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 lead-lag relation of stock returns in emerging markets, and whether this is due to slow diffusion of common information across stocks. We show that returns of highly-investable stocks that allow large access of foreign investment lead returns of non-investable 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-investable 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.

1 Introduction

There are 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 this paper, we argue that foreign equity investment restrictions are a cause of market frictions that impede swift processing of market-wide information, particularly world market information. In emerging markets, not all stocks are accessible to foreign investors and there is a large variation in the degree of accessibility across stocks. Thus, the restriction on foreign equity ownership and its variation across different stocks provide a natural setting to study the impact of market friction on stock return dynamics. Using the degree of accessibility, or "investibility", to measure the severity of market friction in affecting a stock in local markets, we assess whether investibility has a significant influence on the lead-lag relation of stock returns in emerging stock markets and whether this cross-correlation is due to slow diffusion of common information across stocks.

Our main hypothesis is that returns on investable stocks lead those on non-investable stocks. We test for the independent explanatory power of investibility controlling for size, turnover, analyst coverage and intra-industry effect. The main difficulty in detecting the effect of investibility on the lead-lag relation is that investibility may be correlated with other firm characteristics. It could be that stocks with higher foreign ownership restrictions are smaller firms in some particular industries. Furthermore, previous research has identified factors such as size, turnover and analyst coverage as being important determinants of the lead-lag effect. Therefore, it is particularly important to examine the impact of investibility net of firm characteristics that affect the lead-lag relation. We address this concern by employing two different empirical approaches to distinguish the effect of investibility from these other factors that may have positive association with investibility.

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 to April 2003. The

EMDB provides a variable called the degree open factor. This variable measures the extent to which a stock is accessible to foreigners. Based on this measure, we classify stocks into three groups: non-investable (foreigners may not own any share of the stock), partially investable (foreigners may own up to 50% of the stock) and highly investable (foreigners may own more than 50% of the stock).

We find evidence that returns on highly investable stocks lead returns on non-investable stocks. Furthermore, the lead-lag relation is not driven by size and/or trading volume. For every size and turnover groups, we find that the returns on highly-investable stocks lead the returns on non-investable stocks, but not vice versa. We note that partially-investable stocks are on average larger and more actively traded than highly-investable stocks. If our results are driven by size or turnover instead of investibility, we should find that returns on partially-investable stocks lead those on highly-investable stocks. Our evidence shows the opposite. We find that returns on highly-investable stocks lead those on partially-investable stocks.

We show that the lead-lag relation across investibility is not an artifact of the effect of analyst coverage. When we partition our sample stocks into two groups based on the number of analysts following, we find that highly-investable portfolio returns lead non-investable portfolio returns even for the group of stocks that have fewer analysts. Finally, we show that the lead-lag pattern we identify is not driven by intra-industry leader-follower effect. This is important since industry-leader stocks may be highly-investable while industry followers are non-investable. We test for inter-industry vs. intra-industry effects and show that the intra-industry effect is not the only driving force. Lagged returns on highly-investable portfolios in other industries predict current returns on non-investable portfolio, even after controlling for the predictive ability of lagged return on the same-industry highly-investable portfolio. Taken together, our results strongly support the idea that the degree of investibility has significant independent influence on the lead-lag relation in stock returns.

Given the significant impact of investibility on the lead-lag patterns in stock returns, we then examine the source of this pattern. We find that the lead-lag pattern is consistent with differences in the speed of adjustment of stock prices to market-wide information. Using measures that proxy for the delay with which stock prices respond to market information, we find that highly-investable stocks adjust faster to world as well as local market-wide information. That is, the delay with which stock prices adjust to local and world market factors is negatively related to the investibility of stocks. We interpret this evidence as suggesting that the lead-lag relation we find across stocks with different degrees of investibility is due to the slow diffusion of market-wide information from highly-investable stocks to non-investable stocks.

Our paper is closely related and contributes to several strands of literature. First, we contribute to the literature of cross-autocorrelations in stock returns. Since the seminal paper by Lo and MacKinlay (1990a), it is now well documented that returns of large stocks predict the returns of small stocks, but not vice versa. While the lead-lag cross-autocorrelation among stock returns is well documented, its sources are not well understood. An obvious explanation is the nonsynchronous trading argument that stock prices are sampled nonsynchronously, which induces spurious lead-lag effects (Boudoukh, Richardson, and Whitelaw (1994)).[1] Other known determinants of cross-autocorrelations include the number of analyst following (Brennan, Jegadeesh and Swaminathan (1993)), institutional ownership (Badrinath, Kale and Noe (1995)), and trading volume (Chordia and Swaminathan (2000)). 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. That is, the main economic source for the lead-lag cross-autocorrelation is the slow diffusion of information across stocks. By utilizing the unique feature in emerging stock markets that imposes foreign equity ownership restriction impeding the information processing, we lend additional support for the slow information diffusion hypothesis as the leading cause of cross-autocorrelations.

Second, our paper contributes to the literature that studies the effect of stock market liberalization. There is much theory and empirical evidence to support the notion that opening a stock market to foreign investors is beneficial. Extant research shows that stock market liberalizations lower the cost of capital, increase exposure to the world market, change local stocks' return volatility, and improve the information

[1] 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.

environment (Bekaert and Harvey (2000), Henry (2000), Edison and Warnock (2003), Bae, Chan and Ng (2004), Bae, Bailey and Mao (2006)). In particular, Bae, Chan and Ng (2004) find a positive relation between return volatility and the degree to which a stock can be foreign-owned. They argue that highly-investable stocks are more integrated with the world and are therefore more sensitive to the world market factor. Boyer, Kumagai and Yuan (2006) find greater co-movement between accessible stock index returns and crisis country index returns during crisis periods. In this paper, we show that diffusion of market-wide information for investable stocks is faster. To the extent that the speed of information processing measures the degree of informational efficiency, our evidence suggests that foreign equity investment may increase the informational efficiency of local stock markets, confirming another benefit of removing capital barriers.

The rest of the paper is organized as follows. In the next section, we discuss the data and the construction of investibility portfolios. Section 3 presents the lead-lag patterns across investibility. Section 4 explores other potential determinants of the lead-lag effect, and presents tests of the relationship between information diffusion and investibility. Section 5 concludes.

2. Data

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 analysis[2]. The weekly return data of EMDB includes 3,345 stocks from 35 emerging markets covering more than 75% of the total market capitalization for each emerging market.

In addition, the EMDB provides a measure of institutional and firm-level foreign investment restrictions on each stock, and reports a variable called the *degree open factor* that takes a value between zero and one to indicate investable weight of the stock that is accessible to foreigners. We use this variable

[2] 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.

as our measure of the extent of restrictions on foreign investor participation affecting each stock in emerging markets.

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 with missing closing prices, or where closing prices are zero. We also check for errors and delete 45 observations for which the weekly total return exceeds 200%[3]. Finally, we delete country-year observations where 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 about 7% of the weekly observations and 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 to April 2003.

Finally, we collect information on the number of analysts following for our sample stocks from the international files of I/B/E/S. We merge I/B/E/S data with the firms in EMDB, and compute the number of analysts that provide earning forecasts for each firm/year. 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 analysts following is zero for that firm-year observation.

2.1 Descriptive Statistics

Table 1 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 are qualitatively the same if we drop all the stocks from China. In the second column, we report average investibility for each country, measured as the cross-sectional mean of the yearly 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

[3]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.

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 1, 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 U.S. dollars in Sri Lanka, to 2,324 million U.S. dollars in Russia. Stocks in Korea and Taiwan are the most actively traded with an average monthly turnover of around thirty percent, more than thirty times the turnover of those stocks in such markets as Chile, Colombia, Czech, and Morocco. Not surprisingly, monthly stock turnover is low as it is generally less than 10 percent in many of the markets in our sample.

2.2 Investibility groups

In order to assess the impact of the degree of foreign investor restriction on the lead-lag relation of stock returns, we sort stocks in each market in each year into portfolios by their investable weights. Specifically, we first compute the yearly average investibility for each stock based on monthly data from EMDB and then we partition stocks into three groups. We classify stocks with a zero measure of investibility as non-investable, stocks with investable weight between 0.1 and 0.5 as partially-investable, and, finally stocks with investable weight greater than 0.5 as highly-investable.[4]

Lo and MacKinlay (1990a) and Chordia and Swaminathan (2000) document that size and trading volume are important determinants of the lead-lag relations. Since the extent to which a stock is accessible to foreign investors is likely to be positively associated with size and trading volume, we need to control for these factors in order to distinguish the independent influence of investibility on stock returns. Therefore,

[4] The 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).

we also sort stocks in each country independently by size (volume) to form nine size/investibility (volume/investibility) portfolios based on the investibility and size (volume) groups.[5] 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 then compute equally-weighted weekly returns on each portfolio.

Panels A and B of Table 2 present summary statistics and autocorrelations associated with each of the nine size/investibility and turnover/investibility portfolios, respectively. P_{ij} refers to a portfolio of size (turnover) i and investibility j, where i=0 refers to the smallest size portfolio, and i=2 refers to the largest size portfolio. Similarly, j=0 refers to the portfolio of non-investable stocks, and j=2 refers to the portfolio of highly-investable stocks.

We first note that our independent sorts by size and by volume help us control for these effects across non-investable and highly-investable portfolios to a large extent. For example, for every investibility group in Panel A (B), the average size (turnover) of the medium-size (turnover) stocks is larger than that of the smallest size (turnover) stocks, and similarly, the average size (turnover) of the largest stocks is larger than both the smallest-size (turnover) and the medium-size (turnover) stocks. Within each size (turnover) group, non-investable stocks are generally smaller and less heavily traded than the partially- and highly-investable stocks. However, we notice that stocks in the partially-investable portfolio are on average larger and more actively traded than the highly-investable stocks within each size and turnover group. This provides us with an opportunity to test whether investibility has an independent influence on the cross-autocorrelations. In particular, if the lead-lag relation is driven solely by size and volume with no independent effect of investibility, we should then expect partially-investable stock returns to lead highly-investable stock returns. We examine this possibility later and reject such conjecture.

Table 2 also shows that across each investibility group, large stocks outperform small stocks in our

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

sample period. On the other hand, except for the largest stocks and stocks with the lowest turnover, the average return of non-investable portfolio is always higher than that of highly-investable portfolio after controlling for size and volume. For instance, in Panel A, the average weekly return on P_{10} (the portfolio of medium-size and non-investable stocks) is 0.24 percent whereas it is 0.16 percent on P_{12} (the portfolio of medium-size and highly-investable stocks). Similarly, in Panel B, the average weekly return on P_{20} (the portfolio of highest turnover and non-investable stocks) is 0.40 percent compared to 0.18 percent on P_{22} (the portfolio of highest turnover and highly-investable stocks). Such a pattern is consistent with the effect that greater financial liberalization reduces the cost of capital for the highly-investable stocks.

The last two columns of Table 2 present the first-order autocorrelation and the sum of the first four-lag autocorrelations for each of the nine portfolios. First, we note that the decline in the first-order autocorrelations across size (turnover) groups is evident only for non-investable stocks. Second, within size (turnover) groups, non-investable stocks and partially-investable stocks have higher autocorrelation than highly-investable stocks only for the smallest (lowest) size (turnover) group. For example, within the smallest size stocks, the first order autocorrelation is 0.19 for the returns of non-investable stocks and 0.11 for the highly-investable stocks. Interestingly, for mid- and large-size (turnover) groups, the sum of four lagged autocorrelations of highly investable stocks is twice as large as that of non-investable stocks. This result seems counter-intuitive. Highly investable stocks tend to be larger and more actively traded than non-investable stocks. Thus, it appears that these stocks should have smaller magnitude of autocorrelations to the extent they incorporate information in a more speedy way. 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. To the extent that the degree of investibility is positively related to the extent of foreign institutional investors' trading, our result that highly investable portfolio shows higher serial correlation than non-investable portfolio is consistent with Sias and Starks (1997).

As pointed out by Chordia and Swaminathan (2000), we recognize that the autocorrelations by themselves cannot provide unambiguous inferences on the differences in the speed of adjustment of stock prices to information shocks. Therefore, we turn to cross-autocorrelations for testing our hypothesis of the lead-lag relations across investibility groups.

3 Empirical Results

3.1 Cross-autocorrelations across investibility

We begin our analysis by first examining the cross-autocorrelation patterns in stock returns across different investibility groups after controlling for size or volume. Panels A and B of Table 3 present, respectively, the one-lag cross-autocorrelations for size/investibility and turnover/investibility portfolio returns. For brevity, we only report the cross-autocorrelations between the two extreme investibility portfolios within each size and volume group. Panel A shows that for each of the size group *i*, the correlation between the lagged highly-investable portfolio returns ($R_{i2,t-1}$) and the current non-investable portfolio returns ($R_{i0,t}$) is much larger than the correlation between lagged non-investable portfolio returns ($R_{i0,t-1}$) and the current highly-investable portfolio returns ($R_{i2,t}$), where *i*=0, 1, 2 represents small, medium, and large size group, respectively. For example, in the smallest size group, the correlation between lagged highly-investable portfolio returns ($R_{02,t-1}$) and the current non-investable portfolio returns ($R_{00,t}$) is 0.17, while the correlation between the lagged non-investable portfolio returns ($R_{00,t-1}$) and the current highly-investable portfolio returns ($R_{02,t}$) is only 0.04. A similar pattern holds in Panel B for the cross-autocorrelation coefficients between lagged highly-investable portfolio returns and current non-investable portfolio returns in each turnover group. Furthermore, it is important to note that the lead-lag relation observed in Table 3 cannot be solely driven by nonsynchronous trading given that they are also present in the smallest-size and the lowest turnover groups.

In summary, Table 3 presents preliminary evidence that is consistent with the hypothesis that returns on highly-investable stocks lead returns on non-investable stocks. However, we cannot rule out the alternative hypothesis that the pattern we observe in cross-autocorrelations across investibility portfolios is simply a manifestation of a high contemporaneous correlation between highly-investable and non-investable portfolios, coupled with autocorrelations for non-investable portfolios. Under this time-varying expected returns hypothesis, a lead-lag pattern could arise because lagged highly-investable portfolio returns proxy for lagged non-investable stock returns.[6] We address this concern and formally test for the lead-lag relation of stock returns across investibility groups using bivariate Vector Autoregression (VAR), which we present next.

3.2 VAR tests of the lead-lag effect

In this section, we use VAR to formally test our first hypothesis that the degree of accessibility is an important determinant of the cross-autocorrelation pattern in stock returns in emerging markets. Our goal is to assess whether lagged returns on portfolios of highly-investable stocks lead current returns on portfolios of non-investable stocks. A problem we have to deal with is to explicitly control for firm size and stock turnover. This is because both firm size and turnover have been shown to be important determinants of the lead-lag pattern in stock returns and investable stocks tend to be larger in size and more actively traded.

One way to address this concern is to conduct independent sorts by size (volume) and partition stocks into size/investibility (turnover/investibility) portfolios. There are two problems with this approach. First, as we pointed out in Table 2, our independent sorting procedure helps us 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) to employ a two-stage methodology. We first construct returns on

[6]See 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.

investibility portfolios that are net of the effects of firm size, turnover, and some other factors (such as industry and country), and then use these portfolio returns in vector autoregressions to test for the lead-lag relation across investibility groups.

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

$$r_{it} = \beta_{0t} + \sum_{j=0}^{j=2} \beta_{1jt} I_{ij} + \sum_{j=0}^{j=2} \beta_{2jt} size_{ij} + \sum_{j=0}^{j=2} \beta_{3jt} turnover_{ij} + \sum_{j=0}^{j=10} \beta_{4jt} industry_{ij} + \sum_{j=1}^{j=31} \beta_{5jt} country_{ij} + \varepsilon_{it} \quad (1)$$

where r_{it} represents returns on stock i at week t, I_{ij} represents an indicator variable that takes a value of one if stock i is in investibility portfolio j, and zero otherwise. $size_{ij}$ and $turnover_{ij}$ are also indicator variables, defined similarly for the corresponding size and turnover portfolios 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 of portfolio categories to be zero. This allows us to interpret each estimated coefficient as the equal-weighted return on the relevant portfolio group. In particular, we use the estimated intercept and the coefficient on the investibility indicator variable I_j to construct weekly returns on investibility portfolio j. In other words, let R_{jt} denotes the weekly return on investibility portfolio j at time t that is net of size, turnover, industry and country effects, then,

$$R_{jt} = \beta_0 + \beta_{1j,t} \quad for \quad j = 0,1,2. \quad (2)$$

Having constructed the returns on each of the investibility portfolio in this way, we then test for the lead-lag relation between non-investable and highly-investable portfolio returns. Specifically, we estimate the following bivariate vector autoregression:

$$R_{0,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0,t-k} + \sum_{k=1}^{k=K} b_k R_{2,t-k} + u_t \quad (3)$$

$$R_{2,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{0,t-k} + \sum_{k=1}^{k=K} d_k R_{2,t-k} + v_t \tag{4}$$

where $R_{0,t}$ represents the non-investable portfolio returns, and $R_{2,t}$ represents the highly-investable portfolio returns at week t as constructed in equation (2). Using this bivariate system, we test whether the returns on lagged highly-investable portfolio in equation (3) have significant explanatory power in predicting the current returns on the non-investable portfolio, after controlling for lagged non-investable portfolio returns. In addition, we examine whether there is any asymmetry in the cross-autocorrelation between highly-investable and non-investable portfolios by testing the hypothesis $\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k = 0$.

We estimate the VAR specified in equations (3) and (4) using weekly returns up to four lags, K=4. Panel A of Table 4 summarizes the estimation results. The first two rows report the estimated coefficients and P-values for the equation of non-investable portfolio returns, and the next two rows report those for the equation of highly-investable portfolio returns. The first two columns report the coefficient of the one-lag returns and the sum of the coefficients of the first four lagged returns on the non-investable portfolio. The next two columns show the coefficient of the one-lag returns and the sum of the coefficients of the first four lagged returns on the highly-investable portfolio. Panel A indicates that lagged highly-investable portfolio returns predict current non-investable portfolio returns. The coefficient on the one-lag highly-investable portfolio returns is 0.100, and is significant at the five percent level. The sum of the coefficients of the first four lagged returns on highly-investable portfolio is 0.377 and is significant at the one percent level, suggesting that the lead-lag relation extends beyond the one-week horizon. In contrast, we do not find any evidence that lagged returns on non-investable portfolio have any predictive power for the current returns on highly-investable portfolio at one lag or more.

We now formally test whether the ability of lagged highly-investable portfolio returns to predict current non-investable portfolio returns is greater than the ability of lagged non-investable portfolio returns to predict current highly-investable portfolio returns by testing the cross-equation restriction that $\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k = 0$. The last two columns present these tests, where we report the difference in the estimated coefficients, together with the associated p-values. We find that $\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$ is positive and significant, rejecting the hypothesis that the sum of the coefficients is equal across the two equations. We thus conclude that highly-investable portfolio returns lead non-investable portfolio returns.

We next examine the lead-lag relation between the partially-investable portfolio returns and the highly-investable portfolios returns. We replace the non-investable portfolio returns in equations (3) and (4) with returns on partially-investable portfolios and re-estimate the VAR to test this time for the lead-lag relation between partially-investable and highly-investable portfolio returns.

Panel B of Table 4 presents the estimation results. The first two rows report the estimated coefficients and P-values for the partially-investable portfolio returns equation, and the next two rows show the estimated coefficients and P-values for the highly-investable portfolio returns equation. We find strong evidence that lagged highly-investable portfolio returns predict current returns on the partially-investable portfolio. The coefficient on the lagged highly-investable portfolio return in the first row is 0.148 and is significant at 5% level. The sum of the coefficients on the four lags of highly-investable portfolio returns is 0.451 and is significant at one percent level. Similarly to Panel A, we do not find any evidence that would suggest that lagged returns on partially-investable portfolio predict highly-investable portfolio returns. Finally, the cross-equation test confirms that highly-investable portfolio returns lead partially-investable portfolio returns, but not vice versa.

Panel C of Table 4 presents the test results of lead-lag relation between non-investable and partially-investable portfolios. Here the lead-lag relation is not as pronounced as that in Panels A and B of Table 4. Although the magnitude of lagged coefficient estimates on the partially-investable portfolio is larger than that on the non-investable portfolio, the cross-equation tests fail to reject the null hypothesis that the coefficient estimates on lagged partially- and non-investable portfolios are equal, whether one uses the lag one or four in the estimation the VAR. There appears to be no strong lead-lad relation between partially-investable and non-investable portfolios. This result suggests that for the investibility effect to affect lead-lag relation, the degree of investibility has to be beyond a certain threshold.

The two-stage approach to examine the lead-lag relation among different investable portfolios has the advantage of controlling for several determinants that may affect lead-lag relation at the same time to sort out the effect of investibility. The disadvantage of the approach is that one has to assume that common information is spilled over across different markets. This assumption is not unrealistic given increasingly globalized stock markets. Nevertheless, for completeness, we also conduct VAR tests using the weekly returns on the nine size/investibility (turnover/investibility) portfolios that we construct by partitioning stocks *in each stock market* by the degree of investibility and size (turnover). As we noted earlier, however, 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 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 portfolio in each market, we estimate the VAR specified in equations (3) and (4) jointly across all markets for each size (turnover) group.

Panel A of Table 5 presents the VAR results for each size group. The first two rows in each size group are associated with the non-investable portfolio return equation and the next two rows present the results for the highly-investable portfolio return equation. Panel A provides strong evidence that the lagged returns on the highly-investable portfolio predict the current returns on the non-investable portfolio in each size group. The estimated coefficients on the lagged highly-investable portfolio returns range from 0.115 to 0.155, and all of them are significant at the one-percent level. Similarly, the sum of coefficient estimates of the first four lagged returns on the highly-investable portfolio is between 0.272 and 0.376, all significant at the one-percent level. Interestingly, the estimated coefficients on the lagged non-investable portfolio returns for the highly- investable portfolio return equation of each size group are positive and significant, suggesting some ability for lagged non-investable portfolio returns to predict current returns on highly-investable portfolios. However, the magnitude of the individual coefficients is economically much smaller, ranging from only 0.039 to 0.047. Furthermore, there is no predictive ability at longer horizons, as the sum of the coefficients on the four lags is not significant at conventional levels. Finally, the cross-equation tests reported in third last column confirm that the difference between the sum of the coefficients $\sum_{k=1}^{K} b_k$ and $\sum_{k=1}^{K} c_k$ is positive and significant for each size group. We conclude that holding size constant, returns on portfolios of highly-investable stocks lead those on portfolios of non-investable stocks.

We present in Panel B the corresponding VAR results for each turnover group. Overall, the results are similar to those in Panel A. We find that holding turnover constant, lagged returns on the highly-investable portfolios strongly predict current returns on the non-investable portfolios. The predictive power of past highly-investable portfolio returns remains significant beyond the one-week horizon. Except for the lowest-turnover group, the ability of lagged non-investable portfolio returns to predict current highly-investable portfolio returns is limited to one week and is economically insignificant compared to that of lagged highly-investable portfolio returns. The cross-equation test confirms that highly-investable portfolio returns lead non-investable portfolio returns, but not vice versa.

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 problem will not be as serious a problem as with daily return data. Nevertheless, to examine whether our results are driven by non-trading problem, we replicate panel B replacing turnover measure with zero-return measure used in Bekaert, Harvey, and Lundblad (2007). Bekaery, Havery, and Lundblad (2007) and Lesmond (2005) argue that in emerging markets, the proportion of zero daily returns might better capture illiquidity than turnover and is correlated with 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 form nine zero-return/investibility portfolios in each market and estimate the VARs. While not reported, we find that holding zero-return measure constant, lagged returns on the highly-investable portfolios strongly predict current returns on the non-investable portfolios, suggesting that our results are not driven by non-trading problem.

We also examine the lead-lag relation between highly investable portfolio and partially investable portfolio. We check this relationship because we noted in Table 2 that for each size (turnover) group, the partially-investable stocks are on average larger and more actively traded than the highly-investable stocks.

Therefore, if our results are driven by size or turnover and not by investibility, we should find that returns on partially-investable stock portfolios lead those on highly-investable stock portfolios and not vice versa. Panel C of Table 5 presents the results of VAR tests for the lead-lag relation between highly investable portfolio and partially investable portfolio controlling for size. The results show no evidence that partially investable portfolio leads highly investable portfolio. If anything, the evidence indicates that highly investable portfolio leads partially investable portfolio for medium- and large-size groups of stocks. Panel D of Table 5 presents the results of VAR tests for the lead-lag relation between highly investable portfolio and partially investable portfolio controlling for turnover. Again, we find no evidence that partially investable portfolio leads highly investable portfolio. Instead, we find strong evidence that highly investable portfolio leads partially investable portfolio for medium and high turnover groups of stocks.

In summary, the VAR tests in two different approaches covered in this section provide strong evidence that returns on highly-investable portfolios lead non-investable portfolio returns, even after controlling for size and turnover. Our results suggest that the degree of accessibility has an important influence on the cross-autocorrelation of stock returns. In the next section, we explore possible explanations for this lead-lag relation and assess whether slow diffusion of information due to the frictions caused by restricted foreign equity ownership is the source of this lead-lag relation we observe across the investibility groups.

4 Why do highly-investable stocks lead non-investable stocks?

In the previous sections, we document that returns on highly-investable stocks lead returns on non-investable stocks. In this section, we investigate possible explanations for this lead-lag relation across highly-investable and non-investable stock returns.

4.1 Analyst following and the lead-lag relation

Brennan, Jegadeesh, and Swaminathan (1993) find that firms that are followed by many analysts tend to lead those that are followed by fewer analysts. Since highly-investable stocks are more likely to attract analyst coverage, we would expect a positive association between the amount of analyst coverage a firm receives and the degree of its accessibility to foreigners. This being the case, the lead-lag relation could simply be a manifestation of the analyst following effect.

To investigate this possibility, we obtain data on analyst coverage for each firm from I/B/E/S and merge this data with our subsample of firms in markets that have at least fifty stocks on average over the sample period. In each year for each market, we compute the median number of analysts following and partition our sample stocks into two groups based on the yearly median number of analysts. 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 for each market according to the investibility and the analyst coverage groups. We then conduct VAR tests specified in equations (3) and (4) to test for the lead-lag relation using the equally-weighted weekly returns on these six analyst-coverage/investibility portfolios.

Equations (3) and (4) are estimated jointly across all markets for each coverage group. Table 6 presents the VAR results. The first set of 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. The evidence in Table 6 indicates that for each coverage group, lagged returns on the highly-investable portfolio strongly predict current returns on the non-investable portfolio. We note, however, that the lead-lag relation is stronger for stocks with high analyst coverage than for those with low coverage. The presence of a significant lead-lag relation even for those stocks with fewer analysts 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 non-investable portfolio returns to predict current highly-investable portfolio returns in either low or high analyst coverage groups.

In summary, our investigation of the analyst coverage effect in driving the lead-lag relation between highly-investable and non-investable portfolio returns suggests that although analyst coverage strengthens the lead-lag relation, it does not fully explain it.

4.2 Intra- and inter-industry effects on the the lead-lag relation

In a recent paper Hou (2007) argues that the slow diffusion of common information is more relevant across firms within the same industry group and finds that the lead-lag effect previously documented in the literature is predominantly an intra-industry phenomenon. 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 the lead-lag relation we uncover across highly-investable and non-investable portfolio returns may just be an intra-industry effect. It is plausible that highly-investable stocks in a given market may very well be the leaders in their respective industries, and that returns of other stocks in the same industry follow the industry leader returns due to slow diffusion of common information within the industry.

To investigate this possibility, we use the ten 2-digit industry classifications provided by the EMDB and partition stocks in each industry *j* into three investibility portfolios for each of our subsample markets that have more than 50 stocks on average over the sample period. If the lead-lag relation is indeed purely an intra-industry leader-follower phenomenon, we should expect that the lagged returns on highly-investable stocks from the same industry *j* be more important than those from all the other industries in predicting current returns on non-investable stocks of industry *j*. We modify the VAR specified in equations (3) and (4) to include the lagged returns on the highly-investable stocks from all industries other than industry *j* as an additional variable to predict the current returns on non-investable stocks in industry *j*. Specifically, we estimate the following VAR jointly across all industries and all markets:

$$R_{0j,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0j,t-k} + \sum_{k=1}^{k=K} b_k R_{2j,t-k} + \sum_{k=1}^{k=K} f_k R_{2j',t-k,j'\neq j} + u_t \tag{5}$$

$$R_{2j,t} = c_0 + \sum_{k=1}^{k=K} c_k R_{0j,t-k} + \sum_{k=1}^{k=K} d_k R_{2j,t-k} + v_t \tag{6}$$

where $R_{0j,t}$ represents the equal-weighted weekly returns on the portfolio of non-investable stocks in industry *j*, $R_{2j,t}$ represents the equal-weighted weekly returns on the portfolio of highly-investable stocks in industry *j*, and $R_{2j',t-k,j'\neq j}$ is the lag-*k* equal-weighted weekly returns on the portfolio of highly-investable stocks in all other nine industries $j' \neq j$. We formally test the null hypothesis that the lead-lag relation across non-investable and highly-investable portfolio returns is due to pure intra-industry effects. That is, $\sum_{k=1}^{K} f_k = 0$ and $\sum_{k=1}^{K} f_k - \sum_{k=1}^{K} b_k < 0$.

Table 7 presents the estimation results for the VAR specified in equations (5) and (6). Consistent with Hou (2007), there is evidence of an intra-industry effect where lagged returns on the portfolio of highly-investable stocks predict the current returns on the portfolio of non-investable stocks in the same industry. However, we reject the hypothesis that the lead-lag relation is purely an intra-industry phenomenon. We find that the lagged returns on the portfolio of highly-investable stocks in other industries are also important in predicting current returns on the portfolio of non-investable stocks in a particular industry. This suggests that the predictive ability of highly-investable stocks does not solely derive from common industry effects, but extends across industries. Furthermore, the cross-equation test rejects the hypothesis that the ability of highly-investable stocks in other industries is less than that of the highly-investable stocks in own industry.

In conclusion, the evidence in Table 7 indicates that there are important inter-industry effects in the lead-lag relation across highly-investable and non-investable portfolio returns and that the effect of investibility on the cross-correlations in stock returns extends beyond the intra-industry leader-follower relation.

4.3 Speed of price adjustment and the lead-lag relation

In this section, we assess whether the lead-lag relation we identify across the investibility groups is due to slow diffusion of common information across stocks. Our hypothesis is that stocks that have greater investibility to foreign investors adjust faster to market-wide information than those with less investibility. We argue that greater investibility improves the process of information incorporation into stock prices in these markets. To formally test this hypothesis, we first measure the delay with which a firm’s stock price responds to market-wide information, and then test whether there is a negative relationship between our delay measures and the degree of investibility.

We employ two measures to capture the average delay with which stock prices respond to market-wide information. We consider the market return as the relevant source of news to which stocks respond to and construct our delay measures with respect to either the world market returns or the pure local market returns that is net of the impact of world market returns. In each year, we run the following regression for each stock with at least fifteen weekly observations per year:

$$r_{i,t} = \alpha + \sum_{k=0}^{k=4} \delta_{i,k} r_{m,t-k} + \varepsilon_{i,t} \tag{7}$$

where $r_{i,t}$ denotes returns for stock *i* at week *t*, $r_{m,t-k}$ is the *k*th lag of the relevant market return at week *t*, for *k*=0, 1, 2, 3, 4. If the price of stock *i* responds immediately to market news, the coefficient on the contemporaneous market returns would be significantly different from zero, whereas none of the coefficients on the lagged market returns would differ from zero. On the other hand, if stock *i* responds with a delay, we would expect some of the coefficients on the lagged market returns to be significantly different from zero. Using the estimated coefficients from these regressions, we follow Hou and Moskowitz (2005) and construct our first delay measure $delay1$ as the fraction of the variation in individual stock returns that is explained by lagged market returns. It is computed as one minus the ratio of the R_r^2 obtained from restricting the coefficients of lagged market returns to be zero to the R^2 without such restrictions:

$$delay1 = 1 - \frac{R_r^2}{R^2} \tag{8}$$

We estimate the equation (8), first using the world market returns, and then using the residual local market returns[7], and construct the delay measures with respect to each type of market information. Larger values of $delay1$ indicate that greater return variation is captured by lagged market returns and thus suggest greater delay in the response of stock returns to market-wide news.

[7] 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.

Our second delay measure is motivated by McQueen, Pinegar and Thorley (1996) and is constructed from the coefficients estimated in equation (7) as[8]:

$$delay2 = \frac{1}{(1+e^{-x})}, \qquad \text{where } x = \frac{\sum_{k=1}^{K=4} |\delta_{j,k}|}{\delta_{j,0}} \tag{9}$$

If the prices of more investable stocks adjust faster to market-wide information, they should respond faster to all types of market information, whether it is local or world market. We would expect, however, that more investable stocks that are more open to foreign investors to have even greater sensitivity to world market information. We test these hypotheses by regressing the delay measures estimated for each stock in each year on the degree of investibility and a number of control variables.[9]

$$delay_{i,t} = \alpha_0 + \beta investable_{i,t} + \gamma_1 analyst_{i,t} + \gamma_2 size_{i,t} + \gamma_3 turnover_{i,t} + \gamma_4 volatility_{i,t} + \varepsilon_{i,t} \tag{10}$$

where *i* stands for firm and *t* for year. The investable weight and all the control variables are their average values during each of the sample years. $delay_{i,t}$ is the estimated delay measure, $delay1$ or $delay2$, for stock *i* with respect to the world or residual local market returns, $investable_{i,t}$ is the investable weight for stock *i*, $analyst_{i,t}$ is the number of analysts following stock *i*, $size_{i,t}$ is stock *i*'s market capitalization, $turnover_{i,t}$ is the number of shares traded scaled by the number of shares outstanding, and $volatility_{i,t}$ is the standard deviation of the weekly returns for stock *i*. 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. If the degree of investibility improves the process of information incorporation into prices in a

[8]Unlike 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).

[9] 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 (10). Our results are unchanged. Our results do not change if we also control for country and industry fixed effects in equation (10). Our results still hold if we replace the continuous measure of the investibility with three dummies indicating respectively non-, partially- and highly- investable stocks.

way that is not captured by these firm characteristics, we would expect a negative relationship between our delay measures and investibility. That is, $\beta < 0$.

We estimate equation (10) using pooled OLS regression and we adjust the standard errors for clustering at the country level. Table 8 presents the estimation results. Panel A reports the estimated coefficients for the two delay measures with respect to the world market information. We find that higher investibility is associated with smaller price delay. The coefficient estimate of *investable* is -0.147 for *delay1* and -0.058 for *delay2*, both significant at the one percent level. While the coefficient estimates on size, and analyst coverage are also significantly negative, they are smaller in magnitude, lending further support to our hypothesis that investibility has important influence on the speed of stock price adjustment to market information.

Panel A shows that more investable stocks adjust faster to common world market information. In Panel B, we test whether investibility also improves the speed of adjustment for local market news. Again, we find a negative and significant relationship between investibility and our two delay measures with respect to pure local market information. The magnitude of the coefficient estimate of *investable* is smaller: -0.138 for *delay1* and -0.050 for *dela2*. In unreported tests, we test for the equality of the effect of investibility on the delay measures with respect to local vs. world market information and reject the null hypothesis that the coefficients are equal across Panel A and Panel B for both $delay1$ and $delay2$. This suggests that more investable stocks might have even greater sensitivity to world market news.[10]

In summary, Table 8 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 the returns on more investable stocks respond faster to both world market and local market-wide information than the returns on less-investable stocks. Moreover, stocks that are more open to foreign investors have greater sensitivity to world market information than to local market information. We

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

conclude that the lead-lag effect we have documented across portfolio returns of highly-investable stocks and those of non-investable stocks is most consistent with a slower adjustment of stock prices of the latter to common market-wide information.

5 Conclusions

In this paper, we examine a distinct institutional feature of emerging stock markets to investigate the economic significance of the slow information diffusion hypothesis as the leading cause of the lead-lag cross-autocorrelation relation in stock returns. Using the degree of investibility as a proxy to measure of the severity of the segmentation affecting a stock in local markets, we assess whether investibility has a significant influence on the cross-autocorrelations of stocks, and whether this is due to the slow diffusion of common information across stocks.

We find that the degree of foreign investor participation is a significant determinant of the lead-lag cross-autocorrelation patterns in stock returns. Portfolio returns on highly-investable stocks lead those on non-investable stocks, but not vice versa. Moreover, this lead-lag 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 across the investibility groups is not purely an intra-industry effect. Portfolio returns on highly-investable stocks in all the industries other than a particular industry also lead portfolio returns on non-investable stocks from this particular industry, even after controlling for the intra-industry highly investable stock returns.

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 investable stocks respond faster to the world market information as well as to the local market information than the prices of less investable stocks. We interpret these results as providing additional support for the slow information diffusion hypothesis with regard to 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 may yield more informationally efficient stock prices in emerging markets.

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Table 1 Descriptive statistics by country

Table 1 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 provides information regarding the investibility of each stock. It 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 investable weight ranges from zero to one. A stock with zero investable weight is non-investable and a stock with an investable weight of one is fully-investable . For each country, Table 1 presents number of stocks, investable weight, return, volatility, firm size, and turnover. 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 cap 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	Investable 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 2 Summary statistics and auto-correlations by portfolios

For each stock in each year, we compute the average monthly investable weight and sort sample stocks into three investibility groups: non-investable (denoted by 0) if the investable weight is zero, partially-investable (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investable if the investable weight is greater than 0.5. In addition, for each country in each year, we independently sort stocks into three size groups and three turnover groups based on yearly average market capitalization and turnover, respectively. Panels A and B present, respectively, the summary statistics and the autocorrelations associated with each of the nine size/investibility and turnover/investibility portfolios. Portfolio P_{ij} indicates stocks in size (turnover) i and investable group j. $i = 0$ refers to the smallest size or lowest turnover portfolio, and $i = 2$ refers to the largest size or highest turnover portfolio. ρ_1 denotes the first order autocorrelation and $\sum\rho_{t-k}$ is the sum of the first four lag autocorrelations. For each portfolio, we report the equally-weighted size, investable weight, weekly returns and volatility, and turnover.

Panel A Portfolios sorted by size and investable weight

Portfolios (P_{ij})	Market cap (US$ million)	Turnover	Investable	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^{4}\rho_{t-k}$
P_{00}	48	0.06	0.00	0.10	8.25	0.19	0.59
P_{01}	140	0.19	0.29	-0.50	8.44	0.07	0.31
P_{02}	131	0.11	0.95	-0.12	8.21	0.11	0.48
P_{10}	162	0.05	0.00	0.24	6.78	0.10	0.25
P_{11}	365	0.12	0.28	-0.18	7.61	0.11	0.45
P_{12}	349	0.07	0.93	0.16	7.68	0.09	0.49
P_{20}	813	0.04	0.00	0.29	6.64	0.08	0.24
P_{21}	2,021	0.07	0.29	0.14	6.64	0.12	0.44
P_{22}	1,607	0.06	0.92	0.31	6.94	0.08	0.48

Panel B Portfolios sorted by turnover and investable

Portfolios (P_{ij})	Market cap (US$ million)	Turnover	Investable	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^{4}\rho_{t-k}$
P_{00}	357	0.01	0.00	0.04	6.87	0.21	0.66
P_{01}	1,662	0.03	0.27	-0.20	6.35	0.05	0.46
P_{02}	935	0.02	0.93	0.06	6.39	0.08	0.42
P_{10}	181	0.04	0.00	0.16	7.41	0.14	0.36
P_{11}	916	0.07	0.29	-0.08	7.14	0.11	0.46

P_{12}	773	0.05	0.93	0.12	7.35	0.06	0.46
P_{20}	130	0.13	0.00	0.40	8.28	0.07	0.21
P_{21}	641	0.24	0.28	-0.03	8.34	0.17	0.48
P_{22}	611	0.14	0.94	0.18	8.43	0.11	0.50

Table 3 Cross-Autocorrelations after controlling for size and turnover

Table 3 reports the one-lag cross-autocorrelations between highly-investable portfolio returns and non-investable portfolio returns within each size or turnover group. Each year we assign sample stocks into three investibility groups based on their average investable weight: non-investable (denoted by 0) if the investable weight is zero, partially-investable (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investable if the investable weight is greater than 0.5. In addition, for each country in each year, we independently sort stocks into three size groups or three turnover groups based on yearly average market cap or turnover, respectively. Panels A and B present, respectively, the one-lag cross-autocorrelations between the highly-investable portfolio returns and non-investable portfolio returns within each size or turnover group. $R_{ij,t}$ represents the equal-weighted return on the portfolio of size i and investable group j at week t. i = 0 refers to the smallest size or lowest turnover portfolio, and i = 2 refers to the largest size or highest turnover portfolio.

Panel A Portfolios sorted by size and investibility

Size/investable	$R_{00,t}$	$R_{02,t}$	$R_{10,t}$	$R_{12,t}$	$R_{20,t}$	$R_{22,t}$
$R_{00,t-1}$	0.19	**0.04**	0.17	0.07	0.11	0.07
$R_{02,t-1}$	**0.17**	0.11	0.14	0.07	0.08	0.04
$R_{10,t-1}$	0.12	0.04	0.10	**0.03**	0.10	0.04
$R_{12,t-1}$	0.22	0.11	**0.18**	0.09	0.11	0.07
$R_{20,t-1}$	0.08	0.06	0.06	0.03	0.08	**0.04**
$R_{22,t-1}$	0.21	0.10	0.21	0.10	**0.14**	0.08

Panel B Portfolios sorted by turnover and investibility

Turnover/investable	$R_{00,t}$	$R_{02,t}$	$R_{10,t}$	$R_{12,t}$	$R_{20,t}$	$R_{22,t}$
$R_{00,t-1}$	0.21	**0.08**	0.17	0.08	0.13	0.08
$R_{02,t-1}$	**0.20**	0.08	0.18	0.09	0.15	0.13
$R_{10,t-1}$	0.17	0.05	0.14	**0.04**	0.10	0.05
$R_{12,t-1}$	0.22	0.07	**0.20**	0.06	0.15	0.11
$R_{20,t-1}$	0.13	0.03	0.09	0.04	0.07	**0.03**
$R_{22,t-1}$	0.20	0.06	0.20	0.06	**0.15**	0.11

Table 4 Lead-lag relation among non-, partially-, and highly- investable stock returns

Table 4 presents the lead-lag relation across non-investable , partially-investable and highly investable portfolio returns. We first construct weekly returns on investibility portfolios that are net of firm size, turnover, industry and country effects by running the cross-sectional regression in equation (1) in the text, and use the estimated coefficients to compute the weekly return $R_{j\,t}$ on investibility portfolio j at week t as in equation (2) in the text. We then estimate the following VAR:

$$R_{0,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0,t-k} + \sum_{k=1}^{k=K} b_k R_{2,t-k} + u_t$$

$$R_{2,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{0,t-k} + \sum_{k=1}^{k=K} d_k R_{2,t-k} + v_t$$

where $R_{0,t}$ and $R_{2,t}$ are, respectively, the week t returns on the non-investable and highly-investable portfolios as measured in equation (2) in the text. Panel A presents the VAR results. Panel B presents the VAR results for the partially-investable and highly-investable portfolio returns, while Panel C presents the VAR results for the non-investable and partially-investable portfolio returns. The cross-equation null hypothesis is $\sum b_k = \sum c_k$. P values are in parentheses.

Panel A: Lead-lag relation between non- and highly- investable portfolio returns

	Lags of non-investable portfolio returns		Lags of highly-investable portfolio returns		Cross-equation tests	
Dependent	$R_{0,t-1}$	$\sum_{k=1}^{4} R_{0,t-k}$	$R_{2,t-1}$	$\sum_{k=1}^{4} R_{2,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$
$R_{0,t}$	0.013	0.066	**0.100**	**0.377**	0.054	0.366
	(0.81)	(0.57)	**(0.03)**	**(0.00)**	(0.49)	(0.02)
$R_{2,t}$	**0.046**	**0.011**	0.064	0.450		
	(0.46)	**(0.93)**	(0.24)	(0.00)		

Panel B: Lead-lag relation between partially- and highly- investable portfolio returns

	Lags of partially-investable portfolio returns		Lags of highly-investable portfolio returns		Cross-equation tests	
Dependent	$R_{1,t-1}$	$\sum_{k=1}^{4} R_{1,t-k}$	$R_{2,t-1}$	$\sum_{k=1}^{4} R_{2,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$
$R_{1,t}$	-0.006	-0.008	**0.148**	**0.451**	0.145	0.360
	(0.93)	(0.95)	**(0.02)**	**(0.00)**	(0.10)	(0.04)
$R_{2,t}$	**0.003**	**0.091**	0.096	0.386		
	(0.96)	**(0.44)**	(0.12)	(0.00)		

Panel C: Lead-lag relation between non- and partially- investable portfolio returns

	Lags of non-investable portfolio returns		Lags of partially-investable portfolio returns		Cross-equation tests	
Dependent	$R_{0,t-1}$	$\sum_{k=1}^{4} R_{0,t-k}$	$R_{1,t-1}$	$\sum_{k=1}^{4} R_{1,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$
$R_{0,t}$	0.068	0.218	**0.051**	**0.218**	0.036	0.152
	(0.29)	(0.07)	**(0.37)**	**(0.03)**	(0.70)	(0.37)
$R_{1,t}$	**0.015**	**0.066**	0.116	0.345		
	(0.83)	**(0.64)**	(0.07)	(0.01)		

Table 5 VAR for the portfolio returns formed by country

Table 5 presents the VAR estimation results, using the equally-weighted weekly returns on size/investibility and turnover/investibility portfolios constructed by partitioning stocks by the degree of investibility and size or turnover in each country in each year. 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-investable (denoted by 0) if the investable weight is zero, partially-investable (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investable if the investable weight is greater than 0.5. In addition, for each country we independently sort stocks into three size groups or three turnover groups based on yearly average market cap or turnover, respectively. We then compute the equally-weighted return $R_{2,t}$ on each highly-investable portfolio, and the equally-weighted return $R_{0,t}$ on each non-investable portfolio in each size (turnover) group. Finally we estimate the following VAR jointly across all the 12 markets:

$$R_{0,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0,t-k} + \sum_{k=1}^{k=K} b_k R_{2,t-k} + u_t$$

$$R_{2,t} = c_0 + \sum_{k=1}^{k=K} c_k R_{0,t-k} + \sum_{k=1}^{k=K} d_k R_{2,t-k} + v_t$$

where $R_{0,t}$ and $R_{2,t}$ are, respectively, the week t return on the non- and highly- investable portfolio. Panel A and B report the VAR estimation for the size/investibility and turnover/investibility portfolios, respectively. The cross-equation null hypothesis is b_1-c_1=0 and $\sum b_k$-$\sum c_k$ =0. P values are in parentheses.

Panel A: Lead-lag relation between non-investable and highly-investable portfolio returns, controlling for size

		Non-investable returns		Highly-investable returns		Cross-equation tests			
Size	Dependent	$R_{0,t-1}$	$\sum_{k=1}^{4} R_{0,t-k}$	$R_{2,t-1}$	$\sum_{k=1}^{4} R_{2,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$	*Adj R²*	No. obs
Small	$R_{0,t}$	-0.063	0.000	**0.115**	**0.272**	0.068	0.152	0.031	3,766
		(0.00)	(1.00)	**(0.00)**	**(0.00)**	(0.02)	(0.01)		
	$R_{2,t}$	**0.047**	**0.120**	0.049	0.126			0.024	3,766
		(0.02)	**(0.10)**	(0.02)	(0.11)				
Medium	$R_{0,t}$	0.013	-0.102	**0.145**	**0.376**	0.102	0.346	0.035	3,587
		(0.51)	(0.25)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	$R_{2,t}$	**0.043**	**0.030**	0.062	0.211			0.019	3,587
		(0.01)	**(0.51)**	(0.00)	(0.00)				
Large	$R_{0,t}$	0.004	0.010	**0.155**	**0.277**	0.116	0.270	0.023	3,102
		(0.83)	(0.89)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	$R_{2,t}$	**0.039**	**0.007**	0.040	0.194			0.013	3,102
		(0.03)	**(0.88)**	(0.05)	(0.00)				

Panel B: Lead-lag relation between non-investable and highly-investable portfolio returns, controlling for turnover

		Non-investable returns		Highly-investable returns		Cross-equation tests		Adj R^2	No. obs
Turnover	Dependent	$R_{0,t-1}$	$\sum_{k=1}^{4} R_{0,t-k}$	$R_{2,t-1}$	$\sum_{k=1}^{4} R_{2,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$		
Low	$R_{0,t}$	-0.029	0.120	**0.120**	**0.189**	0.089	0.096	0.023	3,850
		(0.11)	(0.06)	**(0.00)**	**(0.00)**	(0.00)	(0.06)		
	$R_{2,t}$	**0.032**	**0.092**	0.068	0.139			0.015	3,850
		(0.03)	**(0.05)**	(0.00)	(0.01)				
Medium	$R_{0,t}$	-0.008	-0.049	**0.192**	**0.462**	0.158	0.436	0.039	3,480
		(0.62)	(0.54)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	$R_{2,t}$	**0.037**	**0.036**	0.056	0.218			0.022	3,480
		(0.02)	**(0.35)**	(0.01)	(0.00)				
High	$R_{0,t}$	-0.030	-0.048	**0.096**	**0.288**	0.105	0.298	0.017	3,784
		(0.14)	(0.42)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	$R_{2,t}$	**-0.010**	**-0.012**	0.071	0.211			0.015	3,784
		(0.57)	**(0.84)**	(0.00)	(0.00)				

Panel C: Lead-lag relation between partially-investable and highly-investable portfolio returns, controlling for size

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

Panel D: Lead-lag relation between partially-investable and highly-investable portfolio returns, controlling for turnover

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

Table 6 VAR controlling for analyst following

Table 6 presents the lead-lag relation between non-investable and highly-investable portfolio returns after controlling for analyst following. We obtain data on analyst coverage for from I/B/E/S, and merge with our subsample of stocks in markets with at least fifty stocks on average during 1989 to 2003. For each market, we construct six portfolios by sorting stocks by investable weight and the number of analysts following each sample stock. Stocks are assigned into three investibility groups: non-investable (denoted by 0) if the investable weight is zero, partially-investable (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investable if the investable weight is greater than 0.5. In addition, for each market in each year, we sort stocks into two groups based on the median number of analysts following. Stocks in each market with more analysts than the median analyst from that market are assigned into a high-coverage group, and all stocks with fewer analysts than the median number 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.

$$R_{0,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0,t-k} + \sum_{k=1}^{k=K} b_k R_{2,t-k} + u_t$$

$$R_{2,t} = a_2 + \sum_{k=1}^{k=K} c_k R_{0,t-k} + \sum_{k=1}^{k=K} d_k R_{2,t-k} + v_t$$

where $R_{0,t}$ and $R_{2,t}$ are, respectively, week t returns on the non- and highly- investable portfolio in each analyst coverage group in each market. The cross-equation null hypothesis is b_1-c_1=0 and $\sum b_k$-$\sum c_k$ =0. P values are in parentheses.

		Non-investable returns		Highly-investable returns		Cross-equation tests		Adj R^2	No. obs
Analyst following	Dependent	$R_{0,t-1}$	$\sum_{k=1}^{4} R_{0,t-k}$	$R_{2,t-1}$	$\sum_{k=1}^{4} R_{2,t-k}$	$b_1 - c_1$	$\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$		
Low	$R_{0,t}$	0.080	0.076	**0.101**	**0.233**	0.080	0.136	0.033	3,208
		(0.00)	(0.31)	**(0.00)**	**(0.00)**	(0.01)	(0.02)		
	$R_{2,t}$	**0.021**	**0.097**	0.135	0.164			0.027	3,208
		(0.29)	**(0.06)**	(0.00)	(0.01)				
High	$R_{0,t}$	-0.078	-0.067	**0.151**	**0.296**	0.115	0.274	0.021	1,657
		(0.01)	(0.39)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	$R_{2,t}$	**0.035**	**0.023**	0.032	0.125			0.003	1,657
		(0.14)	**(0.72)**	(0.26)	(0.08)				

Table 7 Intra-industry and inter-industry effects on the lead-lag relation across the investibility groups

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-investable stocks from other industries $j' \neq j$. For each portfolio, we compute the equal-weighted weekly returns and estimate the following VAR jointly across all industries and markets:

$$R_{0,j,t} = a_0 + \sum_{k=1}^{k=K} a_k R_{0,j,t-k} + \sum_{k=1}^{k=K} b_k R_{2,j,t-k} + \sum_{k=1}^{k=K} f_k R_{2,j'\neq j,t-k} + u_t$$
$$R_{2,j,t} = c_2 + \sum_{k=1}^{k=K} c_k R_{0,j,t-k} + \sum_{k=1}^{k=K} d_k R_{2,j,t-k} + v_t$$

where $R_{0,j,t-k}$, $R_{2,j,t-k}$ and $R_{2,j'\neq j,t-k}$ are weekly return at time t for the non-investable portfolio in industry *j*, highly-investable portfolio in industry *j*, and $R_{2j',t-k,j'\neq j}$ are the lag-*k* equally-weighted returns on the portfolio of highly-investable stocks in all other nine industries in a country. The null hypothesis that the lead-lag relation between non-investable and highly-investable portfolio returns is due to pure intra-industry effects is that $\sum_{k=1}^{K} f_k = 0$ and $\sum_{k=1}^{K} f_k - \sum_{k=1}^{K} b_k < 0$ for *K*=1, 4. P values are reported in parentheses.

	Non-investable in industry *i*		Highly-investable in industry *i*		Highly-investable in other industries		Pure intra-industry effect tests	
Dependent	$R_{0,j,t-1}$	$\sum_{k=1}^{4} R_{0,j,t-k}$	$R_{2,j,t-1}$	$\sum_{k=1}^{4} R_{2,j,t-k}$	$R_{2,j'\neq j,t-1}$	$\sum_{k=1}^{4} R_{2,j'\neq j,t-k}$	$f_1 - b_1$	$\sum_{k=1}^{K} f_k - \sum_{k=1}^{K} b_k$
$R_{0,j,t}$	-0.031	-0.036	0.091	0.187	**0.089**	**0.191**	**-0.002**	**0.002**
	(0.00)	(0.26)	(0.00)	(0.00)	**(0.00)**	**(0.00)**	**(0.95)**	**(0.95)**
$R_{2,j,t}$	0.027	0.052	0.062	0.160				
	(0.00)	(0.01)	(0.00)	(0.00)				

Table 8 Speed of adjustment to world market return

Table 8 presents the estimation results for the following regression:

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

where the dependent variable is one of the delay measures *delay1* and *delay2* constructed for each stock *i* for each year that proxy for the delay with which the stock price on stock *i* responds to market-wide information. *Delay* measures are defined in equations (8) and (9) in the text. In Panel A, *delay1* and *delay2* are measured with respect to the world market returns. In Panel B, *delay1* and *delay2* are measured with respect to pure local market returns. $Investable_{it}$ represents the investable 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 cap, and $turnover_{it}$ is the number of shares traded scaled by the number of shares outstanding. The investable weight and all the control variables in equation (10) are their yearly average values. The standard errors are corrected for clustering at the country-level. p-values are reported in parentheses.

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

Dependent	**investable**	analyst	size	turnover	volatility	intercept
delay1	**-0.147**	-0.029	-0.016	-0.005	-0.004	0.801
	(0.00)	(0.00)	(0.00)	(0.73)	(0.00)	(0.00)
delay2	**-0.058**	-0.012	-0.007	0.003	-0.001	0.836
	(0.00)	(0.00)	(0.00)	(0.68)	(0.12)	(0.00)

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

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