

Do Foreigners Facilitate Information Transmission?

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Abstract

Using the degree of accessibility of foreign investors to emerging stock markets, or investibility, as a proxy to measure the severity of market frictions in affecting stocks in local markets, we assess whether investibility has a significant influence on the diffusion of common information across stocks. We show that returns of highly-investible stocks that allow large access of foreign investment lead returns of non-investible stocks that are closed to foreign investors, but not vice versa. Moreover, this lead-lag effect is not driven by other known determinants such as size, trading volume, or analyst coverage, nor is it due to intra-industry leader-follower effect. These patterns arise because prices of highly-investible stocks adjust faster to market-wide information. Greater investibility reduces the delay with which individual stock prices respond to the global and local market information. The results are consistent with the idea that financial liberalization in the form of greater investibility yields more informationally efficient stock prices in emerging markets.

Market integration is central to the international finance literature. Economists have long studied its welfare gains in terms of risk sharing benefits (Karolyi and Stulz (2003)) and, more recently, have focused on investment and growth benefits associated with financial market integration (Bekaert, Harvey, and Lundblad (2001, 2005)). Following the opening of many emerging markets to foreign equity investors in the late 1980s and early 1990s, there has been a debate about the role of foreign portfolio capital in emerging markets. On one hand, episodes of financial crises have prompted many to question the benefits of the liberalization process. On the other hand, there has been a growing body of empirical evidence that suggests that opening a market to foreign investors is beneficial. This evidence suggests that stock market liberalizations lower cost of capital (Henry (2000a), Bekaert and Harvey (2000)), and increase the efficiency of real investment (Henry (2000b), Mitton (2006), Chari and Henry (2008)).

In this paper, we propose another benefit of stock market liberalizations, improved informational efficiency of local stock markets. By examining the relation between a stock's accessibility to foreigners, or 'investibility', and its stock return dynamics, we show that foreign investors facilitate faster diffusion of market-wide information for investible stocks in emerging markets. We provide three main findings to support our claim. First, the returns of highly-investible stocks that allow large access to foreign investors lead returns of non-investible stocks that are closed to such investors. Second, the slower diffusion of common information across investible and non-investible stocks is not driven by other firm-specific variables such as size, trading volume, analyst coverage, or by intra-industry effects. Finally, we document that delay measures that proxy for the speed with which stock prices respond to market-wide information are negatively associated with the degree of investibility. To the extent that the speed of information processing measures the degree of informational efficiency, our evidence suggests that higher degree of investibility increases the informational efficiency of local stock markets, confirming another benefit of removing capital barriers.

Our motivation for the study comes from a number of theories that suggest a link between the speed of information diffusion and limited stock market participation (Merton (1987), Basak and Cuoco (1998)),

Shapiro (2002), and Hou and Moskowitz (2005)). These models argue that institutional forces, information costs, or transaction costs can delay the process of information incorporation for less visible, segmented firms. In emerging markets, not all stocks are accessible to foreign investors and the level of foreign ownership limit varies widely across different securities. For example, tighter limits can be imposed on foreign ownership in specific industries such as banking, energy, utility, or broadcasting that may be perceived to be especially sensitive to national interests. We argue that these restrictions on foreign equity investment in emerging markets are market frictions that could impede swift processing of market-wide information, in particular of global market information. Global investors are likely to have a greater advantage in processing and impounding global information into stock prices.¹ Stocks that global investors cannot trade are not likely to incorporate global information in a timely way in their prices. Thus, the restriction on foreign equity ownership and its variation across different stocks provide us a natural setting to study the impact of liberalization on information diffusion.

Our main hypothesis is that the diffusion of market-wide information is faster for investible stocks than it is for non-investible stocks. We design our experiment to test this hypothesis in two ways. First, we begin by checking whether returns on investible stocks lead those on non-investible stocks. Specifically, if the degree of investibility has an independent effect on how quickly common information is incorporated into stock prices, then we should observe a lead-lag relation in the return dynamics between investible and non-investible stocks.² We then present a second test of our hypothesis by examining whether delay measures for the speed with which individual stock prices respond to market-wide information are related to the degree of a stock's investibility.

The main difficulty in detecting the effect of investibility on information diffusion through its effect on a lead-lag relation between investible and non-investible stocks is that investibility may be correlated with

¹ Albuquerque, Bauer, and Schneider (2006) develop a model of trading with both local and global private information where global investors have private global information that is valuable for trading in many countries simultaneously.

² Badrinath, Kale, and Noe (1995) argue that due to 'prudence' requirements imposed on institutional investors, institutional investors invest in only a subset of stocks, which is similar to market segmentation caused by foreign equity investment restrictions. They further argue that because of market segmentation, a lead-lag relation will emerge between prices of institutionally favored firms and prices of institutionally unfavored firms.

other firm characteristics that are known to influence cross-stock return dynamics. Previous research has identified factors such as size, turnover, and analyst coverage as being important determinants of a lead-lag effect in returns. It could be that investible stocks are larger and more actively traded firms with more analyst following. Therefore, it is particularly important for our experiment design to examine the impact of investibility, net of these other firm characteristics that might affect the cross-stock return dynamics between investible and non-investible stocks. We address this concern by employing several different empirical approaches.

We obtain return data as well as stock characteristic variables from the Standard & Poor's Emerging Markets Database (EMDB). Our final sample includes stock-level weekly return data from 31 emerging markets for a total of 3,201 distinct stocks over the sample period from January 1989 through April 2003. The key variable for our analysis is a variable provided to us by the EMDB called the degree open factor. This variable allows us to measure the extent to which a stock is accessible to foreigners. Based on this measure, we classify stocks into three groups: non-investible (foreigners may not own any share of the stock), partially investible (foreigners may own up to 50% of the stock) and highly investible (foreigners may own more than 50% of the stock).

We first show that consistent with the slow diffusion of common information across stocks of different degrees of accessibility, returns on highly-investible stocks lead returns on non-investible stocks. This lead-lag relation across investible and non-investible stocks is not driven by size and/or trading volume: for every size and turnover groups, we find that the returns on highly-investible stocks lead the returns on non-investible stocks, but not vice versa. We note that the partially-investible stocks are on average larger and more actively traded than highly-investible stocks in our sample. If our results are solely driven by size or turnover instead of investibility, we should find that returns on partially-investible stocks lead those on highly-investible stocks. Our evidence shows the opposite: returns on highly-investible stocks lead those on partially-investible stocks.

Bae, Bailey, and Mao (2006) show that increased openness to foreign equity investors is associated

with greater analyst coverage³ and Chan and Hameed (2006) find a similar lead-lag relation between the returns of high-analyst following stocks and those of low-analyst following stocks. It is important therefore to check whether the lead-lag relation that we document is an artifact of increased analyst coverage of highly-investible stocks. When we partition our sample stocks into two groups based on the number of analysts following, we find that highly-investible portfolio returns lead non-investible portfolio returns even for the group of stocks that have fewer analysts.

Finally, we test whether the investibility effect on the cross-stock return dynamics is potentially driven by an intra-industry leader-follower effect. It may be that industry-leader stocks are largely open to foreign investors while industry followers are closed to foreign investors. In such case, we might erroneously attribute the impact of the intra-industry dynamics on information diffusion to the degree of investibility. In order to test for this possibility, we distinguish between inter-industry and intra-industry effects and find that the impact of investibility on information diffusion does not necessarily stem from intra-industry dynamics. Specifically, we show that returns on highly-investible portfolios in other industries lead returns on non-investible portfolios, even after the predictive ability of same-industry highly-investible portfolio returns is controlled for.

Taken together, these tests strongly support the idea that the degree of investibility has a significant independent influence on the cross-stock return dynamics between investible and non-investible stocks.

Building on this evidence on the impact of investibility on cross-stock return dynamics, we next investigate whether the degree of investibility is directly related to the speed of adjustment of stock prices to market-wide information. Specifically, using measures that proxy for the delay with which stock prices respond to market information, we find that highly-investible stocks adjust faster to world as well as local market-wide information. The delay with which stock prices adjust to local and world market factors is negatively related to the investibility of stocks. We interpret this result as evidence consistent with the view

³ Baker, Nofsinger and Weaver (2002), and Lang, Lins and Miller (2003) report increased analyst coverage, forecast accuracy and news stories after individual firms cross-list.

that a higher degree of investibility is associated with faster processing of market-wide information and greater informational efficiency.

Our paper is closely related to studies that investigate the effect of stock market liberalization using the measure of investibility. For example, Bae, Chan, and Ng (2004) find a positive relation between return volatility and investibility. They argue that highly-investible stocks are more integrated with the world and therefore are more sensitive to the world market factor. Using investible/non-investible distinction, Chari and Henry (2004) show that investible stocks realize higher risk-sharing benefits when countries liberalize their stock markets. Mitton (2006) shows that investible firms experience increases in sales growth, increases in profitability and efficiency, and lower leverage. Boyer, Kumagai, and Yuan (2006) examine how stock market crises spread globally and show a greater degree of co-movement between investible stock index returns and crisis country index returns during crisis periods. Our investibility measure is also closely related to the capital control measure used in Edison and Warnock (2003) and De Jong and De Roon (2005). While they measure the intensity of capital controls at the country level using the ratio of the market value of the investible stocks to total market capitalization, we follow Bae, Chan, and Ng (2004) and use an investibility measure at the individual firm-level.

Our paper also contributes to the literature on cross-autocorrelation patterns in stock returns. Since the seminal work of Lo and MacKinlay (1990a) showing that returns of large stocks predict returns of small stocks, but not vice versa, the cross-autocorrelation patterns among stock returns have received much attention in the literature. While the lead-lag patterns are now well documented, there is still some debate as to what its sources are. One explanation is the nonsynchronous trading that stock prices are sampled nonsynchronously, which induces spurious lead-lag effects into returns (Boudoukh, Richardson, and Whitelaw (1994)).⁴ Several studies have identified other determinants that give rise to cross-autocorrelations in stock returns such as the number of analyst following (Brennan, Jegadeesh and Swaminathan (1993)), institutional ownership (Badrinath, Kale and Noe (1995)), and trading volume

⁴ However, Lo and MacKinlay (1990b) show that one has to believe in unrealistically thin markets for non-synchronous trading to account for the magnitude of observed cross-correlations.

(Chordia and Swaminathan (2000)). In a recent paper, Hou (2007) shows that the lead-lag effect is predominantly an intra-industry phenomenon. Taken together, these studies suggest that the presence of market frictions causes some stock prices to adjust more slowly to market-wide information than others, generating differences in the speed of adjustment across stock returns. By exploiting a unique feature of emerging stock markets to investigate the relationship of foreign equity ownership restrictions to information diffusion, we lend additional support to the hypothesis of slow information diffusion as a leading cause of cross-autocorrelations.

The rest of the paper is organized as follows. In the next section, we discuss the data and the construction of investibility portfolios. Section II presents the lead-lag patterns across investible portfolios. Section III explores other potential determinants of the lead-lag effect and Section IV presents tests of the relationship between information diffusion and investibility. Section V concludes.

I. Data and Construction of Investibility Portfolios

Two sources of data are used in our analysis. The first is the Standard & Poor's Emerging Markets Database (EMDB). We obtain weekly return, market capitalization, turnover, and trading volume data for each stock covered by EMDB over the period from December 1988 to April 2003. We base our analysis on weekly rather than daily U.S. dollar returns in order to minimize the effect of potential biases associated with nonsynchronous trading on our analysis⁵. The weekly return data of EMDB include 3,345 stocks from 35 emerging markets covering more than 75% of the total market capitalization for each emerging market.

The second data source is I/B/E/S International, from which we obtain information on the amount of analyst activity for our sample stocks. We merge I/B/E/S data with the firm-level data in EMDB and obtain the number of analysts that provide earning forecasts for each firm in every year of our sample. Following the previous literature, if a firm is not covered by I/B/E/S in any given year, we assume that the number of

⁵ We obtain slightly stronger lead-lag relations across investibility groups if we use weekly stock returns in local currency instead of in U.S. dollars.

analysts is zero for that firm-year observation.

A. Measuring investibility

We obtain our measure of a stock's degree of accessibility for foreigners, or investibility, from the EMDB. To indicate the “*quantity of a company's market capitalization a foreign entity can legally own*”, the Standard and Poor's EMDB reports for each stock a variable called the *degree open factor* that takes a value between zero and one.⁶

The EMDB reports that it uses several criteria to determine the investible weight of a stock. It first determines if the market is open to foreign institutions – both in a legal and practical sense – by investigating the extent and the mechanisms with which foreign institutions can buy or sell shares in the local stock exchange and repatriate capital. Second, it evaluates the additional limitations imposed by the government at the industry level or by corporate charters and by-laws at the company level. The investible market capitalization is then determined after applying foreign investment rules, and after any adjustment for corporate holdings, strategic holdings, or government ownership. We use this investible weight reported by the EMDB as our measure of each stock's accessibility for foreign investors in emerging markets.

It is important to be aware of the limitations of the EMDB data and our investibility measure. First, Bae, Chan, and Ng (2004) note that the investible weight recorded by EMDB may sometimes fail to reflect the actual degree of investibility due to delays in adjusting the weights following official changes. However, we do not see this to be of major concern for our purposes and find that our results are not sensitive to these delays. Second, when EMDB chooses stocks for its coverage, it applies two additional criteria based on size and liquidity. We are quite concerned about this bias since size and liquidity are important determinants of the speed of information diffusion, and at the same time they are likely to be correlated with the degree of investibility. To circumvent this problem, in our experiment design, we need to separate the effect of investibility from these other factors.

⁶ S&P Emerging Markets Indices Methodology, Standard & Poor's, August 2007.

Finally, it is possible that the degree of investibility may not necessarily be a good proxy for the degree of foreign ownership – the ownership restrictions may not be binding for foreign investors. In other words, a stock with a high ownership limit may not be necessarily owned by a lot of foreign investors. To check for this possibility, we obtain data on the aggregate amount of foreign institutional ownership in each country as a percentage of the total institutional ownership and examine how this measure is related to the measure of investibility in our sample.⁷ The correlation between the aggregate foreign ownership and the average degree of investibility in a country is 0.332 in our sample and it is significant at the 1% level. In regression analyses, we find that investibility is positively and significantly related to the aggregate amount of foreign ownership, even after various firm characteristics such as size and liquidity are controlled for.⁸ While these analyses are admittedly limited due to their aggregate nature, they suggest that our measure of the degree of investibility does not capture purely firm size and liquidity but proxies also reasonably well for the amount of foreign institutional ownership.

B. Descriptive Statistics

In order to eliminate outliers and data errors, we apply a number of filters to our sample. As in Bae, Chan, and Ng (2004) and Rouwenhorst (1999), we delete observations in which closing prices are either zero or missing. We also check for errors and delete 45 observations for which the weekly total return exceeds 200%.⁹ Finally, we delete country-year observations in which we have only one investibility group for a country after sorting stocks into three investibility groups. As a result of these filters and checks, we lose approximately 7% of the weekly observations and drop 4 countries from the initial sample. Our final sample consists of 1,014,723 weekly observations from 31 emerging markets for a total of 3,201 stocks over the period from January 1989 through April 2003.

⁷ We thank Miguel Ferreira and Pedro Matos for sharing their institutional ownership data at the aggregate level with us.

⁸ These results are available from the authors upon request.

⁹ We verified that these 45 observations are genuine errors by checking whether there are large discrepancies between EMDB and Datastream for these stocks. Keeping these observations does not change our results.

Table I describes the sample stocks and their distribution across each country. The average number of stocks in each country ranges from 16 in Hungary to over 200 in China. Our main results remain qualitatively the same if we exclude China from our analysis. In the second column, we report the average degree of investibility for each country measured as the cross-sectional mean of the yearly average investibility for each stock. The degree to which local stocks are open to foreign investors varies greatly across countries. For example, South Africa (0.78) and Malaysia (0.72) have the highest degree of accessibility to foreign investors. The countries that allow the least access to foreign investors are Jordan with an average degree of investibility of only 5%, Zimbabwe with 8%, and Czech Republic and Sri Lanka with 9%. The average weekly dollar returns range from -0.41 percent in Thailand to 0.48 percent in Argentina, and the average weekly volatility of individual stock returns varies between 4.54 percent in Portugal and 12.98 percent in Russia.

In Table I, we also report the average firm size and turnover. Previous studies have shown that these firm characteristics are important determinants of the speed of stock prices to incorporate information. Our sample stocks vary considerably in size, ranging from only \$21 million in Sri Lanka to \$2,324 million in Russia. Stocks in Korea and Taiwan are the most actively traded with an average monthly turnover of approximately 30 percent – more than 30 times the turnover of those stocks in such markets as Chile, Colombia, Czech, and Morocco.

C. Investibility groups

We assess how the degree of investibility affects the speed of information diffusion by first classifying stocks into different groups according to their investibility. We sort stocks in each market in each year into portfolios by their investible weights. Specifically, we first compute the yearly average investibility for each stock based on the monthly data from EMDB and then we partition stocks into three groups. We classify stocks with a zero measure of investibility as non-investible, stocks with investible weight between 0.01 and 0.5 as partially-investible, and finally stocks with investible weight greater than 0.5 as

highly-investible.¹⁰

As we noted before, firm size and trading volume are important determinants of the speed of information diffusion across stocks (Lo and MacKinlay (1990a) and Chordia and Swaminathan (2000)). Since the extent to which a stock is accessible to foreign investors is likely to be positively associated with its size and trading volume, we need to control for these factors in order to distinguish the independent influence of investibility. Therefore, we also sort stocks in each country independently by size to form nine size/investibility (volume/investibility) portfolios based on a stock's degree of investibility and size (volume).¹¹ Following Chordia and Swaminathan (2000), we use stock turnover as our measure of trading volume. Having partitioned stocks into nine portfolios of investibility and size (volume), we finally compute equally-weighted weekly returns for each portfolio.

In Panels A and B of Table II we present the summary statistics and autocorrelation coefficients for each investibility portfolio within each size and turnover group. In each group, we denote the non-investible portfolio by P_{NI} , the partially-investible portfolio by P_{PI} , and the highly-investible portfolio by P_{HI} . Our independent sorts by size and by volume are successful in controlling for these effects to a large extent. For example, within each investibility group in Panel A (B) the average size (turnover) of the medium-size (turnover) group stocks is larger than that of the small-size (turnover) group stocks; similarly, the average size (turnover) of the large-size group stocks is larger than both the small-size (turnover) and the medium-size (turnover) group stocks. Within each size and turnover group, non-investible stocks are generally smaller, and less heavily traded than the partially- and highly-investible stocks. Surprisingly in contrast, stocks in the partially-investible portfolio are on average larger and more actively traded than the highly-investible stocks. These characteristics of the partially-investible portfolio provide us with an interesting opportunity to test whether investibility has an independent influence beyond that of size and

¹⁰The frequency distribution of investibility is skewed toward both tails. We choose not to have a very fine classifications of stocks based on investibility to minimize the possibility that our measure of investibility does not capture fully all other factors that determine foreign participation. See Bae, Chan and Ng (2004).

¹¹The limited number of stocks in each country in our sample does not allow conducting a three-way sort of investibility, size and turnover.

liquidity on the speed of information diffusion across stocks. If firm size and liquidity are the sole determinants of the speed of information diffusion with no independent effect of investibility, we should then expect partially-investible stock returns to lead highly-investible stock returns. We examine this possibility later and reject such a conjecture.

Table II also shows that within each investibility group, the large-size group stocks outperform small stocks in our sample period. On the other hand, the average return of non-investible portfolio is usually higher than that of highly-investible portfolio. For instance, in Panel A the average weekly return on P_{NI} in the medium-size group is 0.24 percent whereas it is 0.16 percent on P_{HI} in the same size group. Similarly, in Panel B the average weekly return on P_{NI} in the high-turnover group is 0.40 percent compared to 0.18 percent on P_{HI} in the same turnover group. Such a pattern is consistent with the evidence in the literature that greater financial liberalization reduces the cost of capital for internationally integrated companies.

In the last two columns of Table II we present the first-order return autocorrelation and the sum of the first four-lagged coefficient estimates for each investibility portfolio in each size and turnover group. First, the first-order return autocorrelation for the non-investible stocks declines with size and turnover. This suggests that among the non-investible group, greater size and higher volume are important in speeding up the price adjustment process. Second, the non-investible stocks have higher autocorrelation than highly-investible stocks – except for the large-size and high-turnover stocks. For example, the first-order return autocorrelation is 0.19 for the non-investible stocks in the small-size group, while it is 0.11 for the highly-investible stocks. This is consistent with the idea that higher degree of investibility is associated with faster price adjustment.

Interestingly, except for the small-size and low-turnover groups, the sum of the first four lagged autocorrelation coefficients for the highly-investible stocks is twice as large as that for the non-investible stocks. This result seems counter-intuitive at first sight, since highly-investible stocks tend to be both larger and more actively traded than non-investible stocks. To the extent that highly-investible stocks incorporate

information faster, we should in fact observe smaller sum of autocorrelation coefficients for these stocks. On the other hand, it is possible that the degree of investibility is positively related to institutional trading and institutions' correlated trading patterns contribute to higher serial correlation for these stocks than for the non-investible stocks. Sias and Starks (1997) show that portfolio autocorrelation of NYSE stocks is an increasing function of the level of institutional ownership and argue that institutional traders' correlated trading patterns contribute to serial correlation. They also argue that institutional trading helps quickly incorporate market-wide information into prices. To the extent that the degree of investibility is positively related to the extent of foreign institutional investors' trading, our result that highly-investible portfolio shows higher serial correlation than non-investible portfolio is consistent with Sias and Starks (1997).

While the autocorrelation patterns give us some preliminary understanding of the differences in return dynamics across stocks with different degrees of investibility, we recognize that autocorrelation coefficients by themselves cannot provide unambiguous inferences on the differences in the speed of adjustment of stock prices to information shocks (Chordia and Swaminathan (2000)). Therefore, we turn to cross-autocorrelations for testing our hypothesis of information diffusion across investibility groups.

II. Empirical Results

A. Cross-autocorrelations across investible portfolios

We begin our analysis by looking at the cross-autocorrelations of stocks across different investibility groups. In Panels A and B of Table III we present the one-lag cross-autocorrelation coefficients between the highly-investible and non-investible portfolio returns for each size and turnover group, respectively. For brevity, we report the cross-autocorrelations between the two extreme portfolio groups only. Panel A shows that for each size group the correlation between the lagged return on the highly-investible portfolio ($R_{HI,t-1}$) and the current non-investible portfolio return ($R_{NI,t}$) is much larger than the correlation between the lagged non-investible portfolio return ($R_{NI,t-1}$) and the current highly-investible portfolio return ($R_{HI,t}$).

For example, among the small-size group stocks, the correlation coefficient between the lagged return on the highly-investible portfolio ($R_{HI,t-1}$) and the current return on the non-investible portfolio ($R_{NI,t}$) is 0.17, whereas that between the lagged return on the non-investible portfolio ($R_{NI,t-1}$) and the current return on the highly-investible portfolio ($R_{HI,t}$) is only 0.04. We observe a similar pattern in Panel B for the cross-autocorrelation coefficients between the lagged highly-investible portfolio return and current non-investible portfolio return in each turnover group. Furthermore, the pattern observed in Table III cannot be solely driven by nonsynchronous trading, since the same pattern is also present in the large-size and high-turnover stock groups.

In summary, Table III presents preliminary evidence that suggests that returns on highly-investible stocks lead returns on non-investible stocks. This evidence is consistent with the idea that highly-investible stocks adjust faster to common information than non-investible stocks. An alternative explanation is that the cross-autocorrelation pattern is simply a manifestation of a high contemporaneous correlation between highly-investible and non-investible portfolio returns coupled with autocorrelation of the non-investible portfolio returns. In that case, a lead-lag pattern in the cross-autocorrelations could still arise not necessarily because the lagged highly-investible portfolio return predicts the current return on the non-investible portfolio but instead because the lagged returns on highly-investible stocks proxy for lagged returns on non-investible portfolios.¹² In the next section, we address this concern and formally test for the cross-stock return dynamics across investibility groups using a bivariate Vector Autoregression (VAR).

B. VAR tests

B1. Investible portfolio returns

Our first test is designed to assess whether returns on investible stocks lead those on non-investible

¹²See Conrad and Kaul (1988 and 1989), Conrad, Kaul and Nimalendran (1991), Boudoukh, Richardson and Whitelaw (1994), and Hameed (1997) for the time-varying expected return hypothesis to explain the lead-lag cross-autocorrelations.

stocks. If the degree of investibility plays an important role in determining how quickly common information is incorporated into stock prices, we should observe a lead-lag relation in the return dynamics between investible and non-investible stocks. We use a VAR to formally test this hypothesis.

A problem we have to deal with is how to control explicitly for firm size and stock turnover. Investible stocks tend to be larger in size and more actively traded. Therefore, it is crucial to distinguish the effect of size and turnover from that of investibility.

One way to circumvent this problem is to partition stocks by independent sorts of size (volume) into size/investibility (turnover/investibility) portfolios, as we have done so far. There are two issues with this approach, however. First, as we pointed out in Table II, our independent sorting procedure helps control for size and turnover effects to a large extent, but not completely. We need to make sure that our results are not driven by size or turnover effects that we fail to control for. The second problem is that given the limited number of stocks we have available in some markets, our independent sorting procedure does not ensure an adequate representation of all size/investibility (turnover/investibility) portfolios in each market. For these reasons, we follow Bae, Chan and Ng (2004) and employ a two-stage approach that attempts to remove from returns the effect of other firm characteristics. Specifically, in the first-stage, we estimate weekly returns that are net of the effects of firm size, turnover, and other factors such as industry and country, and then, in the second stage, use these returns to compute portfolio returns associated with each investibility group.

To estimate weekly returns that are net of firm size and turnover effects, we first estimate the following cross-sectional regression for each week t during January 1989 to April 2003:

$$\begin{aligned}
 r_{it} = & \beta_{0t} + \sum_{j \in HI, PI, NI} \beta_{1jt} I_{ij} + \sum_{j \in S, M, L} \beta_{2jt} size_{ij} + \sum_{j \in H, M, L} \beta_{3jt} turnover_{ij} + \sum_{j=1}^{10} \beta_{4jt} industry_{ij} \\
 & + \sum_{j=1}^{31} \beta_{5jt} country_{ij} + \varepsilon_{jt}
 \end{aligned} \tag{1}$$

where r_{it} represents returns on stock i at week t ; I_{jt} represents an indicator variable that takes a value of one if stock i is in investibility group j for $j \in (NI, PI, HI)$, and zero otherwise. $size_{ij}$ and $turnover_{ij}$ are also indicator variables defined similarly for the corresponding size and turnover groups for stock i . Since we estimate equation (1) by pooling all stocks in our sample together, we also control for industry and country effects in returns by including industry and country dummy variables, $industry_{ij}$ and $country_{ij}$ for stock i . In the estimation we restrict the sum of the coefficients on each group category to be zero. This allows us to interpret each estimated coefficient as the equal-weighted return associated with the relevant group of stocks.

For example, we restrict the sum of the coefficients $\sum_{j \in HI, PI, NI} \beta_{1jt}$ on the investibility indicator variable to be zero in the estimation and we use the estimated intercept β_{0t} and the coefficient β_{1j} on the investibility indicator variable I_j to construct the week t return on the investibility portfolio j for $j \in (NI, PI, HI)$. In other words, let $R_{HI,t}$ denote the weekly return on highly-investible portfolio at time t that is net of size, turnover, industry and country effects; the weekly return $R_{HI,t}$ on the highly-investible portfolio is given by

$$R_{HI,t} = \hat{\beta}_{0t} + \hat{\beta}_{1,HI,t}.$$

The weekly returns $R_{PI,t}$ and $R_{NI,t}$ on the partially-investible and the non-investible portfolios are constructed similarly.

Having obtained the weekly returns on each investibility portfolio in this manner, we next test whether returns on highly-investible stocks lead those on non-investible stocks. We estimate the following bivariate vector autoregression:

$$R_{NI,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,t-k} + u_t \quad (2)$$

$$R_{HI,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{NI,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,t-k} + v_t \quad (3)$$

where $R_{NI,t}$ represents the return on the non-investible portfolio and $R_{HI,t}$ represents the highly-investible portfolio return at week t . This bivariate VAR system allows us to test formally whether the lagged returns on the highly-investible portfolio in equation (2) have any significant explanatory power in predicting the current returns on the non-investible portfolio when its own lagged returns on the non-investible portfolio are controlled for. In addition, we examine whether there is any asymmetry in the cross-autocorrelation between highly-investible and non-investible portfolios by testing the hypothesis, $\sum_{k=1}^K b_k - \sum_{k=1}^K c_k = 0$.

B2. VAR estimation results

We estimate the VAR specified in equations (2) and (3) using weekly returns up to four lags, $K=4$. In Panel A of Table IV we summarize the main estimation results. The first two rows report the estimated coefficients and the p -values for the first equation – for the non-investible portfolio return ($R_{NI,t}$) -- and the next two rows report the coefficients for the second equation -- for the highly-investible portfolio return ($R_{HI,t}$). The first two columns report the coefficient on the one-lag return and the sum of the coefficients on the first four lagged returns on the non-investible portfolio. The next two columns show analogously the coefficients on the lagged returns on the highly-investible portfolio.

Panel A shows that there is a significant lead-lag pattern across highly-investible and non-investible stock returns. The lagged returns on the highly-investible portfolio predict the non-investible portfolio returns. The coefficient in the first row on the one-lag highly-investible portfolio return is 0.100 and it is significant at the five percent level. Furthermore, the sum of the coefficients on the first four lagged returns on highly-investible portfolio is 0.377; it is also significant at the one percent level, suggesting that the predictive ability of the highly-investible stock returns extends beyond the one-week horizon. In contrast, we do not find any evidence that the lagged returns on the non-investible portfolio have any predictive power for the highly-investible portfolio returns at either one or more lags.

We next formally test whether the ability of lagged highly-investible portfolio returns to predict current non-investible portfolio returns is greater than that of lagged non-investible portfolio returns to predict

highly-investible portfolio returns. The last two columns present these tests: we report the difference in the estimated coefficients together with the associated p -values. We find that the difference ($\sum_{k=1}^K b_k - \sum_{k=1}^K c_k$) is positive and significant, rejecting the hypothesis that the sum of the coefficients is equal across the two equations. We thus conclude that highly-investible portfolio returns lead non-investible portfolio returns but not vice versa.

Next, we turn to the relation between the partially-investible and the highly-investible portfolios returns. We replace the non-investible portfolio returns in equations (2) and (3) with returns on partially-investible portfolios and re-estimate the VAR to test this time for a lead-lag relation between the highly- and partially-investible groups.

Panel B of Table IV presents the estimation results. The first two rows report the estimated coefficients and the p -values for the equation of the partially-investible portfolio return ($R_{PI,t}$); the next two rows show the estimated coefficients and the p -values for the equation associated with the highly-investible portfolio return ($R_{HI,t}$). We find strong evidence that lagged returns on the highly-investible portfolio predict current returns on the partially-investible portfolio. The coefficient on the lagged highly-investible portfolio return in the first row is 0.148 and it is significant at the 5% level. The sum of the coefficients on the first four lags is 0.451 and it is significant at the one percent level. Similarly to Panel A, we do not find any evidence that lagged returns on the partially-investible portfolio predict highly-investible portfolio returns. Finally, the cross-equation test confirms that highly-investible portfolio returns lead partially-investible portfolio returns but not vice versa.

So far, our results are consistent with the conjecture that higher investibility leads to faster adjustment of stock prices to common information. It is also interesting to ask whether there is a threshold level of investibility to have an important effect on the speed of information diffusion. Examining the relation between the non-investible and the partially-investible portfolio returns should shed some light on this question. If having less than fifty percent of a company's market capitalization accessible to foreigners is sufficient to benefit from its effects on information diffusion, we should observe a similar lead-lag relation

between the partially-investible and non-investible portfolio returns.

Panel C of Table IV presents the analogous results for the partially-investible and the non-investible portfolio returns. We see in Panel C that the lead-lag relation is not as pronounced as in Panels A and B. Although the magnitude of coefficient estimates on the lagged returns of the partially-investible portfolio is larger than that of the coefficients on the non-investible portfolio returns, the cross-equation tests fail to reject the null hypothesis that the coefficient estimates on lagged partially- and non-investible portfolios are equal at both the one-week and longer horizons. There does not appear to be a strong predictability relation across partially-investible and non-investible portfolios. This finding suggests that while investibility matters, for its role to be significant, its degree has to be sufficiently high to meet a certain threshold.¹³

B3. Investible portfolio returns by sorting stocks

The two-stage approach we use in the previous section has the advantage of distinguishing the effect of investibility by controlling for several factors that may affect return dynamics at the same time. On the other hand, the disadvantage of this approach is that one has to assume that common market-wide information is spilled over across different markets. This assumption is not unrealistic in an increasingly globalized world. Global investors who have an advantage in collecting and processing global information may trade on their information in many countries simultaneously. Nevertheless, for completeness we also conduct our VAR tests using the weekly returns on investibility portfolios that we construct through our partitioning scheme. Specifically, we independently sort stocks *in each market* by size (volume) and investibility and partition each market into nine size/investibility (volume/investibility) portfolios. As we noted earlier the limited number of stocks we have available in some markets leaves us with an uneven representation of portfolios in each market. We therefore conduct our VAR tests in a subset of twelve markets that have at least fifty stocks on average over the sample period. Using equal-weighted weekly returns on each investibility portfolio in each market, we estimate the VAR specified in equations (2) and (3) jointly across all markets

¹³ We also examine the trivariate VAR where we include non-investible, partially-investible, and highly-investible portfolios in the system and obtain consistent results using three-pairs of bivariate VAR.

for each size and turnover groups.

Table V is the analogue of Table IV for the VAR results using these portfolios. Panel A presents the results within each size group. The coefficient estimates generally confirm the findings in Table IV. The first two rows in each size group are associated with the equation for the non-investible portfolio return ($R_{NI,t}$) and the next two rows present the coefficient estimates for the equation associated with the highly-investible portfolio return ($R_{HI,t}$). Panel A shows that within each size group the lagged returns on the highly-investible portfolio predict the current returns on the non-investible portfolio. The estimated coefficients on the lagged highly-investible portfolio returns range from 0.115 to 0.155 and all of them are significant at the one-percent level. Similarly, the corresponding numbers for the sum of coefficient estimates on the first four lagged returns on the highly-investible portfolio are between 0.272 and 0.376, all significant at the one-percent level. Interestingly, the estimated coefficients on the lagged non-investible portfolio returns in the highly-investible portfolio return equation are also positive and significant in each size group, suggesting some ability of lagged non-investible portfolio returns to predict highly-investible portfolio returns. However, the magnitude of the individual coefficients is economically much smaller, ranging from only 0.039 to 0.047. There is also no evidence of any predictive ability at longer horizons: the sum of the coefficients on the four lags is not significant at conventional levels. Finally, the cross-equation tests reported in the third to last column confirm that the difference between the sums of the coefficients $\sum_{k=1}^K b_k - \sum_{k=1}^K c_k$ is positive and significant for each size group. We therefore conclude that holding size constant returns on portfolios of highly-investible stocks lead those on portfolios of non-investible stocks but not vice versa.

Panel B presents the corresponding VAR results for each turnover group. Overall, the results are very similar to those in Panel A. We find that within each turnover group lagged returns on the highly-investible portfolios strongly predict current returns on the non-investible portfolios. The predictive power of past highly-investible portfolio returns remains significant beyond the one-week horizon. In contrast, the ability of lagged non-investible portfolio returns to predict current highly-investible portfolio returns is limited to

one week except for the low-turnover group, and it is economically insignificant compared to that of the lagged highly-investible portfolio returns. The cross-equation test confirms that highly-investible portfolio returns lead non-investible portfolio returns but not vice versa.

We next examine the dynamics between the highly-investible and the partially-investible portfolio returns. Incidentally, this relationship presents an interesting opportunity. The reason is that partially-investible stocks are on average larger and are more actively traded than the highly-investible stocks within each size and turnover group (see Table II). Therefore, if our results are driven by size or turnover and not by investibility, we should find that returns on partially-investible stock portfolios lead those on highly-investible stock portfolios, and not vice versa.

Panel C of Table V presents the VAR results for the relation between the highly-investible and the partially-investible portfolio returns within each size group. The results show no evidence that returns on the partially-investible portfolio lead returns on the highly-investible portfolio. In contrary, the evidence indicates that lagged returns on the highly-investible portfolio predict partially-investible portfolio returns in both medium- and large-size groups. Panel D of Table V presents the analogous results for each turnover group. Again, we find no evidence that partially-investible portfolio return lead highly-investible portfolio returns. We therefore conclude that the findings in Panels C and D strengthen the evidence that the effect of the degree of investibility on the speed of information diffusion is independent of other factors such as size and liquidity.

C. The issue of non-trading: A different measure of liquidity

An important concern for our exercise is that in emerging markets the extent of non-trading can be very large (Bekaert, Harvey, and Lundblad (2007)). Since we use weekly returns data, non-trading should not be as serious a problem as with daily data. Nevertheless, to examine whether our results are driven by non-trading problem we replicate Panel B of Table V replacing the turnover measure with the zero-return measure of liquidity used in Bekaert et al. (2007) and Lesmond (2005). These authors argue that in emerging markets a liquidity measure based on the proportion of zero daily returns might capture the extent

of illiquidity better than turnover and that it is more closely related to the effective transaction costs obtained from high-frequency data. Therefore, for the sample of stocks that we have daily return data available from the EMDB, we construct the zero-return liquidity measure for each stock and form nine zero-return/investibility portfolios in each market. We then estimate the VARs to test the relation between highly-investible portfolio and non-investible portfolio returns within each liquidity group. In untabulated results, we find that within each liquidity group, lagged returns on the highly-investible portfolios strongly predict current returns on the non-investible portfolios. This gives us additional comfort that our results are not driven by non-trading in our sample or by our failure to proxy for differences in liquidity appropriately.

D. Country-specific VARs

An interesting issue is whether the effect of investibility on return dynamics differs across countries. We explore this possibility by estimating our baseline VAR specified in equations (2) and (3) individually for each of the 12 markets that meet the requirement of having at least 50 stocks on average during our sample period. We find that the cross-equation difference between the sum of the coefficients on lagged highly-investible portfolio returns and lagged non-investible portfolio returns is positive in 11 out of 12 markets. The difference is significant at the 10% level in Brazil, China, Korea, Malaysia, and Mexico. It is interesting to note that these five markets are the ones most heavily invested by foreign investors. As of 2001, the U.S. investors' equity holdings of our sample emerging markets are \$155 billion, 53 percent of which is invested into these five markets.

III. Alternative Explanations of Lead-Lag Effect

A. Analyst coverage

Increased openness to foreign equity investors is likely to attract greater analyst coverage (Bae, Bailey, and Mao (2006)). Brennan, Jegadeesh, and Swaminathan (1993) find that firms that are followed by many analysts tend to lead those that are followed by fewer analysts. They attribute this finding to the effect of the

number of analysts following a firm on the speed of adjustment of a firm's price to new common information. Chan and Hameed (2006) find a similar lead-lag relation in emerging market countries between the returns of high-analyst following stocks and low-analyst following stocks. It is important therefore to determine in our analysis whether the investibility effect we document is purely a manifestation of the increased analyst coverage of highly-investible stocks. We investigate this possibility below.

We measure the intensity of analyst activity as the average number of analysts issuing earning forecasts for a firm during a given calendar year. We obtain data on the number of unique analysts following each firm from the I/B/E/S International and merge this data with our sample of firms.¹⁴ We include in our analysis those firms that do not have earnings forecasts issued for them. We follow the previous literature and assume that the number of analysts following is zero for these cases.¹⁵

In each year we partition the firms in our subsample into two groups based on the yearly median number of analysts in each market. Stocks that have more analysts than the median for that market are assigned into the high-coverage group and stocks that have fewer analysts than the median for that market are assigned to the low-coverage group. We therefore construct six portfolios in each market according to each stock's degree of investibility and analyst coverage. We then conduct the VAR tests specified in equations (2) and (3) to test whether returns on highly-investible stocks lead those on non-investible stocks after we control for the amount of analyst activity.

We estimate equations (2) and (3) jointly across all markets in our subsample within each analyst-coverage group. In Table VI we present the estimation results. The first two rows report the estimated coefficients for the low-coverage portfolios and the second set of two rows present the results for the high-coverage portfolios. We see in Table VI that within each analyst-coverage group the lagged returns on the highly-investible portfolio strongly predict current returns on the non-investible portfolio. The

¹⁴ For this exercise, we require that each market has at least fifty stocks on average over the sample period.

¹⁵ For these firms with no earnings forecasts, this could indeed mean that the number of analysts following is zero, or that the data for the firm is not captured by I/B/E/S International. Since we assume the former, to avoid any biases that might result from underestimating the number of analysts for those firms that are not covered by I/B/E/S, we repeat our analysis after excluding firms with zero analyst coverage. We find our results to be generally robust.

predictive ability of highly-investible stocks is higher among the high-coverage stocks than it is for the low-coverage stocks. This finding suggests that high degree of investibility and high analyst activity are likely to reinforce each other's effect on the speed of information diffusion.

Investibility also has an effect on the return dynamics even among stocks with relatively low level of analyst coverage. This evidence indicates that the degree of investibility has an independent influence that goes beyond the effect of analyst coverage. On the other hand, we find no ability of lagged returns on non-investible stocks to predict current returns on highly-investible stocks in either low- or high-analyst coverage groups.

B. Intra- and inter-industry effects

In a recent paper, Hou (2007) argues that the slow diffusion of common information is more relevant across firms within the same industry group. He finds that industry leaders lead industry followers and once this intra-industry effect is controlled for, there is little evidence of predictability in stock returns.

We are concerned that our finding that highly-investible stock returns predict non-investible stock returns may just be an intra-industry effect. It is plausible that stocks that allow a greater degree of access to foreigners in a given market may very well be the leaders in their respective industries. In such case, we may find that returns of other stocks in the same industry follow the industry leader returns due to slow diffusion of common information within the industry, and we may mistakenly attribute this finding to the influence on investibility. Thus, next we investigate whether intra-industry dynamics can explain our findings.

In order to study intra-industry dynamics we make use of the ten 2-digit industry classifications provided by the EMDB to group the stocks within each market in our subsample into industry portfolios.¹⁶ We then partition each industry group into three investibility portfolios. If our findings are driven purely by an intra-industry leader-follower effect, then we should expect the ability of the lagged returns on

¹⁶ For this exercise, again, we limit our analysis to the markets that meet the requirement of having at least fifty stocks on average over the sample period.

highly-investible stocks in industry j to be more important than highly-investible stocks in other industries in predicting the current returns on non-investible stocks in industry j . We modify the VAR specification given in equations (2) and (3) to accommodate this test. Specifically, in each market we distinguish the highly-investible stocks in industry j from other highly-investible stocks in all other industries and we include their lagged returns as an additional variable in the regression to predict the current non-investible stock returns in industry j . Finally, we estimate the following VAR jointly across all industries and all markets within our subsample:

$$R_{NI,j,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,j,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,j,t-k} + \sum_{k=1}^{k=K} f_k R_{HI,j',t-k,j' \neq j} + u_t \quad (4)$$

$$R_{HI,j,t} = c_0 + \sum_{k=1}^{k=K} c_k R_{NI,j,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,j,t-k} + v_t \quad (5)$$

where $R_{NI,j,t}$ represents the equally-weighted weekly return on the portfolio of non-investible stocks in industry j ; $R_{HI,j,t}$ is the equally-weighted weekly return on the highly-investible stock portfolio in industry j ; and finally, $R_{HI,j',t,j' \neq j}$ represents the equally-weighted weekly return on the portfolio of highly-investible stocks in all other nine industries $j' \neq j$. We test the null hypothesis that the ability of lagged highly-investible stock return to predict non-investible stock returns is a purely intra-industry effect by testing whether the coefficients on highly-investible returns in industries $j' \neq j$ are zero and by comparing the coefficients on industry- j highly-investible stock returns in equation (4) to those on the highly-investible returns in industries $j' \neq j$. That is, $\sum_{k=1}^K f_k = 0$ and $\sum_{k=1}^K f_k - \sum_{k=1}^K b_k < 0$.

Table VII presents the estimation results for the VAR model specified in equations (4) and (5). First, we note that there is evidence of an intra-industry effect consistent with Hou's (2007) findings. The lagged returns on the highly-investible stock portfolio in industry j predict the current returns on the non-investible stocks in the same industry. However, we find that the lagged returns on the portfolio of highly-investible stocks in *other* industries also have significant ability in predicting current returns on non-investible stocks

in a particular industry. The cross-equation test rejects the hypothesis that the ability of highly-investible stocks in other industries is less than that of the highly-investible stocks in own industry.

This evidence strongly rejects the null hypothesis that cross-stock return dynamics that we document associated with investibility is purely an intra-industry phenomenon. Our findings suggest that the predictive ability of highly-investible stocks does not solely derive from the intra-industry leader-follower relation.

C. Reverse causality

Our results suggest that foreign institutional investors' trading facilitates information transmission in that these traders quickly incorporate global market-wide information into prices of local stocks. An alternative interpretation is that foreign traders are informationally disadvantaged relative to local traders in trading local stocks and therefore they tend to trade stocks that are easy to acquire information (Kang and Stulz (1997)). In other words, foreign investors' trading per se does not cause an improvement in information transmission but rather foreign investors tend to invest in a subset of stocks with good information environment.

We believe this reverse causality to be less likely. First, our measure of investibility is to some extent an exogenous variable that is determined by government regulation and/or corporate charters. We note that high foreign ownership can be caused by good information environment. Leuz, Lins, and Warnock (2008) show that foreign investors tend to invest in firms with good corporate governance practice and better information environment. However, it is less likely that stocks with good information environment cause high investibility. Second, while it is reasonable to assume that foreign investors are disadvantaged over firm-specific information of local stocks, there is little reason to believe that they are at a disadvantage over global market-wide information. For these reasons, we believe that foreign investors facilitate information transmission of market-wide information.

IV. Investibility and Speed of Price Adjustment

The preceding sections document that the lagged returns of highly-investible stocks lead those on non-investible stocks and that this finding is robust to controlling for size, volume, analyst activity, and intra-industry dynamics. In this section, we take a more direct look at this relationship. We do this by constructing measures that proxy for the speed of a stock's price adjustment to market-wide information and we test how these measures relate to the degree of a stock's investibility in the cross-section. The null hypothesis is that the degree of investibility bears no relation to how fast a firm's stock price responds to market-wide information.

A. Delay measures

We consider the world market return to be the relevant source of global news to which stocks respond to and employ two measures to capture the average delay with which stock prices respond to market-wide information.

We construct our delay measures by first estimating each year the following regression for each stock with at least fifteen weekly observations per year:

$$r_{i,t} = \alpha + \sum_{k=0}^{k=4} \delta_{i,k} r_{m,t-k} + \varepsilon_{i,t} \quad (6)$$

where $r_{i,t}$ denotes the return on stock i at week t , and $r_{m,t-k}$ is the k^{th} lag world market return at week t , for $k = 0, 1, \dots, 4$. If the price of stock i immediately responds to market news, the coefficient on the contemporaneous market return $r_{m,t}$ should be significantly different from zero and none of the coefficients on the lagged market returns should be different from zero. On the other hand, if stock i shows delay in responding to global market information, we should expect some of the coefficients on the lagged market returns to be significantly different from zero. Using this insight, we use the estimated coefficients obtained from this regression to construct the delay measures.

Our first delay measure -- *delay1* -- captures the fraction of the variation in individual stock returns that

is explained by the lagged market returns in equation (6) (Hou and Moskowitz (2005)). Specifically, it is computed as one minus the ratio of the r-square statistic (R_r^2) obtained from a restricted regression, in which the coefficients of the lagged market returns are set to zero, to the r-square (R_{ur}^2) obtained without such restrictions:

$$delay1 = 1 - \frac{R_r^2}{R_{ur}^2} \quad (7)$$

Larger values of *delay1* indicate that greater return variation is captured by lagged market returns and are indicative of greater delay in the response of stock returns to market-wide news.

Our second delay measure is motivated by McQueen, Pinegar and Thorley (1996) and is constructed from the coefficients estimates in equation (6) as¹⁷:

$$delay2 = \frac{1}{(1 + e^{-x})} \quad \text{where} \quad x = \frac{\sum_{k=1}^{k=4} |\delta_{i,k}|}{\delta_{i,0}} \quad (8)$$

We estimate equation (7) using the world market return and construct the delay measures *delay1* and *delay2* with respect to global market information.

B. Cross-sectional regressions of delay measures

We investigate the relationship between the degree of investibility and the speed with which stock prices adjust to global market information by regressing the delay measures estimated for each stock in each calendar year on the degree of investibility along with a number of control variables:¹⁸

$$delay_{i,t} = \alpha_0 + \beta investable_{i,t} + \gamma_1 analyst_{i,t} + \gamma_2 size_{i,t} + turnover_{i,t} +$$

¹⁷Unlike McQueen, Pinegar, Thorley (1996), we use the absolute value of coefficient estimates since a subset of our sample stocks are negatively correlated with world market returns. Similar measures have been used by Brennan, Jegadeesh, and Swaminathan (1993), and Mech (1993).

¹⁸ In unreported results, instead of estimating delay measure for each firm in each year, we estimate delay measures for the whole sample period. We then compute the mean for investibility and all the control variables for the whole sample period and re-estimate equation (9). Our results are unchanged. We also find our results to be robust to the inclusion of country and industry fixed effects, or to replacing the continuous measure of investibility with three dummies indicating, respectively, non-, partially- and highly-investible stocks, as in the previous sections.

$$\gamma_4 \text{volatility}_{i,t} + \varepsilon_{i,t} \quad (9)$$

where $\text{delay}_{i,t}$ is the relevant delay measure, delay1 or delay2 , for stock i and $\text{investable}_{i,t}$ is the stock i 's average investible weight over calendar year t ; $\text{analyst}_{i,t}$ is a dummy variable that takes a value of one if stock i is covered by an analyst in year t ; $\text{size}_{i,t}$ is stock i 's average market capitalization; $\text{turnover}_{i,t}$ is the average number of shares traded scaled by the number of shares outstanding and $\text{volatility}_{i,t}$ is the standard deviation of weekly returns for stock i in calendar year t . We include other firm characteristics such as size, turnover, and analyst coverage to control for the effects of these variables, as we know from previous work that larger and more liquid stocks and stocks with greater analyst coverage adjust faster to market-wide information. The null hypothesis is that the degree of investibility should bear no relation to how fast prices adjust to market-wide information. Alternatively, if the degree of investibility improves the process of information incorporation into prices in a way that is not captured by these firm characteristics, we should expect to see a negative relationship between our delay measures and the degree of investibility. That is, we expect $\beta < 0$.

We estimate the equation (9) in a pooled OLS regression and adjust the standard errors for clustering at the country level. In Panel of Table VIII we present the estimation results in which we use world market return as a relevant source of market-wide information. In Panel A we present these estimation results. We see that the estimated coefficients on the degree of investibility are negative for both delay measures with respect to the world market information. The coefficient estimates are -0.147 for delay1 and -0.058 for delay2 and both coefficients are significant at the 1% level. These estimates suggest that lower investibility is associated with a greater price delay; conversely, a higher degree of investibility is associated with faster processing of global market information into prices. While the coefficient estimates on size and analyst coverage are also significant and negative, suggesting an important role for these variables, their magnitude is small.

These findings strongly reject the null hypothesis that investibility bears no relation to how fast prices incorporate information. In contrast, we view these findings as lending additional support to our conjecture

that the degree of investibility has an important influence on the speed of stock price adjustment to market-wide information.

C. Speed of price adjustment to local market information

In this section we run a slightly different experiment and see if the degree of a stock's investibility has any influence on the speed with which the stock price adjusts to local market-wide information. Since the degree of investibility determines the amount of *foreign* ownership in a stock, our main conjecture is about the processing of global market information. However, to the extent that foreigners are also better *processors* of the *local* market-wide information we might find the degree of investibility to be an important factor in the incorporation of local market-wide information into prices as well.

Whether foreign investors are more or less informed relative to local investors is a contentious issue in the emerging markets literature. Grinblatt and Kolehharju (2000) and Seasholes (2000) present evidence on the trading behavior of foreign investors that suggest that they have better expertise and talent than local investors. There are also studies, however, that provide evidence to the contrary and show that local investors are better informed (Choe, Kho, and Stulz (2005), Hau (2001), and Dvorak (2005)).¹⁹

Our findings so far provide evidence consistent with the idea that foreign investors are better at processing the global market-wide information. With this literature in view, we try to add to our understanding of this issue by asking in this section whether this information processing advantage spills to the local market-wide information.

For this purpose, we re-estimate the regression in equation (6) this time using the local market return²⁰ and construct the delay measures with respect to the local market information. We then re-estimate the pooled cross-sectional regression in equation (9) to test whether the degree of investibility is related to the

¹⁹ In a closely related paper to ours, Chan, Menkveld, and Yang (2007) use the market segmentation setting in China's stock market to compare the information content of the stock trades between local and foreign investors, and find that the A-shares that locals trade lead the B shares that foreigners trade, suggesting seemingly contradictory evidence to ours. It is important to note, however, that their focus is on firm-specific information, whereas we are concerned with the processing of market-wide information.

²⁰ We measure the pure local market returns as the residual obtained from regressing the weekly local market returns on the weekly world market returns. Both local and world market return data are from Datastream.

speed of adjustment to local market news.

In Panel B, we present the estimation results. Surprisingly, we find that the coefficient estimates on the investibility variable are negative and significant for both delay measures. The magnitude of the coefficients is smaller, however: -0.138 for *delay1* and -0.050 for *delay2*. In unreported results, we test whether the degree of investibility has an equal effect on delay measures with respect to local versus world market information and reject the null hypothesis that the coefficient estimates on investibility are equal across Panels A and B for both delay measures.

The results in Panel B are interesting for what they suggest: First, the degree of investibility has *some* influence on the speed with which prices adjust to local market information. This is surprising to us since our conjecture is about global market information; on the other hand, it is consistent with the idea that foreign investors may be better at processing any market-wide information – whether it is local or global. Second, investibility matters more for global market information as we should expect. More investible stocks have greater sensitivity to world market news.²¹

In summary, Table VIII provides evidence that the degree of investibility has an economically important and significant influence on the speed of stock price adjustment to market-wide information. The evidence suggests that returns on more investible stocks respond faster to world market and, to a smaller extent, to local market-wide information than returns on less-investible stocks. Moreover, stocks that are more open to foreign investors have greater sensitivity to world market information than to local market information. We conclude that this evidence together with the cross-stock return dynamics we documented across highly-investible and non-investible stocks suggests that greater investibility is associated with faster adjustment of stock prices to common information.

²¹ This finding is consistent with Bae, Chan, and Ng (2004). They show that highly-investible stocks are more integrated with the world and are therefore more sensitive to the world market factor.

V. Conclusion

In this paper, we propose another benefit of stock market liberalization by investigating how greater investibility impacts the informational efficiency of local stock markets. We argue that foreign investors can help facilitate the diffusion of market-wide information, in particular global market information, in stock prices. We examine the relation between a stock's accessibility for foreigners and its stock return dynamics and show that greater investibility is associated with faster diffusion of market-wide information in these markets.

Our findings can be summarized as follows: First, we find that the degree of foreign investor participation is a significant determinant of the cross-autocorrelation patterns in stock returns. Portfolio returns on highly-investible stocks lead those on non-investible stocks but not vice versa. We show that this effect is not driven by other known determinants such as size, trading volume, and analyst coverage and remains significant after we control for each of these other variables. While we find evidence supportive of an intra-industry leader-follower effect, we show that the lead-lag effect that we identify is not purely an intra-industry effect. Portfolio returns of highly-investible stocks in industries other than a given industry also lead portfolio returns of non-investible stocks from this industry, even when we control for the effect of same-industry highly-investible stocks.

Second, the degree of investibility has a positive effect on the speed with which stock prices adjust to market-wide information. Specifically, we find that greater investibility reduces the delay with which stock prices respond to market-wide information. We show that prices of more investible stocks respond faster to the world market information as well as to the local market information than the prices of less investible stocks. We interpret these results as providing additional support for the slow information diffusion hypothesis regarding the effect of market frictions on stock return dynamics. Our results are consistent with the view that financial liberalization in the form of greater investibility yields more informationally efficient stock prices in emerging markets.

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Table I. Descriptive statistics by country

This table describes the sample and stock distribution by country. We obtain stock-level return, market capitalization, and turnover data from EMDB for 3,201 distinct stocks in 31 countries over the period of January 1989 - April 2003. EMDB also includes a variable called the ‘degree open factor’ that indicates the amount of stock that foreigners may legally own. The degree open factor or the investible weight ranges from zero to one. A stock with zero investible weight is non-investible and a stock with an investible weight of one is fully-investible. Table I presents the number of stocks, average investible weight, average weekly return and volatility, average firm size, and average turnover for each country. Weekly returns and volatility are the cross-sectional averages of the mean returns and standard deviations of weekly returns over all the sample stocks within the country. Market capitalization is measured as the market value of equity in million U.S. dollars. Turnover is the number of shares traded scaled by the number of shares outstanding. All variables report the cross-sectional average of the time-series means for sample stocks.

Country	No. of stocks	Investible weight	Return (%)	Volatility (%)	Market cap (US\$ million)	Turnover (%)
Argentina	29	0.65	0.48	9.12	595	3.77
Brazil	81	0.56	0.39	11.43	997	3.57
Chile	42	0.45	0.13	5.04	702	0.81
China	202	0.22	0.20	6.56	951	11.64
Colombia	24	0.34	0.07	6.14	289	0.85
Czech Republic	43	0.09	-0.18	7.20	171	0.90
Egypt	67	0.22	-0.14	5.95	149	2.87
Greece	50	0.65	-0.06	6.28	647	4.47
Hungary	16	0.48	0.19	6.78	421	6.86
India	126	0.14	0.00	7.50	558	15.69
Indonesia	60	0.25	-0.20	8.93	240	4.41
Israel	52	0.59	0.14	6.43	710	6.04
Jordan	39	0.05	-0.02	3.79	54	3.82
Korea	164	0.48	0.02	9.57	770	29.68
Malaysia	111	0.72	-0.05	7.58	604	5.37
Mexico	68	0.57	0.09	6.22	913	3.16
Morocco	20	0.33	-0.01	3.57	439	0.78
Pakistan	62	0.18	0.00	6.79	68	4.18
Peru	34	0.40	0.20	6.55	192	4.22
Philippines	47	0.24	-0.11	8.29	346	2.98
Poland	32	0.69	-0.03	6.41	518	5.05
Portugal	30	0.59	0.17	4.54	707	3.02
Russia	28	0.38	0.12	12.98	2,324	1.53
Slovakia	17	0.18	-0.28	9.46	44	3.64
South Africa	71	0.78	0.21	6.46	1,431	2.86
Sri Lanka	46	0.09	0.00	6.49	21	1.17
Taiwan, China	98	0.30	-0.08	6.78	1,484	29.75
Thailand	63	0.26	-0.41	8.17	452	8.27
Turkey	46	0.66	0.46	10.37	536	18.97
Venezuela	17	0.44	0.25	9.04	255	1.89
Zimbabwe	25	0.08	0.41	10.03	85	1.35

Table II. Summary statistics and auto-correlations by portfolios

For each stock in each year, we compute the average investible weight and sort sample stocks into three investibility groups: non-investible (*NI*) if the investible weight is zero, partially-investible (*PI*) if the investible weight is greater than 0 and less than or equal to 0.5, and highly-investible (*HI*) if the investible weight is greater than 0.5. In addition, in each country in each year, we independently sort stocks into three size and three turnover groups based on their yearly average market capitalization and turnover, respectively. Panels A and B present the summary statistics and the autocorrelations associated with each of the nine size/investibility and turnover/investibility portfolios, respectively. ρ_1 denotes the first order autocorrelation and $\sum_{k=1}^4 \rho_{t-k}$ is the sum of the first four lag autocorrelations. For each portfolio, we report the equally-weighted size, investible weight, weekly return and volatility, and turnover.

Panel A: Portfolios sorted by size and investible weight

Size	Portfolio	Market cap (US\$ million)	Turnover	Investible	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^4 \rho_{t-k}$
<i>Small</i>	P_{NI}	48	0.06	0.00	0.10	8.25	0.19	0.59
	P_{PI}	140	0.19	0.29	-0.50	8.44	0.07	0.31
	P_{HI}	131	0.11	0.95	-0.12	8.21	0.11	0.48
<i>Medium</i>	P_{NI}	162	0.05	0.00	0.24	6.78	0.10	0.25
	P_{PI}	365	0.12	0.28	-0.18	7.61	0.11	0.45
	P_{HI}	349	0.07	0.93	0.16	7.68	0.09	0.49
<i>Large</i>	P_{NI}	813	0.04	0.00	0.29	6.64	0.08	0.24
	P_{PI}	2,021	0.07	0.29	0.14	6.64	0.12	0.44
	P_{HI}	1,607	0.06	0.92	0.31	6.94	0.08	0.48

Panel B: Portfolios sorted by turnover and investible

Turnover	Portfolio	Market cap (US\$ million)	Turnover	Investible	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^4 \rho_{t-k}$
<i>Low</i>	P_{NI}	357	0.01	0.00	0.04	6.87	0.21	0.66
	P_{PI}	1,662	0.03	0.27	-0.20	6.35	0.05	0.46
	P_{HI}	935	0.02	0.93	0.06	6.39	0.08	0.42
<i>Medium</i>	P_{NI}	181	0.04	0.00	0.16	7.41	0.14	0.36
	P_{PI}	916	0.07	0.29	-0.08	7.14	0.11	0.46
	P_{HI}	773	0.05	0.93	0.12	7.35	0.06	0.46
<i>High</i>	P_{NI}	130	0.13	0.00	0.40	8.28	0.07	0.21
	P_{PI}	641	0.24	0.28	-0.03	8.34	0.17	0.48
	P_{HI}	611	0.14	0.94	0.18	8.43	0.11	0.50

Table III. Cross-Autocorrelations after controlling for size and turnover

This table reports, for each size and turnover group, the one-lag cross-autocorrelation coefficients between the highly-investible portfolio and the non-investible portfolio returns. Each year we assign sample stocks into three investibility groups based on their average investible weight: non-investible (*NI*) if the investible weight is zero, partially-investible (*PI*) if the investible weight is greater than 0 and less than or equal to 0.5, and highly-investible (*HI*) if the investible weight is greater than 0.5. In addition, in each country in each year, we independently sort stocks into three size and three turnover groups based on yearly average market capitalization and turnover, respectively. Panels A and B present the one-lag cross-autocorrelation coefficients between the equally-weighted highly-investible and non-investible portfolio returns within each size and turnover group, respectively.

Panel A: Portfolios sorted by size and investibility

Size		<i>Small</i>		<i>Medium</i>		<i>Large</i>	
		$R_{NI,t}$	$R_{HI,t}$	$R_{NI,t}$	$R_{HI,t}$	$R_{NI,t}$	$R_{HI,t}$
<i>Small</i>	$R_{NI,t-1}$	0.19	0.04	0.17	0.07	0.11	0.07
	$R_{HI,t-1}$	0.17	0.11	0.14	0.07	0.08	0.04
<i>Medium</i>	$R_{NI,t-1}$	0.12	0.04	0.10	0.03	0.10	0.04
	$R_{HI,t-1}$	0.22	0.11	0.18	0.09	0.11	0.07
<i>Large</i>	$R_{NI,t-1}$	0.08	0.06	0.06	0.03	0.08	0.04
	$R_{HI,t-1}$	0.21	0.10	0.21	0.10	0.14	0.08

Panel B: Portfolios sorted by turnover and investibility

Turnover		<i>Low</i>		<i>Medium</i>		<i>High</i>	
		$R_{NI,t}$	$R_{HI,t}$	$R_{NI,t}$	$R_{HI,t}$	$R_{NI,t}$	$R_{HI,t}$
<i>Low</i>	$R_{NI,t-1}$	0.21	0.08	0.17	0.08	0.13	0.08
	$R_{HI,t-1}$	0.20	0.08	0.18	0.09	0.15	0.13
<i>Medium</i>	$R_{NI,t-1}$	0.17	0.05	0.14	0.04	0.10	0.05
	$R_{HI,t-1}$	0.22	0.07	0.20	0.06	0.15	0.11
<i>High</i>	$R_{NI,t-1}$	0.13	0.03	0.09	0.04	0.07	0.03
	$R_{HI,t-1}$	0.20	0.06	0.20	0.06	0.15	0.11

Table IV. Lead-lag relation among non-, partially-, and highly- investible stock returns

This table presents the lead-lag relation across non-investible, partially-investible and highly-investible portfolio returns. We first construct weekly returns on investibility portfolios that are net of firm size, turnover, industry and country effects by estimating the cross-sectional regression in equation (1) in the text. We then use the estimated coefficients to compute the weekly return R_{jt} on each investibility portfolio j , $j \in (NI, PI, HI)$ at week t , as described in the text. Finally, we estimate the following VAR:

$$R_{NI,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,t-k} + u_t$$

$$R_{HI,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{NI,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,t-k} + v_t$$

where $R_{NI,t}$ and $R_{HI,t}$ are the week t returns on the non-investible and highly-investible portfolios, respectively. Panel A presents these VAR results; Panel B presents the VAR results for the partially-investible and highly-investible portfolio returns finally Panel C presents the VAR results for the non-investible and partially-investible portfolio returns. The cross-equation null hypothesis is $\sum_{k=1}^K b_k - \sum_{k=1}^K c_k = 0$. The p -values are in parentheses.

Panel A: Non-investible and highly-investible portfolio returns

Dependent	Lags of non-investible portfolio returns		Lags of highly-investible portfolio returns		Cross-equation tests	
	$R_{NI,t-1}$	$\sum_{k=1}^4 R_{NI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$
$R_{NI,t}$	0.013 (0.81)	0.066 (0.57)	0.100 (0.03)	0.377 (0.00)	0.054 (0.49)	0.366 (0.02)
$R_{HI,t}$	0.046 (0.46)	0.011 (0.93)	0.064 (0.24)	0.450 (0.00)		

Panel B: Partially-investible and highly-investible portfolio returns

Dependent	Lags of partially-investible portfolio returns		Lags of highly-investible portfolio returns		Cross-equation tests	
	$R_{PI,t-1}$	$\sum_{k=1}^4 R_{PI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$
$R_{PI,t}$	-0.006 (0.93)	-0.008 (0.95)	0.148 (0.02)	0.451 (0.00)	0.145 (0.10)	0.360 (0.04)
$R_{HI,t}$	0.003 (0.96)	0.091 (0.44)	0.096 (0.12)	0.386 (0.00)		

Panel C: Non-investible and partially-investible portfolio returns

Dependent	Lags of non-investible portfolio returns		Lags of partially-investible portfolio returns		Cross-equation tests	
	$R_{NI,t-1}$	$\sum_{k=1}^4 R_{NI,t-k}$	$R_{PI,t}$	$\sum_{k=1}^4 R_{PI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$
$R_{NI,t}$	0.068 (0.29)	0.218 (0.07)	0.051 (0.37)	0.218 (0.03)	0.036 (0.70)	0.152 (0.37)
$R_{PI,t}$	0.015 (0.83)	0.066 (0.64)	0.116 (0.07)	0.345 (0.01)		

Table V. VAR for the portfolio returns formed by country

This table presents the VAR estimation results using the equally-weighted weekly returns on the nine size/investibility and turnover/investibility portfolios. For each of the twelve markets that have at least fifty stocks on average during 1989 to 2003, we partition stocks into three investibility groups: non-investible (*NI*) if the investible weight is zero, partially-investible (*PI*) if the investible weight is greater than 0 and less than or equal to 0.5, and highly-investible (*HI*) if the investible weight is greater than 0.5. In addition, in each country we independently sort stocks into three size and three turnover groups based on their yearly average market capitalization or turnover, respectively. We then compute the equally-weighted return $R_{HI,t}$ on each highly-investible portfolio and the equally-weighted return $R_{NI,t}$ on each non-investible portfolio within each size and turnover groups. Finally we estimate the following VAR jointly across all the 12 markets:

$$R_{NI,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,t-k} + u_t$$

$$R_{HI,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{NI,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,t-k} + v_t$$

where $R_{NI,t}$ and $R_{HI,t}$ are the week t return on the non- and highly- investible portfolio, respectively. Panels A and B report the VAR estimation for each size and turnover group, respectively. The cross-equation null hypothesis is $\sum_{k=1}^K b_k - \sum_{k=1}^K c_k = 0$. The p -values are in parentheses.

Panel A: Non-investible and highly-investible portfolio returns, controlling for size

Size	Dependent	Non-investible returns		Highly-investible returns		Cross-equation tests		Adj R^2	No. obs
		$R_{NI,t-1}$	$\sum_{k=1}^4 R_{NI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$		
Small	$R_{NI,t}$	-0.063 (0.00)	0.000 (1.00)	0.115 (0.00)	0.272 (0.00)	0.068 (0.02)	0.152 (0.01)	0.031	3,766
	$R_{HI,t}$	0.047 (0.02)	0.120 (0.10)	0.049 (0.02)	0.126 (0.11)			0.024	3,766
Medium	$R_{NI,t}$	0.013 (0.51)	-0.102 (0.25)	0.145 (0.00)	0.376 (0.00)	0.102 (0.00)	0.346 (0.00)	0.035	3,587
	$R_{HI,t}$	0.043 (0.01)	0.030 (0.51)	0.062 (0.00)	0.211 (0.00)			0.019	3,587
Large	$R_{NI,t}$	0.004 (0.83)	0.010 (0.89)	0.155 (0.00)	0.277 (0.00)	0.116 (0.00)	0.270 (0.00)	0.023	3,102
	$R_{HI,t}$	0.039 (0.03)	0.007 (0.88)	0.040 (0.05)	0.194 (0.00)			0.013	3,102

Panel B: Non-investible and highly-investible portfolio returns, controlling for turnover

Turnover	Dependent	Non-investible returns		Highly-investible returns		Cross-equation tests		Adj R ²	No. obs
		$R_{NI,t-1}$	$\sum_{k=1}^4 R_{NI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$		
Low	$R_{NI,t}$	-0.029 (0.11)	0.120 (0.06)	0.120 (0.00)	0.189 (0.00)	0.089 (0.00)	0.096 (0.06)	0.023	3,850
	$R_{HI,t}$	0.032 (0.03)	0.092 (0.05)	0.068 (0.00)	0.139 (0.01)			0.015	3,850
Medium	$R_{NI,t}$	-0.008 (0.62)	-0.049 (0.54)	0.192 (0.00)	0.462 (0.00)	0.158 (0.00)	0.436 (0.00)	0.039	3,480
	$R_{HI,t}$	0.037 (0.02)	0.036 (0.35)	0.056 (0.01)	0.218 (0.00)			0.022	3,480
High	$R_{NI,t}$	-0.030 (0.14)	-0.048 (0.42)	0.096 (0.00)	0.288 (0.00)	0.105 (0.00)	0.298 (0.00)	0.017	3,784
	$R_{HI,t}$	-0.010 (0.57)	-0.012 (0.84)	0.071 (0.00)	0.211 (0.00)			0.015	3,784

Panel C: Partially-investible and highly-investible portfolio returns, controlling for size

Size	Dependent	Partially-investible returns		Highly-investible returns		Cross-equation tests		Adj R ²	No. obs
		$R_{PI,t-1}$	$\sum_{k=1}^4 R_{PI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$		
Small	$R_{NI,t}$	-0.035 (0.14)	0.001 (0.99)	0.201 (0.00)	0.266 (0.01)	0.183 (0.00)	0.214 (0.00)	0.028	5,898
	$R_{HI,t}$	0.018 (0.33)	0.052 (0.30)	0.045 (0.06)	0.163 (0.04)			0.020	5,898
Medium	$R_{NI,t}$	0.010 (0.65)	0.035 (0.63)	0.059 (0.03)	0.090 (0.32)	0.032 (0.34)	0.076 (0.24)	0.004	7,910
	$R_{HI,t}$	0.027 (0.16)	0.014 (0.79)	0.033 (0.15)	0.150 (0.03)			0.008	7,910
Large	$R_{NI,t}$	-0.029 (0.24)	0.108 (0.10)	0.048 (0.05)	0.041 (0.52)	0.073 (0.04)	0.014 (0.83)	0.010	8,748
	$R_{HI,t}$	-0.025 (0.31)	0.027 (0.63)	0.045 (0.07)	0.121 (0.06)			0.010	8,748

Panel D: Partially-investible and highly-investible portfolio returns, controlling for turnover

Turnover	Dependent	Partially-investible returns		Highly-investible returns		Cross-equation tests		Adj R ²	No. obs
		$R_{PI,t-1}$	$\sum_{k=1}^4 R_{PI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$		
Low	$R_{NI,t}$	-0.034 (0.11)	0.060 (0.38)	0.017 (0.43)	0.107 (0.22)	0.008 (0.77)	-0.001 (0.98)	0.011	3,934
	$R_{HI,t}$	0.009 (0.67)	0.108 (0.10)	0.051 (0.02)	0.077 (0.37)			0.011	3,934
Medium	$R_{NI,t}$	0.012 (0.60)	-0.023 (0.75)	0.054 (0.06)	0.199 (0.02)	0.072 (0.03)	0.263 (0.00)	0.009	4,103
	$R_{HI,t}$	-0.018 (0.33)	-0.064 (0.19)	0.063 (0.01)	0.274 (0.00)			0.017	4,103
High	$R_{NI,t}$	0.013 (0.58)	0.059 (0.39)	0.117 (0.00)	0.181 (0.02)	0.113 (0.00)	0.147 (0.03)	0.017	3,823
	$R_{HI,t}$	0.004 (0.84)	0.034 (0.44)	0.060 (0.01)	0.150 (0.02)			0.013	3,823

Table VI. The effect of analyst activity

This table presents the lead-lag relation between the non-investible and highly-investible portfolio returns after analyst following is controlled for. We obtain data on analyst coverage from I/B/E/S and merge with our subsample of stocks in markets with at least fifty stocks on average during our sample period. For each market, we construct six portfolios by sorting stocks by investible weight and the number of analysts following each sample stock. Stocks are assigned into three investibility groups: non-investible (*NI*) if the investible weight is zero, partially-investible (*PI*) if the investible weight is greater than 0 and less than or equal to 0.5, and highly-investible (*HI*) if the investible weight is greater than 0.5. In addition, in each market in each year, we sort stocks into two groups based on the median number of analysts following. In each market, stocks with more analysts than the median number of analysts in that market are assigned into a high-coverage group, and all stocks with fewer analysts are assigned into the low-coverage group. We compute the equal-weighted weekly return for each portfolio in each market and estimate the following VAR jointly across the markets.

$$R_{NI,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,t-k} + u_t$$

$$R_{HI,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{NI,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,t-k} + v_t$$

where $R_{NI,t}$ and $R_{HI,t}$ are week t returns on the non- and highly- investible portfolio in each analyst coverage group in each market, respectively. The cross-equation null hypotheses are $b_1 - c_1 = 0$ and $\sum_{k=1}^K b_k - \sum_{k=1}^K c_k = 0$. The p -values are in parentheses.

Analyst following	Dependent	Non-investible returns		Highly-investible returns		Cross-equation tests		Adj R^2	No. obs
		$R_{NI,t-1}$	$\sum_{k=1}^4 R_{NI,t-k}$	$R_{HI,t}$	$\sum_{k=1}^4 R_{HI,t-k}$	$b_1 - c_1$	$\sum_{k=1}^4 b_k - \sum_{k=1}^4 c_k$		
Low	$R_{NI,t}$	0.080 (0.00)	0.076 (0.31)	0.101 (0.00)	0.233 (0.00)	0.080 (0.01)	0.136 (0.02)	0.033	3,208
	$R_{HI,t}$	0.021 (0.29)	0.097 (0.06)	0.135 (0.00)	0.164 (0.01)			0.027	3,208
High	$R_{NI,t}$	-0.078 (0.01)	-0.067 (0.39)	0.151 (0.00)	0.296 (0.00)	0.115 (0.00)	0.274 (0.00)	0.021	1,657
	$R_{HI,t}$	0.035 (0.14)	0.023 (0.72)	0.032 (0.26)	0.125 (0.08)			0.003	1,657

Table VII. Intra-industry and inter-industry effects

Using the ten 2-digit industry classifications provided by EMDB, we construct three investibility portfolios in each industry j in each market. In addition, we construct the portfolio of highly-investible stocks from other industries $j' \neq j$ in each market. For each portfolio, we compute the equal-weighted weekly returns and estimate the following VAR jointly across all industries and markets:

$$R_{NI,j,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{NI,j,t-k} + \sum_{k=1}^{k=K} b_k R_{HI,j,t-k} + \sum_{k=1}^{k=K} f_k R_{HI,j',t-k,j' \neq j} + u_t$$

$$R_{HI,j,t} = c_0 + \sum_{k=1}^{k=K} c_k R_{NI,j,t-k} + \sum_{k=1}^{k=K} d_k R_{HI,j,t-k} + v_t$$

where $R_{NI,j,t}$ and $R_{HI,j,t}$ are weekly returns at time t for the non-investible portfolio in industry j and the highly-investible portfolio in industry j , respectively. $R_{HI,j',t-k,j' \neq j}$ denotes the lag- k equally-weighted return on the portfolio of highly-investible stocks in all other nine industries in a country. The null hypothesis that the lead-lag relation between the non-investible and highly-investible portfolio returns is due to pure intra-industry effects is $\sum_{k=1}^K f_k = 0$ and $\sum_{k=1}^K f_k - \sum_{k=1}^K b_k < 0$ for $K = 1, \dots, 4$. The p -values are reported in parentheses.

	Non-investible in industry j		Highly-investible in industry j		Highly-investible in other industries		Pure intra-industry effect tests	
Dependent	$R_{NI,j,t-1}$	$\sum_{k=1}^4 R_{NI,j,t-k}$	$R_{HI,j,t}$	$\sum_{k=1}^4 R_{HI,j,t-k}$	$R_{HI,j',t-1,j' \neq j}$	$\sum_{k=1}^4 R_{HI,j',t-k,j' \neq j}$	$f_1 - b_1$	$\sum_{k=1}^K f_k - \sum_{k=1}^K b_k$
$R_{NI,j,t}$	-0.031 (0.00)	-0.036 (0.26)	0.091 (0.00)	0.187 (0.00)	0.089 (0.00)	0.191 (0.00)	-0.002 (0.95)	0.002 (0.95)
$R_{HI,j,t}$	0.027 (0.00)	0.052 (0.01)	0.062 (0.00)	0.160 (0.00)				

Table VIII. Speed of price adjustment to common information

This table presents the estimation results for the following regression:

$$delay_{i,t} = \alpha_0 + \beta investable_{i,t} + \gamma_1 analyst_{i,t} + \gamma_2 size_{i,t} + \gamma_3 turnover_{i,t} + \gamma_4 volatility_{i,t} + \varepsilon_{i,t}$$

in which the dependent variable is one of the delay measures (*delay1* and *delay2*) constructed for each stock *i* every year to proxy for the delay with which the stock price on stock *i* responds to market-wide information. *Delay* measures are defined in equations (7) and (8) in the text. In Panel A, *delay1* and *delay2* are measured with respect to the world market return. In Panel B, *delay1* and *delay2* are measured with respect to pure local market return. *Investible_{it}* represents the investible weight associated with stock *i*; *analyst_{it}* is a dummy variable that equals to one if stock *i* is covered by analysts according to I/B/E/S database; *volatility_{it}* is the standard deviation of the weekly return of stock *i*; *size_{it}* is stock *i*'s market capitalization; and *turnover_{it}* is the number of shares traded scaled by the number of shares outstanding. The investible weight and all of the control variables are yearly averages. The standard errors are corrected for clustering at the country-level. The *p*-values are reported in parentheses.

Panel A. Speed of adjustment of individual stock returns to world market information

Dependent	Investible	analyst	size	turnover	volatility	intercept
<i>delay1</i>	-0.147 (0.00)	-0.029 (0.00)	-0.016 (0.00)	-0.005 (0.73)	-0.004 (0.00)	0.801 (0.00)
<i>delay2</i>	-0.058 (0.00)	-0.012 (0.00)	-0.007 (0.00)	0.003 (0.68)	-0.001 (0.12)	0.836 (0.00)

Panel B. Speed of adjustment of individual stock returns to pure local market information

Dependent	investible	analyst	size	turnover	volatility	intercept
<i>delay1</i>	-0.138 (0.00)	-0.040 (0.15)	-0.014 (0.04)	-0.087 (0.19)	-0.001 (0.71)	0.462 (0.00)
<i>delay2</i>	-0.050 (0.01)	-0.014 (0.19)	-0.005 (0.04)	-0.020 (0.40)	0.001 (0.41)	0.688 (0.00)