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STOCK MARKET TRADING AND MARKET CONDITIONS

John M. Griffin
Federico Nardari
René M. Stulz

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Griffin is an Associate Professor of Finance at the McCombs School of Business, University of Texas at Austin. Nardari is an Assistant Professor of Finance at the WP Carey School of Business, Arizona State University. Stulz is the Everett D. Reese Chair of Banking and Monetary Economics, Ohio State University, and a Research Associate at the NBER. We are very grateful to Sriram Villupuram for superb research support. We thank Keith Brown, Stijn Claessens, Martijn Cremers, Enrico Perotti, Simon Potter, Laura Starks, Paul Tetlock, Sheridan Titman, Selim Topaloglu as well as seminar participants at Queen's University, the University of Amsterdam, and the University of Texas at Austin Accounting and Finance mini-conference. The views expressed herein are those of the author(s) and not necessarily those of the National Bureau of Economic Research.

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ABSTRACT

This paper investigates the dynamic relation between market-wide trading activity and returns in 46 markets. Many stock markets exhibit a strong positive relation between turnover and past returns. These findings stand up in the face of various controls for volatility, alternative definitions for turnover, and differing sample periods, and are present at both the weekly and daily frequency. However, the magnitude of this relation varies widely across markets. Several competing explanations are examined by linking cross-country variables to the magnitude of the relation. The relation between returns and turnover is stronger in countries with restrictions on short sales and where stocks are highly cross-correlated; it is also stronger among individual investors than among foreign or institutional investors. In developed economies, turnover follows past returns more strongly in the 1980s than in the 1990s. The evidence is consistent with models of costly stock market participation in which investors infer that their participation is more advantageous following higher stock returns.

John M. Griffin
McCombs School of Business
University of Texas
john.griffin@mail.utexas.edu

Federico Nardari
WP Carey School of Business
Arizona State University
federico.nardari@asu.edu

René M. Stulz
Fisher College of Business
Ohio State University
806A Fisher Hall
2100 Neil Avenue
Columbus, OH 43210-1144
and NBER
stulz@cob.osu.edu

It is part of market folklore that liquidity dries up following poor returns. In bear markets, trading volume is down, brokers make less money, fewer equity issues take place, and stock mergers become scarce. Although there is some evidence of a relation between turnover and past returns, there is neither a comprehensive documentation of it nor a generally agreed upon explanation for it.¹ In this paper, we investigate the relation between volume and lagged returns for 46 markets across the world using weekly data. The use of international data makes it possible to evaluate the robustness of the relation. Further, and perhaps more importantly, we can exploit cross-country differences in the relation to test possible explanations for it.

Our primary trading measure is turnover, or dollar trading volume normalized by market capitalization. Using a trivariate Vector Autoregression (VAR) of the market return, market volatility, and turnover with weekly data from 1993 through 2003, we find that a positive shock to returns leads to a significant increase in volume after ten weeks in 24 countries and to a significant decrease in no country. The economic magnitude of the return-turnover relation is large; a one standard deviation shock to returns leads to a 0.46 standard deviation increase in turnover on average after ten weeks. This effect of returns on volume is 0.72 in developing markets but only 0.26 on average in high-income countries. Perhaps surprisingly, the return-turnover relation is small and insignificantly negative for the U.S. in the 1993-2003 period.

Why is the return-turnover relation typically positive across countries? Why does it vary across countries? Theories of trading based on heterogeneity among rational agents due to

¹ In his review, Karpoff (1987) states that the two stylized empirical facts about the price-volume relation are that there is (1) a positive correlation between volume and the absolute level of the price change and (2) a positive correlation between volume and the level of the price change. Karpoff points out that the latter correlation is more sensitive to sample periods and measurement intervals than the former. The literature Karpoff reviews primarily focuses on this contemporaneous relation. Smirlock and Starks (1988) present evidence of higher volume following intradaily positive price movements for individual stocks, but only during days of information arrival. Lakonishok and Schmidt (1986) document the tendency for daily trading volume on individual stocks to be positively related to past performance. However, Tse (1991) and Saatcioglu and Starks (1998) conclude that there is little evidence that returns lead volume at the market level in Japan and six Latin American markets.

differences in information or taxes do not seem to be helpful to explain the return-turnover relation. For such information asymmetries to explain the return-turnover relation, they would have to increase following positive market returns, but the literature offers no convincing argument for why it should be so. The evidence in Lakonishok and Smidt (1986) is inconsistent with the view that trading for tax reasons is an important determinant of trading volume. The tax trading hypothesis predicts more trading in stocks that have done poorly, and they find the opposite. In any case, tax reasons could not explain results obtained using weekly or daily frequencies.

In models with rational investors, a positive relation between return and volume can arise also because of a shock to the cost of trading.² The net worth of liquidity providers falls as stock prices decrease (as they are long stocks on average). Hence the increase in trading (liquidity) costs leads to a decrease in volume following low past returns. We would expect the liquidity effect to be stronger in markets with relatively less trading activity, but in cross-sectional analysis we find this not to be the case. Additionally, the liquidity costs argument mostly applies to liquidity drying up in down markets. Using an asymmetric VAR we find, instead, that positive shocks to returns are followed by increases in volume of approximately the same magnitude as those following negative shocks to returns.

Binding restrictions to short sales affect the volume of trade since investors who would sell short cannot do so. Hence, if investors want to sell short more following poor market returns,

² Existing models of liquidity predict that a decrease in liquidity is associated with a fall in stock prices. As a result, as investors learn that liquidity is falling or will fall, we would expect a negative return on the market. For this argument to be compelling, it would have to be that the liquidity shocks are viewed as long-lasting. The liquidity explanation implies that the market return does not cause the change in liquidity, but rather the change in liquidity causes the market return. Following the liquidity shock, expected returns would have to be higher and realized returns lower. Recent evidence by Jones (2002) shows that high liquidity predicts low returns. However, as pointed out by Baker and Stein (2003), the magnitude of the decrease in returns associated with an increase in liquidity seems extremely large to be explained by theoretical models where the cost of trading impacts the expected return of stocks.

it would follow that the relation between return and volume is asymmetric. There is little theoretical work on the impact of short-sale restrictions on the volume-return relation in models with rational investors. Diamond and Verrecchia (1987) show that adverse information is incorporated into prices more slowly when short sales are prohibited. Though they do not derive results for volume, it follows from their analysis that fewer trades take place when investors have bad news. Jennings, Starks, and Fellingham (1981) have an extension of Copeland's (1976) sequential trading model where it is more costly to go short than long. Therefore, when uninformed investors interpret news pessimistically, volume decreases.³ Because short sales are prohibited in some countries and not others, our dataset is ideally suited to evaluate whether there is a correlation between short-sale restrictions and the return-turnover relation. Although not the main determinant, we find some evidence that short-sale restrictions are associated with a stronger return-volume relation. However, as previously discussed, we find the return-turnover relation to be rather symmetric, indicating that short sales are an incomplete explanation.

Costs to participate in the stock market as introduced by Allen and Gale (1994) may constitute another important link between trading volume and returns. For instance, in the model of Orosel (1998), high stock returns lead investors who do not participate in the stock market to increase their estimate of the profitability of stock market participation. In equilibrium, market participation rises after an increase of the share price and falls after a drop. Thus participation costs may explain a positive relation between past returns and trading volume. The key to this result, however, is that good news for stocks induces investors to participate more in the stock

³ Karpoff (1986) obtains the same result in a model where the supply of shares is less responsive to news than the demand because of the cost of going short. Hoontrakul, Ryan, and Perrakis (2002) extend Easley and O'Hara (1992) to take into account short-sale constraints. They find a positive correlation between return and volume, but in their theory return follows volume. Yet, many theoretical models make an assumption that essentially prevents short-sales and do not predict an asymmetry between return and volume. For instance, Harris and Raviv (1993) do not find such an asymmetry, but in their model investors can only take long positions.

market. This could be because less informed rational investors find returns informative, as in Brennan and Cao (1997) and Orosel (1998), or it could be because investors have extrapolative expectations for behavioral reasons as in Barberis, Shleifer, and Vishny (1998).

Behavioral theories of volume also make predictions about the relation between return and volume. As shown by Odean (1998b), overconfidence leads to greater trading volume. Odean and Gervais (2001) show that overconfidence grows with past success in the markets. This implies that a positive market return should lead to greater volume. The disposition effect of Shefrin and Statman (1985) also implies that volume follows returns since investors are reluctant to trade after poor returns and eager to lock in gains after a stock increases. Statman, Thorley, and Vorkink (2003) investigate the return-turnover relation in the U.S. and argue that the disposition effect at the stock level and overconfidence at the market level can explain the relation.

The less correlated stock returns are, the more likely it is that some stocks have performed poorly even when the market has performed well which, in the typically imperfectly diversified portfolios of individuals, dilutes the impact of overconfidence and of the disposition effect. We use the average R^2 from market-model regressions for a country's stocks, a measure of market informational efficiency developed by Morck, Yeung, and Yu (2000), to capture how much stocks move together. Additionally, it is difficult for investors to enter or trade in a market with high costs of information, providing another link between high values of the R^2 informational efficiency measure and high participation costs. Therefore, with participation costs, disposition, or overconfidence, we expect the return-turnover relation to be stronger for countries with a high average R^2 . We investigate this hypothesis and find strong support for it.

In our international data, seven countries have separate data for the trading of domestic investors and foreign investors, and four markets also have domestic investors' trading data broken down between individual investors and institutional investors. In contrast to foreign 'hot money' trading activity following past returns and driving the return-volume relation, we find that domestic turnover is more closely related to past returns than foreign turnover. We expect participation costs arguments to be more relevant for individual investors than for institutional investors who are likely to be already participating in the stock market. Also, if behavioral factors are important determinants of the return-turnover relation, we expect the relation to be weaker for institutions than for individuals. Consistent with these predictions, we find evidence that the return-turnover relation is stronger for individual investors.

The participation cost and behavioral hypotheses have different implications for the return-turnover relation across time. First, since the impact of overconfidence and disposition effects on trading decisions should be stronger in periods following high market returns, the return-turnover relation should be empirically stronger in the 1990s relative to the 1980s, since markets performed substantially better in the 1990s. Second, the participation theory suggests, instead, that the return-turnover relation should be weaker in the 1990s than in the 1980s because of greater participation in the 1990s and, conversely, more sidelined investors in the 1980s. In support of the participation story and in contrast to disposition and overconfidence explanations, we find that there is no return-turnover relation in the U.S. and many other advanced markets for the 1993-2003 period, but a significant relation exists for the 1983-1992 period. Additionally, when dividing the 1993-2003 period into two sub-periods, we find much stronger return-turnover relations in developed markets in the earlier period. Moreover, participation models call for a symmetric reaction of volume to past returns, which is consistent with what we find. Overall, the

results of our analysis are consistent with the participation cost explanation for volume following returns, whereas some of the evidence seems difficult to reconcile with at least some aspect of the liquidity, investor protection, overconfidence, disposition, and foreign trading explanations.

The paper is organized as follows. In Section II, we present our data. In Section III, we estimate the relation between returns and volume under a variety of estimation approaches. In Section IV, we use cross-sectional regressions to explain differences in this relation across countries, investigate the role of investors' types, provide evidence on the return-turnover relation across time, and study possible asymmetries in the responses of turnover to positive and negative return shocks. We conclude in Section V.

II. Data and Summary Statistics

We seek to comprehensively examine the relation between returns and volume across markets. As shown by Smidt (1990), the U.S. return-turnover relation can change dramatically through time. To keep our focus on the recent relation rather than on effects caused by long-term trends, and also given the availability of data for more countries recently, we primarily examine the 10.5 years from January 2, 1993 through June 30, 2003. From Datastream International we collect weekly (Wednesday closing price to Wednesday close) market returns, total traded value, and total market capitalization. All three variables are denominated in local currency. Given Datastream's extensive coverage of these three variables, we are able to obtain data for 46 countries.⁴ As it can be seen from Table I, ten-plus years of weekly data are available in all but

⁴ We require a minimum of 150 weekly observations for a country to be included in the sample. For most developing markets, the variables are available starting in the early to mid 1990s. When using daily data, we control for weekends and holidays. For about a fourth of our sample, we cross-checked the returns and volume dates from the Datastream indices with those provided directly by the exchange and, in many cases, did a further cross-check with the dates provided by Yahoo-Finance.

seven countries. Although our focus is at the weekly frequency, in some tests we examine daily data over the same period as well.

Because volume increases with the absolute number of shares available, we follow most other studies and scale aggregate traded value by the week's contemporaneous total market capitalization to form turnover.⁵ In addition, turnover may be influenced by trends in bid-ask spreads, commissions, and availability of information—all factors that might contribute to the general increase in trading activity through time. Therefore, we detrend turnover by first taking its natural log and then subtracting its 20-week (or 100-day for daily data) moving average, as has been proposed and implemented by, among others, Campbell, Grossman, and Wang (1993) and Lo and Wang (2000).

Volatility can also be measured in a variety of ways. Following a large body of literature, our primary measure of volatility is filtered out of a GARCH model. Specifically, we fit an EGARCH (1,1) specification to daily index returns and cumulate the daily estimated volatilities into weekly volatilities. Proposed by Nelson (1991), the EGARCH specification captures the asymmetric relationship between returns and volatility (negative return shocks of a given magnitude having a bigger impact on volatility than positive return shocks of the same magnitude) often shown to characterize equity returns. We also construct weekly volatility measures by cumulating daily absolute and squared residuals from an autoregressive model for daily returns.

Table I presents summary statistics for weekly returns, EGARCH volatility, raw turnover, and log detrended turnover. We also show short-term lead-lag dynamics between turnover,

⁵ We follow Lo and Wang (2000) in scaling by contemporaneous (not lagged) market value. However, for robustness we also replicate our key findings with volume standardized by lagged market value and find similar results. Throughout the paper we mostly use turnover (scaled volume) but for convenience will often refer to it simply as volume. The same turnover measure can be computed by taking the ratio of the total number of shares traded to the total number of shares outstanding.

volatility, and returns. Using World Bank classifications, we separate our sample into high-income and developing nations according to gross national income (GNI) per capita in 1998, the midpoint of our sample.⁶ Panel A reports results for high-income countries, and Panel B reports results for developing countries.

Panel A shows that even in high-income countries volatility varies substantially across markets. Finland (dominated by Nokia) and Taiwan have return volatilities roughly three times greater than those of Australia and Austria. Turnover differences across countries may sometimes be due to differences in market conventions for reporting volume. This should not affect our tests because turnover is detrended relative to its past values, which should capture these differences in reporting conventions. Turnover in Germany, Netherlands, Taiwan, and the US is over two percent per week, meaning that two percent of the outstanding shares trade in a given week (or around 100 percent per year). However, Austria, Belgium, Denmark, Greece, Hong Kong, Ireland, Israel, Japan, Luxembourg, New Zealand, Portugal, and Singapore all have turnover of less than one percent per week. Both volatility and turnover are highly persistent, with an average first-order autocorrelation of 0.82 for volatility and 0.68 for turnover in high-income countries. In contrast, returns have an average autocorrelation of only -0.03 in high-income countries and -0.02 in developing countries. Even after detrending, log turnover is still highly persistent. In the rightmost columns of Table I, we examine the sample correlations between detrended turnover and returns and find that on average they are positive and statistically significant in eight markets, and negative and insignificant in six others. The average contemporaneous correlation between turnover and returns is a positive 0.06. The average

⁶ High-income countries in 1998 are those with income over 9,360 US dollars per capita. Most of the rest of our countries are upper middle-income countries, except for Columbia, Peru, Philippines, Russia, and South Africa, which are lower middle-income, and China, India, and Indonesia, which are classified as lower-income, as their average GNI per capita is less than \$760. For convenience, we refer to upper middle-income, lower middle-income, and low-income countries simply as developing countries.

correlation between returns and the previous period's turnover, as well as the correlation between returns and next week's turnover, is small in these high-income markets.

Developing markets are examined in Panel B. The average volatility of developing markets is 3.55 percent per week, substantially higher than the average in high-income countries (2.56 percent). On average, turnover is lower in developing countries than in high-income countries. Turnover also varies substantially across developing countries, with China, Hungary, South Korea, and Turkey turning over more than 2 percent of the market per week, but with all other developing countries, except for India, having less than one percent of the market turning over in a given week. Similar to high-income countries, there is only weak evidence of heavy turnover foreshadowing future returns, but there is a strong contemporaneous turnover-return relation. The relation between turnover and the previous week's return is significantly positive in 14 of 20 markets and averages 0.12 in developing markets, as compared to only 0.01 in high-income countries. While often informative, simple correlations may give an incomplete picture, especially because they do not control for either past persistence in each series or more long-lasting cross-correlations between series. To fully account for the lead-lag dynamics between series, we turn to Vector Autoregression (VAR) for most of our inferences.

III. The Impact of Returns on Turnover

A. Bivariate relations

Our main tool for evaluating the impact of returns on turnover is Vector Autoregression estimated on a country-by-country basis. Because the return-turnover relation can vary substantially across markets, we use the Hannan-Quinn Information Criterion (HQC) to select the optimal lag length within each country. The lag is usually selected at between two and five.

We first examine the relation between turnover and contemporaneous and past returns without controlling for volatility effects.

We estimate impulse response functions (IRFs) where, say, the lag one effect measures the relation between a one standard deviation shock to returns and next period's turnover. The responses are also expressed in standard deviation units to facilitate interpretation. Typically, to accommodate the contemporaneous correlations among shocks to the different variables in the VAR, the shocks are orthogonalized in the calculation of the IRF. This, however, has two important drawbacks, as argued by Koop, Pesaran and Potter (1996) and by Pesaran and Shin (1998). First, since it imposes the restriction that contemporaneous shocks are uncorrelated, it can give misleading estimates of the effect of shocks if these are actually correlated. Second, it does not produce a unique IRF, as the IRF depends on the ordering of the variables in the VAR. Instead, the Generalized Impulse Response (GIR) analysis proposed by Koop et al. (1996) lets the data decide the correlation structure for innovations across variables and makes the inferences independent of the order in which the researcher places the variables in the VAR. In our case, this is especially important, as an orthogonalized IRF on weekly data with turnover ordered before returns could miss intra-weekly relationships between past returns and current turnover. We, therefore, choose to conduct a GIR analysis. It is important to notice that, in such a framework, the lag one effect includes any contemporaneous correlation between shocks to returns and shocks to turnover. We later examine intra-week causality through the analysis of daily data.

We display the response of turnover to return shocks at lags one, five, and ten from the impulse response functions in Figure 1. Insignificant bars are striped, whereas significant bars are in solid colors. Figure 1 shows that turnover is related to past returns in many markets. The

lag one relation between flows and returns is positive and significant in 25 of 46 markets and significantly negative in only one market. Additionally, the initial response generally increases over time. After ten weeks, a positive return shock is accompanied by an increase in turnover in 34 (significant in 31) markets and a decrease in turnover in 12 markets (significantly negative in only 8). On average, a positive one standard deviation shock to returns is followed by a 0.32 standard deviation increase in turnover after ten weeks. These summary statistics for Figure 1 are found in Panel A of Table II.

However, there are generally large differences in the relation between turnover and returns in high-income countries relative to developing countries. In high-income countries, a one standard deviation shock to returns is followed by a 0.11 increase in turnover after ten weeks. At the same frequency in developing nations, a 0.60 increase in turnover follows a one standard deviation shock to returns. Moreover, even among the high-income countries, the lesser-developed countries (Greece, Portugal, and Taiwan) seem to generally exhibit much stronger effects than established markets. Several of the larger stock markets in the world, like the U.S. and the U.K. (but not Japan), bear a negative relation between turnover and past returns. In sum, the relation between returns and turnover is positive and significant in many countries, but its magnitude varies widely.

B. Controlling for Volatility

It is well known that turnover is positively related to volatility. Although more ambiguous in terms of direction, there is also large evidence that market volatility and returns are correlated. To control for these effects, we estimate Vector Autoregressions with turnover, returns, and EGARCH volatility. Figure 2 presents impulse response functions measuring the effect of a one standard deviation shock to returns on volume from this system. Summary

statistics from Figure 2 are presented in Panel B of Table II and can be compared to Figure 1's summary statistics in Panel A. The patterns across countries are generally similar to those observed in Figure 1, except that the effect of returns on turnover is even larger and more positive than those observed without controlling for volatility. Averaged across all countries, a one standard deviation positive shock to returns is associated with a 0.17 standard deviation increase in next week's volume, a 0.36 standard deviation increase in volume after five weeks, and a 0.46 standard deviation increase in volume after 10 weeks. Positive return shocks are followed by an increase in turnover in 37 markets and significantly so in 24 markets (after ten weeks).

In high-income countries, the 10-week response of turnover to returns is significant in only 8 of 26 markets, whereas the relation is significantly positive in 16 of 20 developing countries. In high-income markets a one standard deviation shock to returns leads to a 0.26 standard deviation increase in turnover after 10 weeks, but in developing markets the effect is nearly three times as large (0.72).

The magnitude of the return-turnover relation varies significantly across countries even within the high-income country and developing country categories. In Taiwan, China, India, Malaysia, Poland, South Korea, Thailand, and Turkey, a one standard deviation increase in weekly returns is followed by a remarkably large increase in turnover (bigger than one standard deviation) after ten weeks. Though Japan and the U.S. were at one time similar in market capitalization, they have very different return-turnover relations. The ten-week response of turnover to returns is 0.42 in Japan but only 0.03 in the U.S. In the high-income markets of Australia, Canada, France, Ireland, the Netherlands, Sweden, Switzerland, and the U.K., turnover

is negatively associated with returns, but significantly positive relations are found in Greece, Hong Kong, Italy, Japan, Portugal, Singapore, and Taiwan.

C. Sensitivity to volatility measures, detrending methods

To examine the sensitivity of our results to our volume detrending method and our approach to estimate volatility, we first measure volatility by using daily data to fit an autoregressive model for returns. We then cumulate the squared daily residuals from this model into weekly volatility measures. We estimate the model with squared residual volatility, detrended turnover, and returns. We also estimate a model where turnover is not detrended, with EGARCH volatility and returns.

Figure 3 shows that the dynamic relation at lag 10 between turnover and returns is similar across countries when cumulative squared residuals are used as the volatility measure. For comparison purposes, we also display the main specification from Figure 2 (with returns, detrended turnover, and volatility) in Figure 3. Using raw turnover in the third specification actually leads to an even stronger relation between turnover and returns in many developing markets. For developing markets, the average response of turnover to returns after 10 weeks is 0.61 using squared residuals and 0.87 using raw turnover, as compared to 0.72 in our base case. In high-income countries, using squared daily residuals gives similar estimates, but using non-detrended turnover leads to a negative and significant volatility/return relation in several large countries (Belgium, France, the Netherlands, Switzerland, UK, and US). In unreported results, we also use specifications with GARCH (1,1) volatility, absolute residual volatility, and detrended volume using a linear or quadratic trend. In all cases, our main results are unchanged. In Section IV. C.3, we will also examine the impact of other volatility measures and control

variables for a subset of countries where we were able to obtain more detailed local and regional volatility and turnover proxies.

D. Subperiod results

One potential explanation for the large differences between high-income and developing countries is that many developing countries suffered severe crises during our sample period. To examine whether our findings are driven by the Asian and/or Russian crises, we divide our sample into two periods, one from January 1993 to June 1997 and the other, post crises, from January 1999 to June 2003. Figure 4 demonstrates that the previously observed regularities are remarkably robust in both periods in developing markets but much less stable in high-income countries. In all but two developing markets, the relation is positive in both subperiods. In the high-income markets, the return-turnover relation is positive in one subperiod and negative in the other for ten markets. The average ten-week response of turnover to returns (shown in Panel D of Table II) in high-income markets is large (0.58) in the first subperiod, but closer to zero (0.12) in the second subperiod. For markets in developing economies the effect is very similar (0.61 and 0.72) across subperiods.

E. Daily Frequency

One should notice that if the weekly response function grows from lag one to lag five and to lag ten (as it does in all significant cases in Figure 2), it must follow that the contemporaneous effects are, at a minimum, of second-order importance. Nevertheless, the lag one impulse response includes the contemporaneous weekly correlations between shocks to returns and shocks to turnover, so it is not clear whether the short-term lag one effect is due to higher returns being followed by higher turnover or to a contemporaneous correlation between the two. To more thoroughly examine lead-lag dynamics, we now estimate a VAR framework at the daily

frequency with returns, turnover, and EGARCH volatility. To be conservative, instead of computing the Generalized Impulse Response function we impose a triangular structure where turnover is ordered before returns and volatility. We then compute an orthogonalized impulse response function so that only lagged (and not contemporaneous) returns (and volatility) are allowed to affect current turnover. Panel E of Table 2 presents summary information regarding the responses of detrended turnover to returns at the one, five, and ten-day frequencies. Positive shocks to returns lead to increases in next day's turnover in all high-income and developing markets, and most of them are significant. In developing markets the positive relation is larger to start with and increases over time, whereas in many high-income markets the return-turnover relation quickly becomes negative. The average five-day response is 0.40 in developing markets and 0.11 in high-income countries. The daily evidence confirms that even at short-term frequencies the return-turnover relation is not a contemporaneous one, and it differs between high-income and developing markets.

IV. Why does turnover follow returns?

A. Discussion and testing of hypotheses

The possible explanations for the return-turnover relation discussed in the introduction have predictions for how the return-turnover relation should vary across countries, time, types of return shocks, and types of investors.⁷

A lack of liquidity could lead to decreases in trading volume following poor prior returns. In Bernardo and Welch (2004), liquidity providers are more risk-adverse when returns decrease, and the fear of future liquidity shocks causes market makers to be unwilling to provide liquidity

⁷ Except for the average R^2 , insider trading enforcement dummy variable, short-sales dummy variable, skewness, trading and GDP data, and number of firms, all other variables are graciously provided by Florencio Lopez-de-Silanes from the database used in La Porta, Lopez-de-Silanes, and Shleifer (2003).

today. Although their focus is on crises, one can see that decreases in returns can cause market makers to provide liquidity and hence trading costs increase and volume decreases. We expect the importance of this effect to be more pronounced in less developed countries because the financial sector is less deep and hence less resilient in such countries. We use trading value to GDP as a proxy for the depth and resilience of the financial sector. Additionally, the liquidity story predictions center on volume drying up after negative returns and do not necessarily make predictions for volume following positive returns.

An important possibility is that in countries with poor investor protection adverse shocks drive investors away from the markets because they are associated with an increase in agency problems and investor expropriation. Consistent with this view, Johnson et al. (2000) argue that managers in countries with poor investor protection used the Asian crisis as an opportunity for expropriation. They demonstrate that those Asian countries with poorer investor protection had larger currency and stock market depreciations during the Asian crisis. The implication for our analysis is that if in countries with poor investor protection negative returns increase the probability that investors are being taken advantage of, poor prior returns may deter investors from trading in equities. Additionally, a proxy for poor investor protection in the trading process is the level of insider trading. To investigate whether the return-volume relation is more prevalent in markets with rampant insider trading, we use the dummy variable of Bhattacharya and Daouk (2002) that takes a value of one in countries where insider trading is actually prosecuted.

Negative news in markets where short sales are not allowed implies that investors who would have sold short simply do not trade. If an explanation of the return-turnover relation is the presence of short-sale restrictions, the relation should be more severe in markets where short

sales are not allowed. To examine this, we use the short-sales dummy variable of Bris, Goetzmann, and Zhu (2003) that takes a value of one when short sales are both allowed and practiced and zero otherwise.

Participation models rely on a group of sidelined investors that do not trade due to costs of participation (like information and trading costs) but will be induced to trade following high past returns. The effects of past returns on volume should be stronger in markets where there are high costs of participation and many individuals with means to invest that do not (sidelined investors). We expect investors to view participation to be less advantageous (or, more costly) in countries with markets that are less informationally efficient and that give the appearance of being rigged by connected individuals. One proxy for the efficiency of markets is the market-model R^2 proposed by Morck, Yeung, and Yu (2000). The level of corruption in a country can proxy for the fairness of the markets. Additionally, participation effects should be more prevalent among individual investors, as most institutional investors have already paid the informational entry costs and are invested, at least to some extent, in equities (although trading activity from institutions may increase due to new mutual fund inflows from individuals investing in their funds). For developed markets one would expect the amount of sidelined investors to be rather small after periods of long run-ups like the 1990s. Thus, the participation hypothesis should call for a stronger return-turnover relation in the 1980s, even among developed markets. Finally, participation models such as Orosel (1998) call for returns to be equally related to both past positive and past negative returns.

Odean (1998b) and Odean and Gervais (2001) argue that investors are overconfident and trade more when their portfolios increase in value and less when they decrease. The disposition effect makes investors reluctant to sell if stock prices have dropped but eager to realize their

gains if the securities they hold have increased in price. In markets where correlations among security returns is low, variation in portfolio returns across investors is likely to be higher and hence past market returns will be less informative about the trading incentives of investors. However, in markets where most securities move together, the portfolios of investors will move in a similar fashion and both overconfidence and disposition predict a strong positive relation between past market returns and future volume.⁸ Hence, overconfidence and disposition, like participation costs, also predict that the strength of the return-turnover relation should be related to a country's market-model average R^2 . The behavioral arguments also imply stronger effects among individual investors, but their times-series predictions differ from those of the participation cost models. Overconfidence should be greater in periods of long-term market run-ups, and disposition effects should also make investors more willing to lock in gains (trade) in such periods.

Another possible explanation for the return-turnover relation is that foreign investors, because of return chasing, tend to both pull money out of a market and lose interest in trading when a market experiences negative returns. Thus, while concerns about 'foreign speculators' often center on directional trading, they can also have implications for total trading activity; namely that a decrease in market liquidity following negative returns could be driven by lack of foreign trading. Papers investigating the trading behavior of foreigners in response to past returns at short-term frequencies, such as Froot, O'Connell and Seasholes (2001) and Griffin, Nardari, and Stulz (2004), analyze the relation between flows (net directional trading imbalances) and past returns, not total foreign trading activity as we do here.

⁸ International diversification could lead investors in a country to have portfolios that are less correlated even if all local securities are highly correlated. The presumption is that international diversification is sufficiently limited that this is not an issue.

We summarize all the main hypotheses which are consistent with the positive volume/return relation and their testable implications in Table III. The explanations for the return-turnover relation generally have competing predictions for cross-sectional differences across countries, different types of investor groups, and changes over time, and often call for the relation to be greater for negative returns. The participation cost explanation is most similar to overconfidence and disposition explanations, although the two differ in terms of their prediction for earlier time-periods.

Though the theories based on heterogeneity among rational investors do not have a compelling reason for why the return-volume relation is positive, we nevertheless want to investigate whether proxies for heterogeneity can explain our results. Chen, Hong, and Stein (2001) find strong evidence for individual securities, and some evidence at the U.S. market level, that high past volume (a proxy for differences in opinion) is related to more negative skewness. Although not directly called for by Chen, Hong, and Stein, we investigate whether countries with more negative skewness have a stronger relation between volume and past returns by constructing a negative skewness measure at the market level. Finally, since we find a strong return-volume relation in less developed countries, we also check whether the naïve explanation that the return-volume relation weakens as a country becomes more developed can explain our results. We use market capitalization scaled by an economy's GDP as a measure of financial development and the log of income per capita as a measure of economic development.⁹

B. Cross-country analysis

The fact that the magnitude of the link between past returns and trading activity varies widely across countries suggests that a cross-country analysis should be fruitful to disentangle

⁹ Trading value scaled by GDP can also be interpreted as a measure of development related to market activity. Pinkowitz, Stulz, and Williamson (2003) provide references and discuss the issue that these two measures at times lead to different inferences.

alternative explanations for this relation. Kaniel, Li, and Starks (2003) use similar cross-country variables to shed light on the relation between returns and volume, but their focus is on understanding the high volume return premium identified for the U.S. by Gervais, Kaniel, and Mingelgrin (2001). With this premium, cross-sectional differences in volume are positively related to future returns. In contrast, our analysis focuses on understanding the relation between past returns and volume.¹⁰

In Table IV, we regress the lag five response of turnover to returns from our main trivariate VAR results presented in Figure 2 on country characteristics.¹¹ We already noted that the return-turnover relation is much stronger in developing countries. In univariate regressions not reported in the table, trading value to GDP, investor protection, and insider trading enforcement are insignificant, while market capitalization scaled by GDP (market development), corruption, the dummy variable for short sales, and the average market-model R^2 are significant. The negative coefficient on financial development, measured by market capitalization to GDP, is consistent with the earlier findings that developing markets have stronger patterns of turnover following returns. The negative coefficient on the short-sales dummy variable is supportive of the hypothesis that restrictions on short sales strengthen the return-turnover relation. The positive coefficient for the market-model R^2 is consistent with the participation and behavioral predictions that the return-turnover relation should be stronger in markets where the majority of stocks move together.

The variables used in the univariate regressions are correlated. We therefore investigate multivariate cross-sectional regression combinations. In bivariate regressions with short sales and market development or average R^2 and market development, market development measured

¹⁰ At the country level we notice that the effect of volume on subsequent returns is mixed and weak.

¹¹ We also obtain extremely similar results using lag ten responses as the dependent variable.

by market capitalization to GDP becomes insignificant, but the significance of either the short-sales dummy or the average R^2 remains. We also include a variety of other combinations, and the average R^2 is highly significant in all specifications. The short-sales dummy variable is negative and significant in some specifications, although marginally so when many variables are added. Corruption is significantly negative at the five percent level in all but the last specification. Since less corrupt countries have a higher value on the corruption index, the negative coefficient indicates that more corrupt countries have a stronger return-turnover relation. In unreported analysis we also run similar regressions to those in the later columns of Table IV, adding gross national product per capita or the number of firms in the countries as of 1997. Neither of these variables is significant, and their inclusion does not affect the importance of R^2 and corruption.

In general, our results provide no evidence in support of the hypothesis that the pattern of turnover following returns is driven by market development, liquidity, poor investor protection, lack of insider trading enforcement, or skewness. There is evidence that the return-turnover relation is stronger in markets with higher levels of corruption and decisive evidence that the positive return-turnover relation is concentrated in markets characterized by high levels of co-movement among stocks. As discussed in Morck, Yeung, and Yu (2000), the countries with high co-movement are countries with poor protection of investor rights, but our results suggest that investor rights matter for the return-turnover relation only insofar as they are related to the level of co-movement across stocks.

C. Trading by investor type

C.1. Foreign trading compared to domestic trading

To examine whether the return-turnover relation is driven by foreign investors, we collect total trading activity data by foreign and domestic investors from seven markets (India,

Indonesia, Japan, Philippines, South Korea, Taiwan, and Thailand) where such data is made available and where we also have reliable turnover and return data.¹² For domestic and foreign turnover, we use domestic and foreign traded values scaled by market capitalization and then detrend the natural logarithm of each series by its 20-week moving average.

In Figure 5 we present impulse response graphs of the dynamic relation between domestic and foreign detrended turnover and shocks to returns from Vector Autoregressions with returns, EGARCH volatility, and detrended turnover for both domestic and foreign investors (similar to the framework in Figure 2 except for the two investor types). In all markets, the trading of domestic investors positively follows returns, and the relation is significant in five markets. Foreign investor trading increases (decreases) after positive (negative) shocks to returns in six markets, but the relation is significant in only four markets. More importantly however, in all seven markets domestic turnover increases at a quicker pace than foreign turnover following positive return shocks.

These results are inconsistent with the notion that ‘foreign speculators’ are driving the return-turnover relation. Under the assumption that foreign investors are more sophisticated than domestic investors, this evidence could also be consistent with the view that the relation is stronger among unsophisticated investors. To more directly test this hypothesis, we turn to an examination of the differences between institutional and individual investors.

C. 2. Institutional and individual trading

The trading of individual investors is generally perceived as more likely to be influenced by behavioral biases like overconfidence and the disposition effect than the trading of

¹² We extend the data sample previously used and described in Griffin, Nardari, and Stulz (2004). In contrast to the earlier paper, this study does not include Slovenia, South Africa, and Sri Lanka because of data quality concerns with these markets discussed in their paper. For our analysis using weekly returns, we are able to add Japan to our sample—the details of this data are described by Karolyi (2002).

institutional investors.¹³ Also, we would expect to see more non-market participants among individual investors than among institutions. Hence, if the return-turnover relation is driven by participation costs, overconfidence, or the disposition effect, which are all consistent with the results of Section IV, we would expect the relation to be much stronger among individual investors. For four markets, Japan, South Korea, Taiwan, and Thailand, we are able to obtain the total trading of domestic institutions and individual investors in addition to the trading of foreign investors.¹⁴

Figure 6 presents the dynamic relation between institutions', individual investors', and foreign investors' detrended turnover and shocks to returns after controlling for EGARCH volatility. The magnitude of the increase in individual investor trading following positive past returns is quite large. After 10 weeks, a one standard deviation shock to returns is followed by a 0.72, 0.83, 1.17, and 1.31 standard deviation increase in individual trading in Japan, South Korea, Taiwan, and Thailand. In contrast, after 10 weeks, a one standard deviation shock to returns leads respectively to only a -0.11, 0.90, 0.59, and 0.74 standard deviation increase in trading by domestic institutions in these markets. In Japan, Taiwan, and Thailand, the trading of individuals is much higher following high returns than the trading of institutions. Except for Korea, the return-turnover relation is similar for domestic institutions and foreign investors indicating that the distinction between institutions and individual investors is the main determinant of the strength in the return-turnover relation.¹⁵ The fact that individual investors are

¹³ Odean (1998a) argues that individuals are subject to disposition effects, and Griffin, Harris, and Topaloglu (2004) find that at the market level individuals are more likely than institutions to sell when the market has gone up—a pattern also consistent with disposition.

¹⁴ Trading by foreign investors is not broken out separately except in Korea and Taiwan, but almost all foreign trading is due to institutions.

¹⁵ We examine the robustness of this relation to the use of non-detrended turnover, log turnover, and turnover detrended with a linear trend and find similar relations.

more responsive to past returns than institutions is consistent with the relation being driven by participation effects or behavioral biases.

C. 3. Robustness issues

We subject our smaller data set of foreign and domestic investors for seven countries used in section C.1. to a variety of controls. We construct a Garman and Klass (1980) range-based volatility measure (as recently implemented by Daigler and Wiley (1999)) as well as a similar measure used by Alizadeh, Brandt, and Diebold (2002). One reason for not using range-based measures throughout our analysis is data availability. The high and low index levels that are necessary for calculating these measures are usually obtained directly from the stock exchange. Nevertheless, we find similar return-turnover effects when using this volatility control.

A further possibility is that our common findings across countries could be driven by regional or world patterns in returns, volatility, or turnover.¹⁶ To examine this possibility we construct regional volatility measures, which are the simple average of the squared residuals from an ARMA model in each market, aggregated across the Pacific Basin region or Europe.¹⁷ For North America, we use the S&P 500 volatility. Likewise, regional turnovers are equally-weighted common currency averages. We estimate VARs, similar to those previously discussed but with range-based volatility estimates, and then, as exogenous variables, regional returns, turnover, and volatility. We estimate various combinations of this specification and again find that weekly domestic turnover is responsive to local returns and that its response is generally much larger than that of foreign trading activity. We also reach similar conclusions at the daily level. In sum, the finding that domestic investors trade more in response to past returns than foreign investors is remarkably robust.

¹⁶ Stahel (2004) finds evidence of common factors in liquidity measures across countries.

¹⁷ When the country of interest is in the region, that country's volatility estimate is excluded from the index.

D. What does the return-turnover relation look like in the 1980s?

While the cross-sectional and investor-type evidence is generally consistent with the participation and behavioral explanations, the two have different predictions for the evolution of the return-turnover relation from the 1980s to the present. We collect the previously used return, turnover, and volatility variables for the period January 2, 1983 to December 31, 1992 and estimate the same VARs described in Section III.B. Datastream return and volume data availability for 150 weeks in the earlier period leaves a sample of 18 high-income and six developing markets. The first striking finding in Figure 7 is that the return-turnover relation is positive at lags one, five, and ten in 23 of the 24 markets, and significantly so in 17 markets at lag five and 16 markets at lag ten. The US and UK exhibit a statistically positive relation between turnover and past returns at lags five and ten, whereas Japan has a positive but insignificant relation. Overall, as summarized in Panel A of Table V, a one standard deviation shock to returns in developed markets is associated with an economically large increase in volume of 0.52 in ten weeks. This effect is much larger than the 0.26 standard deviation increase in turnover for high-income countries in the 1993-2003 period (in Table II). Additionally, we check the robustness of our findings only over the market run-up period of 1993 to February 2000, but in high-income countries the average standard deviation increase in turnover after ten weeks is only 0.30 (not reported), very similar to the response over the entire 1993-2003 period. In the 1983-1992 period, the developing market response of turnover to returns after ten weeks equals 1.31 standard deviations, as compared to 0.72 (0.67) in the 1993-2003 (1993-February 2000) period. Panel B presents results excluding the week of October 19, 1987 and yields similar conclusions. Since costs of trading and the fraction of investors investing in the stock market have been increasing through time, the stronger return-turnover relation in this earlier time

period, even for high-income countries, is strongly consistent with the intuition of participation costs models.

E. Asymmetries

We examine whether the dynamic relationship between lagged returns and trading activity is symmetric in the sense of being driven equally by positive and negative return shocks. The linear VAR structure we have used thus far rules out any asymmetric dynamics, and non-linear specifications have to be used to examine asymmetries. Unless a well-specified theoretical structure is developed, one has to choose among a large collection of non-linear multivariate time series (see Granger and Terasvirta (1993)). In this study we use a Threshold Vector Autoregression (TVAR) model for turnover, volatility, and returns. This model can also be seen as a piecewise linear autoregression in the threshold variable (but non-linear in time).¹⁸ The TVAR specification allows, for instance, the dynamic behavior of turnover to be different depending on the sign and/or the magnitude of lagged returns. We choose the lagged return as the threshold variable, assume two regimes, and then estimate the system through the two-step conditional least-squares procedure suggested by Tsai (1998). As we did for the linear VAR, we then proceed to compute Generalized Impulse Response Functions (GIRF). The details for our computation of GIRFs are reported in the Appendix.

Panel C of Table V presents summary statistics for the responses of turnover to both positive and negative return shocks for 1993-2003. In country-by-country analysis, we test the null hypothesis that positive and negative return shocks have the same accumulated impulse response after ten weeks, and we can reject the null at the five percent level for only two

¹⁸ See Tong (1990) for a comprehensive treatment of threshold autoregression.

countries.¹⁹ Overall, positive shocks are associated with a 0.43 standard deviation increase in volume after ten weeks, whereas a negative shock to return is associated with an average ten-week decrease in volume of 0.46 standard deviations. As summarized in Panel D of Table V, these results carry over essentially unchanged to the 1983-1992 period. We also investigate (but do not report) whether shocks above one standard deviation have different effects than those below one standard deviation. After linear scaling for the size of the shocks,²⁰ large positive and large negative shocks to returns do not lead to appreciably larger effects on volume than small return shocks. Overall, consistent with the Orosel (1998) participation costs model and inconsistent with short-sale, liquidity, investor protection and behavioral arguments, the response of turnover to past returns seems to be broadly symmetric.

V. Conclusion

Market turnover (a liquidity proxy) is strongly related to past returns in many markets. This relation is stronger for developing countries than for developed ones. For the average developing market in our main 1993-2003 period, a one standard deviation weekly shock to returns is followed by a 0.60 standard deviation increase in trading after five weeks. These patterns are pervasive across specifications both with a variety of volatility controls and without controlling for volatility, across alternative mechanisms to measure turnover, and at both the daily and weekly frequency.

¹⁹ To assess the asymmetry of the estimated GIRFs we first sum the response to positive shocks and the response to negative shocks. We then test whether the sum has a mean different from zero by computing the Highest-Density Region (HDR), as in Hyndman (1995), for various confidence levels. The smallest confidence level for which the HDR does not include zero is interpreted as the p-value of the test. These are not fully equivalent to conventional significance tests as the procedure used to compute GIRFs (see the Appendix) ignores parameter uncertainty. This is, however, a widely used approach in producing forecasts for multivariate non-linear models. A similar application is contained in Van Dijk, Franses, and Boswijk (2001).

²⁰ If the response of turnover is linear in shocks to returns, a shock of, say, 1.5 standard deviations to returns should lead to an approximately three times greater effect on volume than a shock of only 0.5 standard deviations.

We use variation in the return-turnover relation across countries to investigate potential explanations for this relation. Explanations based on investor protection, insider trading enforcement, and liquidity are not supported by the cross-country level analysis. We find some evidence that countries with short-sales constraints have a tighter relation between volume and past returns. With informational entry costs, such as learning about a market, the fraction of people that participate, and hence volume, in a market increases with high past returns. Markets where there are higher levels of participation (and hence fewer sidelined investors) are likely to have more heterogeneous information (and low market-model R^2 s). Conversely, less efficient markets (high R^2 s and high levels of corruption) are likely to be characterized by low initial participation and a larger number of sidelined investors, and hence more sidelined investors entering the market following high past returns. With overconfidence and disposition, investors trade more when their portfolios perform well and trade less when their portfolios lose. Since the average portfolio will look like the market when stocks move together, these effects will be attenuated when stocks move together more (high market-model R^2 s). Supporting participation costs and behavioral motivations for trading in relation to past returns, we find that the degree to which stocks in a country move with the market is strongly positively related to the strength of the return-turnover relation. Given that there are lower initial levels of participation and higher informational asymmetry (transaction) costs in more corrupt markets, the finding that the relation is also strong in markets with high levels of corruption is supportive of the participation cost hypothesis.

We find that domestic investors are more sensitive to past weekly and daily returns than foreign investors and institutions. Since the participation and behavioral explanations for the return-turnover relation are more relevant for individuals than institutions, these findings

reinforce those from the cross-section. To distinguish between behavioral and participation stories we examine evidence from earlier periods. Though behavioral biases, like overconfidence, should be greater in a long period of high market returns such as the 1993-2003 period, there should be a greater number of sidelined investors, as well as higher information and transactions costs to trading, in earlier periods, such as the 1980s. Consistent with the participation costs hypothesis, a one standard deviation shock to returns leads to an economically and statistically large (0.57 standard deviation) increase in volume after 10 weeks, even in high-income countries in the 1980s. Additionally, participation costs models, such as Orosel (1998), predict a symmetric response of volume to both positive and negative return shocks, which is what we find using asymmetric VARs. This finding is also inconsistent with short-sale, liquidity, and investor protection explanations which would generally call for turnover to change substantially only following negative returns. Overall, the evidence examined here is largely consistent with models of investor participation, weakly suggestive of short-sale explanations, and generally inconsistent with at least some aspects of other explanations. Hopefully, though, new theoretical work, data, and econometric techniques will help sharpen and enrich our understanding of the volume-return relation.

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Appendix: Generalized Impulse Response Analysis for Threshold VAR

In non-linear models the response at time $t+n$ of a shock occurring at time t depends on the size and magnitude of the shock, on the history of the process up to time t , and on the (size, sign, and correlations of the) shocks occurring in the intermediate periods $t+1, \dots, t+n$. Pesaran and Potter (1997) demonstrate how the last two characteristics may generate inferences that are substantially misleading using Traditional Impulse Response Functions (TIRF). The Generalized Impulse Response Function (GIRF) approach of Koop et al. (1996) corrects the drawback associated with TIRFs. The GIRF is defined as the change in the conditional expectation of y_{t+n} as a result of an exogenous shock (in one or more of the variables) occurring at time t . The conditioning information set is composed of the histories of the system and the shocks hitting it. Therefore, one can compute a variety of GIRFs depending on the subset of histories (e.g., bull or bear markets, expansion, and recession times) and/or shocks of interest (e.g. positive vs. negative, large vs. small). We focus on the effects of different types of return shocks by conditioning on all available histories (one for each available time observation) and on return shocks belonging to a particular subset.

Formally,

$$GIRF(n, V_t, \Omega_{t-1}) = E[y_{t+n} | \Omega_{t-1}, V_t \in \Theta] - E[y_{t+n} | \Omega_{t-1}] \quad (1)$$

where Ω_{t-1} is the information set used at time t to forecast future values of y_t , V_t is the shock to the system, and Θ is the set where return shocks are, say, large and positive.

The GIRF thus represents the difference between a perturbed realization of the variable(s) of interest and its realization in a suitably defined baseline case. Current and future shocks are, thus, integrated out (averaged over). The two expectations involved in the computation of the GIRF are generally not available analytically for non-linear models but can be efficiently estimated by Monte Carlo simulation as illustrated by Koop et al. (1996). Here we only report the essential steps.

1. “Future” values of V_{t+n} , $n=0, 1, \dots, N$, are generated by bootstrapping the observed model residuals. This is done twice: once by imposing that the shock at time t belongs to a particular set (e.g., large and positive) and a second time by allowing the shock at time t to vary randomly across all possible observed residuals.

2. Using the two simulated set of disturbances we then generate two sets of “future” values of y_{t+n} , $n=0, 1, \dots, N$ starting from a given history, $\Omega_{t-1} = \varpi_{t-1}$, and iterating by following the rules of the time series model in equation (1).
3. We repeat 1 and 2 for each available history (i.e., time series observation).
4. We repeat 1, 2, and 3 R times.

By the law of large numbers, the averages across simulations converge to the expectations in (1). In our applications we set $R = 5000$ and simulate the systems for $N=20$ steps ahead. We then standardized the responses so that they have a value of 1 at time $t+1$ and cumulate them over 20 periods. We are especially interested in the reaction of turnover to different return shocks and we, thus, conduct several experiments. Namely, we compute and compare the GIRF of turnover for:

- (a) positive return shocks and negative return shocks,
- (b) large (bigger than 1 or 2 standard deviations) positive return shocks and large negative return shocks, and
- (c) large (between 1 or 2 standard deviations) positive return shocks and small (between 0 or 1 standard deviations) positive return shocks.

The difference between (b) and (c) is that in (b) we compare large positive to large negative and in (c) we compare large to small shocks of the same sign.

Figure 1
Impulse Response Functions from Bivariate VAR

Using weekly returns and detrended turnover data from January 2, 1993 to June 30, 2003 we estimate bivariate VARs of detrended turnover and returns. Turnover is total traded value in a given week scaled by the week's total market capitalization. Turnover is then detrended by subtracting a 20-week moving average. The figure reports the Generalized Impulse Response Function (GIRF) response of turnover to a one standard deviation shock to returns at lags one, five, and ten weeks. Insignificant bars are striped and significant bars are in solid colors. High-income countries are in alphabetical order on the left side of the graph and developing countries are on the right side.

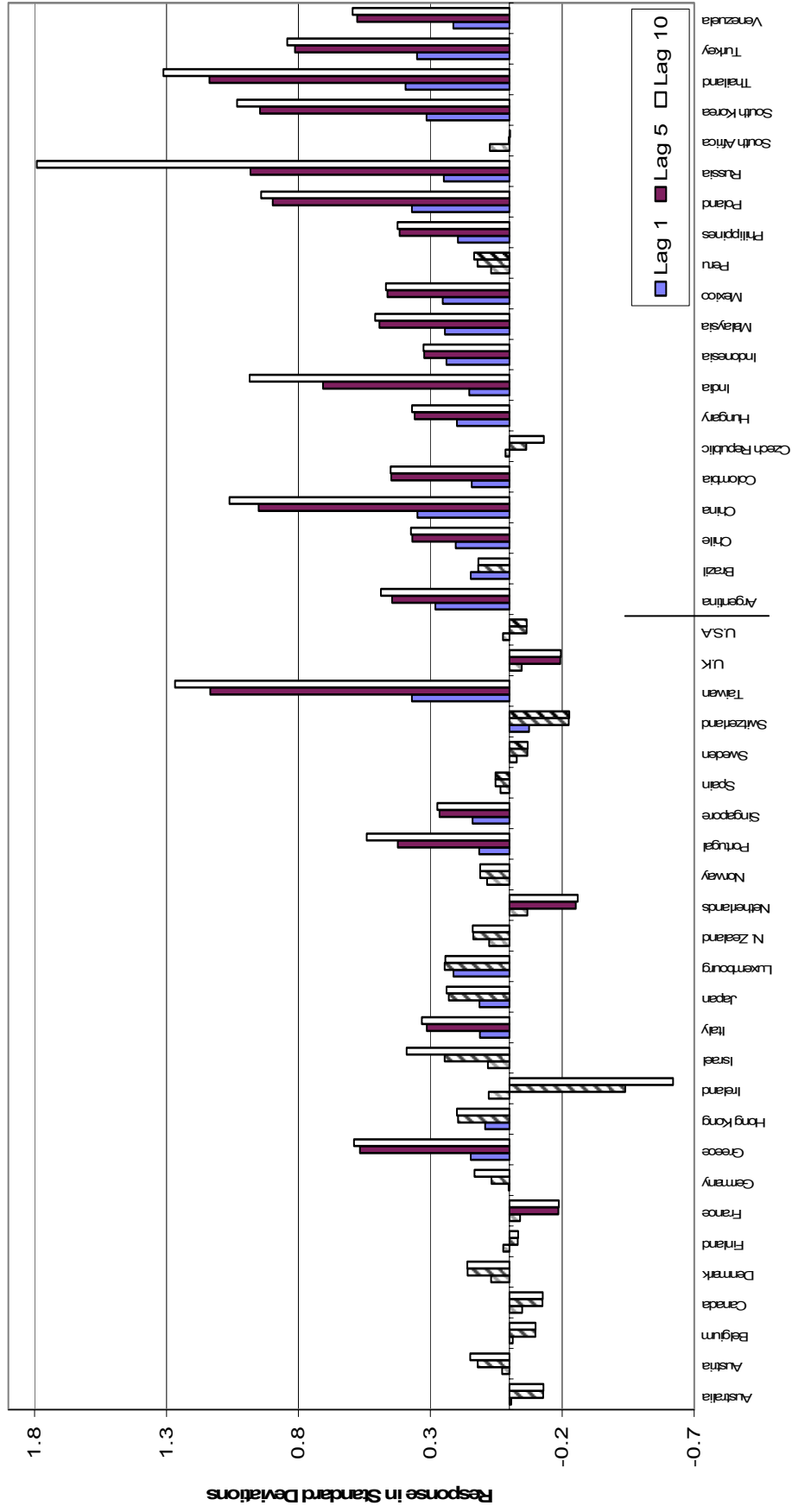


Figure 2
Impulse Response Functions from Trivariate VAR

From January 2, 1993 to June 30, 2003 we estimate weekly trivariate VARs of detrended turnover, returns and volatility. Turnover is total traded value in a given week scaled by the week's total market capitalization. Turnover is then detrended by subtracting a 20-week moving average. Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. The figure reports the Generalized Impulse Response Function (GIRF) response of turnover to one a standard deviation shock to returns at lags one, five, and ten weeks. Insignificant bars are striped and significant bars are in solid colors. High-income countries are on the left side of the graph and developing countries are on the right.

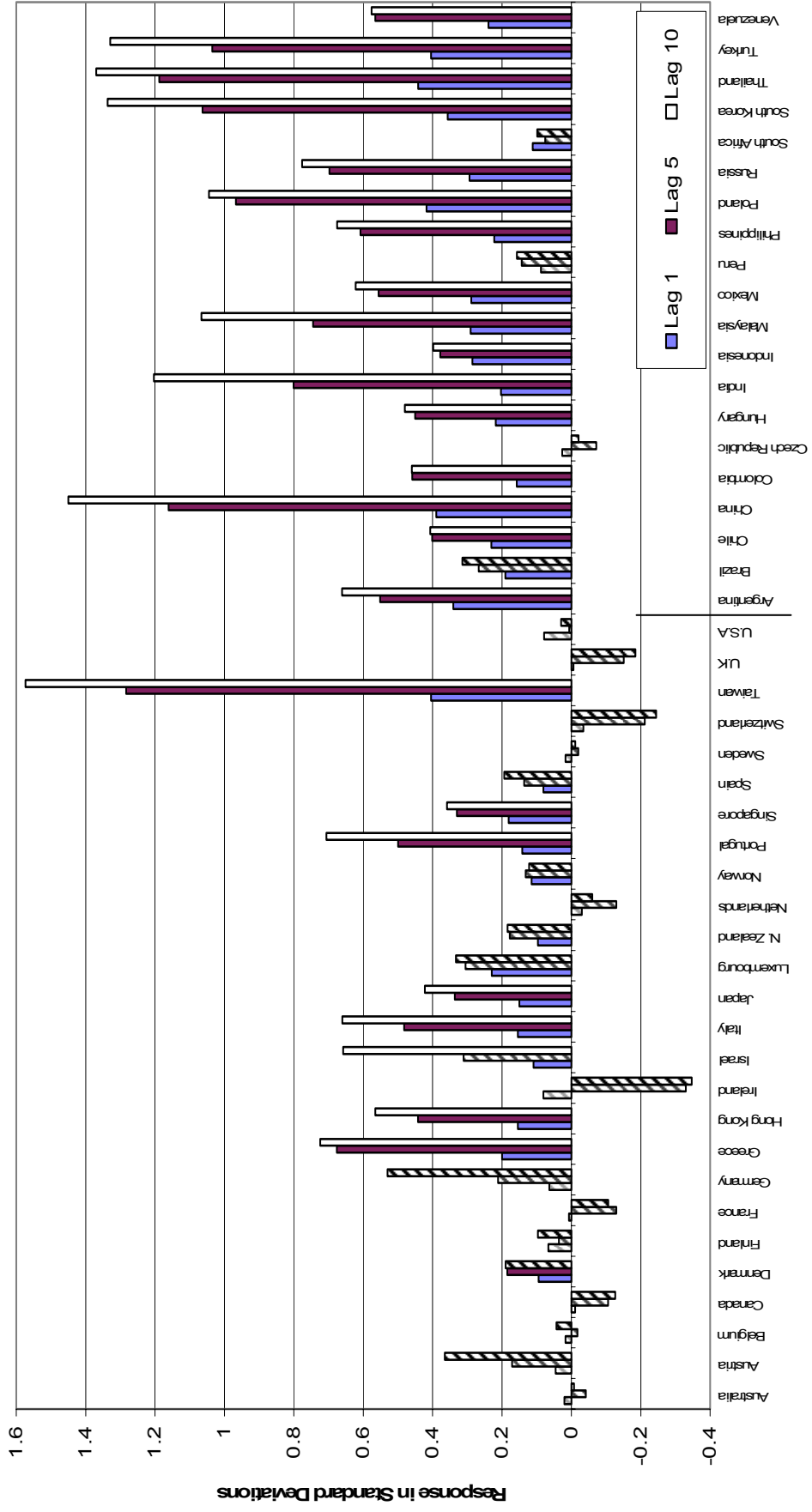


Figure 3

Impulse Response Functions from Trivariate VAR with Squared Residual Volatility and Non-Detrended Turnover

Using weekly return and detrended turnover data from January 2, 1993 to June 30, 2003 we estimate the following trivariate VARs a) Detrended Turnover, Returns and EGARCH Volatility, b) Detrended Turnover, Returns and Squared Residuals Volatility, c) Raw Turnover, Returns and EGARCH Volatility. Raw Turnover is total traded value in a given week scaled by the week's total market capitalization. Detrended Turnover is then computed by subtracting a 20-week moving average from Raw Turnover. EGARCH Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. Squared Residuals Volatility is computed by squaring the residuals of an AR (1) model fitted to the returns series. The figure reports the GIRF response of turnover to a one standard deviation shock to returns at lag 10 weeks. Insignificant bars are striped and significant bars are in solid colors. High-income countries are on the left side of the graph and developing countries are on the right.

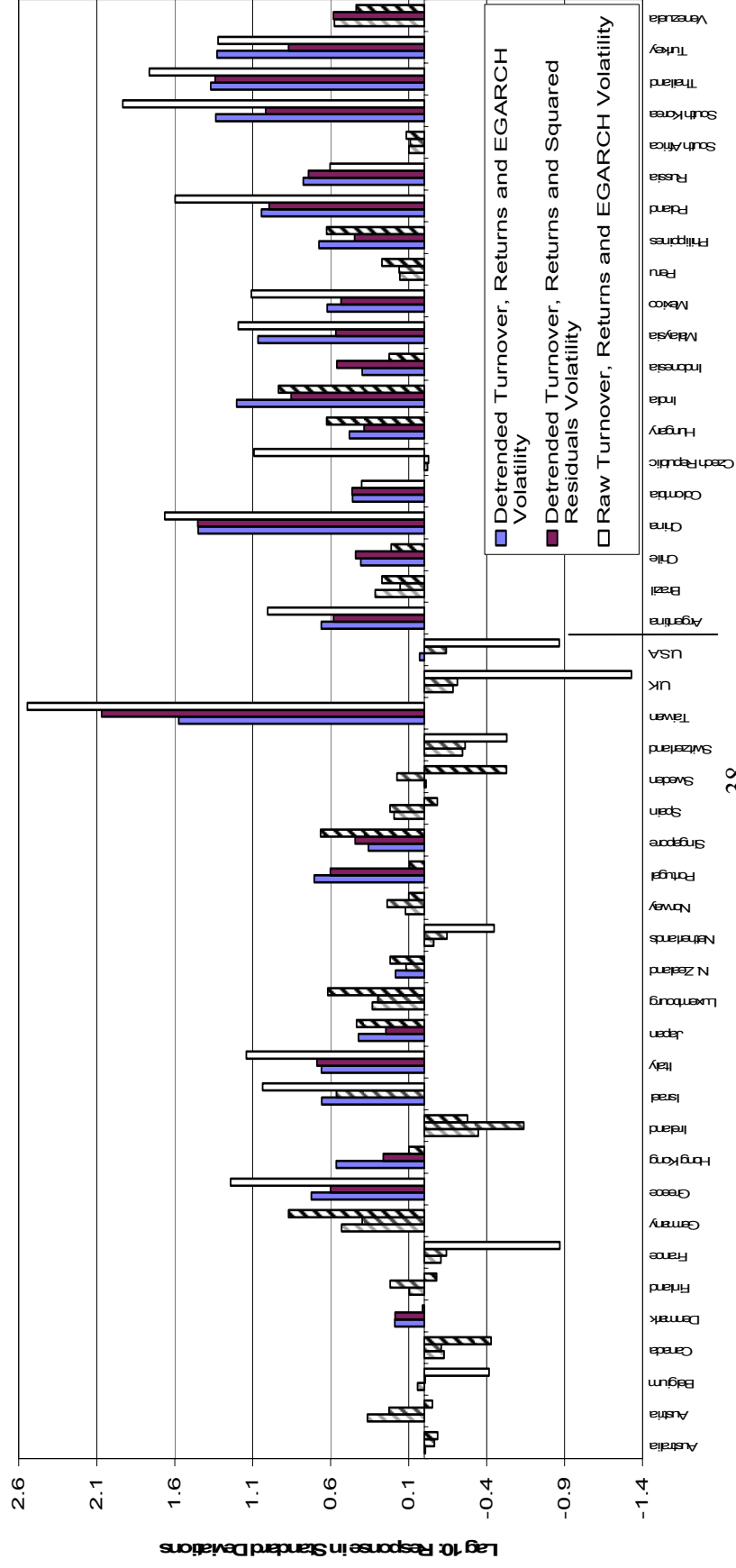


Figure 4

Impulse Response Functions from Trivariate VAR: Sub-periods 1993-1997, 1999-2003

Using weekly return and detrended turnover data we estimate trivariate VARs of detrended turnover, returns and volatility. Turnover is total traded value in a given week scaled by the week's total market capitalization. Turnover is then detrended by subtracting a 20-week moving average. Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. The figure reports the GIRF response of turnover to one a standard deviation shock to returns at lag 10 weeks for two sub-periods: January 2, 1993-June 30, 1997 (pre-crises) and January 1, 1999- June 30, 2003 (post crises). Insignificant bars are striped and significant bars are in solid colors. High-income countries are on the left side of the graph and developing countries are on the right.

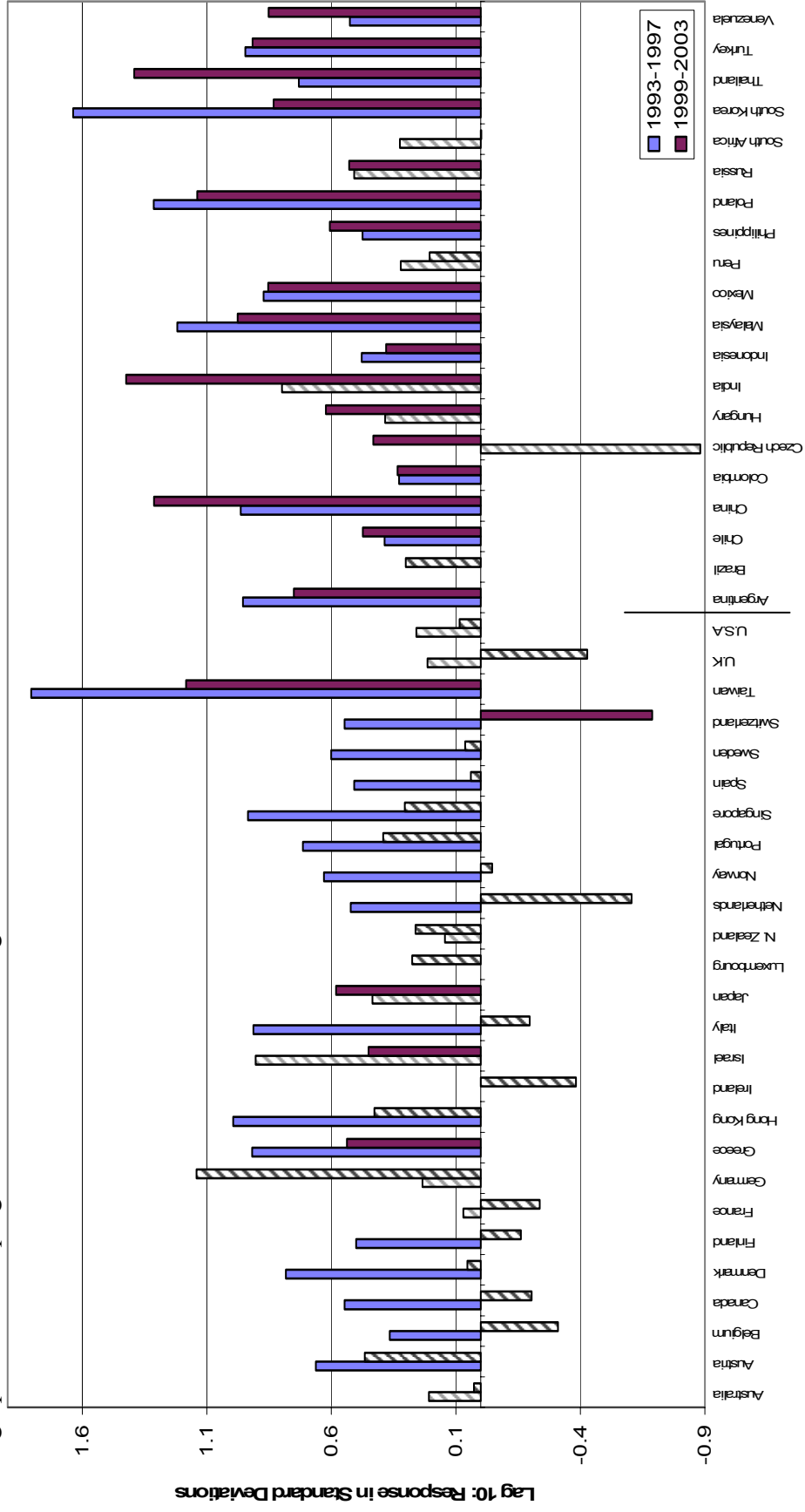


Figure 5
Responses of Foreign and Domestic Turnover to Local Returns

This table shows Generalized Impulse Response functions describing the response of detrended foreign and domestic turnover to a one standard deviation shock in local market returns. The time scale on the horizontal axis is expressed in weeks. Responses are expressed in standard deviation units. For each impulse response functions we also report the 95% confidence intervals (dotted lines), which are computed by Monte Carlo simulation. Results are based on a vector auto regression (VAR) of domestic turnover, foreign turnover, returns, and volatility estimated separately for each country with number of lags chosen by the Hannan-Quinn criterion. All returns are expressed in local currency. Turnover is total traded value by, respectively, foreign and domestic investors in a given week scaled by the week's total market capitalization. Foreign and domestic turnover are separately detrended by subtracting a 20-week moving average. Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. Sample period begins on January 2, 1996 for Japan, Indonesia, Korea and Thailand, on April 1, 1997 for Taiwan, on December 31, 1998 for India and on June 1, 1999 for Philippines. The sample period ends on June 30, 2002 for all countries.

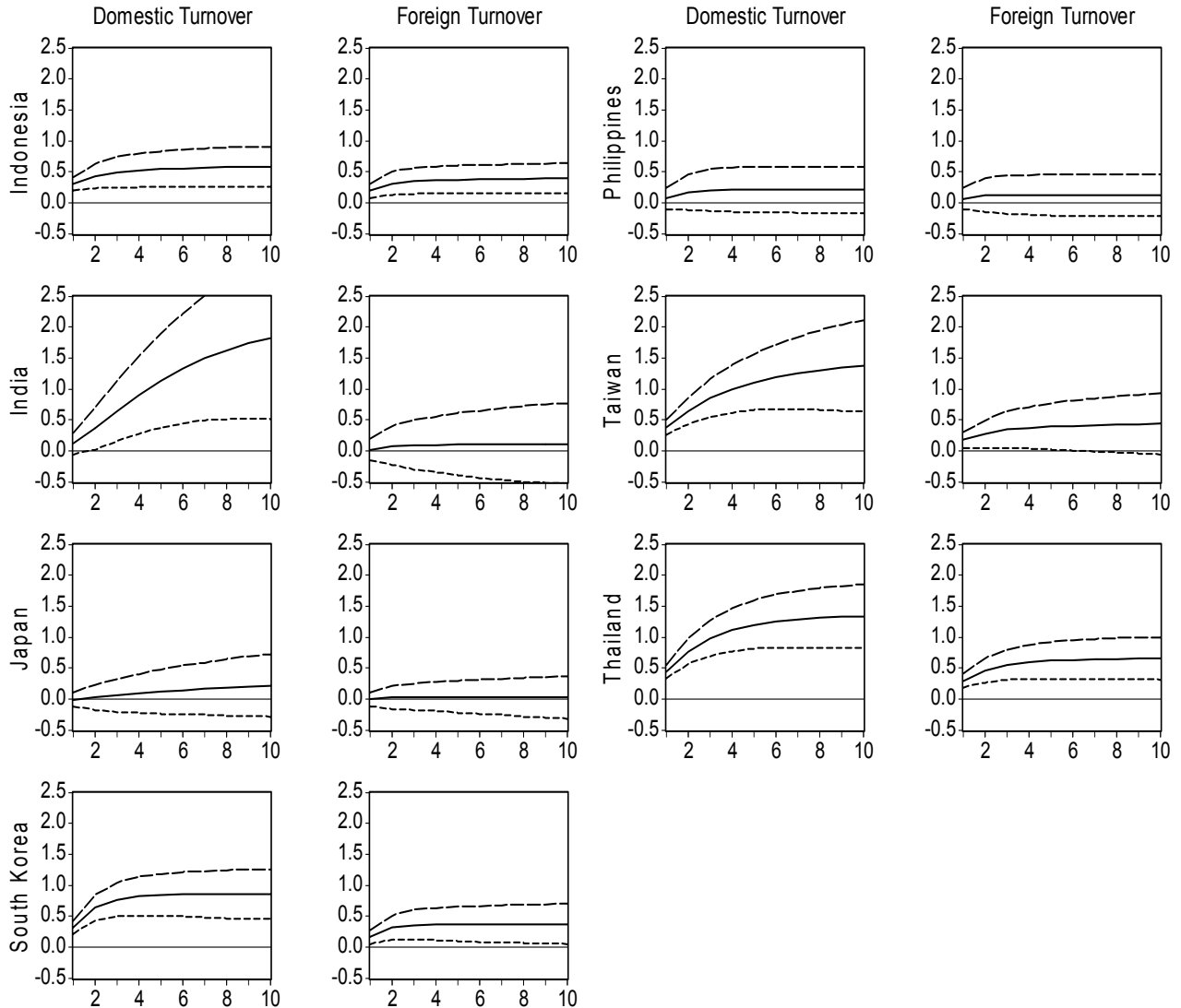


Figure 6

Responses of Institutional, Individual and Foreign Turnover to Local Returns

This table shows Generalized Impulse Response functions describing the response of detrended foreign, domestic institutional, and domestic individual turnover to a one standard deviation shock in local market returns. The time scale on the horizontal axis is expressed in weeks. Responses are expressed in standard deviation units. For each impulse response functions we also report the 95% confidence intervals (dotted lines), which are computed by Monte Carlo simulation. Results are based on a VAR of domestic institutional turnover, domestic individual turnover, foreign turnover, returns, and volatility estimated separately for each country with number of lags chosen by the Hannan-Quinn criterion. All returns are expressed in local currency. Turnover is total traded value by, respectively, foreign, domestic institutional, and domestic individual investors in a given week scaled by the week's total market capitalization. Foreign, domestic institutional, and domestic individual turnover are separately detrended by subtracting a 20-week moving average. Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. Sample period begins on January 2, 1996 for Japan, Korea and Thailand, on April 1, 1997 for Taiwan, on December 31, 1198 for India and on June 1, 1999 for Philippines. The sample period ends on June 30, 2002 for all countries.

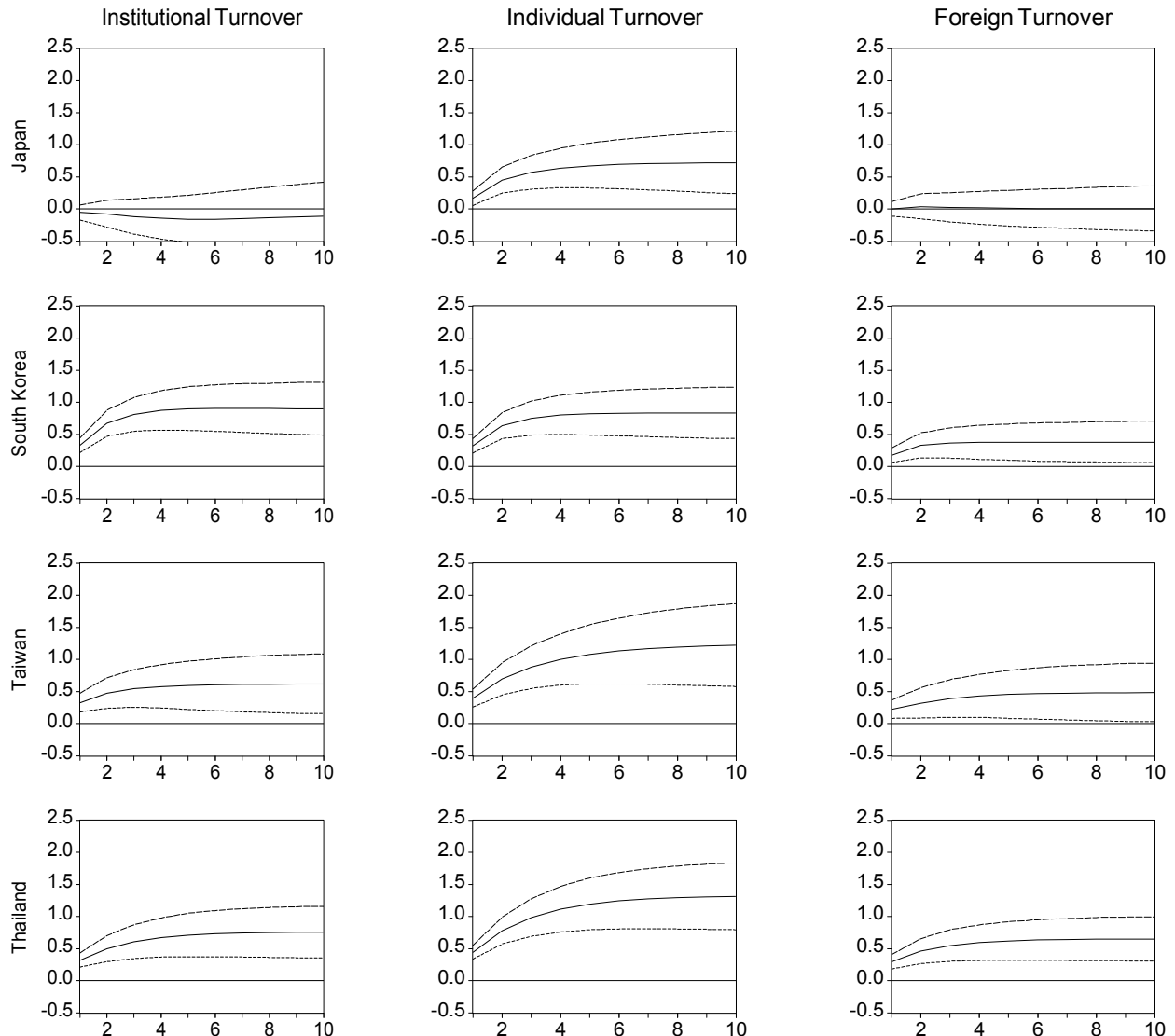


Figure 7
1983-1992 Period

From January 2, 1983 to December 31, 1992 we estimate weekly trivariate VARs of detrended turnover, returns, and volatility. Turnover is the total traded value in a given week scaled by the week's total market capitalization. Turnover is then detrended by subtracting a 20-week moving average. Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. The figure reports the GIRF response of turnover to a one standard deviation shock to returns at lags one, five, and ten weeks. Insignificant bars are striped and significant bars are in solid colors. High-income countries are in alphabetical order on the left side of the graph and developing countries are on the right.

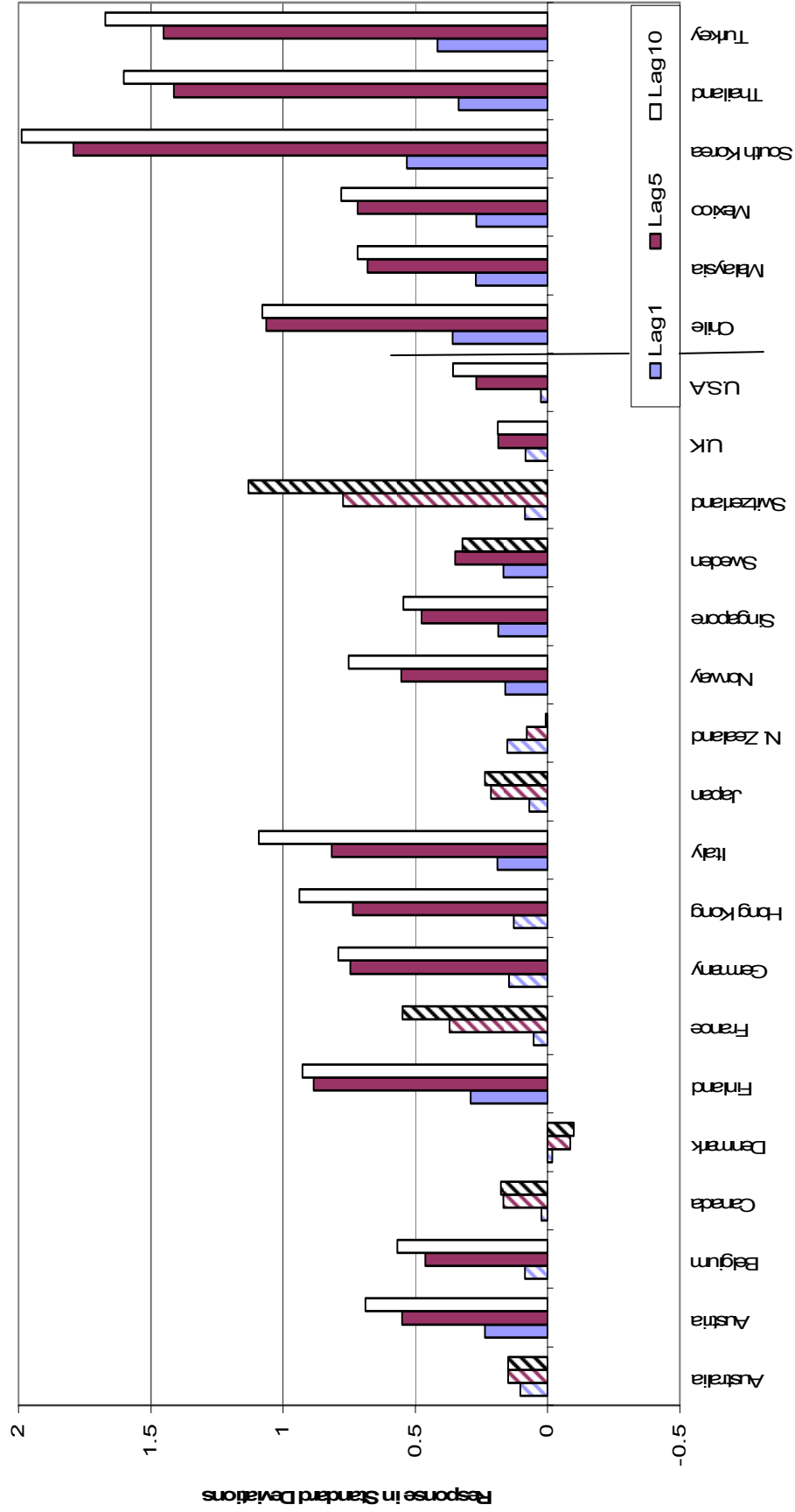


Table 1
Summary Statistics

Weekly DataStream data from 46 markets is used with the beginning of coverage marked in the first column and ending on June 30, 2003 for all countries. For each country, we report the mean (μ), standard deviation (σ), and lag 1 autocorrelation coefficient for weekly value-weighted returns, EGARCH volatility, turnover, and detrended turnover. Units are percent per week. We also report simple correlation coefficients in each market between lagged turnover and returns, the contemporaneous correlation between returns and EGARCH volatility and volatility and turnover in the next two periods and returns as well as the contemporaneous correlation between returns and EGARCH volatility and volatility and turnover. EGARCH volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. Turnover is detrended by first taking its natural log and then subtracting its 200-day moving average. Panel A reports results for high income markets, whereas Panel B reports results for developing markets. The separation comes from using 1998 World Bank classifications to separate our sample into high income (developed) markets and upper middle income, middle income, and lower middle income markets which we refer to as developing.

Panel A: High income Markets

| Country | From | Return | | Volatility | | Turnover | | Det. Log Turnover | | Lead-Lag Correlations | | | | | |
|-------------|------|-----------|--------------|------------|-----------|----------|-----------|-------------------|-------|-----------------------|----------------|----------------|--------------------|--------------------|------------|
| | | $\mu(\%)$ | $\sigma(\%)$ | AC(1) | $\mu(\%)$ | AC(1) | $\mu(\%)$ | AC(1) | μ | AC(1) | T_{t-1}, R_t | T_{t-2}, R_t | T_{t-1}, R_{t-1} | T_{t-2}, R_{t-1} | R_t, V_t |
| Australia | 1993 | 0.20 | 2.02 | -0.14* | 1.78 | 0.75* | 1.03 | 0.50* | 0.01 | 0.22* | 0.02 | 0.01 | -0.10* | -0.08 | 0.15* |
| Austria | 1993 | 0.12 | 1.89 | 0.00 | 1.58 | 0.86* | 0.98 | 0.73* | 0.00 | 0.48* | 0.08* | 0.07 | 0.04 | -0.15* | 0.12* |
| Belgium | 1993 | 0.17 | 2.52 | -0.07 | 1.87 | 0.94* | 0.43 | 0.51* | 0.01 | 0.35* | 0.05 | 0.01 | -0.05 | -0.05 | 0.07 |
| Canada | 1993 | 0.22 | 2.16 | -0.05 | 1.86 | 0.91* | 1.07 | 0.67* | 0.01 | 0.37* | 0.03 | -0.03 | -0.04 | -0.12* | 0.20* |
| Denmark | 1993 | 0.23 | 2.39 | 0.05 | 2.08 | 0.72* | 0.74 | 0.50* | 0.01 | 0.28* | -0.03 | 0.06 | 0.06 | -0.06 | 0.14* |
| Finland | 1993 | 0.41 | 4.99 | -0.07 | 4.44 | 0.93* | 1.02 | 0.80* | 0.04 | 0.43* | 0.02 | 0.03 | -0.03 | -0.08* | 0.06* |
| France | 1993 | 0.18 | 2.87 | -0.10* | 2.60 | 0.94* | 1.30 | 0.72* | 0.02 | 0.34* | 0.00 | -0.03 | -0.10* | -0.08* | 0.16* |
| Germany | 1993 | 0.14 | 2.92 | -0.06 | 2.49 | 0.90* | 2.84 | 0.74* | -0.08 | 0.74* | 0.03 | 0.04 | 0.02 | -0.10* | 0.03 |
| Greece | 1993 | 0.26 | 4.17 | -0.01 | 3.37 | 0.75* | 0.71 | 0.78* | 0.02 | 0.49* | 0.03 | 0.14* | 0.21* | -0.04 | 0.18* |
| Hong Kong | 1993 | 0.15 | 4.26 | -0.08 | 3.43 | 0.81* | 0.86 | 0.57* | 0.00 | 0.44* | 0.07 | 0.11* | 0.07 | -0.03 | 0.17* |
| Ireland | 2001 | -0.14 | 3.00 | 0.12 | 2.76 | 0.74* | 0.81 | 0.80* | 0.13 | 0.72* | -0.04 | 0.00 | -0.15 | -0.27* | 0.21* |
| Israel | 1993 | 0.19 | 3.23 | -0.03 | 3.04 | 0.59* | 0.34 | 0.84* | 0.15 | 0.69* | -0.01 | 0.04 | 0.00 | -0.16* | 0.19* |
| Italy | 1993 | 0.20 | 3.27 | 0.01 | 2.95 | 0.84* | 1.52 | 0.81* | 0.04 | 0.55* | 0.06 | 0.13* | 0.10* | -0.08 | 0.11* |
| Japan | 1993 | -0.04 | 2.73 | -0.05 | 2.57 | 0.82* | 0.80 | 0.54* | 0.01 | 0.51* | 0.04 | 0.12* | 0.06 | -0.04 | 0.19* |
| Luxembourg | 1999 | -0.10 | 3.15 | 0.23* | 2.66 | 0.65* | 0.05 | 0.72* | -0.07 | 0.47* | 0.07 | 0.20* | 0.04 | -0.18* | 0.20* |
| N. Zealand | 1993 | 0.18 | 2.21 | -0.06 | 1.90 | 0.39* | 0.64 | 0.40* | 0.01 | 0.37* | -0.03 | 0.06 | 0.03 | 0.07 | 0.10* |
| Netherlands | 1993 | 0.20 | 2.69 | -0.05 | 2.40 | 0.95* | 2.10 | 0.80* | 0.01 | 0.45* | -0.02 | -0.07 | -0.09* | -0.09* | 0.15* |
| Norway | 1993 | 0.19 | 2.70 | 0.01 | 2.36 | 0.81* | 1.29 | 0.39* | 0.01 | 0.21* | -0.02 | 0.08 | 0.02 | -0.19* | 0.15* |

| | | | | | | | | | | | | | | | |
|--------------------------|------|-------------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|--------------|-------------|
| Portugal | 1993 | 0.19 | 2.40 | 0.09* | 1.92 | 0.78* | 0.79 | 0.61* | 0.08 | 0.56* | 0.17* | 0.21* | 0.16* | -0.07 | -0.02 |
| Singapore | 1993 | 0.04 | 3.03 | -0.01 | 2.56 | 0.82* | 0.66 | 0.77* | 0.02 | 0.49* | 0.07 | 0.16* | 0.08 | 0.03 | 0.24* |
| Spain | 1993 | 0.27 | 2.85 | -0.05 | 2.61 | 0.91* | 1.42 | 0.75* | 0.02 | 0.35* | 0.02 | 0.04 | 0.02 | -0.12* | 0.16* |
| Sweden | 1993 | 0.25 | 3.50 | -0.09* | 3.08 | 0.89* | 1.52 | 0.76* | 0.02 | 0.43* | 0.01 | -0.02 | -0.02* | -0.09* | 0.21* |
| Switzerland | 1993 | 0.19 | 2.61 | -0.08 | 2.17 | 0.90* | 1.28 | 0.58* | 0.01 | 0.37* | -0.01 | -0.07 | -0.09 | -0.15* | 0.22* |
| Taiwan | 1993 | 0.16 | 4.09 | 0.06 | 3.90 | 0.76* | 3.42 | 0.75* | -0.01 | 0.65* | 0.11* | 0.35* | 0.30* | -0.06 | 0.23* |
| U.K | 1993 | 0.14 | 2.26 | -0.09* | 2.03 | 0.94* | 1.48 | 0.81* | 0.02 | 0.37* | 0.02 | -0.03 | -0.08* | -0.05 | 0.17* |
| U.S.A. | 1993 | 0.19 | 2.47 | -0.14* | 2.24 | 0.90* | 2.26 | 0.80* | 0.01 | 0.26* | 0.07 | 0.05 | -0.06 | -0.06 | 0.17* |
| Mean, High income | | 0.16 | 2.94 | -0.03 | 2.56 | 0.82 | 1.21 | 0.68 | 0.02 | 0.45 | 0.03 | 0.06 | 0.01 | -0.09 | 0.15 |

Panel B: Developing markets

| Country | From | Return | | Volatility | | Turnover | | Det. Log Turnover | | Lead-Lag Correlations | | | | | |
|-------------------------|------|-------------|--------------|--------------|-------------|-------------|-------------|-------------------|-------------|-----------------------|----------------|----------------|----------------|----------------|-------------|
| | | $\mu(\%)$ | $\sigma(\%)$ | AC(1) | $\mu(\%)$ | AC(1) | $\mu(\%)$ | AC(1) | μ | AC(1) | T_{t-1}, R_t | T_{t-1}, R_t | T_{t-1}, R_t | T_{t-1}, R_t | R_b, V_t |
| Argentina | 1993 | 0.21 | 4.67 | 0.00 | 3.89 | 0.78* | 0.29 | 0.73* | -0.01 | 0.50* | 0.00 | 0.25* | 0.01 | -0.02 | 0.26* |
| Brazil | 1999 | 0.43 | 3.68 | -0.06 | 3.06 | 0.68* | 0.73 | 0.37* | -0.03 | 0.32* | -0.07 | 0.10 | -0.03 | 0.14* | 0.14* |
| Chile | 1993 | 0.21 | 2.57 | 0.10* | 1.81 | 0.82* | 0.18 | 0.51* | 0.01 | 0.40* | 0.08 | 0.22* | 0.10* | -0.01 | 0.16* |
| China | 1993 | 0.13 | 5.47 | -0.05 | 4.01 | 0.83* | 3.43 | 0.43* | -0.01 | 0.65* | 0.11* | 0.33* | 0.25* | 0.02 | 0.04* |
| Colombia | 1993 | 0.16 | 2.70 | 0.18* | 1.74 | 0.34* | 0.11 | 0.33* | 0.01 | 0.24* | 0.04 | 0.17* | 0.20* | 0.13* | 0.09* |
| Czech Rep. | 1993 | 0.10 | 3.82 | 0.07 | 2.72 | 0.92* | 0.50 | 0.82* | 0.10 | 0.67* | -0.08 | -0.06 | -0.05 | 0.14* | 0.30* |
| Hungary | 1993 | 0.39 | 4.35 | 0.01 | 3.49 | 0.43* | 2.78 | 0.41* | 0.07 | 0.49* | 0.00 | 0.17* | 0.08 | 0.00 | 0.05* |
| India | 1995 | 0.06 | 4.10 | -0.02 | 3.28 | 0.69* | 1.31 | 0.94* | 0.07 | 0.72* | 0.04 | 0.15* | 0.14* | -0.18* | -0.06 |
| Indonesia | 1993 | 0.14 | 4.74 | -0.08 | 3.69 | 0.87* | 0.48 | 0.62* | 0.04 | 0.40* | 0.03 | 0.23* | 0.05 | 0.02 | 0.16* |
| Malaysia | 1993 | 0.08 | 4.23 | -0.04 | 3.05 | 0.69* | 0.47 | 0.65* | -0.01 | 0.51* | 0.05 | 0.23* | 0.13* | 0.09* | 0.11* |
| Mexico | 1993 | 0.26 | 3.46 | 0.03 | 2.95 | 0.84* | 0.83 | 0.54* | -0.01 | 0.41* | -0.02 | 0.22* | 0.11* | -0.11* | 0.09* |
| Peru | 1994 | 0.23 | 2.98 | 0.02 | 2.35 | 0.90* | 0.46 | 0.08 | -0.05 | 0.55* | -0.02 | 0.04 | 0.02 | 0.04 | 0.06 |
| Philippines | 1993 | 0.08 | 3.79 | 0.02 | 2.87 | 0.79* | 0.34 | 0.54* | 0.00 | 0.41* | 0.18* | 0.25* | 0.15* | -0.05 | 0.26* |
| Poland | 1994 | -0.04 | 5.36 | 0.04 | 4.13 | 0.75* | 0.69 | 0.76* | -0.03 | 0.55* | -0.05 | 0.27* | 0.21* | -0.06 | 0.16* |
| Russia | 1995 | 0.48 | 6.74 | 0.06 | 5.56 | 0.51* | 0.16 | 0.71* | 0.01 | 0.55* | 0.05 | 0.26* | 0.18* | -0.09 | 0.02 |
| South Africa | 1993 | 0.28 | 3.16 | -0.03 | 2.35 | 0.68* | 0.60 | 0.77* | 0.03 | 0.48* | -0.06 | 0.04 | -0.05* | -0.04 | 0.13* |
| South Korea | 1993 | 0.12 | 5.07 | -0.06 | 4.53 | 0.91* | 2.61 | 0.82* | 0.02 | 0.61* | 0.07 | 0.28* | 0.25* | 0.02 | 0.29* |
| Thailand | 1993 | 0.00 | 5.15 | 0.02 | 4.12 | 0.86* | 0.82 | 0.67* | 0.00 | 0.57* | 0.06 | 0.36* | 0.25* | 0.05 | 0.25* |
| Turkey | 1993 | 1.16 | 7.46 | 0.06 | 6.89 | 0.66* | 2.27 | 0.65* | 0.02 | 0.51* | 0.08 | 0.34* | 0.23* | -0.05 | 0.25* |
| Venezuela | 1993 | 0.42 | 5.56 | 0.07 | 4.53 | 0.24* | 0.42 | 0.45* | -0.06 | 0.45* | 0.17* | 0.27* | 0.22* | 0.12* | 0.18* |
| Mean, Developing | | 0.24 | 4.45 | -0.02 | 3.55 | 0.71 | 0.97 | 0.59 | 0.01 | 0.50 | 0.03 | 0.21 | 0.12 | 0.01 | 0.15 |
| Mean, All | | 0.20 | 3.69 | 0.00 | 3.06 | 0.76 | 1.09 | 0.64 | 0.01 | 0.47 | 0.03 | 0.14 | 0.07 | -0.04 | 0.15 |

Table II

Summary Statistics of Impulse Response Functions

Using returns and turnover data from January 2, 1993 to June 30, 2003 we estimate bivariate and trivariate VARs of detrended turnover and returns and, respectively, detrended turnover, returns and volatility. Weekly data are used for the VARs in Panel A through D, daily data are used for the VAR in Panel E. Turnover is total traded value in a given week scaled by the week's total market capitalization. Detrended Turnover is computed by subtracting a 20-week moving average from Turnover. EGARCH Volatility estimates are from an EGARCH (1, 1) specification fit to daily index returns and these daily estimated volatilities are cumulated into weekly volatilities. Squared Residuals Volatility is computed by squaring the residuals of an AR (1) model fitted to the returns series. In Panel D the two subperiods are January 2, 1993-June 30, 1997 and post-crises, January 1, 1999- June 30, 2003. For each VAR in Panel A through D we compute the Generalized Impulse Response Function (GIRF) response of returns to a one standard deviation shock to turnover at various lags. For the VARs in Panel E we compute the Orthogonalized IRF. The table reports the mean (μ), median (Med) and standard deviation (σ) of the responses for high income, developing, and all countries. We also report the number of positive (+), negative (-), significantly positive (+ (*)), and significantly negative (- (*)) responses.

| IRF | High income | | | | | | Developing | | | | | | All Countries | | | | | | | | |
|--|-------------|-------|----------|----|----|-------|------------|------|----------|------|---|-------|---------------|-----|----------|------|------|-------|----|---|----|
| | μ | Med | σ | - | + | + (*) | μ | Med | σ | - | + | + (*) | μ | Med | σ | - | + | + (*) | | | |
| Panel A: Bivariate VAR: Returns and Detrended Turnover | | | | | | | | | | | | | | | | | | | | | |
| Lag 1 | 0.06 | 0.05 | 0.10 | 6 | 20 | 1 | 8 | 0.22 | 0.23 | 0.10 | 0 | 20 | 0 | 17 | 0.13 | 0.11 | 0.13 | 6 | 40 | 1 | 25 |
| Lag 5 | 0.09 | 0.09 | 0.31 | 11 | 15 | 3 | 5 | 0.53 | 0.46 | 0.35 | 1 | 19 | 0 | 16 | 0.28 | 0.24 | 0.39 | 12 | 34 | 3 | 21 |
| Lag 10 | 0.11 | 0.12 | 0.36 | 11 | 15 | 7 | 14 | 0.60 | 0.48 | 0.47 | 1 | 19 | 1 | 17 | 0.32 | 0.24 | 0.48 | 12 | 34 | 8 | 31 |
| Panel B: Trivariate VAR: Returns, EGARCH Volatility and Detrended Turnover | | | | | | | | | | | | | | | | | | | | | |
| Lag 1 | 0.09 | 0.08 | 0.10 | 4 | 22 | 0 | 13 | 0.26 | 0.26 | 0.11 | 0 | 20 | 0 | 18 | 0.17 | 0.15 | 0.13 | 4 | 42 | 0 | 31 |
| Lag 5 | 0.18 | 0.15 | 0.33 | 9 | 17 | 0 | 8 | 0.60 | 0.56 | 0.36 | 1 | 19 | 0 | 16 | 0.36 | 0.32 | 0.40 | 10 | 36 | 0 | 24 |
| Lag 10 | 0.26 | 0.19 | 0.41 | 8 | 18 | 0 | 8 | 0.72 | 0.64 | 0.46 | 1 | 19 | 0 | 16 | 0.46 | 0.40 | 0.48 | 9 | 37 | 0 | 24 |
| Panel C: Trivariate VAR: Squared Residual Volatility, Non-Detrended Turnover (Lag 10) | | | | | | | | | | | | | | | | | | | | | |
| Squared Res., Det. Turn. | 0.22 | 0.22 | 0.49 | 9 | 17 | 0 | 8 | 0.61 | 0.56 | 0.39 | 1 | 19 | 0 | 16 | 0.39 | 0.34 | 0.48 | 10 | 36 | 0 | 24 |
| EGARCH, Non-Det. Turn. | 0.12 | -0.02 | 0.81 | 12 | 14 | 6 | 4 | 0.87 | 0.78 | 0.57 | 0 | 20 | 0 | 11 | 0.45 | 0.34 | 0.80 | 12 | 34 | 6 | 15 |
| Panel D: Subperiods (Lag 10) | | | | | | | | | | | | | | | | | | | | | |
| 1993-1997 | 0.58 | 0.55 | 0.39 | 0 | 26 | 0 | 16 | 0.61 | 0.52 | 0.53 | 1 | 19 | 0 | 13 | 0.59 | 0.53 | 0.45 | 1 | 45 | 0 | 29 |
| 1999-2003 | 0.12 | 0.06 | 0.47 | 10 | 16 | 1 | 4 | 0.72 | 0.69 | 0.40 | 0 | 20 | 0 | 17 | 0.38 | 0.39 | 0.53 | 10 | 36 | 1 | 21 |
| Panel E: Daily Trivariate VAR | | | | | | | | | | | | | | | | | | | | | |
| Lag 1 | 0.08 | 0.07 | 0.08 | 0 | 26 | 0 | 17 | 0.17 | 0.17 | 0.09 | 0 | 20 | 0 | 19 | 0.12 | 0.09 | 0.09 | 0 | 46 | 0 | 36 |
| Lag 5 | 0.11 | 0.06 | 0.28 | 11 | 15 | 4 | 11 | 0.40 | 0.38 | 0.27 | 0 | 20 | 0 | 18 | 0.23 | 0.18 | 0.31 | 11 | 35 | 4 | 29 |
| Lag 10 | 0.12 | 0.08 | 0.37 | 10 | 16 | 4 | 9 | 0.46 | 0.43 | 0.30 | 0 | 20 | 0 | 16 | 0.26 | 0.20 | 0.38 | 10 | 36 | 4 | 25 |

Table III

Testable Implications of Hypotheses that Explain Positive Return/Turnover Relation

This table presents evidence related to six main hypotheses consistent with the positive return/turnover relation (discussed in Section IV. A.). Testable implications of the hypotheses are divided into those explanations predicting differences in the return/turnover relation across countries, across investors' types (individual, institutional, or foreign), across time, and differences in responses between positive and negative return shocks.

| Theory | Evidence | Cross- Country | Investor Types | Time-series | Asymmetries |
|--|---|-----------------------|---|--|----------------------------|
| Liquidity | Stronger in markets with less trading volume | | | Decreasing to the extent that liquidity constraints are decreasing | Driven by negative returns |
| Investor Protection | Stronger in markets with less investor protection | | | | Driven by negative returns |
| Short-Sales | Increasing in Short-sale restrictions | | | Decreasing to the extent that short-sale restrictions are decreasing | Driven by negative returns |
| Participation | Stronger in markets with a high R^2 , high corruption | | Stronger for individual investors | Decreasing through time, higher in 1980's | Symmetric |
| Over-Confidence and Disposition | Stronger in markets with a high R^2 | | Stronger for individual investors | Higher in 1990s | Possible |
| Foreign 'Hot-Money' | | | Relation driven by foreign investors, domestic investor trading does not follow returns | | |

Table IV

Cross-sectional regressions

This table reports output from cross-sectional regressions where the dependent variable is the five-week response of turnover to return shocks in each country and the right-hand side variables are explained below. The five-week response of turnover to shocks in lagged returns is obtained from a generalized impulse response function in a VAR with returns, turnover, and volatility as shown and described in Figure 2. Market Cap / GDP is the average of the ratio of stock market capitalization held by small shareholders to gross domestic product for the period 1996-2000. Trading Value / GDP is the ratio of total traded value to GDP in 1995. Investor Protection is the principal component of private enforcement and anti-director rights on a scale from 0 to 10. All the previous variables are constructed and described in La Porta, Lopez-De-Silanes, and Shleifer (2003). Short sales (from Bris, Goetzmann and Zhu (2003)) is a dummy variable that equals one if short sales are allowed. Insider Trading Enforced (from Bhattacharya and Daouk (2002)) is a dummy variable that equals one if insider trading laws exist and are enforced. Average R² (from Morek, Yeung and Yu (2000)) is the average R-squared from the market-model regression across all stocks in a given market. Heteroskedasticity consistent p-values are in parenthesis.

| Independent Variables | Dependent Variable: Five week Response of Turnover to Shocks in Lagged Returns | | | | | | | | | | | | | |
|---------------------------------|---|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Intercept | 0.44 (0.00) | 0.98 (0.00) | 0.60 (0.00) | -0.11 (0.14) | 0.42 (0.00) | 0.98 (0.00) | 0.65 (0.00) | 0.14 (0.28) | 0.43 (0.05) | 0.60 (0.00) | 0.90 (0.00) | 0.10 (0.41) | 0.41 (0.07) | 0.40 (0.07) |
| Market Cap / GDP | | | | | -0.22 (0.22) | | | | | | | | | -0.02 (0.87) |
| Trading Value / GDP | | | | | 0.38 (0.08) | | | | | | | | | |
| Investor Protection | -0.02 (0.27) | | | | 0.00 (0.64) | | | | | | | | | |
| Corruption | | -0.10 (0.00) | | | -0.12 (0.00) | | | | | | | | | |
| Short Sales | | | -0.44 (0.00) | | | -0.35 (0.01) | -0.20 (0.04) | -0.14 (0.09) | -0.05 (0.01) | -0.39 (0.00) | -0.18 (0.08) | -0.19 (0.06) | -0.13 (0.14) | -0.04 (0.08) |
| Insider Trading Enforced | | | | | | | -0.07 (0.39) | | | | | | | |
| Average R² | | | | 2.42 (0.00) | | | | 2.01 (0.00) | 1.68 (0.01) | | | 1.96 (0.00) | 1.64 (0.01) | 1.65 (0.01) |
| Skewness | | | | | 0.25 (0.10) | | | | | 0.12 (0.31) | 0.13 (0.17) | 0.04 (0.69) | 0.05 (0.70) | 0.05 (0.70) |
| Number of observations | 40 | 40 | 45 | 45 | 46 | 40 | 40 | 45 | 40 | 45 | 40 | 45 | 40 | 40 |
| Adjusted R² | 0.00 | 0.40 | 0.29 | 0.52 | 0.10 | 0.46 | 0.25 | 0.56 | 0.57 | 0.30 | 0.45 | 0.55 | 0.56 | 0.55 |

Table V
1983-1992 period and Asymmetries

We estimate weekly trivariate VARs of detrended turnover, returns, and volatility. Detrended turnover and EGARCH (1,1) volatility are calculated as described in Figure 2. Panel A presents summary statistics for the GIRF for the January 2, 1983 to December 31, 1992 period with the full sample. Panel B reports results excluding the week of October 19, 1987. For the VARs in Panel C and D we separately compute the GIRF for positive and negative return shocks. Panel C reports the Threshold VAR results for the 1993-2003 period with separate responses to positive and negative return shocks while Panel D is for the 1983-1992 period. All responses are standardized by the estimated residual variance. The table reports the mean (μ), median (Med) and standard deviation (σ) of the responses for high-+income, developing, and all countries. We also report the number of positive (+), negative (-), significantly positive (+ (*)), and significantly negative (- (*)) responses.

| GIRF | High Income | | | | Developing | | | | All Countries | | | | | | | | | | | | |
|---|-------------|-------|----------|---------|------------|-------|-----|----------|---------------|-------|-------|-----|----------|---------|-------|-------|------|----|----|---|----|
| | μ | Med | σ | + - (*) | + (*) | μ | Med | σ | + - (*) | + (*) | μ | Med | σ | + - (*) | + (*) | | | | | | |
| Panel A: 1983-92 Trivariate VAR (Includes '87 crash) | | | | | | | | | | | | | | | | | | | | | |
| Lag 1 | 0.12 | 0.12 | 0.08 | 1 | 17 | 0 | 6 | 0.36 | 0.35 | 0.10 | 0 | 6 | 0 | 6 | 0.18 | 0.16 | 0.14 | 1 | 23 | 0 | 12 |
| Lag 5 | 0.43 | 0.42 | 0.28 | 1 | 17 | 0 | 11 | 1.19 | 1.24 | 0.44 | 0 | 6 | 0 | 6 | 0.62 | 0.55 | 0.46 | 1 | 23 | 0 | 17 |
| Lag 10 | 0.52 | 0.55 | 0.37 | 1 | 17 | 0 | 10 | 1.31 | 1.34 | 0.52 | 0 | 6 | 0 | 6 | 0.72 | 0.70 | 0.53 | 1 | 23 | 0 | 16 |
| Panel B: 1983-92 Trivariate VAR (Excludes '87 crash) | | | | | | | | | | | | | | | | | | | | | |
| Lag 1 | 0.15 | 0.15 | 0.08 | 1 | 17 | 0 | 9 | 0.37 | 0.36 | 0.09 | 0 | 6 | 0 | 6 | 0.21 | 0.17 | 0.13 | 1 | 23 | 0 | 15 |
| Lag 5 | 0.49 | 0.43 | 0.27 | 1 | 17 | 0 | 14 | 1.26 | 1.26 | 0.38 | 0 | 6 | 0 | 6 | 0.68 | 0.65 | 0.45 | 1 | 23 | 0 | 20 |
| Lag 10 | 0.57 | 0.50 | 0.35 | 1 | 17 | 0 | 14 | 1.40 | 1.43 | 0.45 | 0 | 6 | 0 | 6 | 0.78 | 0.75 | 0.52 | 1 | 23 | 0 | 20 |
| Panel C: 1993-2003 Response of Turnover to Positive and Negative Return Shocks | | | | | | | | | | | | | | | | | | | | | |
| Pos Lag 10 | 0.28 | 0.21 | 0.33 | 5 | 21 | - | - | 0.61 | 0.52 | 0.38 | 1 | 19 | - | - | 0.43 | 0.44 | 0.39 | 6 | 40 | - | - |
| Neg Lag 10 | -0.29 | -0.18 | 0.33 | 24 | 2 | - | - | -0.68 | -0.62 | 0.40 | 20 | 0 | - | - | -0.46 | -0.43 | 0.41 | 44 | 2 | - | - |
| Panel D: 1983-1992 Response of Turnover to Positive and Negative Return Shocks | | | | | | | | | | | | | | | | | | | | | |
| Pos Lag 10 | 0.56 | 0.54 | 0.31 | 1 | 17 | - | - | 1.28 | 1.24 | 0.39 | 0 | 6 | - | - | 0.74 | 0.72 | 0.45 | 1 | 23 | - | - |
| Neg Lag 10 | -0.59 | -0.59 | 0.33 | 17 | 1 | - | - | -1.21 | -1.16 | 0.37 | 6 | 0 | - | - | -0.74 | -0.74 | 0.43 | 23 | 1 | - | - |