiment about the U.S. local market) based on intra-family money shifts between U.S.-based bond funds and equity funds. BKW show that *LNEIO* predicts U.S. equity return reversals.

Non-U.S. investor sentiment measures are based on Morningstar mutual fund flows. Morningstar does not provide corresponding flow shifting measures as ICI does. We therefore proxy for the shifting concept using the relative net flow difference between two different fund categories. Specifically, non-U.S. investor sentiment toward non-U.S. local markets is defined as the flow difference between non-U.S. based local equity fund flows and local bond fund flows (*LEBD*).

$$LEBD_{c,t} = EPNF_{c,t} - BPNF_{c,t},$$

[17] We consider all international funds, including both equity and bond funds, because net exchanges to all international funds indicate assets allocation decision of U.S. investors between U.S. and non-U.S. assets. If we concentrate on international equity funds only, the money exchanges will instead reflect the flow between international equity markets and all other markets including international bond markets. We believe flows to international bond funds also reflect international exposure rather than local exposure. Furthermore, international equity funds dominate international fund industry. In our sample period, the total asset allocation to international bond funds accounts for only 13% of the total assets of all international funds on average. Our results (untabulated) are also robust if we exclude international bond funds.

where $EPNF_{c,t}$ is the sum of the dollar net flows to all local equity funds domiciled in country c, scaled by the sum of the funds' total net assets; $BPNF_{c,t}$ is the sum of the dollar net flow of all local bond funds domiciled in country c, scaled by the sum of the funds' total net assets. In our later section, we will show that similar to *LNEIO* being able to predict return reversals in the U.S. local market, *LEBD* can also predict return reversals in non-U.S. local markets. Thus, the result is consistent with *LEBD* being a local sentiment measure in a similar fashion as *LNEIO*.

2.3 Foreignness measures

We use five measures of the difference between a country and the U.S. to proxy for the degree to which U.S. investors may view the country as an out-group. The first measure is cultural distance between each developed country and the U.S. using cultural score from Geert Hofstede.[18] Hofstede's culture score is built on six dimensions of national culture, including individualism, power distance, masculinity, uncertainty avoidance, long-term orientation and indulgence.[19] For each developed country, we calculate the squared deviation of each dimension between the country and the U.S. We then take the squared root of the average of the six dimensions as the country's cultural distance to the U.S. The second measure is the country's physical distance from the U.S. It is defined as the distance between the country's capital and Washington, DC. The distance measure is computed from Google map for each country. The third measure is ancestral distance, calculated as the fraction of US citizens with ancestors from the country. Data about the fraction of U.S. citizens with ancestors from foreign country is obtained from U.S. Census Bureau. The

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[18] See https://geerthofstede.com/research-and-vsm/dimension-data-matrix/

[19] According to Geert Hofstede, individualism is defined as the extent to which people feel independent, as opposed to being interdependent as members of large groups; Power Distance is the extent to which the less powerful members of organizations and institutions (like the family) accept and expect that power is distributed unequally; Masculinity is the extent to which the use of force is endorsed socially; Uncertainty avoidance deals with a society's tolerance for uncertainty and ambiguity; Long-term orientation deals with change; Indulgence is about the good things in life.

fourth measure is religious distance, i.e., whether protestant is the most popular religion in the country. The fifth measure is a language dummy, defined by whether English is the official language or predominant second language in that country. The measure reflects linguistic distance. Religion and Language data are obtained from The World Factbook published by Central Intelligence Agency (CIA).

Finally, we also construct a composite distance measure which combines the distance information from all the above five measures. We construct it in the following way: The first three variables are continuous variables so we sort countries into terciles based on each variable and then scale the tercile rank into 0 and 1 with 1 representing the most different from the U.S. The last two variables are dummy so we define the religious dummy as 0 if Protestant is the most popular religion in the country and define language dummy equals to 0 if the country's official language or predominant second language is English.

2.4 Summary Statistics

Figure 1A depicts the 6-month moving averages of net exchange of U.S. based international funds from 1992 to 2017. Similarly, Figure 1B and 1C depict the 6-month moving averages of net sales and total assets. As the figure shows, net sales are positive and increasing most of the time, which is consistent with the natural asset growth of U.S. based international fund sector. In contrast, net exchange is balanced between positive and negative values.

Table 1 Panel A reports summary statistics of U.S.-based mutual fund flows, US equity returns, and news tone for the U.S. market. First note that the monthly averages of *LNEIO* and *FNEIO* are around zero. This is consistent with the fact that these measures capture investor asset allocation decisions. In contrast, *FNSR's* average is around 0.59%, capturing the natural growth in asset under management over the sample period. Also note that although we are using flow shift proxies in the analysis if international markets, *LEBD* and *LEED* averages are also around zero. This is very reassuring, that our methodology indeed captures flows shifts. To alleviate the influence of outliers, all sentiment measures are winsorized at 1% and 99% percentiles. It is worth noting that mean (median) of U.S. news tone are similar to that of foreign country news tone, indicating that there are no significant downward (or upward) bias in international news tone relative to U.S. news tone.

3. U.S. Based Foreign Sentiment and International Markets

3.1 The contemporaneous relation between flows and international returns

We start with the contemporaneous relation between sentiment (*FNEIO* and *LEBD*) and international returns. Table 3 reports result of the panel regression of international returns of 21 developed countries on *FNEIO* and *LEBD* from 1992 through 2017.[20] In all panel regressions, we include country fixed effects and cluster standard errors by time (double clustering by time and country does not change results). The results show that *FNEIO* and *LEBD* are both positively related to international returns, regardless of whether *FNEIO* and *LEBD* are included in the same regression or in separate regressions, suggesting that *FNEIO* and *LEBD* capture different aspects of sentiment.

3.2 The relation between flows and subsequent international returns

We then investigate the relation between *FNEIO* and subsequent international returns. Panel A of Table 4, reports results of panel regression in which future international returns are regressed on *FNEIO*. Dependent variables are five returns of alternative horizons including subsequent one-month return and subsequent cumulative returns of three, six, nine, and twelve months. We follow

[20] We choose panel regression for two reasons: (1) it allows us to control country fixed effects; (2) it fits our country-level news tone interaction analysis. In our unreported tables, we confirm that our findings are robust in time-series regression specification.

BKW and control for normalized net sales and redemptions (*FNSR*). To make sure that our findings are not driven by investor's feedback response to return, we control for contemporaneous and lagged market return (up to five lags).[21] The regressions show that *FNEIO* negatively predicts international returns, consistent with it being a sentiment measure. A one standard deviation increase in *FNEIO* is associated with about -1% return in the subsequent month. The economic significance is substantial especially given that the country indices are market-level returns instead of individual stock returns; they are also based on liquid developed stock markets with a combined market value comparable to the U.S. market value. The returns become even more negative over longer horizons, reaching -2.51% over a 6-month horizon and -3.41% over a 12-month horizon. Overall, the results suggest that the negative return predictability of *FNEIO* is strong, particularly in shorter horizons.

In Panel B of table 4, we also include non-U.S. local sentiment (*LEBD*) and U.S. local sentiment (*LNEIO*). The results show that *FNEIO* predicts negative international returns of a similar magnitude as in Panel A. In addition, *LEBD* also predicts reversals in international returns. But, its predictive power of *LEBD* is mainly concentrated at longer horizons. The results suggest that U.S. foreign sentiment as measured by *FNEIO* and non-U.S. local sentiment as measured by *LEBD* have distinctive asset pricing effects on non-U.S. local stock market returns.

When we explore the predictability of U.S. local sentiment (*LNEIO),* we find that *LNEIO* is not able to predict returns in international markets. This stands in contracts to *LNEIO* ability to predict return reversals in the U.S. market (as shown in BKW and confirmed in Panel A of Table 8 of this paper). Moreover, we also find that *FNEIO* is not able to predict returns in the U.S. market (Panel A of Table 8). Put together, the sharp differences in predictability between *FNEIO* and

[21] Following Da, Engelberg and Gao (2014), we control five periods of lagged returns in the regression. Our results are not sensitive to the number of lagged returns controlled in the regression.

LNEIO suggest that U.S. foreign sentiment and U.S. local sentiment are also different and have distinctive asset pricing effects on international and U.S. local stock market returns.

In sum, the fact that *FNEIO* captures foreign sentiment rather than general optimism in both U.S. and foreign markets, and the fact that the return predictability of *FNEIO* is different from those of *LEBD* and *LNEIO* suggest that U.S. foreign sentiment is related to international returns through a channel that is different from the optimism/pessimism about the local markets of both the non-U.S. and U.S. countries (also referred as sentiment contagion).

It is worth noting the coefficients on other controls in the regression. First, there is a positive relation between *FNSR* and future international returns, of which significance is concentrated in shorter terms (below 6 months). Since *FNSR* can reflect the growth in international market investment, this result is consistent with short-term momentum induced by mutual fund flows (Lou 2012). The fact that *FNSR* and *FNEIO* display different predictability patterns also alleviate the explanation that U.S. flows may generate temporary price impact due to hedging demand or liquidity shocks. This is because on average the size of *FNSR* is around six times that of *FNEIO*. Therefore, the former is much more likely to generate temporary price impact than the latter. Second, we also include contemporaneous returns of the U.S. markets as Rapach, Strass and Zhou (2013) show U.S. returns may contain fundamental information about international returns. Our results are not affected by these controls.

3.3 Active actions of U.S. investors

In Online Appendix Table IA1, we perform a validation analysis to support that the foreign sentiment effect we document in Table 4 is related to the active actions of U.S. investors. Specifically, if the negative return predictability of *FNEIO* is driven by U.S. investors' active actions in their foreign investments, the return predictability should be stronger for countries with higher U.S. investors' active participation. We proxy for active participation by constructing an active share measure in the spirit of Cremers and Petajisto (2009). Utilizing the major ETFs tracking foreign country returns (iShares country ETFs), we calculate active share as the difference between the weight of country ETF's AUM in the total AUM of all developed market ETFs and the weight of the country's market cap in the total market cap of all developed markets.[22] Since the market-cap weight is a passive weight, the high (low) value of this difference measure reflects the active overweight (underweight) of U.S. investors relative to the passive weight.

In Table IA1, we include this active share measure in the regression and interact it with *FNEIO*. The coefficient on the interaction term is significantly negative at the 1% level for subsequent returns of all horizons except the first month. The result supports that the foreign sentiment effect is larger when U.S. active share in that country is higher, thus supporting that the effect is related to U.S. investor's active participation.

3.4 Out-of-Sample Predictability

To further gauge the economic significance of the return predictability of *FNEIO*, we perform out-of-sample tests. Welch and Goyal (2008) show that in-sample predictability for a variety of widely accepted market return predictors cannot survive out of sample. Kandel and Stambaugh (1996) and Campbell and Thompson (2008) argue that even out-of-sample R^2 near 0.5% can signal economically significant monthly return predictability. In Table 5, we report the out-of-sample R^2 using both rolling-window and recursive methods. We proxy international returns with a time series of MSCI ACWI exclude US index returns.[23] We use the first half of the sample period as

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[22] We focus on iShares country ETFs because of two reasons. First, iShares launches the industry's first country ETFs. The sample period of the ETFs can match our sample period as much as possible. Historical data of iShares country ETFs tracking developed countries starts from March 1996. Second, iShares also dominates the country ETFs industry (as of Dec 2018, iShares represents more than 75% of non-U.S. developed country ETFs industry).
[23] OOS R^2 does not change qualitatively if we use MSCI EAFE index returns as a proxy.

the starting point for the training period (for the rolling window method, the length of the rolling window equals to the length of half of the sample period). In Table 5, we construct two predictors to reflect the spirit of the foreign sentiment predictability reported in Table 4. Panel A of Table 5 corresponds to the result in Panel A of Table 4. It reports the out-of-sample R^2 of residual *FNEIO*, which is calculated as the residual of regression of *FNEIO* on other control variables in the baseline regression (i.e. *FNSR* and lag returns). To avoid look-ahead bias, we make sure that all information used to estimate residual *FNEIO* is limited to the data available through the training period. Panel B of Table 5 corresponds to the result in Panel B of Table 4. In this panel, we estimate the residual *FNEIO* by regressing *FNEIO* on all control variables in Table 4, Panel B.

The results show that residual *FNEIO* obtains great out-of-sample predictability: with the rolling-window method, the OOS R^2s of forecasting one-month ahead returns are 4% and 4.58% for the two predictors, respectively; with the recursive window method, they are 2.65% and 2.90%, respectively. The predictability gradually declines for predicting longer horizon returns, but can still maintain a OSS R^2 of above 2% for 6-month ahead returns and 0.5% for the 12-month ahead returns using the recursive method.

The magnitude of the out-of-sample R^2 matches with the magnitude of the international return predictors in Rapach, Strass and Zhou (2013). And yet, we differ from Rapach et al. (2013) in that they argue that U.S. fundamentals (returns) are a momentum predictor (i.e., positively predicts) international returns, whereas our U.S. foreign sentiment is a contrarian predictor of international returns.

4. Foreign Sentiment and Public News Tone

In this section, we examine the channel through which foreign sentiment is related to international returns. Dumas, Levis and Osambela (2017) propose a model which accommodates foreign sentiment and public signals. In the model, foreign investors and local investors have the same information set. But foreign investors have greater forecast error than local investors when they process public signals. As a result, foreign investors may mis-react to the public information about local market (i.e., foreign sentiment) relative to local investors.

Following this idea, we examine the role of public news (and public returns) in the relation between U.S. foreign sentiment and international returns. We want to emphasize that our paper is not about testing of Dumas et al. predictions. We build on their intuition regarding a different reaction to publicly available information by local and foreign investors.

4.1 The dynamic relation between news tone and sentiment

To motivate our analysis on the relation between non-U.S. public news and sentiment, we first investigate the lead-lag relation between local public news, *FNEIO* an *LEBD* in a vector auto regression (VAR) analysis. Figure 2 plots these relationships using impulse response functions. Subplots 1 and 3 shows the cumulative response of *FNEIO* and *LEBD* to a one standard deviation shock in local news tone. Correspondingly, Online Appendix Table IA2 reports the results of panel VARs of *FNEIO* (or *LEBD*) on lagged *FNEIO* (*LEBD*), and additional lags of country-level news tone and returns with country fixed effects.[24] The plots show that *FNEIO* positively responds to past non-U.S. local news tone, whereas *LEBD* is not responsive to past local news tone. Subplots 2 and 4 shows the cumulative response of local news tone to a one standard deviation shock in *FNEIO* and *LEBD*, respectively. The plots show that local news tone does not respond to either *FNEIO* or *LEBD*. Overall, the lead-lag relationships suggest that non-U.S. local news tone drives U.S. foreign sentiment whereas it does not drive non-U.S. local sentiment. The asymmetric response of *FNEIO* and *LEBD* to news suggests different mechanisms drive foreign sentiment and

[24] Changing Cholesky order does not affect our results qualitatively.

local sentiment. Our findings are also consistent with the notion that local public news tone affects foreign sentiment rather than the other way around.

4.2 News tone interact with sentiment measures

Given the finding in previous section, we further study how news is related to the foreign sentiment effect. Panel A of table 6 reports the estimates of the panel regression of future international returns on *FNEIO*, *LEBD*, and their interaction with the past 3-month moving average non-U.S. local news tone including the current month. The motivation for the use of 3-month news tone average is the VAR analysis in Online Appendix Table IA2, in which the positive relation between *NewsTone* and *FNEIO* is significant for three months of news tone.[25] For the convenience of interpretation, we sort foreign country-level news tone into quintiles in descending order, and then the quintile ranks are re-scaled between 0 (most positive) and 1 (most negative) as $RSNewsTone$, meaning a reverse-scale news tone. The variable of interest in this panel are two interaction terms: $FNEIO * RSNewsTone$ and $LEBD * RSNewsTone$.

The results first show that the coefficients on the interaction term $FNEIO * RSNewsTone$ is significantly negative in all specifications except for the first month, indicating that the predictive power of *FNEIO* is highly related to the extent of negative news. The more negative the news is, the greater the ability of *FNEIO* to predict international return reversal. For example, Column (5) shows that when news tone is in the top negative quintile ($RSNewsTone = 1$), a one standard deviation decrease in *FNEIO* is associated with almost 11% increase in international return over a horizon of 12 months. In contrast, when news tone is in the bottom negative quintile ($RSNewsTone = 0$), the relation between *FNEIO* and future international returns is no longer significantly negative except for the first month.

[25] Results are similar if we use lagged news tone.

In table 6, Panel B, we further split the *FNEIO* and *LEBD* into positive ("pos") and negative ("neg") parts and interact them with news tone. We find that $FNEIO^{neg} * RSNewsTone$ is negative and statistically significant, whereas $FNEIO^{pos} * RSNewsTone$ is neither statistically nor economically significant. The result suggests that *FNEIO*'s return predictability is mainly driven by the interaction term $FNEIO^{neg} * RSNewsTone$. That is, only when there are bad foreign local news (i.e., high $RSNewsTone$) coupled with U.S. investors shifting money back from foreign markets to the U.S. market (i.e., negative $FNEIO^{neg}$), international stock market prices will significantly move in the opposite direction subsequently, resulting high international returns in the subsequent months. The evidence is therefore consistent with the interpretation that U.S. investor foreign sentiment effect is driven by their overreaction to foreign negative news, which leads to return reversal.

In contrast, interaction of non-U.S. local sentiment (*LEBD*) with public news tone are not significant across all specifications in Panel A of Table 6. $LEBD^{neg} * RSNewsTone$ is also insignificant in Panel B of Table 6. Therefore, non-U.S. local sentiment effect is not related to non-U.S. local news, as well as to overreaction to negative local news. The results support that foreign sentiment and local sentiment effects on returns are driven by different channels and that negative local news tone of foreign countries drives the foreign sentiment effect (we find similar findings in Panel B of Table 8, when we analyze the U.S. market).

Finally, it could be the case the foreign investors respond to local market returns, rather than local *NewsTone*. To test that possibility, in Online Appendix Table IA3, we also explore the interaction of *FNEIO* with past international market returns. In particular, we construct *RSRet* the same way we construct *RSNewsTone* and rerun our analysis. The coefficient of *FNEIO* * *RSRet* is neither economically nor statistically significant. This indicates that foreign investors respond to the information contained in public news and not market returns.

4.3 Foreignness and Negative News

Our finding that foreign sentiment is driven by investor's overreaction to foreign bad news is related to a couple of behavioral bias from the psychology literature. They include attribution bias and outgroup negativity. If U.S. investors display an outgroup negativity type of behavior bias towards foreign countries, such bias should be magnified if the country is perceived more foreign. To support this interpretation, we investigate whether overreaction to foreign bad news increases with U.S. investors' perceived foreignness of a country. Specifically, we examine the six foreignness measures introduced in Section 2.3 that reflect the extent to which U.S. investors may view an international country as an outgroup.

Table 7 reports the estimates of panel regressions of international future returns on *FNEIO*, news tone, foreignness measures and their interactions. To conserve space, we only use the 12-month return as the dependent variable. In each regression, we include one of the foreignness measures (denoted "foreign"), a negative value of the coefficient of the triple interaction term *FNEIO * RSNewsTone * Foreign* indicates that the news-induced foreign sentiment effect increases with the foreignness degree of a country. The results show that the triple interaction coefficient is significantly negative across all measures except the language dummy measure. Turning to the composite foreignness measure in the last column of Table 7, we can evaluate the economic importance of the foreignness measure. The coefficient on *FNEIO * RSNewsTone* is -0.078 and that on *FNEIO * RSNewsTone * Foreign* is -0.081. This means the total effect of *FNEIO * RSNewsTone* is -0.078-0.081=-0.159 for the countries with the highest foreignness degree (i.e., those with *Foreign*=1), while it is -0.078 for the countries with the lowest foreignness degree (i.e., those with *Foreign*=0). Therefore, the news-induced foreign sentiment effect is 104% larger ($= \frac{-0.159}{-0.078} - 1$) for the countries with the highest foreignness degree than for the countries with the lowest foreignness degree.

The results suggest that the degree of a country's foreignness is a significant driver of the negative news-induced foreign sentiment effect. The results are thus consistent with the outgroup negativity bias.

5. Additional Analysis and Robustness Checks

5.1 Analysis of the U.S. Market

Previous sections focus on the international markets for which we have a relative clean foreign sentiment measure (*FNEIO*) and a large panel of countries. For completeness, we also provide a comparable analysis on the U.S. market. Specifically, we examine whether non-U.S. investors flow shifts between the U.S. and non-U.S. markets is related to U.S. market return in a similar fashion as the relation between *FNEIO* and international market returns. If there is indeed a similar relation, then non-U.S. investors flow shifts display a similar foreign sentiment effect on the U.S. market return as the U.S. market is a foreign market to non-U.S. investors. To answer this question, we proxy for the flow shifts between the non-U.S. and U.S. markets using the relative flow difference between non-U.S. based U.S. equity funds and local equity funds in non-U.S. countries. Specifically, the non-U.S. foreign sentiment is defined as the non-U.S. domiciled U.S. equity fund flows minus non-U.S. domiciled local equity fund flows. We calculate this flow difference measure for each developed country, and then aggregate it into a time-series variable (*FEED*), which reflects the average sentiment of non-U.S. investors towards the U.S. market.[26]

[26] We make non-U.S. foreign sentiment (*FEED*) a time-series variable because U.S. market returns are a single time-series.

Table 8 Panel A reports the estimates of time-series regressions of future U.S. returns on *LNEIO* (U.S. investors' local sentiment towards the U.S. market) and *FEED* (the non-U.S. investors' foreign sentiment towards the U.S. market) over our full sample period.

The results show that, similar to the finding in BKW, *LNEIO* significantly negatively predicts U.S. market returns, consistent with it being a U.S. local sentiment measure. *FEED* also significantly negatively predicts U.S. future return, suggesting that non-U.S. investors' foreign sentiment is related to U.S. market returns in the same way as U.S. investors' foreign sentiment is related to international market returns. The effects of *LNEIO* and *FEED* do not subsume each other. Therefore, the effects of U.S. local sentiment and non-U.S. foreign sentiment are distinct from each other. Also note that the economic significance of U.S. local sentiment and non-U.S. foreign sentiment are both large and of similar magnitudes. Interestingly, Rapach, Strauss and Zhou (2013) find that U.S. fundamentals (reflected in U.S. market returns) are a momentum predictor of foreign returns, while non-U.S. fundamentals display limited predictive ability with respect to the U.S. In contrast, our findings indicate that non-U.S. foreign sentiment is also a contrarian predictor of U.S. returns. Thus, behavioral effects seem to play a symmetric role across markets, while U.S. fundamentals dominate in affecting global markets.

We also include *FNEIO* (the U.S. foreign sentiment) in the regression. We find that *FNEIO* is unrelated to U.S. market returns. Therefore, U.S. foreign sentiment towards international markets and non-U.S. foreign sentiment towards the U.S. market are also distinct from each other.

Other controls in the regression include *LNSR* (normalized net sale of equity fund), *FNSR* (normalized net sale of international fund), and contemporaneous and lagged U.S. market returns. These controls do not subsume the results of *FEED* and *LNEIO*.

We then proceed to examine whether the public news channel is also an important channel driving the non-U.S. foreign sentiment effect. Table 8 panel B reports the estimates of the time-series regression of future U.S. returns on positive-negative split of *LNEIO* and *FEED,* and their interactions with the reverse-scale U.S. local news tone. The variables of interest are four interaction terms: $LNEI^{pos} * RSNewsTon$, $LNEIO^{neg} * RSNewsTon$, $FEED^{pos} * RSNewsTone$ and $FEED^{neg} * RSNewsTone$. The first three interaction terms yield generally insignificant coefficients. Therefore, U.S. local news has no significant influence on the U.S. local sentiment effect. Furthermore, U.S. local news does not have significant influence on non-U.S. investors' sentiment towards U.S. market when non-U.S. investors are shifting money towards to the U.S. market.

In contrast, $FEED^{neg} * RSNewsTone$ is significantly negative for return horizons up to the subsequent six months. Therefore, the results suggest that only when local U.S. news are bad (high *RSNewstone*) coupled with non-U.S. investors shifting money away from the U.S. market (i.e., negative $FEED^{neg}$), U.S. stock market prices will significant moves in the opposite direction subsequently, resulting in high returns in the subsequent months. The results are consistent with the interpretation that non-U.S. investors foreign sentiment effect is driven by their overreaction to foreign negative news (in this case, such news is the U.S. local news), which leads to return reversal.

In sum, the analysis of the U.S. market complements our previous finding in international market. In both markets, foreign sentiment strongly respond to local negative news while local sentiment does not. The results suggest that investors around the world appear to overreact to negative news coming out of foreign countries, but they do not overreact to their local news.

5.2 Robustness Checks

In this section, we perform a few robustness checks and address potential alternative explanations. To alleviate the concern that our results are driven by a risk story including changes in fundamentals, risk, and risk aversion, we first examine the relation between U.S. foreign sentiment and ADR price premia, which is the price difference between ADRs and their home counterparts (i.e., the shares of the same firm listed in their home markets).[27] ADRs share the same fundamentals as their home counterparts, and any changes in international fundamentals, risk or risk aversion are expected to change the price of both ADRs and their home shares (see Hwang, 2011). If these changes are the main driver of *FNEIO*, then we would observe no relation between *FNEIO* and ADR premia. However, table 9 shows a significant positive association between U.S. foreign sentiment and ADRs premia with or without a number of controls for ADR characteristics such as the liquidity of both the ADR and its home counterparts and foreign exchange rate. This suggests that when U.S. investors are subject to foreign sentiment, they would trade the ADRs first, thus pushing the ADR price away from the price of their home counterparts, as trading ADRs in the U.S. market is less costly than invest directly in international market. The results are therefore consistent with the sentiment explanation rather than the fundamental explanation.

To further mitigate concerns about changes in risk or risk aversion story, we investigate whether our *FNEIO* can predict subsequent market volatility in both international market and U.S. market. Results in table 10 show that there is no significant relation between *FNEIO* and future return volatility in both international market (panel A) and U.S. market (panel B). Moreover, Panel A of Table 11 shows that our results are robust after controlling for the Pastor and Stambaugh

[27] Monthly ADR price premium is defined as the standardized difference between ADR price and its underlying asset price in local currency adjusted for exchange rates and ADR ratios. ADRs trading data is obtained from CRSP and trading data of ADRs home counterpart is from Datastream. We follow the procedures in Karolyi, Lee and Dijk (2012) to screen ADRs, which address the data quality issues in Datastream.

(2003) liquidity risk factor and changes in VIX.[28] These results support the notion that *FNEIO* captures sentiment and not liquidity or volatility shocks.

To further address the concern that *FNEIO's* return predictive power may be due to liquidity (price pressure), we take advantage of cross-sectional variation of country-level liquidity proxied by country-level market capitalization. We sort the sample of 21 developed foreign countries into four country portfolios by country equity market capitalization. If liquidity is the main driver, then *FNEIO*'s return predictability will be mainly concentrated in smaller countries. However, Panel B of Table 11 shows that *FNEIO*'s return predictability is also significant in medium and large country groups. The foreign sentiment effect is not simply due to lack of liquidity or price pressure.

We also contrast *FNEIO* with BWY global sentiment measure ("GlbSent") and with Hwang popularity score ("PopScore") by running a horse race with all three measures in one regression in Online Appendix Table IA4.[29] The original BWY measure is at annual level, which does not fit our monthly data analysis. We replicate the BWY paper and construct a monthly version of BWY global sentiment measure.[30] The results show that the *FNEIO* return predictability remain similarly strong both statistically and economically as in Table 4 after controlling for BWY global sentiment measure and Hwang's popularity score. The BWY global sentiment measure significantly negatively predict international returns at the horizon of 12 months. This is consistent with the

[28] The implied volatility index for the European market only starts from 1999. Therefore, we use VIX as a proxy for changes in risk or risk aversion given the fact that correlation coefficient between VIX and VSTOXX is approximately 90%.

[29] We thank Jay Ritter for providing the international IPO data for our sample period for constructing the BWY measure. We also thank Byoung-Hyoun Hwang for providing the popularity score data. We further extend it to the end of 2017. We follow BWY and construct the global sentiment measure as first principle component of country-level total sentiment index. For each country, total sentiment index is calculated as the first principle component of four sentiment proxies including volatility premium, first-day return on IPOs, the number of IPOs and market turnover. The Hwang's popularity score measure is nonstationary according to the unit root test, which makes it not directly usable for our panel regressions. We therefore detrend it by taking the first difference.

[30] The correlation between original BWY *yearly* global sentiment measure and our *monthly* version is 85% in the overlapped sample period.

original BWY study, which demonstrates that the measure can predict annual returns. Therefore, the result suggests that the global sentiment measure of BWY reflects a global sentiment that operates over the long run. In contrast, *FNEIO* predicts return reversals for both very short-term (next month) and long-term (next year) returns. Therefore, the foreign sentiment effect we capture is distinct from the global sentiment effect captured by BWY. Likewise, we find the Hwang popularity score is positively related to contemporaneous international returns but not significantly related to future returns.

Finally, as mentioned in subsection 4.2, we also confirm that *FNEIO* is responsive to foreign local news tone instead of foreign market return. Our previous main findings suggest that U.S. investors overreact to foreign negative news. Given the positive correlation between public news and return, a concern is that news may not have incremental explanatory power beyond what is already reflected in foreign return. To examine whether public news tone or market return is the main driver of our findings, we do a horse race by interacting *FNEIO* with both foreign country-level news tone and foreign market return in Online Appendix Table IA3. The results show that the interaction of *FNEIO* with past return yields insignificant coefficients in all specifications. Controlling for the interaction of *FNEIO* with past return, the coefficients on the interaction *FNEIO* with news remain strong as in Table 6. This suggests that our finding is driven by that U.S. investors react to negative news tone instead of negative past return.

5.3 Additional Discussion of Alternative Explanations

We combine some of our findings as well as results in the literature to further discuss the alternative explanations of changes in risk, or risk aversion or the concerns of hedging demand (investors experiencing liquidity shocks).

The first alternative explanation is changes in risk. That is, a decrease in *FNEIO* is a response to an increase in expected market risk, and this increase in risk is the reason for the higher returns going forward. First, note that we do not find changes in risk going forward, and a control for a contemporaneous change in VIX does not alter our findings. Moreover, if changes in risk are the main reason behind the documented return reversals, one would expect local investors to respond somewhat in a similar manner. That is, one should also observe a decrease in local flows into equity (*LEBD*) to some extent. This should result in a positive correlation between *LEBD* and *FNEIO*, since both should be responding to the same change in market conditions. However, we find that *LEBD* and *FNEIO* are negatively correlated. In a similar manner, we find that *LNEIO* and *FEED* are also negatively correlated.

Second, as discussed in BKW, the magnitude and short horizon of the return predictability related to the foreign sentiment is too large to be justified in the Gordon growth model based on the risk consideration. One might argue that this is related to changes in risk aversion, however, several studies also find little evidence that risk aversion changes rapidly (Brunnermeier and Nagel, 2008) and that time varying risk or risk aversion does not necessarily generate a predictable reversal in prices (Campbell and Cochrane, 1999; Kyle and Xiong, 2001). Thus, any changes in investors' actions that result in short-term return reversals seem to be driven by a behavioral explanation rather than a rationale one.

The second alternative explanation is liquidity. One may argue that the U.S. market may be more liquid than international market, which leads to the asymmetric predictability results of *FNEIO*. But this explanation is inconsistent with the fact that non-U.S. investor foreign sentiment can also predict U.S. return reversal but not international returns. Another asymmetric argument is that hedging demand may be stronger on the sell side than on the buy side. In untabulated results, we find both negative and positive *FNEIO* (*FEED*) do not predict return reversals in U.S. (international) return. The results suggest that when investors shift money out of their home market, it cannot predict return reversals in their home market. Recall our earlier finding is that when investors shift money out of their foreign market, it predicts return reversals in their foreign market. Therefore, this asymmetric pattern on the sell side again cannot be explained by the stronger sell-side hedging demand argument.

Second, as far as hedging demand is concerned, if the *FNEIO* return predictability mainly reflects hedging demand, it is difficult to argue why *FNSR* does not generate the same type of hedging demand-based return reversals, as *FNSR* is six times the size of *FNEIO*. Furthermore, hedging demand is usually modeled as hedging endowment shocks (e.g. Campbell, Grossman, and Wang, 1993). Therefore, *FNSR*, which reflects change of savings or income, is arguably a better proxy of endowment changes, than *FNEIO*, which reflects change of pre-existing investments.

Finally, Golez and Karapandza (2018) show that local medias are in fact positively biased rather than negatively biased in producing local news. The news articles from Tomson Reuters that CM use to measure news tone are local news in each country written in English. Thus, one concern is that journalists who write in English may be positively biased towards the U.S. However, this concern cannot explain why non-U.S. investor foreign sentiment also overreact to negative U.S. local news, as such news is supposed to be *positively* biased. The result therefore supports that investors have negative bias. Furthermore, in Table 7, we do not find significant difference in news effect between English and non-English countries, which again supports that our results are not driven by negative bias towards non-English speaking countries in English news articles. In addition, Golez and Karapandza (2018) find media bias in automotive industry in national newspapers, of which journalists are materially different from the journalists of news wires.

Newspapers journalists often publish articles with in-depth analysis, where there is significant room for personal opinions (and biases). In contrast, Thomson Reuters (TR) is a global news aggregator providing newswire services to their subscribers (similar to Bloomberg). Newswire journalists typically monitor a real-time press release feed, and quickly replay the main points to their subscribers. Because they compete over speed, newswire journalists need to produce news articles almost in real-time and their job is not to conduct in-depth analysis (Li, 2018). Therefore, there is much less room for personal opinions (and biases).

6. Conclusion

To explore how foreign sentiment affects local assets, we construct a new and *direct* measure of U.S. based foreign sentiment using mutual fund flow shifts toward international markets. The measure does not rely on market prices and directly reveals investors' allocation decisions.

We first verify that our U.S. foreign sentiment measure is distinct from local sentiment measures in the U.S. and international markets. Our foreign sentiment measure is a contrarian predictor of international markets, while the local sentiment measures are only contrarian predictors of local markets. Thus, while previous studies focused on the "global" sentiment component, our measure is able to tease out the foreign component from local sentiment.

Our second key finding is that we reveal a striking difference in the response of foreign and local investors to local public news. We find that the contrarian predictive ability of U.S. foreign sentiment is driven by overreaction to non-U.S. local public news signals, and in particular overreacting to negative news. In a sharp contrast, non-U.S. local sentiment predictive ability is not driven by mis-reaction to the same local public signals.

Third, we find that the response to local news is stronger in countries that are culturally remote from the U.S. or generally more foreign.

Our results are robust to various controls and potential alternative explanations. A complimentary analysis of the U.S. market provides consistent results, which suggests that sentiment seem to play a symmetric role across the U.S. and international markets.

Overall, our findings shed light on a new behavioral explanation to how foreign sentiment can be generated, consistent with the concept of “foreign sentiment” in Dumas, Lewis and Osambela (2017, RFS).

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Figure 1. Flows and Assets Under Management

This figure depicts the 6-month moving averages of net exchanges (1A), net sales (1B), and total assets (1C) of U.S. based international funds from 1992July to 2017Dec. Dollar units are in millions.

Figure 1A

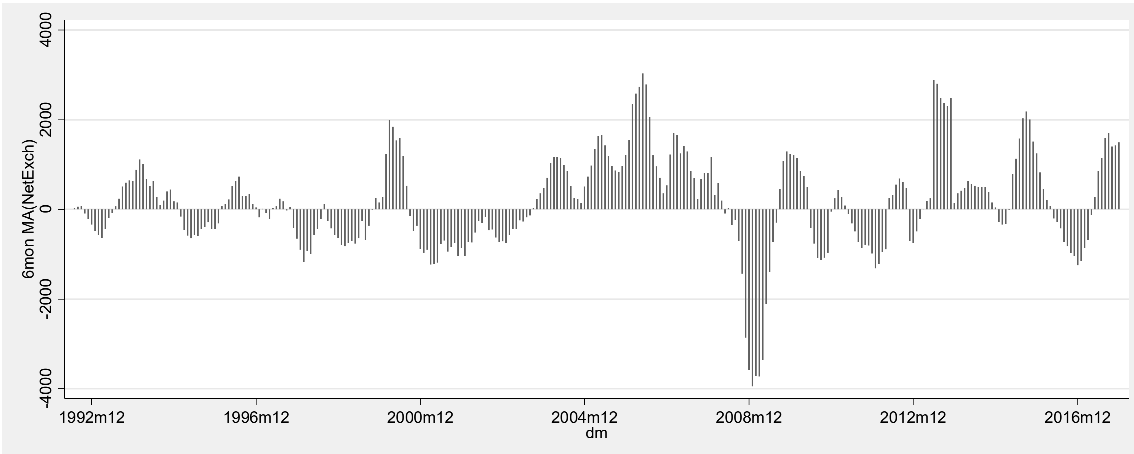


Figure 1B

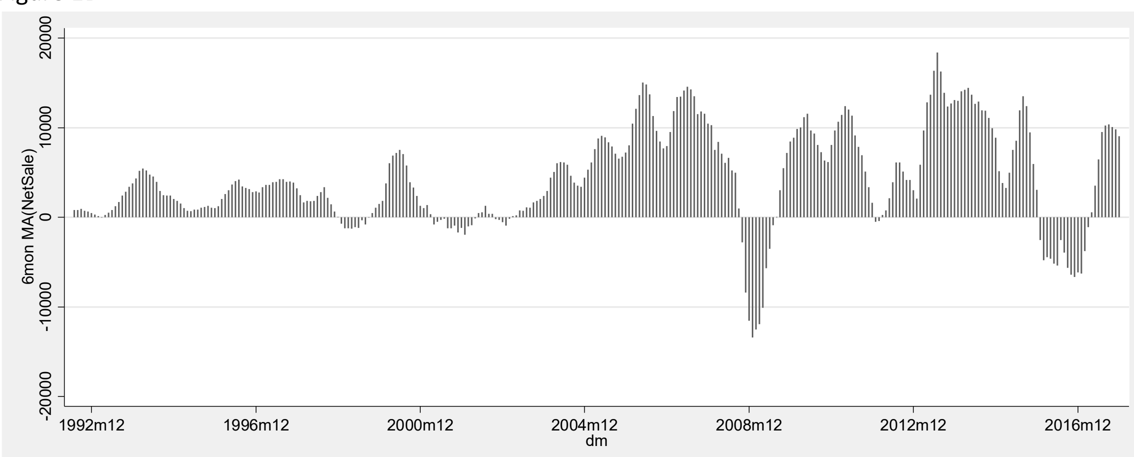


Figure 1C

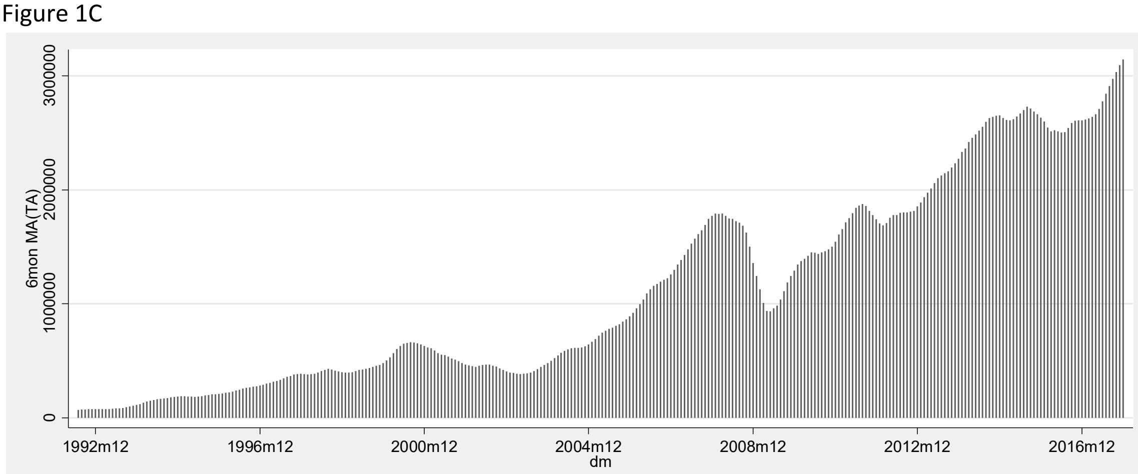


Figure 2. Cumulative Impulse Response Functions of *FNEIO*, *LEBD* and Foreign news tone

The following figures depict the cumulative impulse response functions of *FLOW* (*FNEIO* or *LEBD*), international news tone and international return using a three-equation panel VAR system with four lags of each of the dependent variables.

$$\mathrm{NewsTone_t} = \beta_0 + \sum_{j=1}^{4} \beta_{1j} FLOW_{t-j} + \sum_{j=1}^{4} \gamma_{1j} NewsTone_{c,t-j} + \sum_{j=1}^{4} \delta_{1j} IntRet_{c,t-j} + FE + \varepsilon_{c,t}$$

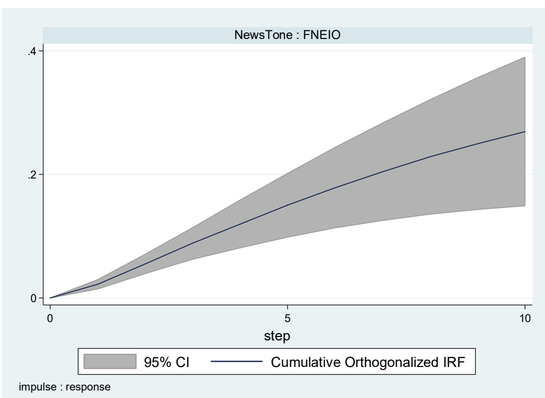
$$\mathrm{IntRet_t} = \beta_0 + \sum_{j=1}^{4} \beta_{2j} FLOW_{t-j} + \sum_{j=1}^{4} \gamma_{2j} NewsTone_{c,t-j} + \sum_{j=1}^{4} \delta_{2j} IntRet_{c,t-j} + FE + \varepsilon_{c,t}$$

$$\mathrm{FLOW_t} = \beta_0 + \sum_{j=1}^{4} \beta_{3j} FLOW_{t-j} + \sum_{j=1}^{4} \gamma_{3j} NewsTone_{c,t-j} + \sum_{j=1}^{4} \delta_{3j} IntR_{c,t-j} + FE + \varepsilon_{c,t}\,.$$

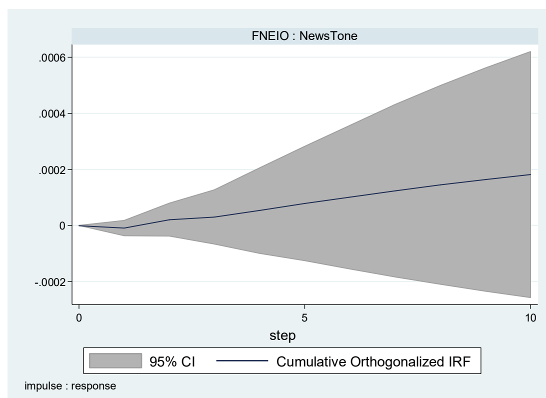
FLOW is *FNEIO* or *LEBD*. Graph 1 depicts the cumulative response of *FNEIO* to a one standard deviation shock in international news tone. Graph 2 depicts the cumulative response of international news tone to a one standard deviation shock in *FNEIO*. Graph 3 depicts the cumulative response of *LEBD* to a one standard deviation shock in international news tone. Graph 4 depicts the cumulative response of international news tone to a one standard deviation shock in *LEBD*. In each graph, the solid black line represents the cumulative impulse response and the dash grey line represent the 95% confidence intervals. Standard errors and confidence interval of the impulse response functions are estimated via 10,000 simulations.

Cumulative Response of

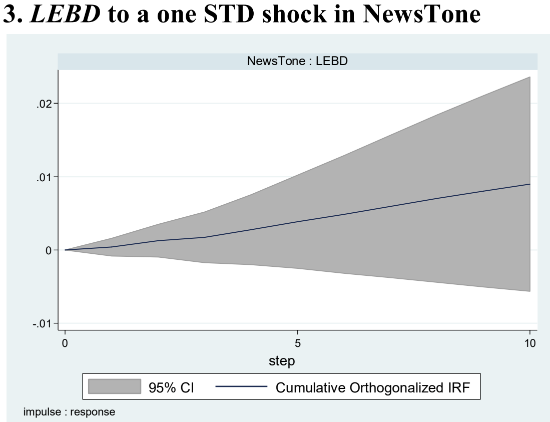
1. *FNEIO* to a one STD shock in NewsTone



2. NewsTone to a one STD shock in *FNEIO*



3. *LEBD* to a one STD shock in NewsTone



4. NewsTone to a one STD shock in *LEBD*

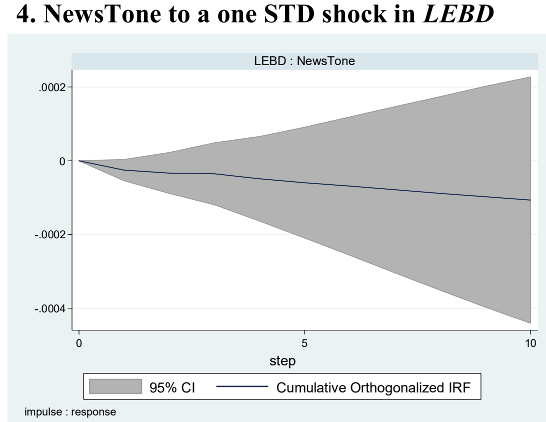


Table 1. Summary Statistics

The table presents the summary statistics of fund flows, news tone and returns. The sample period is from 1992Jan to 2017Dec. Panel A reports summary statistics of the U.S. market. *FNEIO*(%) is the normalized net exchanges into and out of U.S.-based international funds. *FNSR*(%) is the normalized net sales of U.S.-based International fund. *LNEIO*(%) is the normalized net exchanges between U.S.-based equity funds and bond funds. *LNSR*(%) is the normalized net sales of U.S.-based equity funds. *USRet*(%) is valued-weighted return of the SP500 total return index. Panel B reports summary statistics of mutual fund flows, country market returns and country level news tone for 21 developed foreign countries. *LEBD*(%) is defined as the percentage net flow difference between a foreign country(non-U.S.)'s mutual funds investing in their local equity market and bond market. *FEED*(%) is defined as the percentage net flow difference between foreign-based mutual fund investing in U.S. equity and non-U.S. equity. *IntRet*(%) is the return of MSCI country index. The news tone measures are from Calomiris and Mamaysky (2019). For both the U.S. and international markets, country news tone is an aggregation of word tone difference (positive word minus negative word) of each news article that is assigned to the "market" topic. *NewsTone(US)* (%) is the news tone for the U.S., and *NewsTone(Int)* (%) is country-level news tone for each international country.

Variable	N	mean	median	STD	min	max
Panel A						
FNEIO	312	0.01%	0.01%	0.29%	-1.55%	1.34%
FNSR	312	0.59%	0.50%	0.87%	-1.90%	5.57%
LNEIO	312	0.00%	-0.01%	0.12%	-0.72%	0.55%
LNSR	312	0.39%	0.27%	0.59%	-1.18%	2.45%
USRet	312	0.86%	1.28%	4.02%	-16.70%	10.90%
NewsTone(US)	240	-0.45%	-0.43%	0.09%	-0.75%	-0.28%
Panel B						
LEBD	5445	0.01%	0.00%	3.32%	-40.36%	30.74%
FEED	312	-0.03%	0.01%	1.10%	-5.65%	6.19%
IntRet	6552	0.79%	1.01%	6.57%	-37.04%	33.26%
NewsTone(Int)	5040	-0.40%	-0.37%	0.18%	-1.38%	0.05%

Table 2. Correlation

This table reports correlation coefficients among different fund flows. *FNEIO*(%) is the normalized net exchanges into and out of U.S.-based international funds. *LNEIO*(%) is the normalized net exchanges between U.S.-based equity funds and bond funds. *LEBD*(%) is defined as the value-weighted average of percentage net flow difference between foreign-based mutual fund investing in equity market and bond market. *FEED*(%) is defined as the value-weighted average of percentage net flow difference between foreign-based U.S. equity funds and non-U.S. equity funds.

	FNEIO	*LNEIO*	*LEBD*	*FEED*
FNEIO	1.00			
LNEIO	0.39***	1.00		
LEBD	-0.14**	-0.13**	1.00	
FEED	-0.18***	-0.16***	-0.05	1.00

Table 3. Contemporaneous Relation between Flows and International Returns

This table reports results of panel regression of contemporaneous returns of 21 developed countries on *FNEIO* and *LEBD* from 1992Jan-2017Dec.

$$IntRe_{c,t} = \beta_0 + \beta_1 Flow + \beta_2 Control_{c,t} + \delta_{c,t} + \varepsilon_{c,t} ,$$

$Flow$ is $FNEIO_t$ or $LEBD_{c,t}$; $IntRet_{c,t}$ is the monthly return of international country c at month t. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. *LEBD* is defined as the percentage net flow difference between non-U.S. based mutual funds investing in their local equity market and bond market. The regressions include country fixed effects. Control variables include *FNSR* and lag international country return (up to five periods). All flow variables are standardized. Standard errors are clustered by time. P-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
	$IntRet_{c,t}$	$IntRet_{c,t}$	$IntRet_{c,t}$
$FNEIO_t$	0.0119***		0.0126***
	(0.001)		(0.001)
$LEBD_{c,t}$		0.00206	0.00247**
		(0.115)	(0.045)
$FNSR_t$	0.00676*		0.00832*
	(0.084)		(0.059)
$IntRet_{c,t-1}$	0.0282	0.0840	0.0295
	(0.551)	(0.134)	(0.558)
$IntRet_{c,t-2}$	-0.0614	-0.0334	-0.0719
	(0.162)	(0.501)	(0.132)
$IntRet_{c,t-3}$	0.0474	0.0966**	0.0578
	(0.229)	(0.031)	(0.177)
$IntRet_{c,t-4}$	-0.0211	0.0127	-0.0183
	(0.617)	(0.789)	(0.687)
$IntRet_{c,t-5}$	-0.0177	0.00828	-0.0153
	(0.671)	(0.855)	(0.738)
Obs.	6552	5445	5445
R2	0.077	0.021	0.081

Table 4. International Return Predictive Regression

This table reports results of the panel regression of future return of 21 developed countries on *FNEIO* and *LEBD* from 1992Jan-2017Dec.

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 LEBD_{c,t} + \beta_3 Control_{c,t} + \delta_{c,t} + \varepsilon_{c,t}.$$

$IntRet_{c,t+1:t+i}$ is future return of country c over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. *LEBD* is defined as the percentage net flow difference between foreign-based mutual fund investing in equity market and bond market. In Panel A we analyze the predictability of *FNEIO.* In Panel B we also include *LEBD*. The regressions include country fixed effects. Control variables include *LNEIO*, *FNSR*, U.S. return, international return and its lag (up to five periods). All flow variables are standardized. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

Panel A. Foreign sentiment predictability

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.00923***	-0.0151***	-0.0251***	-0.0267**	-0.0341**
	(0.004)	(0.009)	(0.004)	(0.020)	(0.013)
$FNSR_t$	0.00824**	0.0133*	0.0197**	0.0224**	0.0280**
	(0.045)	(0.065)	(0.044)	(0.048)	(0.031)
$IntRet_{c,t}$	0.0878*	0.152*	0.218*	0.179	0.164
	(0.088)	(0.069)	(0.080)	(0.240)	(0.318)
$IntRet_{c,t-1}$	-0.0250	0.0727	0.0521	0.0344	-0.0125
	(0.586)	(0.350)	(0.655)	(0.822)	(0.941)
$IntRet_{c,t-2}$	0.0814**	0.108	0.0979	0.0362	0.0231
	(0.040)	(0.158)	(0.385)	(0.807)	(0.890)
$IntRet_{c,t-3}$	0.00488	0.0133	-0.0438	-0.0937	-0.119
	(0.911)	(0.853)	(0.721)	(0.546)	(0.465)
$IntRet_{c,t-4}$	0.00472	-0.0379	-0.0602	-0.114	-0.0911
	(0.909)	(0.711)	(0.695)	(0.524)	(0.613)
$IntRet_{c,t-5}$	-0.00436	-0.0555	-0.134	-0.144	-0.138
	(0.925)	(0.572)	(0.387)	(0.410)	(0.448)
Obs.	6531	6489	6426	6363	6300
R2	0.026	0.026	0.027	0.025	0.028

Panel B. Foreign and local sentiment predictability

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.0101***	-0.0151**	-0.0233**	-0.0234*	-0.0271*
	(0.009)	(0.015)	(0.022)	(0.070)	(0.064)
$LEBD_{c,t}$	-0.00186	-0.00472**	-0.00848***	-0.0106**	-0.0130**
	(0.148)	(0.028)	(0.009)	(0.023)	(0.021)
$FNSR_t$	0.00959**	0.0145*	0.0201*	0.0188	0.0176
	(0.041)	(0.079)	(0.078)	(0.136)	(0.184)
$LNEIO_t$	-0.00237	-0.00142	-0.00664	-0.00600	-0.00272
	(0.539)	(0.856)	(0.607)	(0.708)	(0.880)
$USRet_t$	0.0896	-0.0450	-0.0192	-0.0419	-0.0338
	(0.416)	(0.833)	(0.954)	(0.917)	(0.939)
$IntRet_{c,t}$	0.0701	0.191**	0.263**	0.209	0.183
	(0.181)	(0.027)	(0.022)	(0.143)	(0.273)
$IntRet_{c,t-1}$	-0.0272	0.0868	0.0548	0.0335	-0.0223
	(0.579)	(0.291)	(0.653)	(0.838)	(0.903)
$IntRet_{c,t-2}$	0.101**	0.130	0.0998	0.0369	0.0256
	(0.018)	(0.113)	(0.411)	(0.817)	(0.885)
$IntRet_{c,t-3}$	0.00633	-0.0000368	-0.0853	-0.125	-0.130
	(0.893)	(1.000)	(0.524)	(0.455)	(0.448)
$IntRet_{c,t-4}$	0.00111	-0.0678	-0.104	-0.160	-0.121
	(0.980)	(0.540)	(0.533)	(0.408)	(0.521)
$IntRet_{c,t-5}$	-0.0196	-0.0918	-0.179	-0.178	-0.148
	(0.691)	(0.392)	(0.285)	(0.344)	(0.439)
Obs.	5445	5403	5340	5277	5214
R2	0.032	0.032	0.031	0.027	0.027

Table 5. Out-of-Sample Predictive Ability of Residual FNEIO

This table reports the out-of-sample R^2 statistics of residual *FNEIO* in predicting future international return with both rolling and recursive estimation method. Similar to Table 4, using residual *FNEIO* captures the unique information that is contained in *FNEIO*. The out-of-sample R^2 measures the proportional reduction in mean squared forecast error (MSFE) of predictive model (alternative model) relative to benchmark model (null model) (Campbell and Thompson, 2008). The benchmark model is $IntRet_{t+i} = \beta_0 + \varepsilon_{t+i}$, where $IntRe_{\ t+i}$ is the cumulative next i-month return of MSIC ACWI exclude USA index. The alternative model is $IntRet_{t+i} = \beta_0 + \beta_1 FNEIOR_t + \varepsilon_{t+i}$, where $FNEIOR_t$ is residual *FNEIO*. We construct two residual *FNEIOs* to reflect the spirit of the foreign sentiment predictability reported in Table 4. Panel A corresponds to the specification in Panel A of Table 4. *FNEIOR_1* is the regression residual obtained by regressing *FNEIO* on *FNSR*, international return and its lags. Panel B corresponds to the specification in Panel B of Table 4. *FNEIOR_2* is obtained by regressing *FNEIO* on *FNSR*, *LEBD*, *LNEIO*, U.S. return, International return and its lags. To avoid look-ahead bias, all information used to estimate residual *FNEIO* is limited to the data available through the training period. The out-of-sample evaluation period is over January 2006 to December 2017.

Panel A: *FNEIOR_1*

	Out-of-Sample R^2				
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
Rolling	4.00%	1.42%	1.74%	0.19%	-0.60%
Recursive	2.65%	2.26%	2.40%	1.25%	0.70%

Panel B: *FNEIOR_2*

	Out-of-Sample R^2				
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
Rolling	4.58%	2.13%	1.87%	0.29%	-0.72%
Recursive	2.90%	2.76%	2.88%	1.61%	1.01%

Table 6. International Return Predictive Regression with News Tone Interaction

This table reports results of the panel regression of future return of 21 developed countries on *FNEIO*, *LEBD*, *NewsTone* together with their interactions. Panel A report results from the following regression:

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 LEBD_{c,t} + \beta_3 RSNewsTone_{c,t} + \beta_4 FNEIO_t * RSNewsTone_{c,t} + \beta_5 LEBD_{c,t} * RSNewsTone_{c,t} + \beta_6 Control + \delta_{c,t} + \varepsilon_{c,t}\,.$$

$IntRet_{c,t+1:t+i}$ is future return of country c over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. *LEBD* is defined as the percentage net flow difference between foreign-based mutual fund investing in equity market and bond market. *RSNewsTone* is a reverse scale news tone measure. To construct the measure, we first sort based on past 3-month moving average country-level *NewsTone* into quintiles in descending order and then re-scale the quintile ranks into values between 0 (most positive) and 1 (most negative). Panel B extends the analysis conducted in Panel A, where we decompose *FNEIO* and *LEBD* into positive and negative flow components.

$$IntRe_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t^{pos} + \beta_2 FNEIO_t^{neg} + \beta_3 LEBD_t^{pos} + \beta_4 LEBD_t^{neg} + \beta_5 RSNewsTone_{c,t} + \beta_6 FNEIO_t^{pos} * RSNewsTone_{c,t} + \beta_7 FNEIO_t^{neg} * RSNewsTone_{c,t} + \beta_8 LEBD_{c,t}^{pos} * RSNewsTone_{c,t} + \beta_9 LEBD_{c,t}^{neg} * RSNewsTone_{c,t} + \beta_{10} Control + \delta_{c,t} + \varepsilon_{c,t}\,.$$

$FNEIO_t^{pos}$ ($FNEIO_t^{neg}$) equals to $FNEIO_t$ if $FNEIO_t$ is positive (negative), and equals to 0 otherwise. $LEBD_{c,t}^{pos}$($LEBD_{c,t}^{neg}$) equals to $LEBD_{c,t}$ if $LEBD_{c,t}$ is positive (negative), and equals to 0 otherwise.

In both panels, the regressions include country fixed effects. Control variables include *FNSR*, international country return and its lags (up to five periods). *FNEIO* and *LEBD* are standardized, while all interaction terms are not. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively. The sample period is from 1996Jan-2015Dec, based on *NewsTone* data availability.

Panel A. Interaction of FNEIO and news tone

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.0101**	-0.00196	0.00381	0.0157	0.0388*
	(0.049)	(0.839)	(0.822)	(0.453)	(0.080)
$LEBD_{c,t}$	-0.00317	-0.00258	-0.0115**	-0.0158**	-0.0197**
	(0.113)	(0.439)	(0.044)	(0.027)	(0.024)
$RSNewsTone_{c,t}$	0.000740	0.00146	0.0113	0.0411	0.0806***
	(0.928)	(0.920)	(0.586)	(0.114)	(0.007)
$FNEIO_t$*$RSNewsTone_{c,t}$	-0.00984	-0.0398**	-0.0666**	-0.105***	-0.147***
	(0.282)	(0.014)	(0.011)	(0.002)	(0.000)
$LEBD_t$*$RSNewsTone_{c,t}$	0.00316	-0.00543	0.00227	0.00725	0.00960
	(0.450)	(0.434)	(0.826)	(0.574)	(0.514)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	4372	4372	4372	4372	4372
R2	0.047	0.052	0.048	0.053	0.061

Panel B. Interaction of FNEIO's positive and negative splits and news tone

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t^{pos}$	-0.0109*	-0.00959	0.00381	0.0110	0.0489*
	(0.083)	(0.416)	(0.845)	(0.676)	(0.095)
$FNEIO_t^{neg}$	-0.00685	0.00301	-0.0196	-0.0177	-0.0241
	(0.459)	(0.864)	(0.515)	(0.603)	(0.540)
$LEBD_{c,t}^{pos}$	-0.00246	-0.00168	-0.0134	-0.0279**	-0.0356***
	(0.540)	(0.796)	(0.174)	(0.013)	(0.007)
$LEBD_{c,t}^{neg}$	-0.00376	-0.00332	-0.0112	-0.00511	-0.00753
	(0.326)	(0.616)	(0.223)	(0.661)	(0.612)
$RSNewsTone_{c,t}$	0.00189	-0.0220	-0.0238	-0.0219	0.0223
	(0.874)	(0.333)	(0.465)	(0.564)	(0.602)
$FNEIO_t^{pos} * RSNewsTone_{c,t}$	-0.0141	0.00510	0.0127	0.0325	-0.0225
	(0.399)	(0.816)	(0.691)	(0.449)	(0.661)
$FNEIO_t^{neg} * RSNewsTone_{c,t}$	-0.0111	-0.0614**	-0.0746	-0.129**	-0.135**
	(0.470)	(0.046)	(0.121)	(0.017)	(0.016)
$LEBD_{c,t}^{pos} * RSNewsTone_{c,t}$	0.00307	0.00125	0.0152	0.0279	0.0437*
	(0.706)	(0.920)	(0.384)	(0.167)	(0.057)
$LEBD_{c,t}^{neg} * RSNewsTone_{c,t}$	0.00336	-0.0128	-0.0103	-0.0158	-0.0228
	(0.626)	(0.301)	(0.558)	(0.454)	(0.365)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	4372	4372	4372	4372	4372
R2	0.048	0.057	0.060	0.074	0.080

Table 7. Return Predictive Regression: FNEIO, News Tone and Foreignness Statistics

This table reports results of panel regression of future return of 21 developed countries on *FNEIO*, news tone, foreignness statistics and their interactions.

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEI\ \ _t + \beta_2 Foreign_c + +\beta_3 RSNewsTone_{c,t} + \beta_4 FNEI\ \ _t * RSNewsTone_{c,t} + \beta_5 Foreign_c * RSNewsTone_{c,t} + \beta_6 Foreign_c * FNEIO_t + \beta_7 FNEIO_t * RSNewsTone_{c,t} * Foreign_c + \beta_8 Control + \delta_{c,t} + \varepsilon_{c,t}.$$

$IntRe\ \ _{c,t+1:t+i}$ is future return of country c over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds and domestic funds. We consider six proxies for foreignness. They are cultural distance, physical distance, ancestral distance, religious distance, language, and a composite distance measure of the above five measures. We sort each country's Hofstede cultural distance from U.S. into tercile and then scale the tercile rank into 0 and 1 with 1 indicating the most culturally remote country from the U.S. We sort physical distance of each country to U.S. into tercile and scale the tercile rank into 0 and 1 with 1 indicating the most physically remote country from U.S. We sort the fraction of U.S. citizens with ancestors from each country into tercile and then scale the tercile rank into 0 and 1 with 1 indicating the most ancestrally remote country from U.S. Religious distance is a dummy that is 0 if protestant is the most popular religion in the country, and 1 otherwise. Language dummy is 0 if country's official language or predominant second language is English, and 1 otherwise. Composite (last column) is the simple average of all five cultural statistics. We first sort past 3-month moving average country-level news tone into quintiles in descending order and then re-scale the quintile ranks into values between 0 (most positive) and 1 (most negative), denoted as *RSNewsTone*. The sample period is from 1996Jan-2015Dec based on *NewsTone* data availability. Control variables are *FNSR*, international return and its lags (up to five periods). The regressions include country fixed effects. *FNEIO* and *LEBD* are standardized. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	CulturalDiff	Distance	Ancestor	Religion	Language	Composite
	$IntRet_{c,t+1:t+12}$	$IntRet_{c,t+1:t+12}$	$IntRet_{c,t+1:t+12}$	$IntRet_{c,t+1:t+12}$	$IntRet_{c,t+1:t+12}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	0.0147	0.0263	0.0309	0.0104	0.0376*	0.0269
	(0.490)	(0.294)	(0.199)	(0.676)	(0.070)	(0.213)
$RSNewsTone_{c,t}$	0.0714***	0.0851***	0.106***	0.109***	0.0873***	0.110***
	(0.009)	(0.009)	(0.002)	(0.000)	(0.005)	(0.000)
$Foreign_c$	-0.0674***	-0.0245	0.0334**	-0.0276**	-0.00848	-0.0346*
	(0.000)	(0.110)	(0.017)	(0.034)	(0.633)	(0.098)
$FNEIO_t$* $Foreign_c$	0.0319**	0.00285	-0.0972**	0.0305**	-0.0144	0.00267
	(0.020)	(0.836)	(0.011)	(0.035)	(0.405)	(0.899)
$RSNewsTone_{c,t}$* $Foreign_c$	0.0410	0.0107	-0.00575	-0.0343	0.00542	-0.0375
	(0.174)	(0.674)	(0.614)	(0.150)	(0.868)	(0.386)
$FNEIO_t$*$RSNewsTone_{c,t}$	-0.0949***	-0.0957**	-0.0312	-0.0867**	-0.131***	-0.0778**
	(0.005)	(0.018)	(0.269)	(0.025)	(0.000)	(0.030)
$FNEIO_t$*$RSNewsTone_{c,t}$* $Foreign_c$	-0.0630**	-0.0506**	-0.0488**	-0.0616***	0.0137	-0.0808**
	(0.018)	(0.034)	(0.048)	(0.004)	(0.599)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4998	4998	4998	4998	4998	4998
R2	0.040	0.037	0.038	0.041	0.036	0.039

Table 8. U.S. Return Predictive Regression

Panel A. U.S. return predictive regression

This panel reports results of time-series regression of U.S. future return on *LNEIO* and *FEED* from 1992Jan-2017Dec.

$$USRet_{t+1:t+i} = \beta_0 + \beta_1 LNEI\quad_t + \ \beta_2 FEE\quad_t + \beta_3 Control_t + \varepsilon_t.$$

$USRet_{t+1:t+i}$ is future U.S. return over the next i months. *LNEIO* is the normalized net exchanges between U.S.-based equity funds and bond funds. *FEED* is defined as *value-weighted average* of percentage net flow difference between foreign-based U.S. equity funds and non-U.S. equity funds. Control variables include *LNSR*, *FNSR*, U.S. return and its lags (up to five periods). All flow variables are standardized. Standard errors are adjusted for serial correlation using Newey-West (1987). *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$USRet_{t+1}$	$USRet_{t+1:t+3}$	$USRet_{t+1:t+6}$	$USRet_{t+1:t+9}$	$USRet_{t+1:t+12}$
$LNEIO_t$	-0.00483	-0.0125*	-0.0197*	-0.0281**	-0.0348*
	(0.245)	(0.098)	(0.063)	(0.043)	(0.071)
$FEED_t$	0.000213	-0.00435	-0.0215	-0.0343**	-0.0406**
	(0.955)	(0.628)	(0.110)	(0.033)	(0.030)
$FNEIO_t$	-0.00657	-0.00763	-0.00963	-0.00676	-0.0112
	(0.124)	(0.337)	(0.385)	(0.608)	(0.513)
$LNSR_t$	0.00156	0.00714	0.0106	0.0213	0.0266
	(0.707)	(0.407)	(0.507)	(0.339)	(0.406)
$FNSR_t$	0.00448	-0.000325	-0.00797	-0.0214	-0.0234
	(0.470)	(0.979)	(0.638)	(0.308)	(0.373)
$USRet_t$	0.127	0.263*	0.404**	0.591**	0.749**
	(0.179)	(0.084)	(0.041)	(0.010)	(0.014)
$USRet_{t-1}$	-0.0190	0.124	0.161	0.243	0.300
	(0.702)	(0.297)	(0.236)	(0.236)	(0.200)
$USRet_{t-2}$	0.107*	0.221**	0.293**	0.324	0.327
	(0.058)	(0.048)	(0.041)	(0.128)	(0.203)
$USRet_{t-3}$	0.0307	0.0206	0.105	0.161	0.120
	(0.642)	(0.828)	(0.557)	(0.501)	(0.681)
$USRet_{t-4}$	0.0562	0.0325	0.114	0.160	0.212
	(0.352)	(0.841)	(0.675)	(0.619)	(0.516)
$USRet_{t-5}$	-0.0693	0.0278	0.00785	-0.0343	0.0453
	(0.397)	(0.832)	(0.972)	(0.901)	(0.876)
Obs.	311	309	306	303	300
R2	0.048	0.078	0.113	0.090	0.090

Panel B. U.S. return predictive regression with news tone interaction

This panel reports results of time-series regression of U.S. future return on *LNEIO*, *FEED* and their interactions with U.S. news tone.

$$USRet_{t+1:t+i} = \beta_0 + \beta_1 LNEIO_t^{pos} + \beta_2 LNEIO_t^{neg} + \beta_3 FEED_t^{pos} + \beta_4 FEED_t^{neg} + \beta_5 RSNewsTone_t + \beta_6 LNEIO_t^{pos} \times RSNewsTone_t + \beta_7 LNEIO_t^{neg} \times RSNewsTone_t + \beta_8 FEED_t^{pos} \times RSNewsTone_t + \beta_9 FEED_t^{neg} \times RSNewsTone_t + \beta_{10} Control + \varepsilon_{c,t}.$$

$USR_{t+1:t+i}$ is future U.S. return over the next i months. *LNEIO* is the normalized net exchanges between U.S.-based equity funds and bond funds. *FEED* is defined as value-weighted average of percentage net flow difference between foreign-based U.S. equity funds and non-U.S. equity funds. $LNEIO_t^{pos}$ ($LNEIO_t^{neg}$) equals to $LNEI_t$ if $LNEIO_t$ is positive (negative); otherwise, it is 0. $FEED_t^{pos}$ ($FEED_t^{neg}$) equals to $FEED_t$ if $FEED_t$ is positive (negative); otherwise, it is 0. We first sort past 3-month moving average country-level news tone into quintiles in descending order and then re-scale the quintile ranks into values between 0 (most positive) and 1 (most negative), denoted as *RSNewsTone*. The sample period is from 1996Jan-2015Dec, based on *NewsTone* data availability. Control variables include *LNSR*, U.S. return and its lags (up to five periods). *LNEIO* and *FEED* are standardized. Standard errors are adjusted for serial correlation using Newey-West (1987). *p*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$USRet_{t+1}$	$USRet_{t+1:t+3}$	$USRet_{t+1:t+6}$	$USRet_{t+1:t+9}$	$USRet_{t+1:t+12}$
$LNEIO_t^{pos}$	-0.00359	-0.00879	0.0282	0.0358	0.0388
	(0.702)	(0.490)	(0.147)	(0.189)	(0.235)
$LNEIO_t^{neg}$	-0.0246*	-0.0194	-0.102***	-0.108**	-0.156***
	(0.067)	(0.415)	(0.003)	(0.019)	(0.010)
$FEED_t^{pos}$	-0.00455	-0.0171	-0.0275	-0.0179	0.0469
	(0.682)	(0.422)	(0.517)	(0.746)	(0.503)
$FEED_t^{neg}$	0.0126	0.0155	0.0199	-0.00661	-0.0254
	(0.101)	(0.360)	(0.436)	(0.845)	(0.559)
$RSNewsTone_t$	-0.0209	-0.0621*	-0.0457	-0.0358	0.00665
	(0.224)	(0.095)	(0.505)	(0.702)	(0.957)
$LNEIO_t^{pos} * RSNewsTone_t$	0.000790	-0.00738	-0.0644	-0.0857	-0.107
	(0.962)	(0.801)	(0.234)	(0.230)	(0.215)
$LNEIO_t^{neg} * RSNewsTone_t$	0.0223	-0.00387	0.0711*	0.0508	0.102
	(0.257)	(0.909)	(0.094)	(0.360)	(0.162)
$FEED_t^{pos} * RSNewsTone_t$	0.0116	0.0448	0.0273	-0.00189	-0.0786
	(0.600)	(0.317)	(0.747)	(0.986)	(0.486)
$FEED_t^{neg} * RSNewsTone_t$	-0.0314**	-0.0678***	-0.110**	-0.0882	-0.112
	(0.024)	(0.009)	(0.031)	(0.256)	(0.208)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	238	238	238	238	238
R2	0.052	0.075	0.118	0.139	0.156

Table 9. American Depository Receipt (ADRs) Premia (Discount) and U.S. Foreign Sentiment

This table reports results of the panel regression of monthly ADR premia (discount) on *FNEIO*. Our sample include 526 ADRs over the period of 1992-2017. Dependent variable is ADR premia (in percentage), *PrcDiff*, which is defined as the ADR price minus home share ADR-ratio adjusted price, and then scaled by home share ADR-ratio adjusted price. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. MV^{ADR} (MV^{Home}) is market value of U.S. ADR (home counterpart). $Amihud^{ADR}$ ($Amihud^{Home}$) is the Amihud illiquidity measure of U.S. ADRs (home counterparts). Turnover ratio is defined as monthly trading volume over number of share outstanding. TO^{ADR} (TO^{Home}) is turnover ratio of U.S. ADRs (home counterparts). Realized volatility is defined as the standard deviation of daily returns within a month. Vol^{ADR} (Vol^{Home}) is the realized volatility of U.S. ADRs (home counterparts). *FX* is the month-end foreign exchange rate at which one U.S. dollar will be exchanged for the currency of a ADR's home country. The regressions include ADR fixed effects. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
	$PrcDiff_{c,t}$	$PrcDiff_{c,t}$	$PrcDiff_{c,t}$
$FNEIO_t$	0.112***	0.109***	0.109***
	(0.004)	(0.003)	(0.003)
$MV_{c,t}^{ADR}$		0.00690	0.00690
		(0.210)	(0.210)
$Amihud_{c,t}^{ADR}$		-0.0109**	-0.0109**
		(0.049)	(0.049)
$TO_{c,t}^{ADR}$		-0.000900	-0.000902
		(0.857)	(0.857)
$Vol_{c,t}^{ADR}$		-3.932	-3.930
		(0.123)	(0.124)
$MV_{c,t}^{Home}$		-0.00248**	-0.00248**
		(0.037)	(0.037)
$Amihud_{c,t}^{Home}$		-0.00133	-0.00135
		(0.592)	(0.588)
$TO_{c,t}^{Home}$		0.0191	0.0192
		(0.560)	(0.558)
$Vol_{c,t}^{Home}$		3.082	3.082
		(0.310)	(0.310)
$FX_{c,t}$			0.00000412
			(0.869)
Obs.	53417	52315	52315
R2	0.226	0.237	0.237

Table 10. FNEIO and Future Return Volatility

Panel A. FNEIO and International return volatility

This panel reports results of the time series regression of future international return volatility on *FNEIO* from 1992Jan-2017Dec.

$$IntRetVol_{t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 Control + \delta_{c,t} + \varepsilon_{c,t}\ .$$

$IntRetVol_{t+1:t+i}$ is defined as the standard deviation of MSCI ACWI exclude USA index daily return over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. The regression include country fixed effects. Control variables include *FNSR*, international return volatility and its lags (up to five periods). All flow variables are standardized. Standard errors are adjusted for serial correlation using Newey-West (1987). *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$IntRetVol_{t+1}$	$IntRetVol_{t+1:t+3}$	$IntRetVol_{t+1:t+6}$	$IntRetVol_{t+1:t+9}$	$IntRetVol_{t+1:t+12}$
$FNEIO_t$	0.000234	0.000344	0.000392	0.000385	0.000346
	(0.207)	(0.163)	(0.150)	(0.174)	(0.277)
$FNSR_t$	-0.000532	-0.000608	-0.000588	-0.000599	-0.000584
	(0.130)	(0.213)	(0.226)	(0.187)	(0.193)
$IntRetVol_t$	0.655***	0.482***	0.339***	0.292***	0.265***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IntRetVol_{t-1}$	-0.0538	-0.0280	0.0123	0.0243	0.0160
	(0.565)	(0.716)	(0.830)	(0.635)	(0.729)
$IntRetVol_{t-2}$	0.0996	0.0698	0.0597**	0.0657**	0.0560**
	(0.107)	(0.104)	(0.039)	(0.016)	(0.043)
$IntRetVol_{t-3}$	-0.0590	-0.00766	0.0252	0.0232	0.0255
	(0.260)	(0.866)	(0.448)	(0.395)	(0.369)
$IntRetVol_{t-4}$	0.128**	0.0852**	0.0742**	0.0510*	0.0583*
	(0.048)	(0.012)	(0.017)	(0.082)	(0.069)
$IntRetVol_{t-5}$	-0.0317	0.0211	0.0368	0.0363	0.0225
	(0.607)	(0.760)	(0.556)	(0.507)	(0.657)
Obs.	312	312	312	312	312
R2	0.528	0.403	0.322	0.291	0.259

Panel B. *FNEIO* and U.S. return volatility

This panel reports results of the time series regression of future U.S. return volatility on *FNEIO* from 1992Jan-2017Dec.

$$USRetVol_{t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 Control + \delta_{c,t} + \varepsilon_{c,t}\,.$$

$USRetVol_{t+1:t+i}$ is defined as the standard deviation of SP500 index daily return over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. The regressions include country fixed effects. Control variables include *FNSR*, U.S. return volatility and its lags (up to five periods). All flow variables are standardized. Standard errors are adjusted for serial correlation using Newey-West (1987). p-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$USRetVol_{t+1}$	$USRetVol_{t+1:t+3}$	$USRetVol_{t+1:t+6}$	$USRetVol_{t+1:t+9}$	$USRetVol_{t+1:t+12}$
$FNEIO_t$	0.000211	0.000354	0.000401	0.000302	0.000321
	(0.374)	(0.230)	(0.227)	(0.384)	(0.411)
$FNSR_t$	-0.000544	-0.000681	-0.000736	-0.000641	-0.000624
	(0.169)	(0.186)	(0.174)	(0.229)	(0.255)
$USRetVol_t$	0.692***	0.530***	0.402***	0.343***	0.302***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$USRetVol_{t-1}$	0.0147	0.0248	0.0401	0.0326	0.0401
	(0.888)	(0.725)	(0.476)	(0.539)	(0.434)
$USRetVol_{t-2}$	0.0720	0.0442	0.0340	0.0473	0.0285
	(0.274)	(0.233)	(0.301)	(0.186)	(0.399)
$USRetVol_{t-3}$	-0.0834	-0.00114	0.0150	0.00948	0.0189
	(0.273)	(0.983)	(0.672)	(0.758)	(0.548)
$USRetVol_{t-4}$	0.126*	0.0664*	0.0511	0.0537	0.0604
	(0.054)	(0.086)	(0.168)	(0.197)	(0.140)
$USRetVol_{t-5}$	-0.0283	-0.000618	0.0240	0.0282	0.0269
	(0.663)	(0.993)	(0.740)	(0.661)	(0.663)
Obs.	312	312	312	312	312
R2	0.594	0.497	0.395	0.344	0.312

Table 11. *FNEIO* Return Predictability Controlling for VIX and Liquidity

Panel A. Predictive return regression with liquidity factor and VIX control

This panel reports results of the panel regression of international future return on *FNEIO*, *LEBD* from 1992Jan-2017Dec.

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 LEBD_{c,t} + \beta_3 \Delta VIX_t + \beta_4 Liq_t + \beta_5 Control_{c,t} + \delta_{c,t} + \varepsilon_{c,t} \ .$$

$IntR_{c,t+1:t+i}$ is future international return over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. *LEBD* is defined as the percentage net flow difference between Non-U.S. based mutual fund investing in equity market and bond market. ΔVIX is the contemporaneous change in VIX, the volatility index of Chicago Board Options Exchange (CBOE). Liq is the Pastor and Stambaugh (2003) traded liquidity factor. The regressions include country fixed effects. Control variables include *LNEIO*, *FNSR*, U.S. return, international counter-level return and its lag (up to five periods). *FNEIO* and *LEBD* are standardized. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.0119***	-0.0163***	-0.0251**	-0.0238**	-0.0255*
	(0.002)	(0.010)	(0.011)	(0.041)	(0.057)
$LEBD_{c,t}$	-0.00210*	-0.00475**	-0.00849***	-0.0105**	-0.0134**
	(0.090)	(0.026)	(0.009)	(0.027)	(0.020)
ΔVIX_t	-0.00255	-0.000753	-0.00163	0.00000428	-0.000412
	(0.114)	(0.742)	(0.637)	(0.999)	(0.917)
Liq_t	-0.0514	0.0532	-0.288	-0.601	-0.761
	(0.626)	(0.796)	(0.410)	(0.188)	(0.115)
$FNSR_t$	0.00987**	0.0146*	0.0202*	0.0195	0.0186
	(0.033)	(0.070)	(0.073)	(0.112)	(0.157)
$USRet_t$	-0.100	-0.111	-0.181	-0.0439	0.00194
	(0.503)	(0.689)	(0.667)	(0.931)	(0.997)
$IntRet_{c,t}$	0.0579	0.189**	0.271**	0.229*	0.193
	(0.220)	(0.030)	(0.019)	(0.098)	(0.233)
$IntRet_{c,t-1}$	-0.00284	0.0918	0.0671	0.0504	-0.00125
	(0.955)	(0.273)	(0.585)	(0.749)	(0.994)
$IntRet_{c,t-2}$	0.112**	0.124	0.0896	0.0282	0.0135
	(0.013)	(0.145)	(0.472)	(0.855)	(0.937)
$IntRet_{c,t-3}$	0.0218	0.00463	-0.0966	-0.163	-0.186
	(0.663)	(0.952)	(0.475)	(0.329)	(0.275)
$IntRet_{c,t-4}$	0.00246	-0.0779	-0.121	-0.203	-0.166
	(0.954)	(0.472)	(0.467)	(0.298)	(0.388)
$IntRet_{c,t-5}$	-0.0131	-0.0991	-0.190	-0.215	-0.186
	(0.799)	(0.367)	(0.271)	(0.256)	(0.330)
Obs.	5519	5475	5409	5343	5277
R2	0.046	0.033	0.033	0.036	0.037

Panel B. Country portfolio return predictive regression

We sort 21 developed countries into four portfolios based on country-level market capitalization and further generate country portfolio returns. Then we estimate the time-series regression by regressing the portfolio return on *FNEIO* for each country portfolio. Each row of the table shows the estimates of *FNEIO* in country portfolio regression. For example, first row displays the coefficient of *FNEIO* in the smallest country portfolio. The dependent variable is equally-weighted future country return. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. Control variables include *FNSR*, portfolio return and its lag (up to five periods). *FNEIO* is standardized and also winsorized at 1% tail of distribution. Standard errors are adjusted for serial correlation using Newey-West (1987). P-values are in parentheses *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Quartile	Ret_{t+1}	$Ret_{t+1:t+3}$	$Ret_{t+1:t+6}$	$Ret_{t+1:t+9}$	$Ret_{t+1:t+12}$
Small	-0.00881**	-0.0191**	-0.0354**	-0.0358	-0.0469
	(0.017)	(0.047)	(0.025)	(0.129)	(0.163)
2	-0.0106**	-0.0144*	-0.0191	-0.0216	-0.0272
	(0.013)	(0.078)	(0.119)	(0.162)	(0.211)
3	-0.0120***	-0.0189**	-0.0263**	-0.0226	-0.0273
	(0.001)	(0.016)	(0.045)	(0.165)	(0.197)
Big	-0.00798***	-0.0129*	-0.0246**	-0.0255*	-0.0311*
	(0.008)	(0.063)	(0.018)	(0.050)	(0.055)

Appendix A. Developed Countries used in the Analysis

This table reports results the list of developed countries used in our analysis. We consider the 22 international developed countries as defined by MSCI in our analyses. To be consistent with Calomiris and Mamaysky (2019) developed countries classification, we remove Hong Kong and end up with 21 developed countries.

Number	Country	Code
1	Australia	AU
2	Austria	AT
3	Belgium	BE
4	Canada	CA
5	Denmark	DK
6	Finland	FI
7	France	FR
8	Germany	DE
9	Greece	GR
10	Ireland	IE
11	Italy	IT
12	Japan	JP
13	Netherlands	NL
14	New Zealand	NZ
15	Norway	NO
16	Portugal	PT
17	Singapore	SG
18	Spain	ES
19	Sweden	SE
20	Switzerland	CH
21	United Kingdom	UK

Table IA1. FNEIO and U.S. Investors' Active Participation

This table reports results of the panel regression of developed countries market return on *FNEIO* and its interaction with ETF active shares from 1996-2017.

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEI\ \ _t + \beta_2 \text{ActiveShare}_{c,t} + \beta_3 FNEI\ \ _t * \text{ActiveShare}_{c,t} + \beta_4 Control + \delta_{c,t} + \varepsilon_{c,t}.$$

$IntRet_{c,t+1:t+i}$ is future return of country c over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. Using iShares ETFs tracking foreign country returns, we calculate active share as the difference between the weight of country ETF's AUM in the total AUM of all developed market ETFs and the weight of the country's market cap in the total market cap of all developed markets. Active shares then are sorted into quintiles, and the quintile ranks are further scaled between 0 (low active share) and 1 (high active share). The regressions include country fixed effects. Control variables include FNSR, international return and its lags (up to five periods). All flow variables are standardized. Standard errors are clustered by time. P-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.00977**	-0.00722	-0.00423	-0.00425	0.00502
	(0.038)	(0.259)	(0.716)	(0.762)	(0.727)
$FNEIO_t$*$ActiveShare_{c,t}$	-0.00340	-0.0126***	-0.0200***	-0.0242***	-0.0265***
	(0.163)	(0.004)	(0.002)	(0.006)	(0.006)
$ActiveShare_{c,t}$	0.000524	0.00141	0.00355	0.00677	0.0105
	(0.788)	(0.690)	(0.482)	(0.298)	(0.162)
$FNSR_t$	0.0102**	0.0116	0.0125	0.0142	0.00784
	(0.034)	(0.141)	(0.294)	(0.292)	(0.591)
$IntRet_{c,t}$	0.0904	0.149	0.212	0.127	0.0556
	(0.131)	(0.113)	(0.144)	(0.477)	(0.772)
$IntRet_{c,t-1}$	-0.0137	0.0848	0.0381	-0.0155	-0.0829
	(0.795)	(0.345)	(0.774)	(0.930)	(0.672)
$IntRet_{c,t-2}$	0.0680	0.114	0.0720	-0.0489	-0.0467
	(0.162)	(0.206)	(0.588)	(0.777)	(0.809)
$IntRet_{c,t-3}$	0.0182	0.0272	-0.0875	-0.163	-0.157
	(0.724)	(0.754)	(0.568)	(0.384)	(0.423)
$IntRet_{c,t-4}$	-0.00956	-0.0861	-0.153	-0.224	-0.184
	(0.843)	(0.462)	(0.400)	(0.287)	(0.383)
$IntRet_{c,t-5}$	-0.0148	-0.0935	-0.235	-0.225	-0.239
	(0.786)	(0.411)	(0.189)	(0.267)	(0.258)
Obs.	4045	4007	3950	3893	3836
R2	0.029	0.025	0.022	0.016	0.010

Table IA2. Lead-lag analysis of Flow, news tone and international return.

This table reports results of panel vector auto-regressions (VAR) of *FNEIO*(*LEBD*) and country-level news tone on lagged *FNEIO*(*LEBD*), news tone and country-level return. Our sample covers 21 developed countries. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. *LEBD* is defined as the percentage net flow difference between foreign-based mutual fund investing in equity market and bond market. Country-level news tone is obtained from Calomiris and Mamaysky (2019). For each country, NewsTone is the monthly country-level news tone measure based on the "Market" topic. The sample period is from 1996Jan-2015Dec. For each of the lagged explanatory variables, the subscript t-j refers to the jth lag of the corresponding variable, where j is from 1-4. For example, $FNEIO_{t-1}$ is first lag of *FNEIO*. Standard errors are clustered by time. *P*-values are in parentheses.

	$FNEIO_t$	$NewsTone_{c,t}$	$LEBD_t$	$NewsTone_{c,t}$
$NewsTone_{c,t-1}$	15.478***	0.492***	-0.684	0.489***
	(0.000)	(0.000)	(0.281)	(0.000)
$NewsTone_{c,t-2}$	19.057***	0.200***	0.819	0.210***
	(0.000)	(0.000)	(0.186)	(0.000)
$NewsTone_{c,t-3}$	8.829**	0.143***	-0.231	0.141***
	(0.011)	(0.000)	(0.695)	(0.000)
$NewsTone_{c,t-4}$	0.230	0.00464	-0.152	0.0141
	(0.944)	(0.818)	(0.754)	0.462
$IntRet_{c,t-1}$	0.448***	0.00165***	-0.002	0.00167***
	(0.000)	(0.000)	(0.759)	(0.000)
$IntRet_{c,t-2}$	0.118***	0.000198	-0.002	0.0002528
	(0.005)	(0.395)	(0.729)	0.283
$IntRet_{c,t-3}$	-0.009	0.00104***	-0.014	0.00106***
	(0.841)	(0.000)	(0.042)	(0.000)
$IntRet_{c,t-4}$	-0.105**	-0.000233	0.004	-0.000168
	(0.010)	(0.35)	(0.536)	0.529
$FNEIO_{t-1}$	0.175***	-0.000198**		
	(0.000)	(0.024)		
$FNEIO_{t-2}$	0.156***	0.000285***		
	(0.000)	(0.001)		
$FNEIO_{t-3}$	0.102***	-0.0001193		
	(0.000)	(0.192)		
$FNEIO_{t-4}$	-0.023	0.0001021		
	(0.237)	(0.3)		
$LEBD_{c,t-1}$			0.212***	-0.00148**
			(0.000)	(0.016)
$LEBD_{c,t-2}$			0.136***	0.0003442
			(0.000)	(0.564)
$LEBD_{c,t-3}$			0.170***	-0.000358
			(0.000)	(0.542)
$LEBD_{c,t-4}$			0.017	-0.000378
			(0.462)	(0.526)
Obs.	4935	4935	4226	4226

Table IA3. Interaction with Both Past News Tone and Past Return

This table reports results of the panel regression of future return of 21 developed countries on *FNEIO*, *LEBD*.

$$IntRe_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 RSNewsTone_{c,t} + \beta_3 RSRet_{c,t} + \beta_4 FNEI_{t} * RSNewsTone_{c,t} + \beta_5 FNEIO_t * RSRet_{c,t} + \beta_6 Control + \delta_{c,t} + \varepsilon_{c,t}\,.$$

$IntRet_{c,t+1:t+i}$ is future return of country c over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. We first sort past 3-month moving average country-level news tone into quintiles in descending order and then re-scale the quintile ranks into values between 0 (most positive) and 1 (most negative), denoted as *RSNewsTone*. The sample period is from 1996Jan-2015Dec. We follow the same procedure to transform the past 3-month moving average country-level return into the reverse scaled return measure, denoted as *RSRet*. The regressions include country fixed effects. Control variables include *FNSR*, international lag country return. *FNEIO* is standardized. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	-0.0114*	0.000171	-0.00309	0.00800	0.0221
	(0.098)	(0.989)	(0.873)	(0.733)	(0.390)
$RSNewsTone_{c,t}$	0.000288	-0.0000533	0.0137	0.0468*	0.0942***
	(0.970)	(0.997)	(0.484)	(0.062)	(0.001)
$RSRet_{c,t}$	-0.0000782	0.0503***	-0.0206	-0.0996*	-0.169***
	(0.996)	(0.009)	(0.597)	(0.057)	(0.003)
$FNEIO_t$*$RSNewsTone_{c,t}$	-0.0119	-0.0359***	-0.0588**	-0.0811***	-0.116***
	(0.130)	(0.009)	(0.011)	(0.010)	(0.001)
$FNEIO_t$*$RSRet_{c,t}$	0.00539	-0.00463	0.00913	-0.00829	0.00409
	(0.513)	(0.719)	(0.632)	(0.736)	(0.882)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	4998	4998	4998	4998	4998
R2	0.042	0.047	0.039	0.048	0.060

Table IA4. *FNEIO*, Global Sentiment and *PopScore*

This table reports results of the panel regression of international future return on *FNEIO*, *Popscore* and BWY Global Sentiment from 1992Jan-2017Dec.

$$IntRet_{c,t+1:t+i} = \beta_0 + \beta_1 FNEIO_t + \beta_2 Popscore_{c,t} + \beta_3 GlbSent_t + \beta_3 Control_{c,t} + \delta_{c,t} + \varepsilon_{c,t} \,.$$

$IntRet_{c,t+1:t+i}$ is future international return over the next i months. *FNEIO* is the normalized net exchanges into and out of U.S.-based international funds. We follow Baker, Wurgler and Yuan (2012) and construct the global sentiment measure as first principle component of country-level total sentiment index. For each country, total sentiment index is calculated as the first principle component of four sentiment proxies including volatility premium, first-day return on IPOs, the number of IPOs and market turnover. Following Hwang(2011), we construct *Popscore* as the country popularity score among U.S. people from Gallup Survey. The regressions include country fixed effects. Control variables include *LNEIO*, *FNSR*, U.S. return, international return and its lag (up to five periods). *FNEIO* and *LEBD* are standardized. Standard errors are clustered by time. *P*-values are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$IntRet_{c,t}$	$IntRet_{c,t+1}$	$IntRet_{c,t+1:t+3}$	$IntRet_{c,t+1:t+6}$	$IntRet_{c,t+1:t+9}$	$IntRet_{c,t+1:t+12}$
$FNEIO_t$	0.0126***	-0.00974**	-0.0172**	-0.0302**	-0.0308**	-0.0330**
	(0.008)	(0.025)	(0.032)	(0.021)	(0.044)	(0.048)
$GlbSent_t$	-0.000985	0.000295	-0.000657	-0.00487	-0.0136	-0.0288*
	(0.729)	(0.917)	(0.899)	(0.568)	(0.248)	(0.050)
$PopScore_{c,t}$	0.00274*	0.0000104	-0.00528	-0.0100	-0.0147	-0.0162
	(0.063)	(0.996)	(0.287)	(0.116)	(0.118)	(0.106)
$FNSR_t$	0.00597	0.00768	0.0138	0.0227	0.0262	0.0269
	(0.228)	(0.136)	(0.153)	(0.108)	(0.129)	(0.157)
$IntRet_{c,t}$		0.0840	0.150	0.189	0.126	0.112
		(0.168)	(0.136)	(0.187)	(0.478)	(0.546)
$IntRet_{c,t-1}$	0.0149	-0.0211	0.0988	0.0721	0.0380	-0.0157
	(0.789)	(0.677)	(0.261)	(0.577)	(0.814)	(0.928)
$IntRet_{c,t-2}$	-0.0668	0.0846*	0.0738	0.0841	-0.00989	-0.00243
	(0.196)	(0.082)	(0.394)	(0.503)	(0.949)	(0.989)
$IntRet_{c,t-3}$	0.0504	0.0207	-0.0151	-0.0868	-0.127	-0.140
	(0.282)	(0.671)	(0.841)	(0.522)	(0.452)	(0.443)
$IntRet_{c,t-4}$	-0.00985	-0.0488	-0.0549	-0.103	-0.164	-0.0917
	(0.838)	(0.275)	(0.639)	(0.541)	(0.407)	(0.640)
$IntRet_{c,t-5}$	-0.0725	0.0147	-0.0228	-0.132	-0.135	-0.109
	(0.110)	(0.780)	(0.837)	(0.441)	(0.507)	(0.596)
Obs.	2541	2540	2538	2535	2532	2529
R2	0.086	0.028	0.025	0.032	0.033	0.040