Foreign Equity Ownership Restriction, the Lead-Lag Cross-Autocorrelations and Information Diffusion in Emerging Market Stock Returns*

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Abstract

Using the degree of accessibility in emerging markets, or investibility, as a proxy to measure of the severity of the market frictions affecting a stock in local markets, we assess whether investibility has a significant influence on the cross-autocorrelations of stocks in emerging markets, and whether this is due to the slow diffusion of common information across stocks. We show that returns of portfolios of highly-investable firms lead returns of portfolios of non-investable firms, but not vice versa. Moreover, this lead-lag effect is not driven by other known determinants such as size, trading volume, or analyst coverage and is not a purely intra-industry phenomenon. These patterns arise because stock prices of highly-investable firms adjust faster to market-wide information. We confirm that greater investibility reduces the delay with which individual stock prices respond to the global and local market information. Our findings support the slow information diffusion hypothesis as a cause of the lead–lag effect in stock returns. The results also provide insights as to why financial liberalization in the form of greater investibility might yield more informationally efficient stock prices in emerging markets.

Keywords: lead-lag cross-autocorrelations, information diffusion, investibility, emerging markets. JEL Classification: G12, G14, G15.

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1 Introduction

Understanding how information is transmitted and how it is incorporated into stock prices is of paramount importance in financial economics. 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 that stock prices are sampled nonsynchronously, which induces spurious lead-lag effects (Boudoukh, Richardson and Whitelaw (1994)). However, Lo and MacKinlay (1990b) show that one has to believe in unrealistically thin markets for nonsynchronous trading to account for the magnitude of observed cross-correlations.

Other known determinants of cross-autocorrelations include the number of analyst following, institutional ownership, and trading volume. Brennan, Jegadeesh and Swaminathan (1993) find that returns on firms followed by many analysts tend to lead returns on firms followed by fewer analysts. Badrinath, Kale and Noe (1995) show that returns on firms with high institutional ownership lead the returns on firms with low institutional ownership. Chordia and Swaminathan (2000) provide evidence that returns on stocks with high trading volume lead returns on stocks with low trading volume. A recent paper by Hou (2005) shows that the lead-lag effect is predominantly an intra-industry phenomenon. He shows that returns on big firms lead returns on small firms within the same industry. Once this effect is accounted for, little evidence of predictability across industries can be found. 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.

In this paper, we further investigate the economic significance of the slow information diffusion hypothesis as the leading cause of cross-autocorrelation. In so doing, we take advantage of a unique institutional aspect of emerging stock markets. In emerging markets, not all firms 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", as a measure of the severity of the friction affecting a stock in local markets, we assess whether investibility has a significant influence on the cross-correlations of stock returns and whether this is due to the slow diffusion of common information across stocks.

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. Our main argument is that foreign equity investment restrictions are a cause of market frictions that impede swift processing of market-wide information, particularly world market information. Therefore, there will be a positive relation between the degree of investibility and information diffusion of market-wide information, which in turn leads to the lead-lag relation across stocks with different degrees of investibility.

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 firms with higher foreign ownership restrictions are smaller firms in some particular industries. Further, previous research has identified factors such as size, turnover and analyst coverage as being important determinants of 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 attempt to distinguish the effect of investibility from the factors that may have positive association with investibility in several ways. Our empirical methods control for size, turnover and analyst coverage, and test for the independent explanatory power of investibility.

To examine the impact of investibility on the lead-lag relation in emerging markets, we obtain return data as well as other firm characteristic variables from the Standard & Poor's Emerging Markets Database (EMDB). Our final sample includes firm-level weekly return data of 31 emerging markets for a total of 3,201 distinct firms 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 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). Our main hypothesis is that returns of highly-investable stocks lead those on non-investable stocks. We find the consistent evidence as our hypothesis. Further, the lead-lag relation is not driven by size and/or trading volume. For every size and turnover groups, we find that the returns of highly-investable stocks lead the returns of non-investable stocks, but not vice versa. We also find that partially-investable stocks are on average larger and more actively traded than the highly-investable stocks, and yet returns of highly-investable stocks lead those of partially-investable stocks. If our results are driven by size or turnover and not by investibility, one should find that returns on partially-investable stocks lead those on highly-investable stocks. Our evidence shows otherwise.

We show that the lead-lag relation across investibility is not an artifact of the effect of analyst coverage. When we partition our sample firms 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 firms that have fewer analysts. Finally, we show that the lead-lag pattern we identify is not driven by an intra-industry phenomenon. This is important since industry-leader firms 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 return 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 accessibility has significant independent influence on the cross-autocorrelation patterns in stock returns.

Given the significant impact of investibility on the lead-lag patterns in stocks returns, we next 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 of average delay with which a stock price responds to information, we find that highly-investable firms adjust faster to market-wide information. That is, the delay with which the stock price adjusts to local and world market factors is negatively related to investibility. We interpret this evidence as suggesting that the lead-lag relation we find across firms with different degrees of investibility is due to the slow diffusion of market-wide information from highly-investable firms to non-investable firms.

Our paper is closely related and contributes to the several strands of literature. First, we contribute to the literature of cross-autocorrelations in stock returns. While the statistical relation of cross-autocorrelation is well documented, the literature is mixed in reaching the conclusion as to its source. Extant explanations include nonsynchronous trading, time-varying expected returns, and slow information diffusion. By utilizing a unique feature in emerging 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, we contribute to the literature that studies the importance of market frictions on portfolio choices and determination of asset prices. Numerous papers have examined the effect of incomplete information, short-sale constraints, taxes, transaction costs, and even noises arising from behavioral biases. In this paper, we show that limited stock market participation imposes a significant cost on the affected stocks in processing information.

Finally, 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 firms' volatility, and improve the information 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 (2005) 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 degree of informational efficiency, 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 firm-level return, market capitalization, turnover, and trading volume data for each firm covered by EMDB over the period from December 1988 to April 2003. We base our analysis on weekly returns rather than daily data in order to minimize the effect of potential biases associated with nonsynchronous trading on our analysis. The weekly data of EMDB includes 3,345 firms from 35 emerging markets covering more than 75% of the total market capitalization for each emerging market.

In addition, for each firm, the EMDB provides information regarding the investibility of a stock. It provides a measure of the extent of institutional and firm-level foreign investment restrictions on the firm's stock, and reports a variable called the "degree open factor" that takes a value between zero and one to indicate the investable weight of a stock that is accessible by foreigners. We use this variable as our measure of the extent of the severity of the restriction on foreign investor participation affecting each stock.[1]

In order to eliminate outliers and 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%.[2]. Finally, we delete country-year observations where we have only one investibility group after sorting firms into investibility groups. As a result of these filters and checks, we lose about 7% of the

[1] See Bae, Chan and Ng (2004) for a similar measure of the extent of investibility for local markets.

[2] We verified that these are genuine errors by checking whether there are large discrepancies between EMDB and Datastream for these observations.

weekly observations and 4 countries from the initial sample. Our final sample consists of 1,014,723 weekly observations from 31 countries for a total of 3,201 distinct firms over the period from January 1989 to April 2003.

Finally, we collect information on the amount of analyst coverage on our sample firms 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 a firm each year. Following the previous literature, if a firm is not covered according to 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 firms and their distribution across each country. The average number of firms in each country ranges from 16 in Hungary to over 200 in China. 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 firm. 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 amount of 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 -0.42 percent in Thailand to 0.49 percent in Brazil, and the average weekly volatility of individual stock returns varies between 4.54 percent in Portugal, and 12.96 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 adjustment of stock prices to information. Our sample firms vary considerably in size, ranging from only 21 million dollars in Sri Lanka, to 2.3 billion dollars in Russia. Firms in Korea and Taiwan are the most actively traded with an average monthly turnover of thirty percent, nearly thirty times the turnover of those firms in markets such as Chile, Colombia, Morocco and Zimbabwe. Not surprisingly, 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 cross-autocorrelations of stock returns, we form stock portfolios by the investable weight of each stock. To form investibility portfolios, we first compute the yearly average investibility for each firm in our sample in each year and then we partition stocks into three groups. We assign stocks with a zero measure of investibility into the *non-investable* portfolio, stocks with an investable weight between 0.1 and 0.5 into the *partially-investable* portfolio, and stocks with an investable weight greater than 0.5 into the *highly-investable* group.[3]

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 in stock returns. We sort firms in each country independently by size (volume) to form nine size/investibility (volume/investibility) portfolios based on the investibility and size (volume).[4] Following Chordia and Swaminathan (2000), we use turnover as our measure of trading volume. Having partitioned stocks into nine portfolios of investibility and size (volume), we then compute the equally-weighted weekly portfolio return on each portfolio.

Panels A and B of Table 2 present the 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 $j = 2$ is the highly-investable stocks portfolio.

We first note that our independent sorts by size and by volume help us control for

[3]The frequency distribution of investibility is skewed toward both tails. We choose not to have a very fine classifications of stocks based on investibility in order 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).

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

these effects across non-investable and highly-investable portfolios to a large extent. For example, in Panels A and B, the average firm 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 in every investibility group. Non-investable firms are generally smaller and less heavily traded than the partially- and highly-investable firms within each size and volume group. However, we notice that firms in the partially-investable portfolio are on average larger and more actively traded than the highly-investable firms 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 expect partially-investable stock returns to lead highly-investable stock returns. We test this hypothesis formally later in Table 4 and reject this conjecture.

Table 2 shows that across each investibility group, large firms outperform small firms in our 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 return on P_{10} (the portfolio of medium-size and non-investable stocks) is 0.24 percent per week whereas it is 0.16 percent per week for P_{12} (the portfolio of medium-size and highly-investable stocks). Similarly, in Panel B, the average return on P_{20} (the portfolio of highest turnover and non-investable stocks) is 0.40 percent per week compared to 0.18 percent per week on P_{22} (the portfolio of highest turnover and highly-investable stocks). Such a pattern is consistent with the effect of greater financial liberalization on 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 associated with each portfolio. First, we note that the first-order autocorrelations decline across size (turnover) groups, but only for non-investable firms. Second, within size (turnover) groups, non-investable firms and partially-investable firms have higher autocorrelation than highly-investable firms only for the smallest (lowest) size (turnover) group. For example, within the smallest size firms, the first order autocorrelation is 0.19 for the returns of non-investable firms and 0.11 for the highly-investable firms. As pointed out by Chordia and Swaminathan (2000), we recognize that the autocorrelations by themselves could not provide unambiguous inferences on the differences in the speed of adjustment of stock prices, and turn to cross-autocorrelations for testing our hypotheses.

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 controlling for size and 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 groups 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 $i = 0, 1, 2$ represent the three size groups. 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 0.18 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 0.03. 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 volume group. Furthermore, it is important to note that the lead-lag patterns observed in Table 3 cannot be solely driven by nonsynchronous trading given that they are also present in the smallest-size and the highest turnover groups.

In summary, Table 3 presents the 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 the 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. [5] We address this concern and formally test for the independent effect of lagged highly-investable returns in our VAR tests, which we present next.

3.2 VAR tests of the lead-lag effect

In this section, we present tests of 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 firms lead current returns on portfolios of non-investable firms. A problem we have to deal with is the necessity to explicitly control for size and volume. This is because both firm size and volume 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 are more actively traded.

One way to address this concern is to conduct independent sorts by size (volume) and partition stocks into nine size/investibility (turnover/investibility) portfolios. There are two problems with this approach. First, as we pointed in Table 2, our independent sorting procedure helps us control for size and volume effects to a large extent, but not completely. We need to make sure that our results are not driven by size or volume effects that we fail to control for. The second problem is that given the limited number of firms we have available in some markets, our independent sorting procedure does not ensure an adequate representation of all nine size/investibility (turnover/investibility) portfolios in each market. For these reasons, we employ a two-stage methodology. We first construct investibility portfolio returns that are net of firm size and volume effects, and then use these portfolio returns in vector autoregressions to test for lead-lag effects. For completeness, we

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

also report test results using returns on the nine size/investibility (turnover/investibility) portfolios that we construct by partitioning stocks in a subset of markets where we have at least fifty firms on average.

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 our sample period:

$$\begin{aligned} r_{it} = {} & \beta_{0t} + \sum_{j=0}^{j=2} \beta_{1jt} I_j + \sum_{j=0}^{j=2} \beta_j size_j + \sum_{j=0}^{j=2} \beta_{3jt} turnover_j + \\ & \sum_{j=0}^{j=10} \beta_{4jt} industry_j + \sum_{j=1}^{j=31} \beta_{5tjt} country_j + \epsilon_{it} \end{aligned} \quad (1)$$

where r_{it} represents return on stock i at week t, I_j represents an indicator variable that takes a value of one if stock i is in investibility portfolio j, and zero otherwise, and $size_j$ and $turnover_j$ are also indicator variables, defined similarly for the corresponding size and turnover portfolios. 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, $industry_j$ and $country_j$ 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 equally weighted return on the relevant portfolio group. In particular, we use the estimated intercept and the coefficients on the investibility indicator variable I_j to construct weekly returns for each investibility portfolio j. In other words, let R_{jt} denote the weekly return on investibility portfolio j at time t that is net of size, turnover, industry and country effects. Then,

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

Having constructed the returns on each of the investibility portfolios 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 using weekly returns

$$R_{0t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0t-k} + \sum_{k=1}^{K} b_k R_{2t-k} + u_t \qquad (3)$$

$$R_{2t} = c_0 + \sum_{k=1}^{K} c_k R_{0t-k} + \sum_{k=1}^{K} d_k R_{2t-k} + v_t \qquad (4)$$

where R_{0t} represents the non-investable portfolio weekly return at time t, and R_{2t} represents the highly-investable portfolio return, as constructed in equation (2) . Using this bivariate system, we test whether the returns on lagged highly-investable stocks in equation (3) have significant explanatory power in predicting the current returns on the non-investable stocks, after controlling for lagged non-investable stock returns. In addition, we test whether there is an asymmetry in this lead-lag relation by testing formally the restriction $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$.

We estimate the VAR specified in equations (3) and (4) using weekly returns and four lags, $K = 4$. Panel A of Table 4 summarizes the estimation results. The first row reports the estimated coefficients for the non-investable portfolio return equation, and the second row reports those for the highly-investable portfolio return equation. The first two columns report the coefficient on the one-lag return of the non-investable portfolio return and the sum of the four lagged coefficients on the non-investable portfolio returns. The next two columns show the estimated coefficient on the one-lag return on the highly-investable portfolio return and the sum of the estimated coefficients on the four lags of the highly-investable portfolio returns. Panel A indicates that lagged highly-investable portfolio returns predict current non-investable portfolio returns. The coefficient on the one-lag highly-investable portfolio return is 0.101, and is significant at conventional significance levels. The sum of the coefficients on the four lags of highly-investable portfolio returns is 0.375 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 non-investable portfolio lagged returns have any predictive power for the current highly-investable portfolio returns 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 restriction $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$. The last two columns present these cross-equation tests, where we report the difference in the estimated coefficients, together with the associated p-values. $\sum_{k=1}^{K} b_k - \sum_{k=1}^{K} c_k$ is positive and significant, rejecting the hypothesis that the sum of the coefficients is equal across the two equations. We conclude that highly-investable portfolio returns lead non-investable portfolio returns.

Panel B of Table 4 examines the lead-lag relation between the *partially-investable* portfolio returns and the highly-investable portfolios returns. 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. 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, where the first row presents the estimated coefficients for the partially-investable portfolio return equation, and the second row shows the estimated coefficients for the highly-investable portfolio return 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. The sum of the coefficients on the four lags of highly-investable portfolio returns is 0.438 and is also significant at the one percent level. Similarly to Panel A, we do not find any evidence that would suggest that lagged returns on partially-investable portfolio help 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. The results provide strong evidence that the lead-lag relation we find across investibility portfolios is not driven by size (turnover) and that investibility has an independent influence on the lead-lag effect in stock returns.

For completeness, we also conduct our VAR tests using the weekly returns on the nine size/investibility (turnover/investibility) portfolios we construct by partitioning stocks in each market by the average degree of investibility and size (turnover). As we noted earlier, however, the limited number of firms 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 firms on average over the sample period. Using the equally weighted weekly returns on each portfolio in each market, we estimate the VAR specified in equations (5) and (6) jointly across all markets for each size (turnover) group.

Panel A of Table 5 presents the VAR results for each size group, where the first row in each size group is associated with the non-investable portfolio return equation and the second row presents 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-portfolio return range from 0.11 to 0.15, and all of them are significant at the one-percent level. Similarly, the sum of the estimated coefficients on the four lags of the highly-investable portfolio returns are between 0.27 and 0.37. They are all significant at the one-percent level. Interestingly, the estimated coefficients on the lagged non-investable portfolio returns in the second row 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. 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 in Panel A that, holding size constant, returns on portfolios of highly-investable firms lead those on portfolios of non-investable firms.

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..

In summary, the test results in this section provide strong evidence that returns on highly-investable portfolios lead non-investable portfolio returns, after controlling for size and volume.[6] This suggests 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 the slow diffusion of information due to the frictions caused by limited accessibility can be the source of this lead-lag relation we observe.

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

In the previous sections, we document that returns on highly-investable stocks lead non-investable stock returns, even after controlling for size, turnover, industry and country effects. 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.

[6] In unreported results, we test for the lead-lag relation between highly-investable and non-investable portfolio returns, after controlling for size and turnover simulatenously. We find that the first-lag coefficient and the sum of the four lag coefficients on highly-investable portfolio returns remain positive and significant.

To investigate this possibility, we obtain data on analyst coverage for each from I/B/E/S and merge this data with our subsample of firms in markets that have at least fifty firms on average over the sample period. In each year for each market, we compute the median number of analysts following and partition our sample firms into two groups based on the yearly median number of analysts. Firms that have more analysts than the median for that market are assigned into the high-coverage group, and firms 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. We then conduct our 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 associated with 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 firms with high analyst coverage than for those with less coverage. The presence of a significant lead-lag relation even for those firms with fewer analysts indicates that the degree of accessibility 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 coverage groups.

Although the results in Table 6 do not control for possible size and volume effects at the same time, we address this issue by considering cross-sectional regressions that simultaneously controls for all these effects in the next section. 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 lead-lag relation

In a recent paper, Hou (2005) 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 firms in a given market may very well be the leaders in their respective industries, and that returns of other firms in the same industry follow the industry leader returns due to a 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 we partition stocks in each industry j into three investibility portfolios in each of our subsample markets that have more than 50 firms on average over the sample period. If the lead-lag relation is indeed purely an intra-industry phenomenon, we should expect that the lagged returns of highly-investable firms from the same industry j should be more important than those from different industries in predicting current returns of non-investable firms of industry j. Specifically, we modify the VAR specified in equations (3) and (4) to include the lagged returns on the highly-investable firms from all other industries as an additional variable predicting the current returns on non-investable firms. We estimate the following VAR jointly across all industries and all markets:

$$R_{0j,t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0j,t-k} + \sum_{k=1}^{K} b_k R_{2j,t-k} + \sum_{k=1}^{K} f_k R_{2j',t-k,j'\neq j} + u_t \quad (5)$$

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

where $R_{0j,t}$ represents the equally weighted weekly return on the portfolio of non-investable firms in industry j, $R_{2j,t}$ represents the equally weighted weekly return on the portfolio of highly-investable firms in industry j and $R_{2j',t-k,j'\neq j}$ is the lag-k equally weighted weekly return on the portfolio of highly-investable firms 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 $\sum_{k=1}^{K} f_k < \sum_{k=1}^{K} b_k$.

Table 7 presents the estimation results for the VAR specified in equations (5) and (6). Consistent with Hou (2005), there is evidence of an intra-industry effect where lagged returns on the portfolio of highly-investable firms predict the current returns on the portfolio of non-investable firms 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 firms in other industries are important in predicting current returns on the portfolio of non-investable firms in a particular industry. This suggests that the predictive ability of highly-investable firms 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 firms in other industries is less than that of the highly-investable firms 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 effects of investibility on the cross-correlations in stock returns extends beyond the intra-industry phenomenon.

4.3 Speed of price adjustment and the lead-lag relation

In this section, we assess whether the lead-lag relation we identify across highly-investable and non-investable portfolio returns is due to the slow diffusion of common information across stocks. Our hypothesis is that firms that have greater investibility adjust faster to market-wide information than those with less accessibility to foreign investors. 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 a firm's stock price responds 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 the world market return or the local market return. Specifically, we run the following regression of each stock's return on the contemporaneous and lagged market returns for each year during our sample period for every individual stock with at least fifteen observations per year:

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

where $r_{i,t}$ denotes the individual stock return i in week t, $r_{m,t-k}$ is the kth lag of the relevant market return in week t, for $k = 0, 1, .., 4$. If the stock price responds immediately to market news, then the coefficient on the contemporaneous market return will be significantly different zero and none of the coefficients on the lagged market return should differ from zero. On the other hand, if stock i responds with a delay, then we would expect some of the coefficients on the lagged market return 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 lagged coefficients to be zero to the R^2 with no restrictions:

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

We estimate the equation (8), first using the world market return, and then using the residual local market return[7], and construct the delay measure with respect to each type of market information. Larger values of $delay1$ would 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.

Our second delay measure is motivated by McQueen, Pinegar and Thorley (1996) and

[7] We measure the pure local market return, as the residual obtained from regressing the local market return on the world market return.

is also constructed from the coefficients estimated in equation (8) as[8]:

$$delay2 = \frac{1}{1 + e^{-|x|}} \qquad \text{where } x = \frac{\sum_{k=1}^{k=4} \delta_{ik}}{\delta_{i0}} \tag{9}$$

If the stock prices of highly-investable firms 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 highly-investable firms might have greater sensitivity to world market news. We test this hypothesis by regressing each firm's average delay measure on the average degree of investibility and a number of control variables:

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

where $delay_{it}$ is the estimated delay measure, $delay1$ or $delay2$, for firm i with respect to the world or local market return, $investable_{it}$ represents the average investable weight for firm i, $analyst_{it}$ measures the number of analysts following for firm i, $volatility_{it}$ is measured as the standard deviation of the weekly return for firm i, $size_{it}$ is firm i's market capitalization, and $turnover_{it}$ is measured as the number of shares traded scaled by the number of shares 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 firms and firms 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 way that is not captured by these firm characteristics, we should expect a negative relationship between our delay measures and investibility. That is, $\beta < 0$.

We estimate equation (8) using pooled OLS regression and we correct the standard errors for clustering at the firm level. Table 8 presents the estimation results. Panel A reports the estimated coefficients for the delay measures $delay1$ and $delay2$ with respect to the world market information. We find that higher investibility is associated with smaller delay. The coefficient estimates are -0.251 and -0.100 and both are significant at the one

[8]Unlike McQueen, Pinegar, Thorley (1996), we use the absolute value of x since a subset of our sample firms might be negatively correlated world market returns. Similar measures have been used by Brennan, Jegadeesh, and Swaminathan (1993), and Mech (1993).

percent level. While the coefficient estimates on size, turnover, and analyst coverage are also significantly negative, they are much smaller in magnitude, lending further support to our hypothesis that investibility has important influence on the speed of adjustment of stock prices.

Panel A shows that highly-investable firms adjust faster to common world market information. If the presence of market frictions impedes the information transmission process, we would expect this effect to be relevant for all market-wide 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 our delay measures with respect to local market information and investibility. The magnitude of the coefficient estimates is smaller: -0.136 and -0.044 for $delay1$ and $delay2$, respectively. In unreported test, we test for the equality of the effect of investibility on the delay 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 $delay2$ at the one percent level.

In summary, Table 8 provides evidence that the degree of investibility has an economically important and significant influence on the speed of adjustment of stock prices to market-wide information. The evidence suggests that stock prices of highly-investable firms respond faster to world market information than to local market-wide information, but adjust faster to all market-wide information than do the stock prices of less-investable firms. We conclude that the lead-lag effect we have documented across returns of highly-investable portfolios and those of non-investable portfolio is most consistent with a slower adjustment of the stock prices of the latter to common information, lending further support to the slow information diffusion hypothesis.

5 Conclusion

In this paper, we examine a distinct institutional feature of emerging 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. Returns of portfolios of highly-investable firms lead returns of portfolios of non-investable firms, 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 effect, we show that the lead-lag effect we identify is not a purely intra-industry effect. Returns of portfolios highly-investable firms in other industries also lead returns of portfolios of non-investable same-industry firms, even after controlling for the intra-industry effect.

The degree of investibility has a positive effect on the speed with which prices adjust to information. Specifically, we find that greater accessibility reduces the delay with which stock prices respond to market-wide information. We show that stock prices of highly-investable firms respond faster to the world market information as well as the local market information. We interpret these results as providing additional support for the slow information diffusion hypothesis. Our results are also consistent with the view that financial liberalization in the form of greater investibility may yield more informationally efficient stock prices in emerging markets, to the extent that faster information processing leads to more efficient stock prices.

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Table 1: Descriptive statistics

Table 1 describes the sample firms, and their distribution across each country. We obtain firm-level return, market capitalization, and turnover data from EMDB for 3,201 distinct firms in 31 countries over the period January 1989 - April 2003. EMDB also provides information regarding the investibility of a 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-investible. For each country, Table 1 presents number of firms, investable weight, return, volatility, firm size, and turnover. Weekly return and volatility are the cross-sectional averages of the mean returns and standard deviations over all the sample firms within the country. Size is measured as the market value of equity in million dollars. Turnover is the number of shares traded scaled by the number of shares outstanding at the beginning of the month. All variables report the cross-sectional average of the time-series means for sample firms.

Country	No of firms	Investable Weight	Return (%)	Volatility (%)	Size	Turnover
Argentina	29	0.65	0.49	9.13	595	0.04
Brazil	81	0.56	0.40	11.42	997	0.04
Chile	42	0.45	0.13	5.04	702	0.01
China	202	0.22	0.19	6.55	951	0.12
Colombia	24	0.34	0.07	6.14	289	0.01
Czech Republic	43	0.09	-0.26	7.14	171	0.01
Egypt	67	0.22	-0.14	5.75	149	0.03
Greece	50	0.65	-0.05	6.28	647	0.04
Hungary	16	0.48	0.20	6.79	421	0.07
India	126	0.14	0.00	7.50	558	0.16
Indonesia	60	0.25	-0.14	8.88	240	0.04
Israel	52	0.59	0.12	6.42	710	0.06
Jordan	39	0.05	-0.02	3.79	54	0.04
Korea	164	0.48	0.02	9.57	770	0.30
Malaysia	111	0.72	-0.06	7.58	604	0.05
Mexico	68	0.57	0.09	6.23	913	0.03
Morocco	20	0.33	-0.01	3.57	439	0.01
Pakistan	62	0.18	0.00	6.80	68	0.04
Peru	34	0.40	0.21	6.54	192	0.04
Philippines	47	0.24	-0.11	8.30	346	0.03
Poland	32	0.69	-0.03	6.41	518	0.05
Portugal	30	0.59	0.17	4.54	707	0.03
Russia	28	0.38	0.04	12.96	2,324	0.02
Slovakia	17	0.18	-0.27	9.44	44	0.04
South Africa	71	0.78	0.20	6.47	1,431	0.03
Sri Lanka	46	0.09	0.00	6.50	21	0.01
Taiwan	98	0.30	-0.08	6.78	1,484	0.30
Thailand	63	0.26	-0.42	8.17	452	0.08
Turkey	46	0.66	0.47	10.37	536	0.19
Venezuela	17	0.44	0.25	9.04	255	0.02
Zimbabwe	25	0.08	0.40	10.05	85	0.01

Table 2: Summary statistics and auto-correlations by portfolios

For each firm in each year, we compute the average annual investable weight and sort sample firms into three investibility groups: non-investible (denoted by 0) if the investable weight is zero, partially-investible (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investible if the investable weight is greater than 0.5. In addition, for each country in each year, we independently sort firms 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 firms in size (turnover) i and investible 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 $\sum_{k=1}^{4} \rho_k$ is the sum of the first four lag autocorrelations. For each portfolio, we report the equally-weighted size, investable weight, and turnover. Weekly portfolio returns are equally-weighted.

Panel A: Portfolios sorted by size and investable weight

Portfolios	Size	Turnover	Investable Weight	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^{4} \rho_k$
P00	48	0.06	0.00	0.10	8.25	0.19	0.59
P01	140	0.19	0.29	-0.49	8.43	0.07	0.32
P02	131	0.11	0.95	-0.13	8.20	0.11	0.48
P10	162	0.05	0.00	0.24	6.78	0.09	0.24
P11	365	0.12	0.28	-0.18	7.61	0.11	0.46
P12	349	0.07	0.93	0.16	7.68	0.09	0.49
P20	813	0.04	0.00	0.28	6.62	0.07	0.22
P21	2,021	0.07	0.29	0.15	6.63	0.11	0.44
P22	1,607	0.06	0.92	0.31	6.95	0.08	0.48

Panel B: Portfolios sorted by turnover and investable weight

Portfolios	Size	Turnover	Investable Weight	Return (%)	Volatility (%)	ρ_1	$\sum_{k=1}^{4} \rho_k$
P00	357	0.01	0.00	0.03	6.86	0.20	0.64
P01	1,662	0.03	0.27	-0.20	6.36	0.06	0.46
P02	935	0.02	0.93	0.06	6.39	0.08	0.42
P10	181	0.04	0.00	0.17	7.38	0.13	0.34
P11	916	0.07	0.29	-0.07	7.14	0.11	0.46
P12	773	0.05	0.93	0.12	7.35	0.06	0.46
P20	130	0.13	0.00	0.40	8.29	0.07	0.20
P21	641	0.24	0.28	-0.02	8.33	0.17	0.49
P22	611	0.14	0.94	0.18	8.43	0.11	0.50

Table 3: Cross-autocorrelations

Table 3 reports the one-lag cross-autocorrelations between highly-investible portfolio returns and non-investible portfolio returns within each size or turnover group. Each year, sample firms are assigned into three investibility groups based on their average investable weight: non-investible (denoted by 0) if the investable weight is zero, partially-investible (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investible if the investable weight is greater than 0.5. In addition, for each country in each year, we independently sort firms into three size groups or three turnover groups based on yearly average market capitalization and turnover, respectively. Panels A and B present, respectively, the one-lag cross-autocorrelations between with the highly-investible portfolio returns and non-investible portfolio returns within each size and turnover group. R_{ijt} represents the equally weighted return on the portfolio of size i and investible 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 investable weight

Size/Investable Weight	R_{00t}	R_{02t}	R_{10t}	R_{12t}	R_{20t}	R_{22t}
R_{00t-1}	0.19	**0.03**	0.17	0.07	0.10	0.07
R_{02t-1}	**0.18**	0.11	0.14	0.07	0.09	0.04
R_{10t-1}	0.11	0.03	0.09	**0.02**	0.09	0.04
R_{12t-1}	0.22	0.10	**0.18**	0.09	0.12	0.07
R_{20t-1}	0.07	0.05	0.06	0.03	0.07	**0.04**
R_{22t-1}	0.21	0.10	0.21	0.10	**0.14**	0.08

Panel B: Portfolios sorted by turnover and investable weight

Turnover/Investable Weight	R_{00t}	R_{02t}	R_{10t}	R_{12t}	R_{20t}	R_{22t}
R_{00t-1}	0.20	**0.08**	0.17	0.07	0.12	0.08
R_{02t-1}	**0.21**	0.08	0.19	0.09	0.15	0.13
R_{10t-1}	0.16	0.05	0.13	**0.03**	0.10	0.04
R_{12t-1}	0.23	0.07	**0.21**	0.06	0.15	0.11
R_{20t-1}	0.13	0.03	0.08	0.04	0.07	**0.03**
R_{22t-1}	0.20	0.06	0.20	0.06	**0.14**	0.11

Table 4: Lead-lag relation across investibility portfolios

Table 4 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 running the cross-sectional regression in equation (3), and use the estimated coefficients to compute the weekly return R_{jt} on investibility portfolio j as in equation (4). We then estimate the following VAR jointly across all markets:

$$R_{0t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0t-k} + \sum_{k=1}^{K} b_k R_{2t-k} + u_t \quad (3)$$

$$R_{2t} = c_0 + \sum_{k=1}^{K} c_k R_{0t-k} + \sum_{k=1}^{K} d_k R_{2t-k} + v_t \quad (4)$$

where R_{0t} and R_{2t} are, respectively, the week t returns on the non-investable and highly-investable portfolios as measured as in equation (2) in the text. Panel A presents the VAR results for equations (3) and (4). In Panel B, we replace the non-investable portfolio returns with returns on the partially-investable portfolio returns R_{1t} and estimate the corresponding VAR. Panel B reports the estimation results. The cross-equation null hypothesis is $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$. p-values are reported in parentheses.

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

	Non-investible portfolio returns		Highly-investible portfolio returns		Cross-equation tests	
Dependent	R_{0t-1}	$\sum_{k=1}^{4} R_{0t-k}$	R_{2t-1}	$\sum_{k=1}^{4} R_{2t-k}$	$b_1 = c_1$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
R_{0t}	0.014	0.068	**0.101**	**0.375**	0.053	0.359
	(0.80)	(0.56)	(**0.03**)	(**0.00**)	(0.50)	(0.02)
R_{2t}	**0.048**	**0.016**	0.060	0.443		
	(**0.44**)	(**0.90**)	(0.27)	(0.00)		

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

	Partially-investible portfolio returns		Highly-investible portfolio returns		Cross-equation tests	
Dependent	R_{1t-1}	$\sum_{k=1}^{4} R_{1t-k}$	R_{2t-1}	$\sum_{k=1}^{4} R_{2t-k}$	$b_1 = c_1$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
R_{1t}	−0.005	0.004	**0.148**	**0.438**	0.145	0.333
	(0.92)	(0.97)	(**0.02**)	(**0.00**)	0.10	0.05
R_{2t}	**0.003**	**0.105**	0.094	0.371		
	(**0.96**)	(**0.37**)	(0.13)	(0.00)		

Table 5: Lead-lag relation across size/investibility and turnover/investibility portfolios

Table 5 presents the VAR estimation results, using the equally-weighted weekly returns on size/investibility and turnover/investibility portfolios constructed by partitioning firms by the degree of investibility and size or turnover. Using a subsample of twelve markets that have at least fifty firms on average over the sample period, we partition firms into three investibility groups: non-investible (denoted by 0) if the investable weight is zero, partially-investible (denoted by 1) if the investable weight is greater than 0 and less than or equal to 0.5, and highly-investible if the investable weight is greater than 0.5. In addition, we independently sort firms into three size groups or three turnover groups based on yearly average market capitalization and turnover, respectively. We then compute the equally-weighted return R_{2t} on each highly-investable portfolio, and the equally-weighted return R_{0t} on each non-investable portfolio in each size (turnover) group i, and estimate the following VAR jointly across all markets:

$$R_{0t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0t-k} + \sum_{k=1}^{K} b_k R_{2t-k} + u_t \quad (3)$$

$$R_{2t} = c_0 + \sum_{k=1}^{K} c_k R_{0t-k} + \sum_{k=1}^{K} d_k R_{2t-k} + v_t \quad (4)$$

where R_{0t} and R_{2t} are, respectively, the week t returns on the non-investable and highly-investable portfolios. Panel A and B, respectively, report the VAR estimation results for equations (3) and (4) size/investibility and turnover/investibility portfolios. The cross-equation null hypothesis is $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$. p-values are reported in parentheses.

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

		Non-investible portfolio returns		Highly-investible portfolio returns		Cross-equation tests			
Size	Dependent	R_{0t-1}	$\sum_{k=1}^{4} R_{0t-k}$	R_{2t-1}	$\sum_{k=1}^{4} R_{2t-k}$	$b_1 = c_1$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$	Adj R2	No. obs
Small	R_{0t}	−0.063	−0.003	**0.115**	**0.271**	0.068	0.154	0.031	3,754
		(0.00)	(0.97)	(**0.00**)	(**0.00**)	(0.02)	(0.01)		
	R_{2t}	**0.047**	**0.117**	0.05	0.126			0.024	3,754
		(**0.02**)	(**0.10**)	(0.02)	(0.11)				
Medium	R_{0t}	0.011	−0.107	**0.148**	**0.380**	0.105	0.351	0.036	3,566
		(0.57)	(0.23)	(**0.00**)	(**0.00**)	(0.00)	(0.00)		
	R_{2t}	**0.043**	**0.029**	0.062	0.217			0.020	3,566
		(**0.02**)	(**0.52**)	(0.00)	(0.00)				
Large	R_{0t}	0.005	0.011	**0.154**	**0.274**	0.115	0.266	0.023	3,090
		(0.81)	(0.88)	(**0.00**)	(**0.00**)	(0.00)	(0.00)		
	R_{2t}	**0.039**	**0.008**	0.038	0.19			0.013	3,090
		(**0.03**)	(**0.86**)	(0.06)	(0.00)				

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

Turnover	Dependent	Non-investible portfolio returns R_{0t-1}	Non-investible portfolio returns $\sum_{k=1}^{4} R_{0t-k}$	Highly-investible portfolio returns R_{2t-1}	Highly-investible portfolio returns $\sum_{k=1}^{4} R_{2t-k}$	Cross-equation tests $b_1 = c_1$	Cross-equation tests $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$	Adj R2	No. obs
Low	R_{0t}	−0.03	0.116	**0.121**	**0.188**	0.089	0.096	0.022	3,832
		(0.10)	(0.07)	**(0.00)**	**(0.00)**	(0.00)	(0.06)		
	R_{2t}	**0.032**	**0.092**	**0.068**	**0.137**			0.014	3,832
		(0.03)	**(0.05)**	**(0.00)**	**(0.01)**				
Medium	R_{0t}	−0.01	−0.056	**0.194**	**0.468**	0.158	0.436	0.039	3,462
		(0.62)	(0.49)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	R_{2t}	**0.036**	**0.031**	0.057	0.229			0.024	3,462
		(0.02)	**(0.42)**	(0.01)	(0.00)				
High	R_{0t}	−0.03	−0.048	**0.095**	**0.287**	0.105	0.298	0.017	3,769
		(0.14)	(0.42)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	R_{2t}	**−0.01**	**−0.012**	0.071	0.211			0.015	3,769
		(0.57)	**(0.83)**	(0.00)	(0.00)				

Table 6: The effect of analyst coverage on the lead-lag relation across investibility

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

$$R_{0t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0t-k} + \sum_{k=1}^{K} b_k R_{2t-k} + u_t \quad (3)$$

$$R_{2t} = c_0 + \sum_{k=1}^{K} c_k R_{0t-k} + \sum_{k=1}^{K} d_k R_{2t-k} + v_t \quad (4)$$

where R_{0t} and R_{2t} are, respectively, the week t returns on the non-investable and highly-investable portfolios in each analyst coverage group in each market. The cross-equation null hypothesis is $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$. p-values are reported in parentheses.

Analyst coverage	Dependent	Non-investible portfolio returns R_{0t-1}	Non-investible portfolio returns $\sum_{k=1}^{4} R_{0t-k}$	Highly-investible portfolio returns R_{2t-1}	Highly-investible portfolio returns $\sum_{k=1}^{4} R_{2t-k}$	Cross-equation tests $b_1 = c_1$	Cross-equation tests $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$	Adj R2	No. obs
Low	R_{0t}	0.08	0.076	**0.101**	**0.233**	0.079	0.137	0.033	3,199
		(0.00)	(0.31)	**(0.00)**	**(0.00)**	(0.01)	(0.02)		
	R_{2t}	**0.021**	**0.096**	0.135	0.164			0.027	3,199
		(0.29)	**(0.06)**	(0.00)	(0.01)				
High	R_{0t}	−0.078	−0.068	**0.151**	**0.297**	0.115	0.274	0.021	1,654
		(0.01)	(0.38)	**(0.00)**	**(0.00)**	(0.00)	(0.00)		
	R_{2t}	**0.036**	**0.023**	0.032	0.124			0.003	1,654
		(0.14)	**(0.71)**	(0.26)	(0.08)				

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

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

$$R_{0j,t} = \alpha_0 + \sum_{k=1}^{K} a_k R_{0j,t-k} + \sum_{k=1}^{K} b_k R_{2j,t-k} + \sum_{k=1}^{K} f_k R_{2j',t-k,j' \neq j} + u_t \quad (5)$$

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

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

	Non-investible in industry i		Highly-investible in industry i		Highly-investible in other industries		Pure intra-industry effect tests	
Dependent	$R_{0j,t-1}$	$\sum_{k=1}^{4} R_{0j,t-k}$	$R_{2j,t-1}$	$\sum_{k=1}^{4} R_{2j,t-k}$	$R_{2j' \neq j,t-1}$	$\sum_{k=1}^{4} R_{2j' \neq j,t-k}$	$f_1 < b_1$	$\sum_{k=1}^{4} f_k < \sum_{k=1}^{4} b_k$
$R_{0j,t}$	−0.032	−0.039	**0.093**	**0.189**	**0.088**	**0.188**	0.005	0.001
	(0.00)	(0.22)	(**0.00**)	(**0.00**)	(**0.00**)	(**0.00**)	(0.86)	(0.99)
$R_{2j,t}$	**0.027**	**0.048**	0.063	0.162				
	(**0.00**)	(**0.01**)	(0.00)	(0.00)				

Table 8: Speed of adjustment to market-wide information
Table 8 presents the estimation results for the following regression:

$$\begin{aligned} delay_{it} &= \alpha_0 + \beta investable_{it} + \gamma_1 analyst_{it} + \\ &\quad \gamma_2 volatility_{it} + \gamma_3 size_{it} + \gamma_4 turnover_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

where the dependent variable is one of the delay measures *delay*1 and *delay*2 constructed for each firm i that proxy for the delay with which the stock price on firm i responds to market-wide information. Delay measures are defined in equations (8) and (9). In Panel A, *delay*1 and *delay*2 are measured with respect to the world market return and in Panel B, *delay*1 and *delay*2 are measured with respect to pure local market return. $Investable_{it}$ represents the investable weight associated with firm i, $analyst_{it}$ measures the number of analysts following firm i, $volatility_{it}$ is measured as the standard deviation of the weekly return of firm i, size is firm i's market capitalization, and turnover is the number of shares traded scaled by the number of shares outstanding. The standard errors are corrected for clustering at the firm-level. p-values are reported in parantheses.

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

	investable	analyst	volatility	size	turnover	intercept
*delay*1	−0.251	−0.044	−0.010	−0.043	−0.025	1.011
	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.00)
*delay*2	−0.100	−0.012	−0.002	−0.016	0.012	0.919
	(0.00)	(0.04)	(0.00)	(0.00)	(0.29)	(0.00)

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

	investable	analyst	volatility	size	turnover	intercept
*delay*1	−0.136	−0.029	−0.003	−0.036	−0.130	0.529
	(0.00)	(0.01)	(0.04)	(0.00)	(0.00)	(0.00)
*delay*2	−0.044	−0.016	0.000	−0.015	−0.050	0.729
	(0.00)	(0.00)	(0.85)	(0.00)	(0.00)	(0.00)