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**Vaalmikki Argoon, Spiros Bougheas and Chris Milner**

Produced By:

Centre for Finance, Credit and Macroeconomics
School of Economics
Sir Clive Granger Building
University of Nottingham
University Park
Nottingham
NG7 2RD

Tel: +44(0) 115 951 5619
Fax: +44(0) 115 951 4159
enquiries@cfcm.org.uk

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Vaalmikki Arjoon, Spiros Bougheas* and
Chris Milner
(School of Economics, University of Nottingham, UK)

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**Abstract**

Using daily, stock level data for the early development of the equity market of Trinidad and Tobago over the period 2001 to 2008, this paper investigates the influence of the degree of institutional ownership of stock on lead-lag, stock return relationships. Using a VAR modelling approach to identify cross autocorrelation between more and less institutionally favoured stocks and controlling for a range of other possible conditioning influences (firm size, analyst coverage and liquidity), the study finds strong evidence of institutionally owned stocks leading the returns of stocks held more by individual investors.

JEL Classification*: G14, G23*

Key words*: Cross autocorrelation, institutions, emerging market*

* Corresponding author: Spiros Bougheas, School of Economics, University of Nottingham, Nottingham, NG7 2RD, UK. Phone: 44 115 8466108; Fax: 44 115 9514159; email: spiros.bougheas@nottingham.ac.uk.

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### 1. Introduction

Over the past 30 years, we have learnt a lot about emerging markets finance. The bulk of the research focuses on issues related to the impact of market integration and financial liberalization on asset prices and their relationship to those in developed economies. Out of this line of research we now understand, for example, that emerging markets are relatively inefficient and are characterized by infrequent trading. In these circumstances asset returns are not normally distributed, have high serial correlation and are slow to adjust to current information.[1]

Slow price adjustment has also been documented for prices of both individual stocks and portfolios traded in developed economies. In particular, numerous studies provide evidence of lead-lag effects in cross-autocorrelations of stock returns, strongly suggesting that some stocks react to information faster than other stocks. One explanation offered for these lead-lad effects is variation in institutional ownership between stocks.[2] Data analyses of stock returns from the New York Stock Exchange (NYSE) provide strong support for this hypothesis (Badrinath *et al.* 1995; Sias and Starks, 1997; Chuang and Lee, 2011).

Financial liberalization and market integration encourage the inflow of institutional investors in emerging markets, and therefore this provides a natural testing ground for the view that differences in the level of institutional investment across stocks account for lead-lag relationships; specifically, for the hypothesis that the prices of stocks with a high level of

[1] For reviews of this extensive literature, see Bekaert and Harvey (2002, 2003).

[2] Alternative explanations include non-synchronous trading (Lo and MacKinlay, 1990), variations in analyst coverage (Brennan *et al.* 1993) and variations in liquidity (Chordia and Swaminathan, 2000).

institutional investment lead those of stocks with low institutional investment. One serious obstacle for this type of work has been the lack of data from emerging markets on either/both individual stock returns or/and information about institutional ownership. This study fills this gap in the literature by analyzing data from the Trinidad and Tobago Stock Exchange (TTSE). This emerging market is in its embryonic stages of development and has experienced a high level of investment activity over this past decade. In addition, its regulatory, microstructure and information environments are substantially less developed than the NYSE. For instance, there is a high level of transactions costs and thin trading in the market. Moreover, the scale of operations in this market is relatively small and provides a very different setting from the NYSE. (Appendix table A.1 provides some comparative data on scales of trading activity in TTSE and NYSE for the period covered by this study.)

One feature of this study is that it uses individual stock/firm level data from an emerging market in its embryonic stages of development. The existing literature applies portfolio level data, when exploring lead-lag effects.[3] Any findings of the lead-lag effects could be attributable to a lead-lag relation between some (or even few) of the stocks of the portfolios.[4] This gives rise to the possibility that the results may not be reflective of the true cross-autocorrelation between all the stocks in the portfolios. Here we apply our empirical analysis to returns data at the individual stock level to investigate cross-autocorrelation. This provides an unambiguous depiction of any lead-lag effects between the returns of stocks with a high institutional investment and those with a low one.

[3]See, for example, Bohl and Brzeszczyński (2006) and Gebka *et al.* (2006). Using data on foreign ownership rather than institutional ownership, taken from the EMDB database of emerging stock markets, Bae *et al.* (2012) also analyse the relationship between lead-lag cross-autocorrelations and the speed of adjustment to new information, but again using portfolio data. Also, the markets in this study are mainly secondary emerging markets (e.g. South Africa, Malaysia, Brazil and Portugal), which are much larger than the TTSE in terms of market capitalization and number of listed firms. They also have liquidity far superior to that of the TTSE.
[4]The use of individual stocks it also more appropriate for embryonic markets like the TTSE where there is very little trading in portfolios.

Sias and Starks (1997) review various theoretical attempts to explain how the presence of institutional investors affects the behaviour of stock prices. The underlying mechanism can be summarized as follows. Cross-autocorrelation arises as institutional traders gather extensive information for the subset of stocks which they invest in, that is, institutionally favoured stocks. When institutional investors trade in the information they collect the prices of the corresponding stocks will reflect the information set observed by these investors. While some of this information is stock specific, a portion will be general in nature, and therefore, relevant to the pricing of stocks that are held by non-institutional investors (institutionally, unfavoured stocks). By observing the prices of the institutionally favoured stocks, non-institutional investors will find information relevant to the pricing of the rest of the stocks. By trading on this information, they will transmit the informational content from the lagged prices of the institutionally favoured to the current prices of the unfavoured stocks. This results in a lead-lag, cross-autocorrelation relationship where the lagged returns of the institutionally favoured stocks can forecast the future returns of the institutionally unfavoured stocks.

For our empirical tests, and in line with the dominant methodology employed in the literature, we apply a VAR framework to assess lead-lag cross-autocorrelation between ‘high’ and ‘low’ institutionally owned stocks in the TTSE. This ensures that any observed lead-lag cross-autocorrelation is not a spurious manifestation of the autocorrelation of the low institutional ownership equity returns and the contemporaneous correlations between the low institutional ownership and the high institutional ownership equity returns. Given that in their studies of the NYSE, Badrinath *et al.* (1995) and Sias and Starks (1997) find that firm size is correlated with the level of institutional investment, we control for the effects that firm size might have on the lead-lag relation in our sample. We control also for variations in the level of analysts coverage (Brennan *et al.* 1993) and variations in liquidity (Chordia and Swaminathan, 2000) that have also been offered as possible causes of the cross-autocorrelation relationship. Overall, our findings suggest that the prices of institutionally owned stocks react much faster to new information than the prices of stocks mostly held by individual investors.

We organize the remainder of the paper as follows. In Section 2 we present the modelling framework that we employ to test the institutional ownership hypothesis. In Section 3 we describe our data set and provide some preliminary descriptive statistics of the relation between institutional ownership and the cross autocorrelation in equity returns. In Section 4 we report our empirical results and in Section 5 we conduct a series of robustness checks. Finally, we conclude in Section 6.

## 2. Modelling Framework

We hypothesise that the returns of stocks with a high level of institutional ownership (institutionally favoured stocks) lead the returns of stocks with a low institutional ownership (institutionally unfavoured stocks).[5] This lead-lag relation would arise when the institutionally favoured stocks reflect market-wide information faster that the institutionally unfavoured stocks.[6] We assume that institutional investors engage in more information-gathering activities compared to individual investors. They therefore attain new and current market-wide information before individual investors. This allows them to update their valuations on the stocks which they hold in a timely fashion, so that the prices of these stocks

[5] Institutional investors only hold a subset of stocks for which the volume of information and the expected benefits of information collection are large relative to the costs. In addition, these stocks must satisfy legal “prudence” requirements (see Merton, 1987).

[6] Recall that the information gathered by investors pertain to the stocks that they invest in. While some of this information is firm specific, a portion is general in nature and applicable to the pricing of all stocks, that is, market-wide information.

will reflect this information quickly. The individual investors, who receive this information later, will update their valuations with a lag.

To examine the above hypothesis, we use a vector autoregression framework, where we evaluate whether returns of *HI* stocks lead the returns of *LO* stocks , where *HI* denotes a firm with high institutional ownership (i.e. are institutionally favoured) and *LO* denotes the stocks of firm with low institutional ownership (institutionally unfavoured). Such lead-lag effects can be tested using the following bivariate VAR:

$$R_{LO,t} = \alpha_{LO} + \sum_{k=1}^{K} a_k R_{LO,t-k} + \sum_{k=1}^{K} b_k R_{HI,t-k} + \varepsilon_t \tag{1}$$

$$R_{HI,t} = \alpha_{HI} + \sum_{k=1}^{K} c_k R_{LO,t-k} + \sum_{k=1}^{K} d_k R_{HI,t-k} + u_t \tag{2}$$

where $R_{LO,t}$ and $R_{HI,t}$ are the returns of stock *LO* and *HI*, respectively, at time *t*. $\sum_{k=1}^{K} b_k$ in equation (1) and $\sum_{k=1}^{K} c_k$ in equation (2) are the sums of the cross-autoregressive coefficients. The number of lags in each equation is selected using the Akaike and Schwartz information criteria. Since the regressors are the same for both equations (1) and (2), the VAR can be efficiently estimated by running ordinary least squares (OLS) on each equation individually.

In equation (1), if the lagged values of $R_{HI}$ can predict the contemporaneous value of $R_{LO}$, while controlling for the predictive power of the lagged values of $R_{LO}$, then $R_{HI}$ is said to *Granger-cause* $R_{LO}$.[7] We examine whether the sum of the cross-autoregressive coefficients (the coefficients related to the lagged values of $R_{HI}$) in equation (1), $\sum_{k=1}^{K} b_k$ , is statistically

[7] We control for the lagged values of $R_{LO}$ to ensure that the cross-autocorrelation between $R_{HI}$ and $R_{LO}$ is not a restatement of $R_{LO}$'s own return autocorrelation. Under this framework, we are therefore controlling for the possibility that the lagged values of $R_{HI}$ are simply noisy proxies for the lagged values of $R_{LO}$.

different from zero.[8] This is achieved using a Wald test. If $\sum_{k=1}^{K} b_k$ is found to be statistically different from zero, this implies that the lagged *HI* returns have predictive power for the current *LO* stock returns, independent to that of the lagged *LO* returns. This version of the Granger causality test also indicates the sign of predictability; that is, we are able to discern whether the causal relationship from *HI* to *LO* is positive or negative, using the sign attached to the sum of the cross-autoregressive coefficients. Similarly, equation (2) allows us to determine whether the lagged returns of *LO* are able to forecast the current returns of *HI*, by testing whether the cross-autoregressive coefficient is $\sum_{k=1}^{K} c_k$ is statistically different from zero, while controlling for the predictive power of the lagged $R_{HI}$ values.

Next, we formally test whether the ability of the lagged values of $R_{HI}$ to predict the current value of $R_{LO}$ is better than the ability of the lagged values of $R_{LO}$ to predict the current value of $R_{HI}$. This is a formal test of asymmetry in the cross-autocorrelation between the returns of the *HI* and *LO* stocks and therefore establishes whether *HI* leads *LO*. To achieve this purpose, we conduct a *cross-equation test* by evaluating whether the sum of the cross-autoregressive coefficients in equation (1), $\sum_{k=1}^{K} b_k$, is greater than the sum of the cross-autoregressive coefficients in equation (2), $\sum_{k=1}^{K} c_k$, where $\sum_{k=1}^{K} b_k$ should be statistically different from zero. We conduct this cross-equation test using a Wald test to assess the null hypothesis that $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$. If the null is rejected, and the sum of the $b_k$ coefficients is greater than the sum of the $c_k$ coefficients $\left( \sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k \right)$, we would conclude that the ability of the lagged returns

[8] This is consistent with Brennan *et al.* (1993), Sias and Starks (1997), Chordia and Swaminathan (2000), Hou (2007) and Chuang and Lee (2011).

of *HI* to predict the current *LO* returns (even after controlling for the own autocorrelation of *LO*) is better than the ability of the lagged *LO* returns to predict the current *HI* returns. This indicates that the returns of *HI* lead the returns of *LO*. Such a result can be attributed to *HI* having a faster speed of adjustment to information than *LO*.

As noted earlier, this version of the Granger Causality test not only considers predictability but also the sign of the predictability, that is, the sign attached to $\sum_{k=1}^{K} b_k$ and $\sum_{k=1}^{K} c_k$. Consider that both $\sum_{k=1}^{K} b_k$ and $\sum_{k=1}^{K} c_k$ are statistically (1) different from zero and (2) $\sum_{k=1}^{K} b_k \neq \sum_{k=1}^{K} c_k$. Brennan *et al.* (1993) shows that if the lagged returns of *LO* predict the current returns of *HI* with a negative sign, that is, if $\sum_{k=1}^{K} c_k$ is negative, while $\sum_{k=1}^{K} b_k$ is positive, then the inequality $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$ is met and it can be concluded that *LO* reacts to information more sluggishly in relation to *HI*. Therefore *HI* leads *LO*.

Chordia and Swaminathan (2000) point out that taking the sign into account makes this version of the Granger Causality test more reliable for assessing lead-lag effects than the conventional Granger Causality test. The conventional test evaluates for predictability by jointly testing whether the slope coefficients corresponding to the lagged returns of *HI* are *LO* are equal to zero. This test, however, ignores the sign attached to the coefficients. Therefore, it may be a case, for example, that the test finds that the coefficients attached to $R_{LO,t-k}$ in equation (2) are statistically jointly different from zero. However, all or the majority of these slope coefficients might be negative, implying that the overall predictability of *LO* is negative. This means that *LO* reacts to information more slowly than *HI* (provided that the slope coefficients of *HI* are all statistically different from zero and most/all are positive).

However, the test only reports whether *LO* predicts or *Granger causes HI* and is not able to discern the sign of predictability, which is a clear disadvantage of the test compared to the test applied in this study.

### 3. Data and Preliminary Statistics

Our sample consists of each firm listed for trading on the TTSE over the period January 2001 to December 2008. To be included in the sample, a firm must have been listed for trading on the market for the entire sample period. Thirty firms meet this criterion and are therefore used in our analysis. For each of these firms, we obtain data on their daily stock returns from the TTSE. We also use data on their daily volume traded and annual market capitalisation from the exchange. Annual data on the percentage of shares held by institutional investors in each firm is compiled using the yearly company reports produced by the Trinidad and Tobago Securities and Exchange Commission (TTSEC).[9] These institutional investors mainly comprise of financial companies such as banks, insurance companies, pension funds and investment advisors, to name a few.[10] For the purpose of this study, we measure institutional ownership in each firm using the average of the annual portion of stocks owned by these institutional investors over the sample period. We base our analysis on the mean institutional ownership, as there were no significant changes in the annual level of institutional investment in each firm over the sample period.

Lo and MacKinlay (1990) report that the returns of large firms lead the returns of small firms, that is, the lagged returns of large firms are correlated with the contemporaneous returns of

[9] Our sample period starts from January 2001 as information on the level of institutional ownership for each firm is only available from this date. Note also that automated trading on the market commenced only in March, 2000.

[10] Note that the finance literature does not consider the government itself to be an institutional investor. It regards the government to be a separate class of investor. This is noted by Harris (2002), who points out that there are three broad classes of investors, namely individual and institutional investors, and the government. Therefore, the portion of TTSE shares owned by the government is not included as part of our measure of institutional ownership.

small firms. In our sample, the cross-sectional correlation between the mean firm size and level of institutional ownership is statistically significant at the 5% level: $\rho$ = 0.391.[11] This positive correlation naturally leads to the question of whether the firm size effects are subsumed by the institutional ownership effects, or vice versa. We therefore control for any effects which firm size may have on the lead-lag relationship. By controlling for such effects we are able to discern whether the cross-autocorrelation is actually attributed to institutional ownership and not due to the effects of differences in size of the listed firms.

To control for the effects of firm size, five size based quintiles are formed, by ranking the 30 listed firms in our sample according to their average firm size over 2001 to 2008.[12] Each stock is assigned to one of five quintiles, with six stocks in every quintile. For each one of these quintiles, we test whether the daily returns of the stock with the highest mean level of institutional ownership (*HI*) leads the daily returns of the stock with the lowest mean level of institutional ownership stock (*LO*). [13]

Table 1 presents descriptive statistics for the *HI* and *LO* firms in each size quintile $i$=1,...,5.[14] Quintile 1 is the highest size based quintile and 5 is the lowest. Note that in each quintile, the *HI* (*LO*) firms represented in this table not only have the highest (lowest) mean institutional ownership, but also have the highest (lowest) institutional ownership in the same quintile for each year in the sample period. For example, the stock RBL has the highest institutional ownership (1) on average and (2) in each year, for quintile 1 over the sample period. There

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[11] A number of other studies find that firm size is highly and positively correlated with the level of institutional ownership (for example Badrinath *et al.*, 1995; Sias and Starks, 1997; Næs and Skjeltorp, 2003; Rubin, 2007).

[12] Firm size is measured using the ratio of the firm's market capitalisation to the overall market capitalisation. A higher value of this ratio indicates a larger the firm size. To rank the listed firms according to size, we take the average value of the firm size for each firm over the eight year sample period.

[13] As is noted earlier, we use the mean level of institutional investment, as the annual levels for each stock do not substantially change over the sample period. In fact, we find that there are no cases where some stocks are classed as *HI* / *LO* in some years but not in other years. Therefore, those stocks with the highest and lowest institutional ownership in each size quintile remain the same in each year of the sample period.

[14] Note that the various *HI* (*LO*) stocks do not belong to the same sector.

are no cases where stocks are classed as *HI* / *LO* in some years but not in other years. This is because the degree of institutional ownership in each firm only changes marginally over the sample period. In which case, the average degree of institutional ownership provides a consistent picture of the level of institutional ownership among stocks and is appropriate for ranking stocks as *HI* and *LO*.

Table 1: Summary Statistics for Size-Institutional Ownership Stocks

| | | ***Stock Returns*** | | ***Volume*** | | | |
|---|---|---|---|---|---|---|---|
| ***Quintile*** | ***Stock*** | ***Mean%*** | ***Std. Dev. %*** | ***Mean*** | ***Std. Dev.*** | ***Mean Size*** | ***Mean Institutional Ownership*** |
| *1* | *HI* | *0.082* | *2.203* | *35576.720* | *134181.700* | *0.154* | *0.830* |
| | *LO* | *-0.009* | *0.913* | *64716.560* | *446588.900* | *0.061* | *0.600* |
| *2* | *HI* | *0.141* | *2.625* | *29675.340* | *366772.400* | *0.025* | *0.820* |
| | *LO* | *0.015* | *1.489* | *6146.278* | *26377.720* | *0.035* | *0.520* |
| *3* | *HI* | *0.111* | *1.359* | *1916.907* | *32558.760* | *0.020* | *0.860* |
| | *LO* | *0.089* | *0.883* | *9654.590* | *130277.600* | *0.018* | *0.410* |
| *4* | *HI* | *0.091* | *1.416* | *114973.300* | *464173.000* | *0.009* | *0.770* |
| | *LO* | *0.012* | *1.779* | *38142.300* | *119344.900* | *0.006* | *0.300* |
| *5* | *HI* | *0.124* | *3.196* | *3766.313* | *17789.570* | *0.003* | *0.730* |
| | *LO* | *0.172* | *1.595* | *5562.937* | *23340.030* | *0.002* | *0.280* |

Table 1 shows that for the majority of the quintiles, the overall mean and standard deviation of the daily returns for the *HI* stocks are higher than those of the *LO* stocks. The table also reports the mean size and institutional ownership for the *HI* and *LO* stocks in each quintile over our sample period. We find that in four quintiles, the mean institutional ownership tends to increase with firm size, implying that institutional investors favour large capitalised stocks over small capitalised stocks. This pattern is also found by Chuang and Lee (2011). In quintile 2, however, we find that institutional ownership decreases with size. This provides an opportunity to test whether institutional ownership has an independent influence on the cross-autocorrelation patterns. Such a result may suggest that some institutional traders invest in smaller stocks for the purpose of portfolio diversification or increasing profits, despite the possibility of incurring high information set-up costs associated with these stocks. If institutional ownership does indeed have an independent effect, then the returns on the *HI* stock should lead the returns on the *LO* stock in quintile 2. If, on the other hand, institutional ownership is simply a proxy of firm size, then the *LO* stock returns should lead the *HI* stock returns in quintile 2.

Further, the table shows that the mean volume of *HI* and *LO* stocks traded does not increase with firm size. We also find that the cross-sectional correlation between the average volume traded and the average firm size of the thirty stocks in our sample is statistically insignificant: $\rho = 0.233$.[15] In this regard, volume does not proxy for firm size, which implies that any relation uncovered between and liquidity and the lead-lag relation is independent of firm size. We also find that the volume traded does not proxy for the level of institutional ownership. The table shows that the mean and the standard deviation of the volume of *HI* stocks traded are lower than those of the *LO* stocks in three quintiles (1, 3 and 5). Moreover, the cross-sectional correlation between these variables, which is computed using the thirty stocks in our sample, is not statistically significant: $\rho = 0.154$. Such a finding is in contrast to Sias and Starks (1997), who point out that high institutionally owned stocks should be more liquid, as there are lower transaction costs associated with such stocks.[16] This, however, may not hold in the case of an emerging market such as the TTSE, as microstructures are different. Specifically, there are more severe thin-trading and transaction cost problems associated with the stocks in this market, in relation to developed markets. Therefore, it may be possible that

[15] This is in contrast to Chordia and Swaminathan (2000), who find that volumes traded are highly and positively correlated.
[16] Sias and Starks (1997) conducted their analysis on institutional investment and return autocorrelation / cross-autocorrelation using stocks from the NYSE.

some stocks with a high institutional ownership may not trade very often, and would therefore have a lower liquidity.

Table 2: Own Autocorrelation Coefficients

| **Quintile** | **Stock** | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ |
|---|---|---|---|---|---|---|
| 1 | $R_{HI}$ | -0.027 | 0.035 | 0.043 | 0.028 | 0.025 |
| | $R_{LO}$ | 0.109** | 0.149** | 0.023 | 0.049* | -0.014 |
| 2 | $R_{HI}$ | 0.032 | 0.046 | 0.046 | 0.051* | 0.028 |
| | $R_{LO}$ | -0.058** | 0.110** | 0.060** | 0.026 | 0.048 |
| 3 | $R_{HI}$ | -0.405** | 0.082** | 0.010 | -0.001 | 0.022 |
| | $R_{LO}$ | 0.302** | 0.183** | 0.122** | 0.073** | 0.044 |
| 4 | $R_{HI}$ | 0.083** | 0.071** | 0.044 | 0.032 | 0.041 |
| | $R_{LO}$ | 0.0545* | 0.109** | 0.096** | 0.074** | 0.039 |
| 5 | $R_{HI}$ | 0.072* | 0.024 | 0.034 | 0.029 | 0.023 |
| | $R_{LO}$ | -0.244** | 0.078** | -0.025 | 0.071** | 0.049* |

Note: ** and * refers to statistical significance at the 5% and 10% level.

Table 2 reports, for each quintile, the first- through fifth-order autocorrelation coefficients for the returns of the *HI* and *LO* stocks. We find that the majority of the autocorrelation coefficients on the *HI* stocks are not statistically significant, with the *HI* stock in the largest quintile having no significant coefficients. By contrast, the bulk of the statistically significant autocorrelation coefficients for the *LO* stocks are positive. The low autocorrelation in the *HI* stocks is consistent with the hypothesis that the high institutionally owned stocks adjust quickly to common information. In addition, the positive autocorrelation in *LO* stocks suggests that these stocks adjust slowly to information.

Table 3: Cross-Correlation Coefficients

| | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 |
|---|---|---|---|---|---|
| $\rho(R_{LO,t}\,R_{HI,t})$ | 0.052* | 0.202** | 0.151** | 0.135** | -0.015 |
| $\rho(R_{LO,t},R_{HI,t-1})$ | 0.0593** | 0.2655** | 0.0863** | -0.0356* | 0.0114 |
| $\rho(R_{HI,t},R_{LO,t-1})$ | 0.1420** | -0.0810** | 0.0788** | -0.0450* | 0.0348* |
| $\rho(R_{LO,t},R_{HI,t-2})$ | 0.1212** | 0.0957** | 0.0301 | 0.0602** | 0.0091 |
| $\rho(R_{HI,t},R_{LO,t-2})$ | 0.0636** | 0.0209 | 0.0155 | 0.0382* | 0.0147 |
| $\rho(R_{LO,t},R_{HI,t-3})$ | -0.0149 | 0.0392* | -0.0153 | 0.0466* | 0.2287** |
| $\rho(R_{HI,t},R_{LO,t-3})$ | 0.0051 | 0.0126 | 0.0139 | -0.0194 | -0.0038 |
| $\rho(R_{LO,t},R_{HI,t-4})$ | 0.0138 | 0.0110 | 0.0265 | 0.0801** | -0.0106 |
| $\rho(R_{HI,t},R_{LO,t-4})$ | 0.0120 | 0.0061 | -0.0143 | 0.0570** | -0.0786** |
| $\rho(R_{LO,t},R_{HI,t-5})$ | 0.0599** | 0.0751* | 0.0007 | 0.0911** | 0.0056 |
| $\rho(R_{HI,t},R_{LO,t-5})$ | -0.0039 | -0.0113 | 0.0324 | -0.0312 | 0.0034 |

Note: ** and * refers to statistical significance at the 5% and 10% level.

Finally, Table 3 provides some initial evidence of lead-lag cross-autocorrelation between the *HI* and *LO* stocks. Specifically, it reports the contemporaneous correlations between both types of stocks for each quintile. It also provides the first- through fifth-order cross-autocorrelations coefficients between the lagged returns on the *HI* stocks and the current returns on the *LO* stocks in each quintile. We find that the contemporaneous correlation between the *HI* and *LO* stocks of the first four quintiles is positive and statistically significant. In addition, for each quintile, the extent to which the lagged *HI* returns are correlated with the current *LO* returns is greater than the extent to which the lagged *LO* returns are correlated with the current *HI* returns. This asymmetry in the cross-autocorrelation provides some preliminary evidence consistent with the hypothesis that the lagged returns of the high institutionally owned stocks predict the current returns of the low institutionally owned stocks better than vice versa. However, this cross-autocorrelation pattern could be a manifestation of the high autocorrelation in the returns of the *LO* firms (observed in Table 2) coupled with high contemporaneous correlation between the between the *HI* and *LO* firms.[17] The lagged returns of the *HI* firms may be noisy proxies for the lagged returns of the *LO* firms, and once the lagged returns of the *LO* firms are controlled for, this cross-correlation pattern could disappear. It is essential therefore to control for the lagged *LO* returns in the VAR analysis.

## 4. Empirical Results

Table 4 presents the results of the bivariate VAR analysis. The VARs are estimated using the returns of the highest (*HI*) and lowest (*LO*) institutionally favoured stocks in five size quintiles: ($LO_1$, $HI_1$), ($LO_2$, $HI_2$), ($LO_3$, $HI_3$), ($LO_4$, $HI_4$), ($LO_5$, $HI_5$). The suffixes 1…5 denote the size quintiles, with 1 representing the highest quintile and 5 the lowest. The number of lags in each VAR is selected on the basis of the Akaike Information Criteria (AIC) and the Schwarz Information Criteria (SIC). Where these two criteria indicate different lag lengths, the lesser lag length is chosen for the sake of parsimony. The sum of the coefficients reported is the sum of the cross-autoregressive slope coefficients, namely $\sum_{k=1}^{K} b_k$ from equation (1) or $\sum_{k=1}^{K} c_k$ from equation (2), as per the dependent variable.

There is strong evidence that the lagged returns of the highest institutionally owned stocks (*HI*) predict the contemporaneous returns on the stocks with the lowest institutional ownership (*LO*). For each size quintile, the Wald (a) statistics are statistically significant, implying that the sum of the slope coefficients corresponding to the lagged returns of the *HI*

[17] This is also pointed out by Boudoukh *et al.* (1994), Hameed (1997) and Hou (2007).

stocks, $\sum_{k=1}^{K} b_k$ , is typically different from zero. In addition, $\sum_{k=1}^{K} b_k$ is positive in each quintile, which implies that the cross-autocorrelation relationship between stock *HI* and *LO* is positive. There is, however, little evidence that the lagged returns on *LO* stocks reliably forecast the current returns on *HI* stocks. We find that for four size quintiles (2, 3, 4 and 5), the sum of the coefficients on the lagged returns of the *LO* stocks are not statistically different from zero, as implied by the insignificant Wald (a) statistics. For these four quintiles, therefore, the lagged returns of the *LO* stocks are unable to predict the current returns of the *HI* stocks.

Furthermore, the results also show that for each size quintile, the ability of the lagged *HI* stock returns to predict the current *LO* stock returns exceeds the ability of the lagged *LO* stock returns to predict current *HI* stock returns. For each of the five pairs of regressions, the sum of the $b_k$ coefficients on the lagged *HI* stocks are found to exceed the sum of the $c_k$, coefficients on the lagged *LO* stocks $\left(\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k\right)$ while the Wald (b) test statistic rejects the null hypothesis that $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ . These results confirm our hypothesis that the returns of the *HI* stocks lead the returns of the *LO* stocks.

Table 4: Vector Autoregressions for the Size-Institutional Ownership Stocks

| Quintile | Dependent Variable | Lag Length | Sum of Coefficients | Wald (a) | Wald (b) | *HI* leads *LO* |
|---|---|---|---|---|---|---|
| 1 | $R_{LO1,t}$ | 3 | 0.395 | 10.464** | 7.357** | Yes |
| | $R_{HI1,t}$ | 3 | 0.060 | 11.052** | | |
| 2 | $R_{LO2,t}$ | 3 | 0.706 | 64.059** | 71.663** | Yes |
| | $R_{HI2,t}$ | 3 | -0.024 | 0.947 | | |
| 3 | $R_{LO3,t}$ | 2 | 0.139 | 18.143** | 5.922** | Yes |
| | $R_{HI3,t}$ | 2 | 0.010 | 0.024 | | |
| 4 | $R_{LO4,t}$ | 6 | 0.201 | 9.506** | 7.717** | Yes |
| | $R_{HI4,t}$ | 6 | -0.022 | 0.227 | | |
| 5 | $R_{LO5,t}$ | 7 | 0.692 | 11.492** | 10.120** | Yes |
| | $R_{HI5,t}$ | 7 | 0.015 | 0.063 | | |

Note: ** and * refers to statistical significance at the 5% and 10% level.

As an initial check on the reliability of our base results we investigated the cross-autocorrelation between an equally weighted market portfolio (*MP*) and first *HI* stocks and then *LO* stocks. These estimation results are set out in Appendix tables A.2 and A.3 respectively. Overall, these results indicate that the stocks returns of firms with high institutional ownership lead the market portfolio, while the returns of *MP* lead the returns of *LO*. The above results are consistent with the faster adjustment of institutionally favoured stocks than the market portfolio (which is a mixture of *HI* and *LO* stocks) to new information, but with the market portfolio adjusting to current information more quickly than the low institutional ownership stocks. By the time that low institutionally owned stocks reflect new information, this information will have already been incorporated in the historical returns of the market portfolio, giving rise to a lead-lag effect from the market portfolio to the low institutionally owned stocks.

## 5. Further Robustness Analysis

Brennan et al. (1993) document that the level of analyst coverage received by firms also affects the speed of stock price adjustment to information. The higher the number of analysts covering a firm, the greater the information generated about that firm. This increases the number of informed investors, which in turn causes its share price to reflect more information rapidly. As such, the prices of stocks with higher analyst coverage impound information faster than those stocks with a lower coverage. This gives rise to a lead-lag effect where the firms with high analyst coverage lead the returns of firms with low analyst coverage.

In our sample, the cross-sectional correlation between analyst coverage and institutional investors is statistically significant at the 5% level: $\rho$ = 0.382. This positive correlation naturally leads to the question of whether the analyst coverage effects are captured by the institutional ownership effects, or vice versa. We therefore repeat the above cross-autocorrelation analysis, while controlling for any effects which the level of analyst coverage received by the listed firms may have on the lead-lag relationship.

We control for the effects of analyst coverage similar to the manner in which we previously controlled for firm size. Five analyst coverage quintiles are formed, by ranking all listed firms according to the average analyst coverage received by each of them (measured by the number of analysts following each firm/stock over the period 2001 to 2008).[18] In each quintile, we test whether the returns of the highest institutional ownership stock leads the returns of the

[18] The analyst coverage of a particular firm is defined as the number of analysts making annual earnings forecasts for that firm in December of the previous year. To rank the listed firms, we take the average of the number of analysts for each firm over the eight year sample period. This information is obtained from the research department of the TTSEC. This measure of analyst coverage is also used in Brennan *et al.* (1993) and Chuang and Lee (2011).

lowest institutionally owned stock. This testing is also conducted in a bivariate VAR framework, and the results are presented in Table 5.

Table 5: Vector Autoregressions for the Analyst-Institutional Ownership Stocks

| **Quintile** | **Dependent Variable** | **Lag Length** | **Sum of Coefficients** | **Wald (a)** | **Wald (b)** | ***HI* leads *MP*** |
|---|---|---|---|---|---|---|
| 1 | $R_{MP,t}$ | 3 | 0.129 | 18.263** | 1.469 | No |
| | $R_{HI1,t}$ | 3 | 0.009 | 0.011 | | |
| 2 | $R_{MP,t}$ | 4 | 0.337 | 27.394** | 4.131** | Yes |
| | $R_{HI2,t}$ | 4 | -0.003 | 0.002 | | |
| 3 | $R_{MP,t}$ | 4 | -0.001 | 0.001 | 2.379 | No |
| | $R_{HI3,t}$ | 4 | -0.245 | 2.467 | | |
| 4 | $R_{MP,t}$ | 6 | 0.043 | 34.377** | 0.297 | No |
| | $R_{HI4,t}$ | 6 | -0.787 | 0.332 | | |
| 5 | $R_{MPt}$ | 3 | 0.105 | 7.113** | 4.114** | Yes |
| | $R_{HI5,t}$ | 3 | 0.052 | 0.606 | | |

Note: ** and * refers to statistical significance at the 5% and 10% level.

We find that the results are generally consistent with those in Table 4. Table 5 confirms that there is a lead-lag cross-autocorrelation from the *HI* to the *LO* stocks. Specifically, the extent to which the informational content of the historical returns of the *HI* stocks is relevant to the current pricing of the *LO* stocks is greater than vice versa.

Finally, we explore whether the institutional ownership role in the identified lead-lag effect holds if we control for the effect of liquidity[19]. For this purpose, we estimate equation (3), which captures the effect of liquidity on the lead-lag relation from the *HI* to the *LO* stocks in each size-based quintile:

[19] As pointed earlier, Chordia and Swaminathan (2000) argue that variation in liquidity across stocks is a possible reason for lead-lag effects.

$$R_{LOi,t} = \alpha_{LOi} + \sum_{k=1}^{K} a_{1,k} R_{LO,t\text{-}k} + \sum_{k=1}^{K} a_{2,k} Liq_{LO,t\text{-}k} + \sum_{K=1}^{K} b_{1,k} R_{HI,t\text{-}k} + \sum_{K=1}^{K} b_{2,k} Liq_{HI,t\text{-}k} +$$
$$\sum_{k=1}^{K} b_{3,k} \left(R_{HI} * Liq_{HI}\right)_{t\text{-}k} + \sum_{k=1}^{K} b_{4,k} \left(R_{HI} * Liq_{LO}\right)_{t\text{-}k} + \varepsilon_t \qquad (3)$$

where $R_{HI,t}$ and $R_{LO,t}$ denote the returns of the stocks *HI* and *LO* respectively at time *t*. $Liq_{LO,t}$ and $Liq_{HI,t}$ denote the liquidity of low institutional ownership and high institutional ownership stocks respectively, on day *t*. We measure liquidity using the volume of *LO* and *HI* stocks traded on each day.[20 21]

The results of this estimation are presented in Table 6. Panels A to E of this table provide the results for each size- based quintile, with Panel A reporting the results for the largest quintile (dependent variable - $R_{LO,1}$) and Panel E reporting the results for the smallest quintile (dependent variable - $R_{LO,5}$). We present the sum of the coefficients of each explanatory variable in the regression in column (2). Column (3) gives the Wald test statistics for the null hypothesis that the sums of the coefficients of the explanatory variables are statistically different significantly different from zero. The Joint test is a Wald test of the null hypothesis that the coefficients of all explanatory variables are jointly significant.

Table 6: Impact of Liquidity on Cross-autocorrelation

[20] Jones *et al.* (1994) and Datar *et al.* (1998) argue that volume traded and volume related measures of liquidity are highly correlated with the number of trades (trading frequency), which is the most direct measure of liquidity. To this end, we measure liquidity using the daily volume of stocks traded.

[21] We control for liquidity, specifically the volume traded, since there is likely to be a causal relationship between volume traded and stock returns. Evidence of this is given in a number of studies including Jennings, Starks and Fellingham (1981), Gallant, Rossi and Tauchen (1992), Heimstra and Jones (1994), Blume, Easley and O'Hara (1994) and Brennan, Chordia and Subramanyam (1998).

| Equation (1) | Sum of Coefficients | Wald Test |
|---|---|---|
| **Panel A: (Quintile 1) Dependent Variable - $R_{LO1,t}$** | | |
| $R_{LO1,t}$ | 0.213 | 23.998** |
| $R_{HI1,t-k}$ | 0.393 | 10.319** |
| $Liq_{HI1,t-k}$ | 1.12E-09 | 0.021 |
| $Liq_{LO1,t-k}$ | 3.23E-10 | 0.039 |
| $R_{HI1,t-k}$* $Liq_{HI1,t-k}$ | 1.30E-06 | 11.924** |
| $R_{HI1,t-k}$* $Liq_{LO1,t-k}$ | -2.14E-05 | 3.449* |
| AIC/SIC = 3 Joint test = 126.429** Adj-$R^2$ = 0.086 | | |
| **Panel B: (Quintile 2) Dependent Variable - $R_{HI2,t}$** | | |
| $R_{LO2,t}$ | 0.195 | 16.746** |
| $R_{HI2,t-k}$ | 0.096 | 0.833 |
| $Liq_{HI2,t-k}$ | -1.58E-08 | 0.171 |
| $Liq_{LO2,t-k}$ | 5.45E-09 | 3.510* |
| $R_{HI2,t-k}$* $Liq_{HI2,t-k}$ | 6.51E-06 | 45.886** |
| $R_{HI2,t-k}$* $Liq_{LO2,t-k}$ | -8.33E-06 | 14.369** |
| AIC/SIC=3 Joint test: Wald = 455.097** Adj-$R^2$ = 0.354 | | |
| **Panel C: (Quintile 3) Dependent Variable - $R_{LO3,t}$** | | |
| $R_{LO3,t}$ | 0.408 | 144.962** |
| $R_{HI3,t-k}$ | -0.044 | 0.774 |
| $Liq_{HI3,t-k}$ | 2.35E-09 | 0.051 |
| $Liq_{LO3,t-k}$ | -1.33E-09 | 0.263 |
| $R_{HI3,t-k}$* $Liq_{HI3,t-k}$ | 8.09E-08 | 16.230** |
| $R_{HI3,t-k}$* $Liq_{LO3,t-k}$ | -1.69E-07 | 0.1389 |
| AIC/SIC=3 Joint test = 212.324**Adj-$R^2$ = 0.143 | | |
| **Panel D: (Quintile 4) Dependent Variable - $R_{LO4,t}$** | | |
| $R_{LO4,t}$ | *0.298* | *34.539*** |
| $R_{HI4,t-k}$ | *0.117* | *3.952*** |
| $Liq_{HI4,t-k}$ | *2.01E-09* | *0.913* |
| $Liq_{LO4,t-k}$ | *2.89E-09* | *0.187* |
| $R_{HI4,t-k}$* $Liq_{HI4,t-k}$ | *2.48E-05* | *9.185*** |
| $R_{HI4,t-k}$* $Liq_{LO4,t-k}$ | *-4.14E-05* | *10.361*** |
| AIC/SIC = 4 Joint test: Wald = 131.941 ** Adj-$R^2$ = 0.081 | | |
| **Panel E: (Quintile 5) Dependent Variable - $R_{LO5,t}$** | | |
| $R_{LO5,t}$ | -0.151 | 6.898** |
| $R_{HI5,t-k}$ | 0.123 | 27.719** |
| $Liq_{HI5,t-k}$ | 2.67E-08 | 0.445 |
| $Liq_{LO5,t-k}$ | -2.81E-08 | 0.709 |
| $R_{HI5,t-k}$* $Liq_{HI5,t-k}$ | 4.81E-05 | 9.253** |
| $R_{HI5,t-k}$* $Liq_{LO5,t-k}$ | -2.47E-05 | 5.861** |
| AIC/SIC=3 Joint test: Wald = 252.218** Adj-$R^2$ = 0.162 | | |

Note: ** and * refers to statistical significance at 5% and 10%

It is clear from Table 6 that the liquidity of the *HI* stocks influences the extent to which the *HI* stocks lead the *LO* stocks. We find that the sum of the coefficients on the lagged interaction term $R_{HI} * Vol_{HI}$ is positive in each quintile, and strongly significant in all five quintiles. The results are consistent with a hypothesis that the lead-lag relation from the returns of the *HI* stocks to the returns of the *LO* stocks is stronger when the *HI* stocks are more liquid. This can be attributed to the *HI* stocks responding to contemporaneous market-wide information more rapidly when their liquidity increases.

The results in Table 6 further suggest that the ability of the *HI* returns to lead the *LO* returns diminishes with an increase in the *LO* stock liquidity. In four quintiles (1, 2, 4 and 5), we find that the sum of the coefficients on the lagged interaction term $R_{HI} * Vol_{LO}$ is negative and statistically different from zero. Such findings arise as higher liquidity in the *LO* stocks reduces the delay to which new market-wide information is reflected in the prices of these stocks. Although information is impounded in the *HI* stocks first, causing *HI* to lead *LO*, a faster adjustment of the *LO* stocks to new information lowers the extent to which the informational content of the lagged *HI* stocks returns are useful for the future pricing of the *LO* stocks. This could have implications for arbitrage activity in the equity market. Arbitrageurs, who are aware of the lead-lag relation from *HI* to *LO* stocks, may attempt to profit by using the historical prices of the *HI* stocks to predict the future prices of the *LO* stocks.

## 6. Conclusions

In this paper we consider whether differences in the level of institutional investment across firms can give rise to lead-lag cross-autocorrelations in an emerging equity market setting. We use firm level data from the TTSE for the embryonic stage of development of an emerging equity market, one which experienced a high level of institutional investment over the period of investigation. In addition, its microstructures, regulatory and information environments are under-developed, making it an ideal setting to assess lead-lag relations in an emerging market context. The use of firm level data enables us to accurately represent the pattern of lead-lag effects between stocks with different institutional ownerships, which could otherwise be hidden if portfolio level data were used.

We apply this data in a vector autoregression (VAR) framework and find that the level of institutional ownership among stocks is a significant determinant of lead-lag cross-autocorrelation in stock returns. Specifically, the returns of stocks with a high level of institutional ownership have substantial predictive power and lead the returns of stocks with a low institutional ownership. We attribute this result to the tendency of stocks with a low level of institutional ownership to react to information more slowly than the high institutional ownership stocks. Such results are consistent with previous studies that explored whether lead-lag effects arise due to differences in institutional investments across portfolios in the NYSE (see Bardinath *et al.*, 1995; Sias and Starks, 1997; Chuang and Lee; 2011). This suggests the level of institutional investment in equities can influence the speed of adjustment and give rise to lead-lag effects in international stock markets, regardless of whether they are developed or emerging (even in their very early stages of development). We also show that the returns of the high institutionally owned stocks lead the returns of the TTSE market portfolio. This suggests that the high institutionally owned stocks adjust to information faster than the aggregate market portfolio. By contrast, the market portfolio returns are found to lead the returns on the low institutionally owned stocks, indicating that the speed of adjustment of the low institutionally owned stocks is lower than that of the market portfolio.

Additional analysis reveals that the liquidity of the high institutionally owned stocks can improve the extent to which the returns on these stocks lead the returns on the low institutionally owned stocks. This is because an increase in the liquidity of the high institutionally owned stocks tends to improve its speed of adjustment to information. However, the extent to which the high institutionally owned stocks lead the returns of the low institutionally owned stocks is tempered by the liquidity of the low institutionally owned stocks. Such a finding is due to the speed of adjustment of the low institutionally favoured stocks increasing with the liquidity of these stocks.

The findings have important implications for informational efficiency. First, evidence of cross-autocorrelation among stocks indicates return predictability. In particular, the returns of the low institutionally owned stocks and the equally weighted market portfolio can be predicted using the past returns of the high institutionally owned stocks. This predictability is a clear violation of the defining property of market efficiency, which is the unpredictability of stock price increments. Second, the returns of the high institutionally owned stocks lead the returns on the low institutionally owned stocks and the market portfolio. This implies that the high institutionally owned stocks adjust faster to information than the low institutionally owned stocks and the market portfolio.[22] This is because institutional investors tend to actively gather information on the stocks they invest in. As such, they are able to revise their valuations of the stocks which they hold and their trading will reflect this information quickly. Individual investors, however, tend to gather less information than institutional investors. Therefore, the price adjustment of the high institutionally owned stocks would be faster than that of the stocks that are mostly held by individual investors. This suggests that the high institutionally owned stocks are more informational efficient than the low institutionally owned stocks.

[22] Brennan *et al.* (1993) provide a theoretical proof of this.

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## Appendix Tables

Table A.1: Scale of Trading Activity on the TTSE relative to the NYSE.

| | Listed Firms | | Market Capitalisation (USD Millions) | | Average Daily Equity Transactions | | Average Daily Equity Volume Traded (000's) | |
|---|---|---|---|---|---|---|---|---|
| | **TTSE** | **NYSE** | **TTSE** | **NYSE** | **TTSE** | **NYSE** | **TTSE** | **NYSE** |
| **2001** | 30 | 2,400 | $ 5,074 | $ 11,026,586 | 333 | 1,304,249 | 783 | 1,182,728 |
| **2002** | 30 | 2,366 | $ 7,682 | $ 9,015,270 | 356 | 2,098,293 | 625 | 1,396,677 |
| **2003** | 32 | 2,308 | $ 10,857 | $ 11,328,953 | 421 | 2,779,818 | 2,798 | 1,355,376 |
| **2004** | 33 | 2,293 | $ 17,191 | $ 12,707,578 | 361 | 3,732,446 | 2,204 | 1,411,917 |
| **2005** | 33 | 2,270 | $ 17,170 | $ 13,632,303 | 588 | 4,864,504 | 1,340 | 1,987,472 |
| **2006** | 33 | 2,280 | $ 15,385 | $ 15,421,167 | 687 | 5,056,978 | 1,415 | 2,262,047 |
| **2007** | 33 | 2,273 | $ 16,363 | $ 15,650,832 | 723 | 8,936,640 | 1,834 | 2,794,631 |
| **2008** | 33 | 1,963 | $ 12,739 | $ 9,208,934 | 700 | 12,760,728 | 1,607 | 3,208,106 |

Table A.2: Vector Autoregressions for the Size-High Institutional Ownership Stocks and the Market Portfolio

| **Quintile** | **Dependent Variable** | **Lag Length** | **Sum of Coefficients** | **Wald (a)** | **Wald (b)** | ***HI* leads *MP*** |
|---|---|---|---|---|---|---|
| 1 | $R_{MP,t}$<br>$R_{HI1,t}$ | 4<br>4 | 0.337<br>-0.003 | 27.394**<br>0.002 | 4.131** | Yes |
| 2 | $R_{MP,t}$<br>$R_{HI2,t}$ | 2<br>2 | 0.384<br>0.122 | 23.142**<br>19.868** | 9.657** | Yes |
| 3 | $R_{MP,t}$<br>$R_{HI3,t}$ | 3<br>3 | 0.105<br>0.052 | 7.113**<br>0.606 | 4.114** | Yes |
| 4 | $R_{MP,t}$<br>$R_{HI4,t}$ | 2<br>2 | 0.081<br>0.010 | 9.624**<br>0.016 | 0.871 | No |
| 5 | $R_{MPt}$<br>$R_{HI5,t}$ | 3<br>3 | 0.074<br>0.441 | 35.857**<br>6.531** | 4.491** | Yes |

Note: ** and * refers to statistical significance at the 5% and 10% level

Table A.3: Vector Autoregressions for the Size-Low Institutional Ownership Stocks and the Market Portfolio

| **Quintile** | **Dependent Variable** | **Lag Length** | **Sum of Coefficients** | **Wald (a)** | **Wald (b)** | ***MP* leads *LO*** |
|---|---|---|---|---|---|---|
| 1 | $R_{LO1,t}$<br>$R_{MP1,t}$ | 4<br>4 | 0.394<br>0.151 | 4.655**<br>42.301** | 1.746 | No |
| 2 | $R_{LO2,t}$<br>$R_{MP2,t}$ | 4<br>4 | 1.159<br>0.045 | 29.705**<br>4.3117** | 27.150** | Yes |
| 3 | $R_{LO3,t}$<br>$R_{MP3,t}$ | 4<br>4 | 0.086<br>0.075 | 3.146**<br>1.273 | 0.020 | No |
| 4 | $R_{LO4,t}$<br>$R_{MP4,t}$ | 4<br>4 | 2.144<br>0.049 | 19.646**<br>19.073** | 18.748** | Yes |
| 5 | $R_{LO5,t}$<br>$R_{MP5,t}$ | 4<br>4 | 0.065<br>0.049 | 5.926**<br>0.007 | 8.686** | Yes |

Note: ** and * refers to statistical significance at the 5% and 10% level.