Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries

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This article 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 of turnover, differing sample periods, and are present at both the weekly and daily frequency. The relation is more statistically and economically significant in countries with high levels of corruption, with short-sale restrictions, and in which market volatility is high.

Do investors trade more when markets have done well in the recent past? If their trading relates to past returns, why do they behave that way? Answering these questions is important to our understanding of the determinants of trading volume, liquidity, and stock returns. Furthermore, answers to these questions can help market makers and liquidity providers obtain forecasts of trading intensity, portfolio managers devise efficient trading strategies, and regulators and policymakers find ways to improve the liquidity and efficiency of financial markets.

In this article, we examine the relation between past weekly returns and stock turnover (trading value normalized by market capitalization) at the market level across 46 countries. First, we investigate whether there is a positive relation between volume and past returns in our sample. Second, we use the cross-sectional variation in the relation across countries to advance our understanding of the determinants of the return–volume

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relation. Third, we use information about trading by investor types, asymmetries in the response of turnover to past returns, dynamics from earlier time periods, and daily data to further enhance our understanding of the relation. To our knowledge, this is the first study that attempts to comprehensively determine whether the return–volume relation holds across countries and to investigate the determinants of cross-country differences.

There is on average a positive relation between past returns and turnover in our sample of countries. Using a trivariate vector autoregression (VAR) of 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 1 standard deviation (SD) shock to returns leads to a 0.46 SD increase in turnover on average after 10 weeks.

After documenting the existence and robustness of the return–turnover relation, we show that there is substantial cross-sectional variation across the 46 countries. Strikingly, the relation is much stronger for developing markets than for high-income countries. Furthermore, it weakens in recent years for high-income countries. For example, in our sample, the return–turnover relation is close to zero and insignificant for the United States and the United Kingdom from 1993 to 2003 but positive and significant in the prior 10 years.

There is a vast theoretical literature on why investors trade. The main reasons for trading identified in the literature are information asymmetries, differences of opinion, portfolio rebalancing needs, taxes, and life-cycle considerations.[1] Many papers predict a positive relation between the absolute value of market returns and trading because more information arrives to investors when return moves are large. The existence of this relation is well-established empirically.

In this article, however, we are not concerned about why investors trade but about why they might trade more following positive returns and less following negative returns. Unfortunately, the literature does not provide fully testable models of the return–volume relation. The observation of Gallant, Rossi, and Tauchen (1992) that the "empirical literature on price–volume relations tends to be very data-based and not guided by rigorous, equilibrium models of market behavior" (p. 201) is still true today. Nevertheless, the existing literature provides a number of reasons why trading volume might be positively related to past returns, and these reasons guide our examination of the cross-sectional determinants of the strength of the return–volume relation. The message from the theoretical arguments we consider is that the return–volume relation should be

[1] This literature is recently discussed in Chordia, Huh, and Subrahmanyam (2006).

stronger when short sales are not permitted, when markets are less efficient, when institutions supporting the functioning of the stock market (such as investor protection and intermediaries who provide liquidity) are weaker, when an economy is more opaque, when an economy is riskier and less correlated with other economies, and when individual investors are relatively more important.

We find that the return–volume relation is stronger in more opaque economies and in more volatile economies. In contrast, the relation is much weaker for stock markets that are more highly correlated with world stock markets. Variables that proxy for financial development, liquidity, and minority shareholder protection are not helpful in explaining the return–volume relation. Most strikingly, the return–volume relation is significantly positive after five weeks in 16 out of 21 countries that do not allow short sales but only in 8 countries out of 25 that allow short sales. In univariate regressions, we find evidence that the relation is stronger in countries where short sales are not allowed, where corruption is higher, where institutional investors are less important, and where equity markets are less well developed. The return–volume relation is stronger in markets with weaker informational efficiency. Morck, Yeung, and Yu (2000) argue that a market is less informationally efficient when stock returns are more highly correlated as measured by the average R^2 from market-model regressions. We find that the average R^2 is strongly positively related to the intensity of the return–volume relation. However, a market's volatility and correlation with the world markets explain much of average R^2 making it difficult to interpret the role of R^2 in our cross-sectional regressions.

Theories that emphasize behavioral biases suggest that the return–volume relation should be stronger in the trading of individual investors. In seven countries we have data for the trading of foreign investors, who tend to be institutional investors. We find that the relation is weaker for foreign investors, which is consistent with our finding that the relation is stronger for individuals. We show that the return–turnover relation was strong in developed markets in the prior 10-year period (1983–1992). This is also generally consistent with our cross-sectional evidence of the return–volume relationship being less pronounced as efficiency increases.

A number of earlier papers have examined the relation between past returns and trading activity. These papers reach different conclusions using assorted sample periods and disparate estimation approaches. This is not surprising because the theoretical arguments we discuss suggest that the relation between past returns and trading activity depends on a number of factors that change through time and differ across countries: It is thus important to evaluate this relation on recent data and across countries. Hiemstra and Jones (1994) found evidence of daily returns Granger-causing NYSE volume, and Statman, Thorley, and Vorkink

(2006) show that "market-wide trading activity in NYSE/AMEX shares is positively correlated to past shocks in market return" using monthly data from 1962 through 2001. In contrast, however, Gallant, Rossi, and Tauchen (1992) found that volume increases following large absolute price changes using daily returns from 1928 to 1987, but they cannot conclude that volume increases are greater following large positive price changes than large negative price changes. Using the past five-day return, Chordia, Roll, and Subrahmanyam (2001) found a positive relation between negative past returns and dollar volume of the US market using daily data from 1988 through 1998 but an insignificant negative relation between positive past returns and volume. In a study of the turnover of individual firms, Chordia, Huh, and Subrahmanyam (2006) conclude that "past return is by far the most significant predictor of turnover" and find that higher positive and negative returns lead to substantially higher turnover.[2] Tse (1991) and Saatcioglu and Starks (1998) conclude that there is little evidence that returns lead volume at the market level in, respectively, Japan and six Latin American markets.

Because of the empirically established relation between volatility and both returns and volume, we carefully control for volatility in our VAR specification using an array of volatility measures, including EGARCH filters, squared residuals, and range-based measures. Controlling for volatility strengthens the importance of the return–turnover relation. Through impulse response analysis of the VAR and a detailed look at the dynamics of daily data, we find that the positive contemporaneous relation between returns and volume that the previous literature has observed (Karpoff 1987, Gallant, Rossi, and Tauchen 1992) is dwarfed in economic importance by a stronger relation between volume and past returns. Finally, through the use of a threshold VAR, we take a novel look at the importance of both positive and negative return shocks on volume and at the impact of return shocks of different sizes. In descriptive analysis, we find that average positive shocks and average negative shocks have a fairly symmetric impact on turnover. We also find that larger positive return shocks lead to proportionally larger increases in volume than smaller positive return shocks, but the picture is more subtle for negative shocks. In general, the decrease in trading for large negative shocks—the left tail of the return distribution—is less than that for other negative shocks. Though the econometric techniques we use here do not permit evaluation of the statistical significance of the differing impact between large and small negative shocks, the evidence suggests that

[2] In addition, Smirlock and Starks (1988) presented evidence of higher volume following intradaily positive price movements for individual stocks, but only during days of information arrival, and Lakonishok and Smidt (1986) showed a positive relation between daily trading volume on individual stocks and past performance. Using data on individual investor accounts, Glaser and Weber (2005) find that past market returns have a larger effect on individuals trading than their past portfolio returns.

further research is required to evaluate the impact of large negative shocks on trading.

The article is organized as follows. In Section 1, we review the theoretical arguments that make predictions for the determinants of the return–volume relation. Section 2 describes the sample and displays summary statistics. We estimate the relation between past returns and volume in Section 3. In Section 4, we investigate possible explanations through the use of cross-country regressions, data on investors' types, estimation of the return–volume relation for earlier periods, exploration of potential asymmetries, and data at the daily frequency. We conclude in Section 5.

1. Theoretical Determinants of the Return–Volume Relation

Though the literature offers no fully specified model of the return–volume relation that we could estimate directly, the vast theoretical literature on the determinants of trading volume is helpful in identifying factors that affect the return–volume relation. This literature motivates the variables we use in our cross-sectional regressions. We address the various theories in turn.

1.1 Informed investors and short-sale costs

Informed investors trade to take advantage of information they have and to rebalance their portfolio (Wang, 1994). Because they have valuable information about the payoffs of risky assets, they buy when assets are undervalued and sell when they are overvalued. Further, as He and Wang (1995) show, the arrival of private information can lead to a pattern of increasing volume. If informed investors are not concerned that their private information will be revealed publicly in the short run, they may delay trading so that they do not have to hold their position for as long and hence do not have to bear as much risk. Consequently, without a significant risk of full disclosure, private information will be incorporated in prices slowly, so that increased buying by insiders will follow price increases. In Diamond and Verrecchia (1987), adverse information is incorporated into prices at a slower rate 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 receive bad news. This would presumably be true even if short sales are not prohibited but are simply more costly than buy trades. In sum, we would expect the return–volume relation to be stronger in more opaque and riskier economies as long as short sales are costly.

1.2 Uninformed investors and short-sale restrictions

Rational uninformed investors can find it optimal to adopt trend-following trading strategies. For investors who do not have access to private information, past returns may contain signals about the private information of informed investors (Wang 1993) and about the state variables that determine expected returns (Williams 1977). Brennan and Cao (1997), for instance, model the trading of foreign investors who have access to information later than domestic investors. The informational disadvantage of foreign investors leads them to be trend followers. In their model, it is critical that foreign investors be less well-informed at the beginning of the period. We conjecture that past returns are a more important source of information when investors have access to less reliable public information and when information is incorporated in prices slowly because of limited market efficiency. As long as investors with an informational disadvantage find it more expensive to take short positions than long positions, they will trade less following poor returns, which will affect the volume of trading adversely. Jennings, Starks, and Fellingham (1981) extend Copeland's (1976) sequential trading model assuming that it is more costly to go short than long. In their model, volume is lower when uninformed investors interpret news pessimistically.[3] The intuition of the Brennan and Cao (1997) model suggests that the return–volume relation should be weaker as markets become more efficient and information is incorporated in prices more quickly.

1.3 Liquidity effects

In models with rational investors, a positive relation between return and volume can arise if negative returns decrease liquidity.[4] In Bernardo and Welch (2004), liquidity providers are more risk averse when stock prices decrease, and the fear of future liquidity shocks causes market makers to provide less liquidity. Although their focus is on crises, poor returns can generally increase the costs of providing liquidity for market makers because they become more capital constrained. Suppose that the liquidity providers are naturally long in the market. As stock prices fall, market makers increase their inventory positions and also take losses on their inventory positions, hence they become less willing to acquire stocks and offer liquidity more reluctantly. With these liquidity effects, volume falls

[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) extended Easley and O'Hara (1992) to take into account short-sale constraints. They found 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 although investors can only take long positions in their model.

[4] Existing models of liquidity predict that a decrease in liquidity is associated with a fall in stock prices. As a result, unanticipated adverse news about liquidity should be associated with a negative return on the market. This explanation implies that the change in liquidity causes the market return. Consistent with this argument, recent evidence in Jones (2002) shows that high liquidity predicts low returns. However, as pointed out by Baker and Stein (2004), 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.

following poor returns because the cost of trading increases. Liquidity effects would seem more likely to be important in countries with undercapitalized or underdeveloped financial intermediaries.

1.4 Participation

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 a share price increase 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 market. This could be because less informed rational investors find returns informative, as in Brennan and Cao (1997) and Orosel (1998); because positive returns draw the attention of investors in a similar way that Gervais, Kaniel, and Mingelgrin (2001) posit that high volume in individual stocks draws attention; or because investors have extrapolative expectations that relate expected gains from stock market trading to past returns for behavioral reasons. We would expect participation effects to be stronger in countries where there is more uncertainty about future fundamentals and less information. Given the costs involved in deciding to participate in the markets, these models do not seem capable of predicting a return–volume relation at the daily frequency.

1.5 Overconfidence

Following Odean (1998b), there is an increasing literature that emphasizes the relation between trading and overconfidence. In Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001), overconfidence grows with past success in the markets. These papers therefore imply that volume should increase following positive returns when such returns build confidence. However, if investors are extremely overconfident because of having performed well for a long time, then recent past returns will not matter as much. Though these papers do not rely on short-sale constraints to establish a positive relation between returns and volume, Hong, Scheinkman and Xiong (2005) showed that in the presence of short-sale constraints, overconfidence can lead to bubble-like phenomena, where investors buy stocks hoping to resell them at a higher price to more optimistic investors. We would expect overconfidence effects to be stronger in countries where security returns are highly correlated. If security returns have low correlation, it is more likely that some investors will do poorly while others do well, so that only a fraction of investors will become overconfident. Further, we would expect overconfidence to be important for individual investors and less for institutional investors.

1.6 Disposition effect

The disposition effect of Shefrin and Statman (1985) implies that volume follows returns because investors are reluctant to trade after poor returns and eager to lock in gains after stock price increases. Lakonishok and Smidt (1986), Odean (1998a), and Grinblatt and Keloharju (2000) all find evidence in support of the disposition effect. We would expect the disposition effect to be more important in countries where individual investors are more important. Further, higher correlation among stocks in a country implies that when the market has a negative return, more individual stocks will also have a negative return. Consequently, the fraction of stocks affected by the disposition effect is higher in countries with higher correlation among stocks.

1.7 Momentum investing

Momentum or positive feedback traders want to buy following stock price increases and sell after stock price decreases (DeLong et al. 1990, Hong and Stein 1999). Momentum investors are therefore more active following large absolute price moves. However, when there are restrictions on short sales or momentum investors choose not to short securities, momentum investors only sell the stocks they own and thus are more active in up markets than down markets. The empirical evidence indicates that domestic (Grinblatt, Titman, and Wermers 1995) and foreign (Froot, O'Connell, and Seasholes 2001) institutional investors chase past returns. Consequently, if the return–volume relation is driven by momentum investing, we would expect it to be stronger in countries where institutional or foreign investors are more active.

2. Data and Summary Statistics

We seek to comprehensively examine the relation between returns and volume across markets. As shown by Smidt (1990), the US 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 a larger number of countries over more recent periods, we primarily examine the 10.5 years from January 2, 1993 through June 30, 2003. From Datastream International, we collect weekly (Wednesday close 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. As can be seen from Table 1, at least 10 years of weekly data are available in

Table 1
Summary statistics

Country	From	Return			Volatility		Turnover		Det. log turnover		Lead–lag correlations				
		μ (%)	σ (%)	AC (1)	μ (%)	AC (1)	μ (%)	AC (1)	μ	AC (1)	T_{t-1}, R_t	T_t, R_t	T_{t+1}, R_t	R_t, V_t	T_t, V_t
Panel A: high-income markets															
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*
New 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*
UK	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*
USA	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	0.02	−0.09	0.15

Table 1
(continued)

		Return			Volatility		Turnover		Det. log turnover		Lead–lag correlations				
Country	From	μ (%)	σ (%)	AC (1)	μ (%)	AC (1)	μ (%)	AC (1)	μ	AC (1)	T_{t-1}, R_t	T_t, R_t	T_{t+1}, R_t	R_t, V_t	T_t, V_t
Panel B: developing markets															
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 Republic	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	3.60	−0.01	2.99	0.77	1.11	0.64	0.01	0.47	0.03	0.13	0.06	−0.05	0.15

Weekly data from 46 markets are used with the beginning of coverage marked in the first column and the ending on June 30, 2003 for all countries. All the series are from Datastream. For each country, we report the mean (μ), standard deviation (σ), and lag one autocorrelation coefficient for weekly value-weighted market returns, EGARCH volatility, turnover, and detrended turnover. Units are percent per week. We also report correlation coefficients in each market between lagged turnover and returns, the contemporaneous correlation between turnover and returns, the correlation between 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 the total traded value in a given week scaled by the week's total market capitalization. Turnover is detrended by first taking its natural log and then subtracting a 20-week moving average. Panel A summarizes results for high-income markets, whereas Panel B summarizes 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.

*Significance at the 5% level.

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

To verify the reliability of our volume data, we collected series that were not compiled by Datastream. We targeted market indices that have broad coverage in terms of both turnover and market capitalization and span a comparably long time series. At the daily or weekly frequency, we were able to obtain alternative volume series for 22 of our 46 countries: 12 high-income and 10 developed markets. Sometimes, the series represents only one of a country's exchanges. Nevertheless, the correlations between the Datastream and the alternative series exceed 0.89 for 16 of the 22 countries and are above 0.70 for 20 of the 22 countries.[5]

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.[6] 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 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 larger impact on volatility than positive return shocks of the same magnitude) often shown to characterize equity index returns. We also construct weekly volatility measures by cumulating daily absolute and squared residuals from an autoregressive model for daily returns.

Table 1 presents summary statistics for weekly returns, EGARCH volatility, raw turnover, and log detrended turnover. We also show contemporaneous relations among turnover, volatility, and returns, as well as short-term lead–lag dynamics between turnover and returns. Using World Bank classifications, we separate our sample into high-income

[5] 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.

[6] Lo and Wang (2000) convincingly argue in favor of using turnover over alternative measures of trading activity. 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 article, we mostly use turnover (scaled volume) but for convenience will often refer to it simply as volume.

and developing nations according to gross national income (GNI) per capita in 1998, the midpoint of our sample.[7] Panel A summarizes results for high-income countries, and Panel B summarizes results for developing countries.

Panel A summarizes 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 United States is over 2% per week, meaning that 2% of the outstanding shares trade in a given week (or around 100% per year). However, Austria, Belgium, Denmark, Greece, Hong Kong, Ireland, Israel, Japan, Luxembourg, New Zealand, Portugal, and Singapore all have turnover of less than 1% per week. Both volatility and turnover are quite persistent, with an average first-order autocorrelation of 0.82 for volatility and 0.68 for turnover in high-income countries. In unreported results, we use the average absolute value of returns as a rough volatility proxy and find a much lower average autocorrelation of 0.17. In contrast, returns have an average autocorrelation of nearly zero. Because both positive and negative autocorrelations cancel out in the averaging, we also take the absolute value of the autocorrelation in each country and then average across countries. We still find an average absolute autocorrelation of only 0.06. In contrast, log turnover is still persistent after detrending. In unreported tests, we also test for stationarity of the detrended turnover series and find that an Augmented Dickey-Fuller test decisively rejects the null hypothesis of a unit root at any conventional confidence level for each of the country series. Checking the autocorrelation function of detrended turnover confirms that persistence is typically limited to the first five or six lags. This level of persistence will be captured in the VAR by the appropriate choice of lag length. Therefore, our inferences should not be clouded by long-memory or non-stationarity in the turnover data, a proposition we also test by examining the VAR residuals.[8]

[7] High-income countries in 1998 are those with income over 9360 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.

[8] As clearly illustrated by Lo and Wang (2000), the trade-off here is between not imposing too much structure on the data by detrending and conducting meaningful statistical inference. The optimal solution would be a fully specified model of the trend component. In its absence, the adopted approach appears to be a reasonable compromise followed in numerous studies. Our robustness checks indicate that detrending (and/or) the detrending method do not appreciably alter our relevant conclusions.

In the rightmost columns of Panel A, we examine the sample correlations between detrended turnover and returns and find that on average they are positive and statistically significant in eight high-income markets, and negative and insignificant in six others. The average contemporaneous correlation between turnover and returns is 0.06 for high-income markets. The average 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% per week, substantially higher than the average in high-income countries (2.56%). 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% of the market per week, but with all other developing countries, except for India, turning over less than 1% of the market 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 relation between return and turnover. In developing markets, the correlation 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.[9]

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 VAR for most of our inferences.

3. Estimating the Return–Volume Relation

The theories discussed above do not offer a specific model to assess the relation between turnover and returns. Thus, our statistical approach differs substantially from the asset pricing framework for turnover as recently applied by Cremers and Mei (2005) for the purpose of estimating turnover factors from the cross-section of US stocks. International studies such as Bekaert and Harvey (1997) model volatilities through the use of both world and local information. Our main tool for evaluating the return–volume relation is VAR on a country-by-country basis. We also estimate VARs with world returns and volatilities to evaluate the sensitivity of our results to the inclusion of these global variables.

[9] We also perform rolling correlations of the past four-week return with the next four-week turnover with rolling windows of three years. We see no evidence of structural breaks in the data which is consistent with our sample period occurring after the market liberalization dates estimated in Bekaert and Harvey (1995). Nevertheless, these results highlight the importance of VAR results we will estimate for the earlier 1993–1997 and the later 1999–2003 subperiods.

3.1 Impulse response estimation

We estimate impulse response functions (IRFs) where the lag one effect measures the relation between a 1 SD 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 procedure, however, has two important drawbacks, as argued by Koop, Pesaran, and Potter (1996) and by Pesaran and Shin (1998). First, because 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 intraweekly relationships between past returns and current turnover. Therefore, we 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 use a VAR analysis of daily data to examine intraweek relationships.[10]

3.2 Bivariate VAR

We first examine turnover and past returns without controlling for volatility effects. The cumulative impulse response of turnover to volume shocks is typically extremely similar at ten and twenty weeks.[11] Thus, in Figure 1 we display the response of turnover to return shocks at lags one, five, and ten from the IRFs. Insignificant bars are striped. Figure 1 shows that turnover is related to past returns in many markets. The lag one relation between turnover and returns is positive and significant in 25 of

[10] Because the return–turnover relation can vary substantially across markets, we use the Hannan-Quinn Information Criterion (HQC) to select the optimal lag length for the VAR within each country. The selected lag is usually between two and five. Interestingly, this lag length roughly corresponds to the four-week period of information delay found by Hou and Moskowitz (2005) when regressing US individual stock returns on past market returns.

[11] Even though we do not observe a reversal in volume, it is possible that the impact of returns on volume switches signs at longer horizons, reversing the shorter-term effects. Given the use of an unrestricted VAR, weekly data and detrended turnover (which forces the response to approach zero), our structure is not designed for capturing reversals over longer periods. In their US analysis of monthly data over 1962–2002, Statman, Thorley, and Vorkink (2006) find that the cumulative effects of shocks dissipate after eight months. Our analysis shows that most of the return–volume effect occurs in the first five weeks. Using monthly data and moving to longer horizons would lump together contemporaneous and lagged effects.

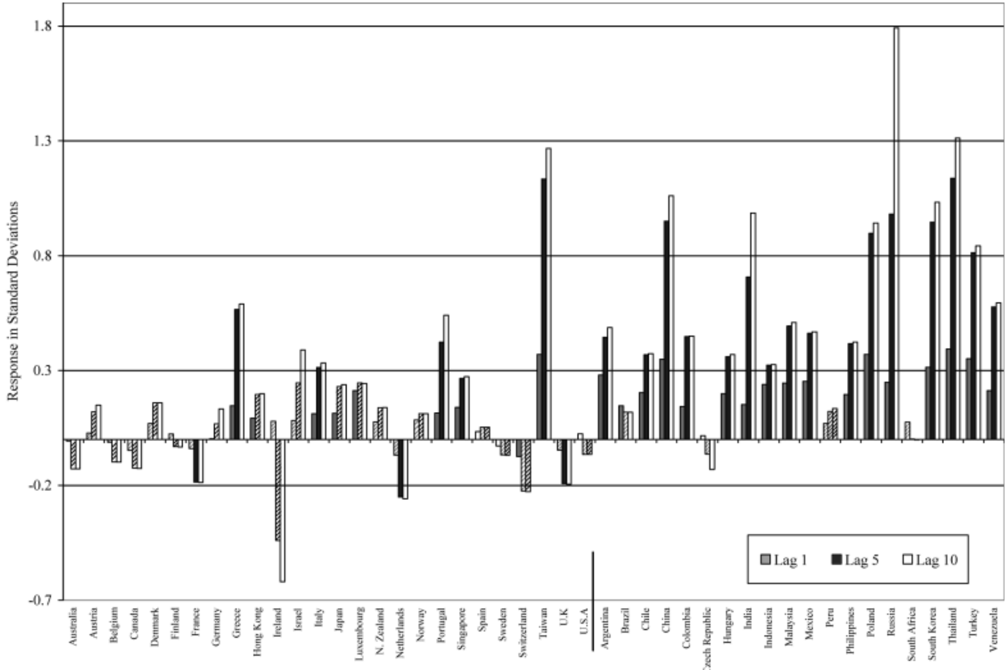

Figure 1
Impulse response functions from bivariate vector autoregressions (VARs)
Weekly returns and detrended turnover data from January 2, 1993 to June 30, 2003 are used to estimate country-by-country bivariate VARs of detrended turnover and returns. The figure reports the generalized impulse response function (GIRF) of turnover to a 1 SD shock to returns at lags one, five, and 10 weeks in each country. All responses are standardized by the estimated residual standard deviation. Turnover is total traded value n a given week scaled by the week's total market capitalization. Turnover is detrended by first taking its natural log and then subtracting a 20-week moving average. Insignificant bars are striped. Significance is assessed by constructing 95% confidence intervals through Monte Carlo simulation. High-income countries are in alphabetical order on the left side of the graph and developing countries are on the right.

46 markets and significantly negative in only one market. Additionally, the cumulative 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 1 SD shock to returns is followed by a 0.32 standard deviation increase in turnover after 10 weeks. These summary statistics for Figure 1 are found in Panel A of Table 2.

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 1 SD shock to returns is followed by a 0.11 SD increase in turnover after 10 weeks. At the same frequency in developing nations, a 0.60 increase in turnover follows a 1 SD shock to returns. Comparing these results to others in the literature is difficult because of the differing measurement intervals, time periods, methodologies, US focus, and estimation on individual securities. The closest paper in terms of methodology is Statman, Thorley, and Vorkink (2006). They estimate a monthly bivariate VAR at the market level using NYSE/AMEX detrended volume and return data from 1962 to 2002 and find that a 1 SD shock to market returns leads to a significant 3% increase in next month's turnover. Our results in Figure1 show a small negative relation. We will later show that we also find a stronger positive US relation if we focus on an earlier time period which is consistent with the diminishing effects of past returns that they find in the United States.[12] In sum, the relation between past returns and turnover is positive and significant in many countries, but its magnitude varies widely.

3.3 Controlling for volatility

As discussed in the introduction, it is well known that turnover is positively related to volatility. Without controlling for volatility, the impact of returns on turnover may be counterbalanced by these volatility effects, leading to a weaker overall response to return shocks. Although more ambiguous in terms of direction, there is also considerable evidence that market volatility and returns are correlated. To control for these effects, we estimate VARs with turnover, returns, and EGARCH volatility.[13] Figure 2 presents IRFs measuring the effect of a 1 SD shock to

[12] In individual firm regressions, they find that individual firm turnover is positively related to past market returns in a 1993–2002 subperiod but that the magnitude of this effect is much smaller than in earlier subperiods. They find that the relation between turnover and individual stock returns is positive in earlier years of the sample but negative in the 1993–2002 period.

[13] We check for the adequacy of the VAR specification by conducting tests for whiteness of the residuals. Specifically, following Lutkepohl (1991), we run a Portmanteau test for the overall significance of residual autocorrelation. The null hypothesis that residual autocorrelations are zero up to five lags is rejected only in a few instances (as it should be expected if the test has good size properties) and confirms that most, if not all, of the dependencies are captured by the VAR.

Table 2
Summary statistics of impulse response functions

	High income							Developing							All countries						
IRF	μ	Med	σ	–	+	– (*)	+ (*)	μ	Med	σ	–	+	– (*)	+ (*)	μ	Med	σ	–	+	– (*)	+ (*)
Panel A: bivariate VAR: local currency 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: local currency 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: returns, squared residual volatility, detrended turnover; returns, EGARCH volatility, non-detrended turnover (lag 10)																					
Squared residuals, detrended turnover	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-detrended turnover	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: trivariate VAR ($ returns); quadrivariate VAR (local returns with currency returns)																					
3-variable VAR: lag 10	0.22	0.16	0.41	9	17	0	7	0.69	0.60	0.47	1	19	0	16	0.43	0.37	0.49	9	36	0	23
4-variable VAR: lag 10	0.19	0.07	0.42	9	17	0	6	0.62	0.51	0.48	1	19	0	14	0.38	0.28	0.49	9	36	0	20
Panel E: local effects after global controls—five-variable VAR; lagged world return and volatility as exogenous variables																					
Lag 10	0.16	0.08	0.48	10	16	2	5	0.53	0.41	0.42	1	19	0	12	0.32	0.27	0.49	11	35	2	17
Panel F: subperiods – trivariate VAR: local returns, EGARCH volatility, and detrended turnover (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

The Vector autoregressions (VARs) use weekly returns and turnover data from January 2, 1993 to June 30, 2003 and include combinations of turnover, equity returns, volatility, and currency returns. For each country-level VAR, we compute the generalized impulse response function (GIRF) of turnover to a 1 SD shock to returns at various lags. Turnover is total traded value in a given week scaled by the week's total market capitalization. Detrended turnover is computed by first taking turnover's natural log and then subtracting a 20-week moving average. 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 return series. In Panel D, the response measured in the trivariate VAR is that to the past local market dollar return; whereas the four-variable VAR is in local currency but includes the change in the local market rate with the dollar. In Panel E, a specification with local dollar returns, volatility, and turnover also includes a world market return and world market volatility as exogenous variables. In Panel F, the VAR in Panel B is estimated for two subperiods: pre-crises, January 2, 1993 to June 30, 1997 and post-crises, January 1, 1999 to June 30, 2003. 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.

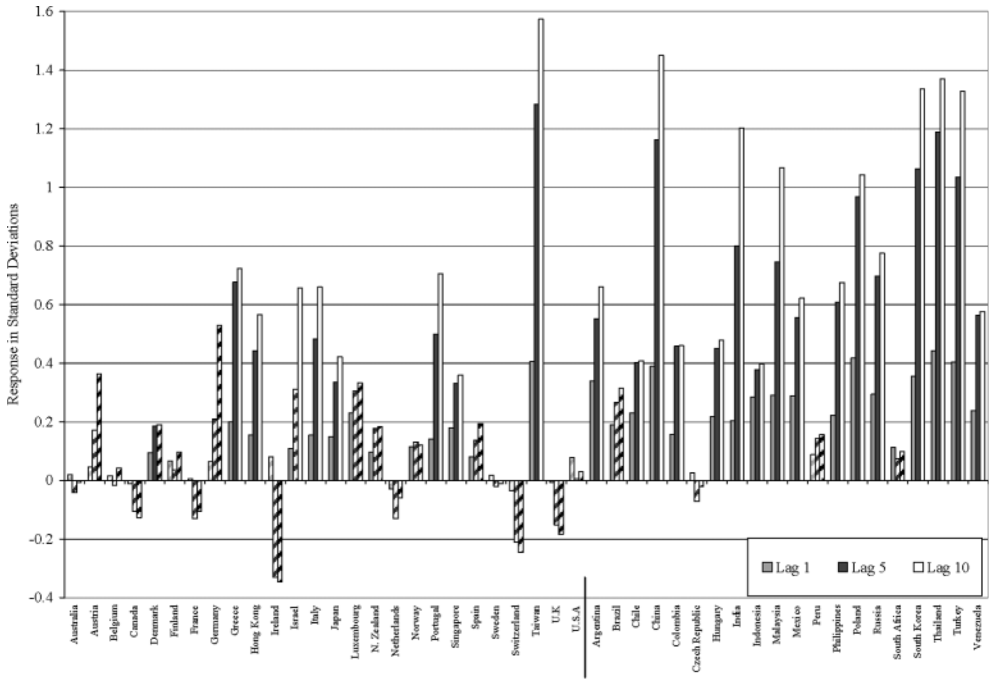

Figure 2
Impulse response functions from trivariate vector autoregressions (VARs)
The within-country trivariate vector autoregressions of detrended turnover, returns, and volatility use weekly returns and detrended turnover data from January 2, 1993 to June 30, 2003. The figure reports the generalized impulse response function (GIRF) of turnover to a 1 SD shock to returns at lags 1, 5, and 10 weeks in each country. All responses are standardized by the estimated residual standard deviation. Turnover is total traded value in a given week scaled by the week's total market capitalization. It is detrended by first taking its natural log and then subtracting a 20-week moving average. Volatility estimates are from an EGARC (1,1) specification fit to daily index returns, and these daily estimated volatilities are cumulated into weekly volatilities. Insignificant bars are striped. Significance is assessed by constructing 95% confidence intervals through Monte Carlo simulation. High-income countries are on the left side of the graph and developing countries are on the right side.

returns on volume from this system. Summary statistics from Figure 2 are presented in Panel B of Table 2 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 relation between past returns and turnover is even larger and more positive than those observed without controlling for volatility. Averaged across all countries, a 1 SD positive shock to returns is associated with a 0.17 SD increase in next week's volume, a 0.36 SD increase in volume after five weeks, and a 0.46 SD 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 10 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 1 SD shock to returns leads to a 0.26 SD 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 1 SD increase in weekly returns is followed by a remarkably large increase in turnover (bigger than 1 SD) after 10 weeks. Though Japan and the United States were at one time similar in market capitalization, they have very different return–turnover relations. The 10-week response of turnover to returns is 0.42 in Japan but only 0.03 in the United States. In the high-income markets of Australia, Canada, France, Ireland, the Netherlands, Sweden, Switzerland, and the United Kingdom, there is an insignificant negative relation between turnover and returns, but significantly positive relations are found in Greece, Hong Kong, Italy, Japan, Portugal, Singapore, and Taiwan. This evidence shows that taking into account the volatility–volume relation generally strengthens the return–volume relation.

3.4 Sensitivity to volatility measures, detrending methods, the role of currency, and global information

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 and again estimate a trivariate VAR with squared residual volatility, detrended turnover, and returns. We also estimate a model where turnover is not detrended, with EGARCH (1,1) volatility and returns. Panel C of Table 2 summarizes that these modifications lead to little change in our main results. 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.[14] We also estimated our baseline trivariate VAR excluding or winsorizing all values in the highest and lowest percentiles and obtained extremely similar results.

The returns used in our current analysis are all in local currency. Turnover is invariant to the numeraire currency because the currency conversion affects both the value of trade shares and the market capitalization. The response of turnover to returns may be linked to currency movements embedded in the local stock market return. We investigate this in two ways. First, we estimate our main trivariate VAR system using dollar denominated returns and volatilities computed from these dollar returns. As summarized in Panel D of Table 2, the average response of turnover to dollar returns after 10 weeks is 0.22 in high-income countries and 0.69 in developing countries. Second, we also estimate a VAR with the dollar cross-rate currency return in addition to turnover, the local return, and volatility. The average response of turnover to dollar returns after 10 weeks is 0.19 in high-income countries and 0.62 in developing countries.[15]

Another possibility is that the return–volume relation is driven by world returns. This seems unlikely because the effects are higher in emerging markets where correlations with world returns are low. Nevertheless, Panel E examines the same dollar return specification as the first regression in Panel D except that both lagged world dollar returns and lagged EGARCH (1,1) world volatilities are also included in the VAR and treated as exogenous variables. Panel E summarizes the response of turnover to local market dollar returns. Overall, the average response after 10 weeks is 0.16 in high-income countries and 0.53 in developing countries. Even though the responses in the developing markets are slightly lower than the 0.72 in our base case, the patterns are similar across countries, and the responses are still positive for 19 out of 20 developing countries. We also estimate VARs with regional measures of lagged returns and volatility and find extremely similar results to the ones with the global controls. Overall, the method of calculating volatility or turnover, controlling for the currency of denomination, and controlling for world or regional returns and volatility does not materially affect the return–turnover relation.

[14] In unreported results, we use specifications with GARCH (1,1) volatility or absolute residual volatility and detrended volume using a linear or quadratic trend. We also estimate a specification similar to Hiemstra and Jones (1994) where volatility is controlled for by standardizing the returns by EGARCH filtered volatility. Here, we use a bivariate VAR with the standardized returns and volatility. In all cases, the results are very similar to our main results (in Panel B of Table 2).

[15] In unreported analysis, we find that turnover is consistently insignificantly related to past currency movements.

3.5 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 3 demonstrates that the previously observed regularities are remarkably robust in both periods in developing markets but much less in high-income countries in the later subperiod. In all but two developing markets, the relation is positive in both subperiods. In the high-income markets, the return–turnover relation is positive and significant in 16 of 26 markets in the 1993 to 1997 period but significantly positive in only four markets in the second subperiod. The average 10-week response of turnover to returns (shown in Panel F of Table 2) 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 increases slightly from the first (0.61) to the second (0.72) subperiod.

To further examine potential time-variation in the return–volume relation, we also estimate our weekly VARs over rolling four-year windows beginning in January 1993 and update every year, so that the last window covers the 2000–2003 period. In a number of high-income countries, the relation dissipates slowly across years while the relation is persistently positive over time in most developing countries. These results (not reported in a table) further reinforce our findings from the two subperiods suggesting that high-income countries tend to exhibit a decreasing return–volume effect over time and that developing countries responses are large, positive, and quite similar in magnitudes over different time spans.

4. Why does Turnover Follow Returns?

Table 3 summarizes the empirical implications of the various theoretical arguments discussed in Section 1. These arguments make sharp predictions concerning the cross-sectional variation in the return–volume relation. Nevertheless, the theories that underlie these predictions are not mutually exclusive. According to these cross-sectional predictions, the return–volume relation should be more pronounced in countries with less transparency, short-sale restrictions, an underdeveloped financial system, more uncertainty, concentrated returns, and with more momentum profits. Four of the theories predict that the relation should be stronger among individual investors but only the momentum trading explanation predicts that institutional investors will drive the relation. Overconfidence theories predict that the return–volume relation should

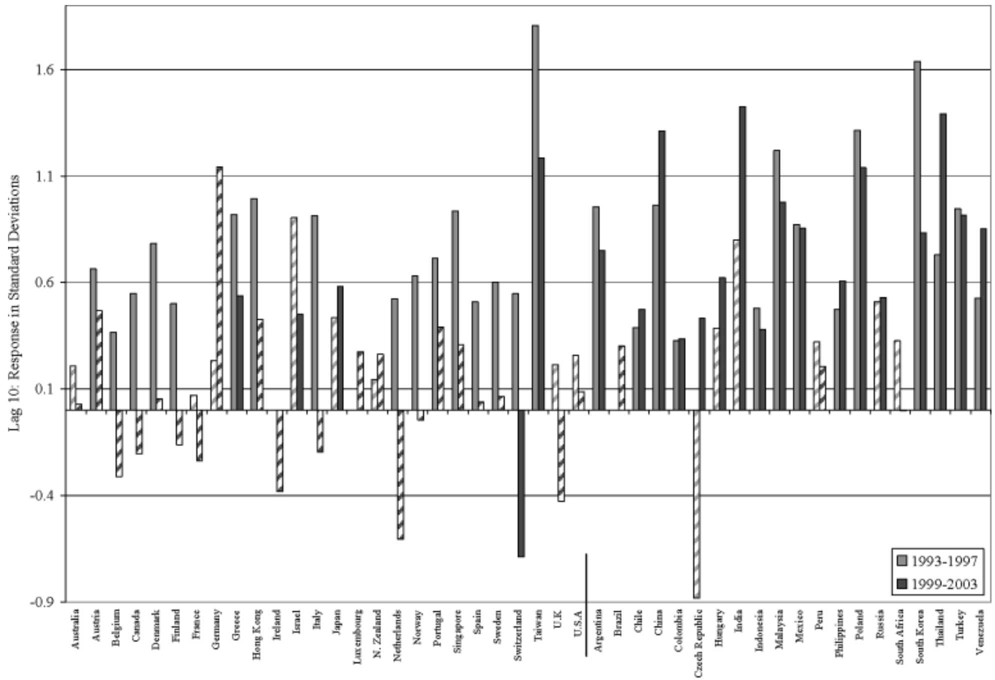

Figure 3
Subperiods 1993–1997 and 1999–2003
Weekly return and detrended turnover data are used to estimate trivariate vector autoregressions (TVARs) of detrended turnover, returns, and volatility. The figure reports the GIRF of turnover to a 1 SD shock to returns at lag 10 weeks in each country for two subperiods: January 2, 1993–June 30, 1997 (pre-crises) and January 1, 1999–June 30, 2003 (post-crises). All responses are standardized by the estimated residual standard deviation. Turnover is total traded value in a given week scaled by the week's total market capitalization. Turnover is detrended by first taking its natural log and then 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. Insignificant bars are striped. Significance is assessed by constructing 95% confidence intervals through Monte Carlo simulation. High-income countries are on the left side of the graph and developing countries are on the right.

Table 3
Testable implications of hypotheses that predict a positive return–turnover relation

Theory	Cross country	Investor types	Time series	Asymmetries	Daily frequency
Informed trading and short-sale constraints	Stronger in more opaque countries with short-sale restrictions		Weakens as disclosure and efficiency increase	With short-sale restrictions, less trading following negative returns	Yes
Uninformed investors and short-sale constraints	Stronger in more opaque countries with short-sale restrictions	Stronger for individual investors	Weakens as disclosure and efficiency increase	With short-sale restrictions, less trading following negative returns	Yes
Liquidity	Stronger in markets with weak financial intermediaries		Decreasing to the extent that liquidity constraints are decreasing	Driven by negative returns	Yes
Participation	Stronger in markets with more uncertainty, less information	Stronger for individual investors	Decreasing through time as more investors participate	Symmetric	No
Overconfidence	Stronger in markets with concentrated returns	Stronger for individual investors	Weakens following long periods of high returns like the 1990s for developed markets	Possible	Possible
Disposition	Stronger in markets with concentrated returns	Stronger for individual investors		Possible	Possible
Momentum	Stronger in markets with larger momentum profits	Stronger for foreign or domestic institutional investors		With short-sale restrictions, less trading following negative returns	Possible

Testable implications of the hypotheses are divided into those explanations predicting differences in the return–turnover relation across countries, across investor types (individual, institutional, or foreign), across time, and in responses to positive and negative return shocks. The last column asks whether these effects should also be present within the week or at the daily frequency.

be higher in periods and economies where positive returns build confidence. Once investors are highly overconfident, negative (or positive) returns over a week are unlikely to decrease (or increase) overconfidence and to affect the volume of trading. It follows that overconfidence theories predict a strong return–volume relation in economies that have experienced poor stock market performance, so that we would not expect a strong return–volume relation in developed economies that performed well in the 1990s. The participation explanation predicts that the relation should become less pronounced as transaction and information costs fall over time (and, hence, weaker in the 1990s). In terms of asymmetries, the explanations that rely on short-sale costs and liquidity imply that the relation is driven by trading volume drying up following periods of negative returns. The participation theories call for a symmetric relation.

4.1 Proxies for the determinants of the return–volume relation

We now examine the predictions on how the relation should vary across countries. We first describe the proxies we use for each theory summarized in Table 3.

4.1.1 Informed trading and short-sale constraints. The prediction is that there should be a stronger return–volume relation in more opaque countries with short-sale restrictions. Disclosure forces information to be incorporated in prices quickly. To measure disclosure, we use the disclosure index of La Porta, Lopez-de-Silanes, and Shleifer (2006). We also use the number of analysts, the precision of analyst forecasts, and dispersion of analyst forecasts from Chang, Khanna, and Palepu (2000). More risk makes informed investors more cautious and reduces the speed with which information is incorporated into prices. Our proxies for risk are a country risk index, an index of political risk, the volatility of GDP growth, and the volatility of the market's return. Finally, we proxy for short-sale costs with the short-sales dummy variable of Bris, Goetzmann, and Zhu (2006) that takes a value of 1 when short sales are both allowed and practiced and 0 otherwise.[16]

4.1.2 Uninformed investors and short-sale constraints. The predictions of this theory are similar to the predictions of the theory that focuses on informed investors. This theory focuses on the use of past returns for uninformed investors. Uninformed investors can use correlated variables to extract more information from past returns. This means that we would

[16] Chen, Hong, and Stein (2001) found strong evidence for individual securities, and some evidence at the US market level, that high past volume (a proxy for differences in opinion) is related to more negative skewness. We investigate the role of skewness in explaining the return–volume relation, but we find that the relation between volume and past returns is not related to a measure of market-level negative skewness.

expect the return–volume relation to fall as the correlation between local and world returns increases.

4.1.3 Liquidity. We expect the liquidity effect to be stronger in poorer countries and countries that are less financially developed. Our proxy for economic development is the log of GDP per capita. Our proxies for financial development are a country's market capitalization to GDP and turnover. We also use direct trading costs measures for liquidity: transaction costs and relative minimum tick-size proxies from Swan and Westerholm (2005).

4.1.4 Participation. Participation models rely on a group of sidelined investors who do not trade due to costs of participation (like information and trading costs) but who 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 (i.e., 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. Morck, Yeung, and Yu (2000) propose the market-model R^2 as a proxy for market efficiency where higher R^2 is associated with lower informational efficiency. The level of corruption in a country can proxy for the fairness of the markets. 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. 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, we also use the ability to engage in insider trading without being prosecuted as a proxy for poor investor protection in the trading process. In particular, we use the dummy variable of Bhattacharya and Daouk (2002) that takes a value of 1 in countries where insider trading is actually prosecuted.

4.1.5 Overconfidence. Overconfidence theories imply high volume when investors are overconfident. As investors acquire overconfidence, positive returns are associated with an increase in volume. Hence, we expect the return–volume relation to be strong when markets have been performing poorly. Following a period of spectacular performance, we would expect poor returns for a short period of time to have no impact on overconfidence and hence on trading volume. We would therefore expect the return–volume relation to be stronger in markets that have a mixed record in the recent past.

4.1.6 Disposition effect. Because we expect psychological biases to be more important for individuals than for institutional investors, turnover should be more positively related to past returns for individuals than institutions. This implies that the return–volume relation should be stronger in countries where institutional investors are less important.

4.1.7 Momentum. Because institutions have been shown to be strong momentum investors, we would expect the relation to be stronger for institutional investors and stronger in countries with short-sale restrictions. We also use profits to momentum strategies as a proxy for momentum effects.[17] A related momentum folklore is that foreign investors, because of return chasing, tend to both pull money out of a market and lose interest in trading when that market experiences negative returns. Thus, while concerns about "foreign speculators" often center on directional trading, these concerns also have implications for total trading activity, namely that a decrease in trading volume following negative returns could be driven by lack of foreign trading. In contrast, if foreign investors are more sophisticated, they might trade less in response to past returns. 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.

4.2 Cross-country analysis

In Table 4, we regress the five-week response of turnover to returns from our main trivariate VAR results presented in Figure 2 on the proxies for our various theories individually.[18] We display our explanatory variables into broad categories of regulatory, economic and financial development, transaction costs, information environment, economic risks, and properties of the market return. Turning to the first three legal/regulatory proxies, we

[17] The relation between momentum profits and momentum traders is unclear. If a market has a large number of momentum traders, we might expect them to eliminate momentum profits but yet there is ample evidence that US mutual funds trade on momentum but have not eliminated the effect. For example, Grinblatt, Titman, and Wermers (1995) show that institutions trade on momentum at quarterly frequencies at the firm level.

[18] Kaniel, Li, and Starks (2006) 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 United States 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. We also obtain extremely similar results using lag ten responses as the dependent variable.

see that the return–volume relation is much weaker in countries without short-sale restrictions. Insider trading and investor protection have no explanatory power. We then turn to three measures of development. The traditional proxies for financial development, stock market capitalization to GDP and turnover, explain little of the return–volume relation, but the log of GDP per capita is inversely related to the return–volume relation. The two proxies for cost of trading explain nothing.

We then consider proxies for the information environment. The analyst measures are significant, but they have low R^2. In contrast, the disclosure index is highly significant and has a high R^2. Because corrupt countries have less transparency, corruption is also used as an index of opaqueness. We find that corruption is strongly associated with the return–volume relation and has the third highest R^2 of all our variables. The market model R^2 of Morck, Yeung, and Yu (2000), which they argue is a proxy for market efficiency, has substantial explanatory power in our regressions. Though it is tempting to attribute all of its success to its role as a proxy for market efficiency, which would be consistent with our other results, it is possible that R^2 is successful for other reasons. For instance, Griffin, Kelly, and Nardari (2006) point out that R^2 is mostly related to market volatility and the number of firms in a market. We examine three economic risk measures (GDP growth volatility, trade balance to GDP volatility, country risk, and political risk) and find a positive relation between the economic risk measures and the return–volume relation. Next, we use measures of the properties of the returns of the market index. We find that the return–volume relation increases with volatility and that volatility is the second most successful variable in explaining the

Table 4
Cross-sectional simple regressions

Variables	Coef. (p value)	Number of Observations	Adjusted R^2
Regulatory			
Short sales dummy	−0.44 (0.00)	45	0.29
Insider trading dummy	−0.07 (0.59)	46	−0.02
Investor protection	−0.02 (0.27)	40	0.00
Economic and financial development			
Market cap/GDP	−0.41 (0.00)	46	0.13
Trading/GDP	−0.20 (0.25)	45	0.01
Log GDP per capita	−0.18 (0.00)	44	0.25
Trading Costs			
Transactions costs	0.00 (0.94)	29	−0.04
Relative minimum tick	0.04 (0.20)	29	−0.03
Information environment			
Number of analysts	−0.02 (0.00)	44	0.10
Forecast error	1.43 (0.00)	44	0.16
Forecast dispersion	1.42 (0.01)	43	0.14
Disclosure	−0.34 (0.00)	40	0.38
Corruption	−0.11 (0.00)	46	0.41
R^2	2.42 (0.00)	45	0.52

Table 4
(continued)

Variables	Coef. (p value)	Number of Observations	Adjusted R^2
Economic risk			
Variable GDP growth	156.87 (0.00)	43	0.18
Trade sector/GDP	0.00 (0.79)	44	−0.02
Country risk	−0.01 (0.00)	46	0.27
Political risk	−0.02 (0.00)	43	0.31
Properties of market returns			
Market volatility	22.00 (0.00)	46	0.46
Correlation with World market	−1.43 (0.00)	46	0.39
Company Herfindahl	0.07 (0.76)	45	−0.02
Industry Herfindahl	−0.35 (0.05)	45	0.02
Number of listed firms	0.00 (0.01)	45	0.02
Other			
Momentum	−0.02 (0.00)	38	0.18
Mutual fund own	−0.12 (0.00)	43	0.12

The dependent variable is the five-week response of turnover to return shocks in each country obtained from a generalized impulse response function in a vector autoregression (VAR) with returns, turnover, and volatility (Figure 2). Log (GDP) per capita is the natural logarithm of per capita gross domestic product (in US dollars) in 2000. Investor protection is the principal component of private enforcement and antidirector rights on a scale from 0 to 10. Market cap/GDP is the average of the ratio of stock market capitalization held by shareholders to gross domestic product for the period 1996–2000. All the previous variables are constructed, used, and described in La Porta, Lopez-De-Silanes, and Shleifer (2006). Trading/GDP is the average annual ratio of total equity traded value and GDP for the period 1993–2003 (source: Datastream). The trading costs variables, transaction costs estimates, and relative minimum tick size are from Swan and Westerholm (2005). The number of analysts, the precision of analyst forecasts, and dispersion of analyst forecasts are from Chang, Khanna, and Palepu (2000). Disclosure is a measure of transparency used by Jin and Myers (2006): higher values indicate less disclosure. Corruption is the average for the 1993–2003 period of the corruption perception index published by transparency international—higher values of the index indicate less corruption. Short sales (Bris, Goetzmann, and Zhu 2006) is a dummy variable that equals 1 if short sales are allowed as of the end of 1998 (which is also the mid-point of our sample period). Insider Trading (Bhattacharya and Daouk 2002) is a dummy variable that equals 1 if insider trading laws exist and are enforced as of the end of 1998. Average R^2 (Morck, Yeung, and Yu 2000) is the average R^2 from the market-model regression across all stocks in a given market for 1998. The variance of the growth rate in real GDP [VAR GDP growth from Bris, Goetzmann, and Zhu (2006)] is computed over the period 1993–2001. The ratio of trade in goods to GDP (TradeSector/GDP from the WDI World Bank database) is the average between 2000 and 2003. Country risk is the average over the period 1993–2003 of the Country Risk Index published by Euromoney. Political risk is the average for the period between 1984 [or, 1985, or 1986, depending on the country from Erb, Harvey, and Viskanta (1996)] and 1996 of the index compiled by ICRG. For both indices, higher values indicate lower risk. Market volatility is the sample standard deviations of weekly equity market local currency returns over the period 1993–2003. The correlation with world is computed for the period 1993–2003 between country equity returns and returns on the Datastream world market index. For the major markets (United States, United Kingdom, Japan, Germany, and France), the world index excludes the own country. The Herfindahl indices (Bris, Goetzmann, and Zhu 2006) indicate the degree of industry concentration and firm concentration. They are time-series averages of annual values for the period 1993–2001. The number of listed firms (Bris, Goetzmann, and Zhu 2006) is the average between 1993 and 2001 of the firms with common stock prices available on Datastream for a given country at the end of each year. Momentum is the average winner minus loser return from 1975 or when first available until December 2000 from Griffin, Martin, and Ji (2003). The percentage of mutual fund ownership in 2001 from Khorana, Servaes, and Tufano (2005) is rescaled as a fraction of total stock market capitalization. (Luxembourg is removed because of the extremely large relative size of its mutual fund industry.) Heteroskedasticity (White) consistent p values are in parenthesis.

return–volume relation. The fourth most successful variable overall is the correlation between the local market and the world market. A concern is that our results might be artificially induced by differences in index construction across countries. We use two Herfindhal indices to measure the extent of diversification included in indices. The first Herfindahl index uses the index shares of individual companies and the second uses index shares of industries. We also include the number of firms listed on the exchange. The explanatory power of all three of these variables is trivial. We include here a regression that uses a measure of momentum profits. We find that the return–volume relation is weaker in countries where the profits of momentum strategies are higher. One way to interpret this result is that profits will be low in countries with considerable momentum trading. If that is the correct interpretation, then the evidence using momentum profits is supportive of the momentum explanation of the return–volume relation. Mutual fund ownership is negatively related to the return–volume relation. Because the literature has shown that institutions are more likely to engage in momentum trading, we interpret this evidence as inconsistent with the momentum explanation.

Table 4 makes it possible to eliminate some explanations for the return–volume relation. It is implausible that a positive return–volume relation results from low financial development, from index construction, or from investor rights as proxied by the antidirector rights index. Consequently, there is no support for the liquidity theory.

The variables that are successful in Table 4 tend to be highly correlated. For instance, corruption has a correlation of –0.64 with market volatility and of –0.58 with the R^2 measure. To assess more precisely why certain variables are related to the return–volume relation, we estimate multiple regressions with our most powerful explanatory variables from Table 5. The first regression uses the log of GDP per capita, short-sales, and corruption. In that regression, the log of GDP per capita is not significant. The strong coefficients of short-sales and corruption generally hold up in regressions that do not include variables based on returns. For instance, the next regression includes the short-sales dummy, the country risk measure, corruption, disclosure, and the market capitalization divided by GDP. Only the short-sales dummy variable and corruption are significant in that regression. The regression has an adjusted R^2 of 0.52. We show in regression (3) that corruption and short sales alone have an adjusted R^2 of 0.48. The next regression adds R^2 to regression (3). The adjusted R^2 becomes 0.60 and all three variables are significant. We then show in regression (5) that volatility and correlation with the world market have roughly the same explanatory power as R^2. If R^2 is added to regression (5), it is not significant. However, in regression (6) we add the part of R^2 that is not explained by volatility and correlation with the world market. All three variables are significant in that regression. In a regression not reported, we add to regression (6) the short-sale dummy and corruption. We find neither of the added variables to be significant and no improvement in the adjusted R^2. In regression (7), we add the short-sale dummy and the country risk index to the regression. While the short-sale dummy is not significant, the country risk index is and the other variables are all significant. Next, regression (8) uses the short-sale

Table 5
Cross-sectional multiple regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regulatory										
Short sales dummy	−0.36 (0.01)	−0.39 (0.01)	−0.27 (0.01)	−0.16 (0.06)			−0.13 (0.23)	−0.22 (0.04)	−0.27 (0.01)	−0.17 (0.03)
Economic and financial development										
Market cap/GDP		−0.03 (0.87)								
Log GDP per capita	0.12 (0.12)									
Information environment										
Disclosure		0.06 (0.75)						0.09 (0.57)		
Corruption	−0.12 (0.00)	−0.16 (0.03)	−0.08 (0.00)	−0.05 (0.01)				−0.06 (0.09)	−0.09 (0.00)	−0.05 (0.01)
R^2				1.54 (0.00)				0.99 (0.11)		1.64 (0.00)
Orthogonalized R^2						0.64 (0.04)	0.70 (0.02)			
Economic risk										
Country risk		0.01 (0.24)					0.01 (0.04)			
Properties of the index return										
Market volatility					15.96 (0.00)	17.46 (0.00)	20.07 (0.00)	9.66 (0.10)		
Correlation with world market					−0.90 (0.00)	−0.86 (0.00)	−1.09 (0.00)			
Other										
Momentum										−0.01 (0.08)
Mutual fund own									−0.06 (0.02)	
Number of obs.	44	39	45	45	46	45	45	39	42	38
Adjusted R^2	0.51	0.52	0.48	0.60	0.58	0.62	0.65	0.64	0.53	0.69

The dependent variable is the five-week response of turnover to return shocks in each country obtained from a generalized impulse response function in a VAR with returns, turnover, and volatility (as described in Figure 2). Sources for the variables are reported in Table 4. Log (GDP) per capita is the natural logarithm of per capita gross domestic product (in US dollars) in 2000. Market cap/GDP is the average of the ratio of stock market capitalization to gross domestic product for the period 1996–2000. Disclosure is a measure of transparency: higher values indicate less disclosure. Corruption is the average for the 1993–2003 period of the corruption perception index where higher values indicate less corruption. Short sales is a dummy variable that equals 1 if short sales are allowed as of the end of 1998. Average R^2 is the average R^2 from the market-model regression across all stocks in a given market for 1998. Orthogonalized R^2 is the residuals from regressing average R^2 on volatility and correlation with world market. Country risk is the average over the period 1993−2003 of the country risk index. Market volatility is the sample standard deviations of weekly equity market local currency returns over the period 1993–2003. The correlation with the world market is computed for the period 1993–2003 using the Datastream world market index. For the major markets (United States, United Kingdom, Japan, Germany, and France), the world index excludes the own country. Momentum is the average winner minus loser return from 1975 (or, when first available) until December 2000. Mutual fund ownership is the percentage of equity market capitalization held by mutual funds at the end of 2001 (excluding Luxembourg). Heteroskedasticity (White) consistent p values are in parenthesis.

dummy, R^2, disclosure, corruption, and volatility. Strikingly, only the short-sale dummy and corruption are significant. Regression (9) shows that in a regression with the short-sales dummy, corruption, and mutual fund ownership, all variables are significant but the explanatory power of this regression is less than specifications including R^2. In a regression not reported that includes R^2, momentum profits, and mutual fund ownership, only R^2 is significant. Finally, regression (10) includes the short-sale dummy, R^2, corruption, and momentum profits. All variables are significant and the R^2 of that regression, 0.69, is the highest.[19]

In general, our results provide evidence against the hypothesis that the pattern of turnover following returns is driven simply by economic development, liquidity, poor investor protection, or lack of insider trading enforcement. In contrast, we find that the return–volume relation is strong in countries with short-sale constraints, opaque countries (corruption and idiosyncratic volatility are high), low mutual fund ownership, and countries with high market volatility and a low correlation with world markets. We also saw, however, that significance depends somewhat on which variables are included in the regressions, which is perhaps not surprising given the fact that many variables are highly correlated. We also estimate many other unreported regression specifications and obtain similar inferences. In addition, we estimated the regressions of Tables 4 and 5 using the lag 5 response of turnover to dollar returns from the five-variable VAR in Table 2 Panel E where we estimate the volume–return relation after controlling for both past global returns and volatility. Our conclusions are not affected by the use of the five-variable VAR lag 5 response.

Unfortunately, most of our theoretical arguments make the predictions for which we find support in our regressions. To distinguish between these arguments, we therefore turn to how the relation differs across investor types, how the relation changes through time, asymmetries, and the effect at the daily frequency.

4.3 Trading by investor type

4.3.1 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 where such data is made available and where we also have reliable turnover and return data.[20] Trading volume by foreigners represents 10, 39, 33, 39,

[19] To allow the precision of the estimates to affect inferences, we also estimate specifications identical to Tables 4 and 5 except that the dependent variables are impulse response coefficients standardized by their standard errors from the first-stage IRF estimation. We find extremely similar inferences.

[20] 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).

14, 9, and 33% of average trading volume in India, Indonesia, Japan, Philippines, South Korea, Taiwan, and Thailand, respectively. In Figure 4, we present impulse response graphs of the dynamic relation between domestic and foreign detrended turnover and shocks to returns from VARs 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

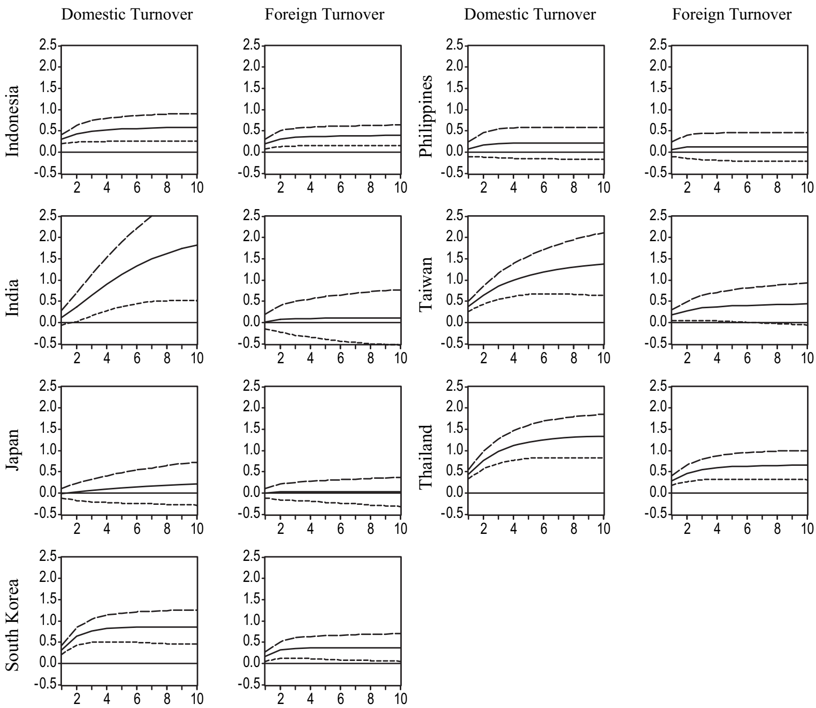

Figure 4
Responses of foreign and domestic turnover to local returns
This figure shows generalized impulse response functions describing the response of detrended foreign and domestic turnover to a 1 SD shock in local market returns. The time scale on the horizontal axis is expressed in weeks. Responses are expressed in standard deviation units. For each impulse response function, we also report the 95% confidence intervals (dotted lines), which are computed by Monte Carlo simulation. Results are based on a vector autoregression (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 foreign and domestic investors in a given week scaled by the week's total market capitalization. Foreign and domestic turnover are separately detrended by first taking their natural logs and then subtracting the respective 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 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.

(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.

4.3.2 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 institutional investors. Also, we would expect to see more nonmarket participants among individual investors than among institutions. Hence, if the return–turnover relation is driven by participation costs, overconfidence, or the disposition effect, 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.[21]

Figure 5 presents the dynamic relation between the detrended turnover of institutions, individual investors, and foreign investors 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 1 SD shock to returns is followed by a 0.72, 0.83, 1.17, and 1.31 SD increase in individual trading in Japan, South Korea, Taiwan, and Thailand. In contrast, after 10 weeks, a 1 SD shock to returns leads to only a –0.11, 0.90, 0.59, and 0.74 SD increase in trading by domestic institutions in these markets. In Japan, Taiwan, and Thailand, the responses of individuals to past trading volume is much higher than that of institutions.[22] Except for South 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. For our smaller data set, we construct a Garman and Klass (1980) range-based volatility measure [as recently implemented by Daigler and

[21] Domestic institutions are on average responsible for 50, 18, 8, and 7% of all volume and domestic individuals for 17, 68, 82, and 60% in Japan, South Korea, Taiwan, and Thailand, respectively. Trading by foreign investors is not broken out separately into institutional and individual groups except in Korea and Taiwan, but almost all foreign trading is due to institutions in these two countries.

[22] We examine the robustness of these relations to the use of non-detrended turnover, log turnover, and turnover detrended with a linear and/or a quadratic trend and find similar relations.

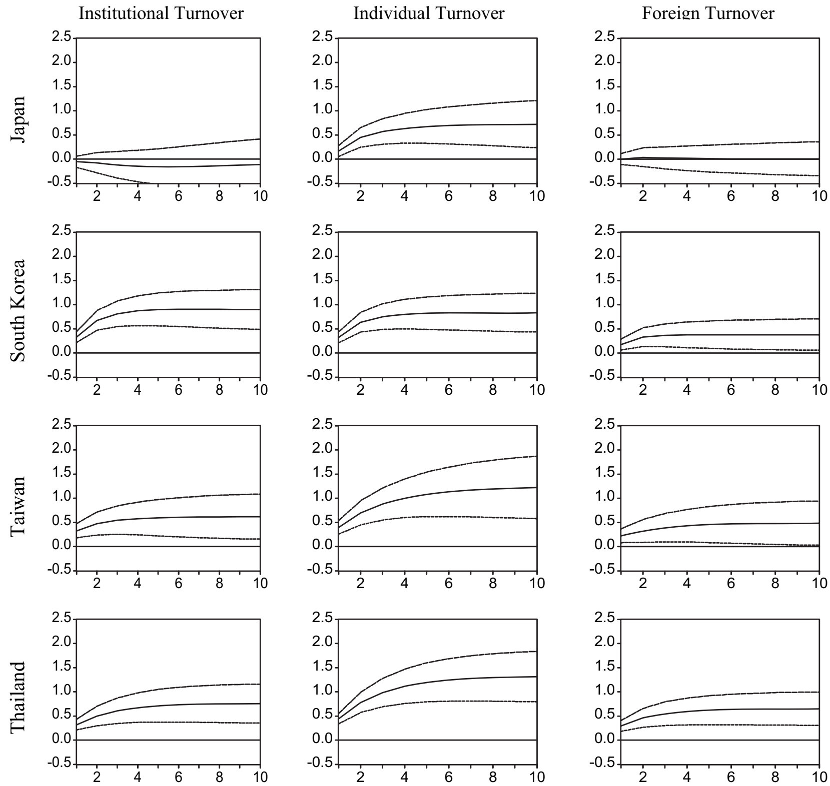

Figure 5
Responses of institutional, individual and foreign turnover to local returns
This figure shows generalized impulse response functions describing the response of detrended foreign, domestic institutional, and domestic individual turnover to a 1 SD shock in local market returns. The time scale on the horizontal axis is expressed in weeks. Responses are expressed in standard deviation units. For each impulse response function 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 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 first taking their natural logs and then subtracting the respective 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, and on April 1, 1997 for Taiwan. The sample period ends on June 30, 2002 for all countries.

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.

4.4 What does the return–turnover relation look like in the 1980s?

We collect the return, turnover, and volatility measures for the period January 2, 1983 to December 31, 1992 and estimate the same VARs described in Section 3.2. We require that Datastream return and volume data are available for at least 150 weeks in the earlier period. With this requirement, we have a sample of 18 high-income and six developing markets. The first striking finding in Figure 6 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 United States and United Kingdom 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 6, a 1 SD shock to returns in high-income countries is associated with an economically large increase in volume of 0.52 SD in 10 weeks. This effect is much larger than the 0.26 SD increase in turnover in the 1993–2003 period (Table 2). 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 10 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 10 weeks equals 1.31 SD, as compared to 0.72 SD in the 1993–2003 period. Panel B presents results excluding the week of October 19, 1987 and yields similar conclusions.

The decrease in the extent of the return–volume relation from the 1980s to the 1990s for many developed countries is not surprising in light of some of the theories discussed in this article. First, short sales have become less costly. Second, models incorporating participation costs call for a stronger link between participation and past returns when participation costs are high. Because costs of trading have been decreasing through time and the fraction of investors investing in the stock market has been increasing through time, the stronger return–turnover relation in this earlier time period, even for high-income countries, is consistent with the intuition of participation costs models. Third, institutional investors have become more important over time. Fourth, developed countries' markets performed extremely well for a long period of time, so that overconfidence theories would imply that volume should not be affected much by returns.

4.5 Asymmetries

A number of papers find asymmetries in the return–volume relation. For instance, Chordia, Roll, and Subrahmanyam (2001) found that the daily market dollar volume is not significantly related to the previous week's positive market move but that volume is positively related to the previous

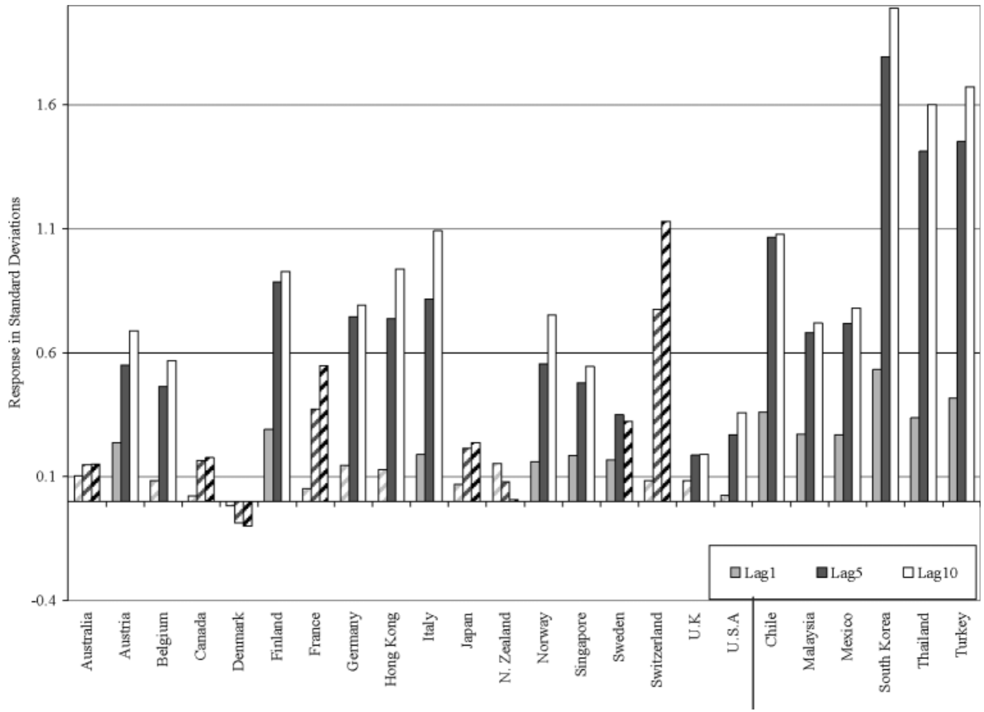

Figure 6
1983–1992 period
Using weekly return and detrended turnover data from January 2, 1983 to December 31, 1992, we estimate weekly trivariate VARs of detrended turnover, returns, and volatility. The figure reports the GIRF of turnover to a 1 SD shock to returns at lags 1, 5, and 10 weeks. All responses are standardized by the estimated residual standard deviation. Turnover is the total traded value in a given week scaled by the week's total market capitalization. Turnover is detrended by first taking its natural log and then 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. Insignificant bars are striped and significant bars are shaded (or solid white). High-income countries are in alphabetical order on the left side of the graph and developing countries are on the right side.

week's negative market move. At the individual stock level, Chordia, Huh, and Subrahmanyam (2006) found that turnover increases for past positive stock returns but also increases for negative returns. However, the increase in turnover they document for positive returns is much larger than the increase for negative returns. 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 and/or being affected differently by return shocks of different sizes. Such an investigation offers a useful robustness test since, for instance, if the relation were due solely to positive returns, it would seem difficult to explain it with short-sale restrictions. The linear VAR structure we have used thus far rules out any asymmetric dynamics: the response to a positive shock is equal in magnitude but opposite in sign to the response to a negative shock of the same size. Additionally, the linearity assumption forces the response to a 1 SD shock to be half the response to a 2 SD shock. Without a well-specified theoretical structure, one is left with a multitude of possible nonlinear specifications (Granger and Terasvirta 1993).

We use a threshold vector autoregression (TVAR) which is most easily understood as a piecewise linear VAR in the threshold variable.[23] We use the lagged return as the threshold variable. This TVAR specification allows the dynamic response of turnover to be different depending on the sign and/or the magnitude of lagged returns. We first assume two regimes characterized by, respectively, positive and negative past returns. In this manner, we can compare whether negative return shocks are associated with a larger magnitude of volume decreases than the volume increases associated with positive return shocks as one might expect with short-sales constraints. The details for our computation of GIRFs for the TVAR specification are reported in the Appendix.

Panel C of Table 6 presents summary statistics for the responses of turnover to both positive and negative return shocks for 1993–2003. Overall, positive shocks are associated with a 0.43 SD increase in volume after 10 weeks, whereas a negative shock to return is associated with an average 10-week decrease in volume of 0.44 SD. As summarized in Panel D of Table 6, this interesting symmetry in the results carries over essentially unchanged to the 1983–1992 period.

We also investigate (but do not report) the separate effects of small (below 1 SD), medium (between 1 and 2 SD), and large (between 2 and 5 SD) shocks both for positive and negative return shocks.[24] Given the mix of drivers for the relation, we find no

[23] See Tong (1990) for a comprehensive treatment of threshold autoregression.

[24] On average across countries, for the bivariate TVAR with non-detrended turnover, the positive medium-sized shocks represent 10.2% of the sample and the negative medium shocks 9.6%. The upper tail contains

Table 6
1983–1992 period, asymmetries, and daily frequency

	High income							Developing							All countries						
GIRF	μ	Med	σ	–	+	– (*)	+ (*)	μ	Med	σ	–	+	– (*)	+ (*)	μ	Med	σ	–	+	– (*)	+ (*)
Panel A: 1983–1992 trivariate VAR (includes 1987 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: 1983–1992 trivariate VAR (excludes 1987 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																					
Positive Lag 10	0.28	0.21	0.33	5	21	–	–	0.61	0.53	0.38	1	19	–	–	0.43	0.44	0.39	6	40	–	–
Negative Lag 10	–0.29	–0.20	0.35	24	2	–	–	–0.61	–0.54	0.37	20	0	–	–	–0.44	–0.43	0.39	41	5	–	–
Panel D: 1983–1992 response of turnover to positive and negative return shocks																					
Positive Lag 10	0.62	0.60	0.35	1	17	–	–	1.29	1.38	0.47	0	6	–	–	0.79	0.74	0.48	1	23	–	–
Negative Lag 10	–0.65	–0.65	0.37	17	1	–	–	–1.16	–1.26	0.41	6	0	–	–	–0.77	–0.74	0.4	23	1	–	–
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

We estimate trivariate vector autoregressions (VARs) of detrended turnover, returns, and volatility and display the response (in standard deviations) of turnover to a 1 SD shock to returns. Detrended turnover and EGARCH (1,1) volatility are calculated as described in Figure 2. Weekly data are used for the VARs in Panel A through D, and daily data are used for the VAR in Panel E. Panel A presents summary statistics for the GIRF for the January 2, 1983 to December 31, 1992 period. Panel B summarizes results over this period excluding the week of October 19, 1987. For the VARs in Panels C and D, we separately compute the GIRF for positive and negative return shocks. Panels C and D summarize the threshold VAR (TVAR) results with separate responses to positive and negative return shocks for the 1993–2003 and 1983–1992 periods, respectively. For the VARs in Panel E over the 1993–2002 period, for daily returns, we compute the orthogonalized IRF where detrended turnover and EGARCH (1,1) volatility are calculated as in Panels A and B. The table summarizes 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.

compelling reason why the relation should be exactly linear. To investigate the issue, we scale the responses of each group by the average size of the shock within that group, so that if the effect of turnover on returns were strictly linear, the response would be equal across return shock groups.[25] We examine the relation across groups for bivariate and trivariate models with non-detrended turnover series, as well as our baseline trivariate specification (as in panel B of Table 2). For positive return shocks, the average responses of turnover to large and medium return shocks are of similar size and are generally larger (after controlling for the size of the initial shocks) than the (still positive) turnover responses to small positive return shocks. Small negative shocks to returns lead to proportionally larger decreases in turnover. For both the bivariate and trivariate VAR with non-detrended turnover, we find that medium and large negative return shocks actually lead to small increases in turnover. However, in the trivariate TVAR with detrended turnover, medium-sized negative return shocks lead to small decreases in turnover in emerging markets and only miniscule increases in developed markets. Importantly, all types of negative shocks are associated with decreases in turnover in countries with short-sale restrictions, whereas for countries without such restrictions medium and large negative shocks are associated with small increases in volume. This additional evidence is supportive of the role of short-sale restrictions in the return–volume relation. The fact that medium and large negative return shocks are not associated with a drying up of trading volume is inconsistent with the liquidity explanation. These nonlinearities may be due to interactions of more than one explanation, but it is important to remember that this evidence is descriptive and that no statistical tests of its significance are possible within this estimation approach.[26]

Our main conclusion is that the relation is fairly symmetric with respect to positive and negative returns, with the caveat that small negative returns shocks (representing 74.5% of all negative return shocks), rather than large ones, seem to be the driver for the decrease in turnover following negative return shocks.[27] The use of the nonlinear TVAR

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

[26] As explained in the Appendix, the GIRFs are computed assuming that the model (i.e., the parameters) is known. Therefore, there is no sampling variability and, consequently, no confidence intervals on which we can base formal statistical inference. Although limiting, this is the approach more commonly adopted both in the econometric literature and in applications.

[27] The finding that medium and large negative return shocks have a much smaller effect on turnover is perhaps consistent with an offsetting volatility effect associated with large negative returns. Although this effect should be captured in EGARCH volatility, if the negative return is accompanied by increased volatility not completely captured in the EGARCH specification then there would be a positive effect on turnover (entering through volatility) which is offsetting the decrease in turnover that normally occurs through a large decrease in returns.

model comes with the costs of less precise estimation within groups (the tail-end observations are sparse and vary widely across countries), lack of formal confidence intervals for the GIRF, and potential model misspecifications—there is, clearly, an array of possible nonlinear specifications with little guidance from theory regarding the specific form of nonlinearity. Our analysis here indicates that the linear approximation used throughout the article is, by and large, appropriate but also that nonlinear models might capture the return–volume relation better for tail-end negative return observations. If theory produces more direct predictions about the form of nonlinearities, then future research should focus more on what can be learned from these tail observations.

4.6 Daily frequency

Participation models call for longer-term effects while liquidity effects can happen quickly. Our other theories are rather silent on the role of daily returns. Our analysis with weekly VARs shows that the 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 within week effects are, at a minimum, of second-order importance. Nevertheless, the lag one weekly effects are large and significant. These weekly 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 weekly correlation between turnover and returns. We now estimate a triangular VAR at the daily frequency.[28] Panel E of Table 6 presents summary information regarding the responses of detrended turnover to returns at the one-, five- (one-week), and 10-day (two-week) 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 one-day response is 0.17 in developing markets and increases to 0.40 after five days. In high-income countries, the average five-day response of 0.11 is only slightly higher than the one-day response. The daily evidence confirms that even at short-term frequencies the return–volume relation is not driven by a contemporaneous correlation and differs between high-income and developing markets. Further, the quick one-day response presents some evidence that participation costs (at least

[28] 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.

in terms of those costs traditionally modeled) are not likely to explain the short-term return–volume relation.

5. Conclusion

Market turnover (a liquidity proxy) is strongly and positively related to past returns in many markets. This relation is much stronger for developing countries than for developed ones. In our main 1993–2003 period, a 1 SD weekly shock to returns in developing markets is followed by an economically large 0.72 SD (0.60) increase in trading after 10 (5) weeks. The response in high-income markets is around one third as large. The return–volume relation is pervasive across specifications with a variety of volatility controls and using alternative mechanisms to measure turnover. Though we find a rather consistent pattern that turnover follows returns in many large developed markets such as the United States and the United Kingdom from 1983 to 1992, we also find that the relation has diminished through time and is insignificant in the 1993–2003 period for many of the developed markets. The return–volume relation is strongest in countries with high corruption, high market volatility, high market-model R^2, low correlation with the world market, and short-sale constraints.

As explained in Section 1, theories that have implications for volume following returns make predictions using as building blocks the informativeness of past returns for informed/uninformed investors, short-sale costs and constraints, liquidity effects, investor participation effects, behavioral biases (such as overconfidence and the disposition effect), and momentum trading. Many of these theories have similar predictions. As a result, we find support for many of them. However, our cross-sectional evidence does not appear to be supportive of liquidity effects. Further, there is no evidence that momentum trading alone leads to the return–volume relation. This is because the return–turnover relation is weaker in countries where institutional investors are more important, and prior literature has shown institutions to be more likely to engage in momentum trading. Short-sale constraints and liquidity explanations predict that trading dries up following negative returns. Our findings that volume increases following positive returns and decreases after negative returns present additional evidence against the liquidity explanation and also demonstrate that short-sale constraints are not a complete explanation.

We would expect the effect predicted by most theories to be stronger in opaque markets that are less informationally efficient because past returns are likely to be more informative in those markets. Furthermore, since individuals are more likely to be uninformed or to be affected by behavioral biases, their trading is expected to depend more on past returns than the trading of institutions. Indeed, in addition to the cross-sectional evidence that the relation is stronger in countries with a smaller mutual fund industry, we examine markets with volume data both for individuals and institutional investors and find that the relation is strongest among individual investors. These explanations of the return–volume relation also make it possible to understand why it has become weaker in developed markets through time. Developed markets have become more efficient through time, institutional investors have become more prevalent, and it has become easier to take short positions. Further, developed markets performed well for a long period of time, so that overconfidence theories would not predict a strong return–volume relation because poor returns in a given week are unlikely to have much impact on overconfidence after an extended period of high returns. Overall, perhaps because of less precise predictions, participation costs and behavioral explanations are most consistent with the features of the return–volume relation, but we also find some evidence for a partial influence of short-sale constraints entering through the actions of uninformed investors.

Our primary contribution is to document the characteristics, dynamics, intensity, and variation across countries in the return–volume relation. Our explanations related to existing theory are mostly suggestive since no theoretical work has jointly modeled the interactions between the many forces that influence the dynamic relation between volume and returns. It is our hope that this article will lead to the development of theoretical models and to new empirical analysis that can then be used to sharpen our understanding of the return–volume relation further. We view this complex task as particularly important for developing markets as policy-makers, and regulators seek to understand and structure markets in such a way that their liquidity will be resilient to periods of market declines. Our results should make clear to investors and regulators that turnover is more sensitive to adverse return shocks in markets with short-sale restrictions and corruption. These results should help investors in devising trading strategies that take into account the dynamics of market turnover and regulators to devise reforms that make market liquidity less sensitive to returns.

Appendix: Threshold VAR and GIR Analysis

Denoting with y_t the vector containing turnover, volatility, and return at time t, the TVAR model is specified as follows

$$y_t = c_j + \sum_{i=1}^{p} \phi_i^{(j)} y_{t-i} + v_t^{(j)} \text{ if } h_{j-1} < z_{t-d} \leq h_j \tag{A1}$$

where $j = 1,..., s$ is a regime indicator, z_t is defined as the threshold variable, d is the delay in the threshold variable, the hs are the threshold values, c_j and $\phi^{(j)}$ are regime-dependent parameters, the errors v_t have zero mean and are serially uncorrelated within and across regimes with constant (within regimes) but regime-dependent covariance matrix Σ_j, and p is the VAR order. It can be seen that the specifications in (A1) amounts to a piecewise linear VAR. In our implementation, z_t is the return variable, we first assume two regimes ($s = 2$) and $d = 1$. We estimate the system parameters 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). In nonlinear models, the response at time $t + n$ of a shock occurring at time t depends on three things: (1) the size and magnitude of the shock; (2) the history of the process (i.e, the sequence of observations) up to time t; and (3) the characteristics (size, sign, and correlations) of the shocks occurring in the intermediate periods $t + 1,...t + n$. Pesaran and Potter (1997) demonstrate how (2) and (3) may generate inferences that are substantially misleading using traditional (or, orthogonalized) impulse response functions (TIRF). The generalized IRF 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 types of shocks hitting it. Therefore, one can compute a variety of GIRFs depending on the subset of histories 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,

$$GIRF(n, V_t, \Omega_{t-1}) = E[y_{t+n} | \Omega_{t-1}, V_t \in \Theta] - E[y_{t+n} | \Omega_{t-1}] \tag{A2}$$

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 nonlinear 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}, $n = 0, 1,...N$, are generated by bootstrapping the realized 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 sets of disturbances, we then generate two sets of "future" values of y_{t+n}, $n = 0, 1,...N$ starting from a given history, $\Omega_{t-1} = \varpi_{t-1}$, and iterating by following the dynamics in (A1) and using the parameter estimates of the assumed TVAR model.
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 (A2). In our applications we set $R = 5000$ and simulate the systems for $N = 10$ steps ahead. We then standardized the responses so that they have a value of 1 at time $t + 1$ and cumulate them over ten periods. We are especially interested in the reaction of turnover to different return shocks, thus we conduct several experiments. Namely, we compute and compare the GIRF of turnover for

(a) positive return shocks and negative return shocks, or
(b) small (<1 SD), medium (between 1 and 2 SD), and large (between 2 and 5 SD) for both positive and negative return shocks.

In (a), the GIRF (A2) needs to be computed twice. For the response to positive shocks, the perturbed realizations are simulated using error terms bootstrapped from the (regime dependent) set of positive return residuals; the baseline realizations are then generated based on shocks bootstrapped from all residuals. For the response to negative shocks, the perturbed realizations are simulated using error terms bootstrapped from the (regime dependent) set of negative return residuals; the baseline realizations are, again, generated based on shocks bootstrapped from all residuals. In (b), positive and negative shocks are split into groups depending on their size and on the regime. With three sizes (small, medium and large) and two regimes, six sets of residuals are formed. The simulation proceeds by bootstrapping residuals from the appropriate set and generating the corresponding (perturbed and baseline) series values.

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