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Trading Volume, Volatility, and the Serial Correlation of Stock Market Returns

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ABSTRACT

In this paper we study the dynamic relationship between trading volume, volatility, and stock returns at international stock markets. We test a number of theoretical models which suggest that the trading volume and volatility can predict future behavior of stock returns. Our analysis uses both semi-nonparametric (Flexible Fourier Form) and parametric techniques. Our findings suggest that the main factor driving the magnitude of the return reversals is stock market volatility and not trading volume. First, apart from a direct effect on expected returns with mixed signs, we find no evidence of the trading volume affecting the serial correlation of stock market returns, as predicted by Campbell *et al.* (1993) and Wang (1994). Second, the stock market volatility has a negative and statistically significant impact on the serial correlation of the stock market returns, consistent with the "positive feedback" trading model of Sentana and Wadhwani (1992). Third, the lagged trading volume is positively related to the stock market volatility, supporting the "information flow" theory (Clark, 1973). Moreover, we find that taking into account both trading volume and volatility improves the accuracy of the out-of-sample forecasts of the stock market behavior.

JEL codes: G12, G14

Key words: Trading Volume, Volatility, Return Reversal, Feedback Trading.

I. Introduction

In this paper we study the dynamic relationship between trading volume, volatility, and the serial correlation of stock returns. More specifically, we test a variety of theoretical models which suggest that, conditional on past returns, the trading volume and volatility have power in predicting the future behavior of stock returns. Campbell, Grossman, and Wang (1993) and Wang (1994) present models where traders can learn valuable information about a security by observing both past prices and volume. Sentana and Wadhwani (1992) show that −in the presence of "feedback traders"− stock market volatility, and past prices are useful indicators of the future behavior of stock returns.

By evaluating the theoretical predictions of the abovementioned models against the observed empirical patterns of the return-volume-volatility relationship we seek to test the validity of the economic stories underlying these models. This is important for a further understanding of the role of the trading volume and volatility in asset pricing. In particular, since volume and volatility both serve as measures of the information flow (see, for instance, Andersen, 1996), examining the links between stock returns, volume, and volatility provides a further understanding of how new information is impounded in stock prices. Nowadays, stock markets are becoming increasingly more complex in their structure, but also more competitive among each other. The increased accessibility of information and investors searching for arbitrage opportunities caused many previously recorded pricing "anomalies" to disappear or to lose their economic significance (Schwert, 2002). In this context, a deeper understanding of the role of the trading volume and the volatility in the dynamics of security prices might help investors to identify future patterns of the stock market which can be exploited in their investment decisions.

The majority of studies examining the role of the trading volume and volatility in the dynamics of the stock returns do this in a parametric setting, usually postulating some parametric specification for the return generating process. This approach may lead to erroneous conclusions due to potential model misspecification. Instead, in our study we also rely on a nonparametric approach, one which is not only easy to implement, but also does not require any specific assumptions regarding the data generating process (beyond regularity conditions). Moreover, while most of the previous studies concentrate on examining only one specific relationship (volume-volatility, volatility-autocorrelation, and so on), we study the dynamics of the stock returns by controlling for *both* trading volume *and* volatility effects. This approach, as we show, sheds a new light on some stylized facts described in the empirical volume-return literature.

We use daily data on the closing trading level and volume of nine major developed markets. We also include the Hong Kong stock market as one of the largest and most influential among the emerging stock markets. Our major findings are as follows. First, apart from a direct effect on expected returns, but with mixed signs, we find no or at most very weak evidence of the trading volume having any *direct* impact on the serial correlation of stock market returns. Second, we find that the serial correlation of stock market returns is inversely related to the stock market volatility. Third, we find that an increase in the volume leads to a subsequent increase in the stock market volatility. Fourth, we find that taking into account the lagged trading volume and volatility (in the way indicated) leads to superior out-of-sample forecasts of the future behavior of stock markets compared to a benchmark random walk with drift model.

Taken together, these findings shed a new light on the volume-return reversal relationship documented by previous studies, such as Campbell, Grossman, and Wang (1993), Conrad, Hameed, and Niden (1994), and others. In contrast to these studies our findings suggest that it is the stock market volatility that plays a major role in the magnitude and the sign of the return reversal, supporting the "feedback trading" model of Sentana and Wadhwani (1992), while the trading volume appears to play a secondary role. Our results suggest that the role of the stock market volatility extends beyond being just a risk measure. Instead, we find that taking into account a time-varying volatility is important for understanding the dynamics of price momentum and reversals. Moreover, it appears that the information about *both* stock market volatility *and* trading volume can be exploited in designing momentum or contrarian investment strategies.

The remainder of the paper is organized as follows. In Section II we review the existing literature on the volume-volatility-return dynamics. Section III describes the data. In Section IV we present our hypotheses and discuss the methodology used in our study. The empirical findings are reported and discussed in Sections V and VI. Finally, in Section VII we make our concluding remarks and discuss some potential directions for further research.

II. Literature Review

A number of theoretical models have been proposed, linking the (lagged) trading volume and the serial correlation of stock returns. Campbell *et al.* (1993) introduce a model establishing such a link. In their model there are two types of investors both with Constant Absolute Risk Aversion (CARA) utility function. The first type has a constant risk aversion parameter, while the risk aversion of the second type may change over time. Trading is induced by, and is positively related to, the changes (in absolute value) in the risk aversion of the type 2 investors, which leads to an increase in the expected return rewarding the type 1 investors for accommodating the buying/selling pressure. The implication of this model is that the serial correlation of the stock returns is negatively related to the trading volume. Wang (1994) generalizes the model of Campbell *et al.* (1993) by allowing for information asymmetry among the investors. In his model informational and non-informational trading lead to a different dynamic relationship between the trading volume and the serial correlation of the stock returns. Llorente, Michaely, Saar, and Wang (2002) present a simplified version of the Wang (1994) model in which investors trade either to share risk or to speculate on private information. In their model returns generated by risk-sharing trades exhibit a negative autocorrelation while the returns generated by the speculative trades are positively serially correlated, thus, leading to momentum in stock prices.

The relationship between the trading volume and stock return reversals/momentum has been a focus of a substantial body of empirical studies as well. In line with their model predictions, Campbell *et al.* (1993) report a negative relationship between the lagged trading volume and the serial correlation of stock market returns for the US data at a daily frequency. Conrad, Hameed, and Niden (1994) examine the profitability of weekly contrarian strategies based on a high/low volume filtration for stocks listed on the US stock markets. They report that a high number of transactions is associated with a return reversal in subsequent periods, while a low volume is more likely to generate momentum. On the contrary, Cooper (1999) reports that for large capitalization stocks a decline in volume is associated with return reversals and *vice versa*. A positive relationship between the magnitude of momentum and the lagged turnover is also reported by Lee and Swaminnathan (2000), and Chan, Hameed, and Tong (2000).

More recently, Gianneti *et al.* (2006) study the behavior of stock markets during night trading sessions. They find that extreme positive or negative stock price movements are followed by reversals the next day. Interestingly, they find that reversals are more pronounced following extreme stock price movements with less trading volume (and lower liquidity). Wang an Yu (2004) use a contrarian portfolio approach to examine the short horizon return predictability in the US futures markets. They report that return reversals are more pronounced following periods of high trading volume. Wang and Chin (2004) examine the interactions between past returns and past trading volume in the context of predicting the future returns in China's stock market. They report low-volume stocks to experience a continuation while the returns on high-volume winner stocks are more likely to experience a reversal. Connolly and Stivers (2003) find substantial momentum (reversals) in consecutive weekly returns of US firms when the latter week has unexpectedly high (low) turnover.

There is also a large literature relating volatility and stock returns (for a recent example, see, for instance, Ang, Hodrick, Xing, and Zang, 2006). Here, we focus on this link via the serial correlation in stock returns. Such a possible link has been suggested by Sentana and Wadhwani (1992) in their so-called "feedback trading" model. In this model two types of investors are assumed to be present: mean-variance (or "smart money") traders and feedback traders, whose demand is assumed to be a function of past stock returns. This function is increasing in past returns if the investors follow a "positive feedback" investment strategy ("momentum") and decreasing if they follow a "negative feedback" ("contrarian") strategy. Sentana and Wadhwani (1992) show that in equilibrium the serial correlation of the stock returns is decreasing (increasing) in the stock return volatility if the investors are "momentum" ("contrarian") traders.

A number of empirical studies investigating the link between volatility and the serial correlation in stock returns has been conducted as well. LeBaron (1992) explores the relation between serial correlation and volatility for several different stock return series at both daily and weekly frequencies for the US markets. He reports a negative relation between the serial correlation of the stock returns and the volatility, a finding which is consistent with investors following a "positive feedback" strategy. Sentana and Wadhwani (1992) report similar results based on a large span of daily data on a US aggregate stock market index. Koutmous (1997) extends these previous studies beyond the US market borders by studying the impact of volatility on the serial correlation for several other national markets. His findings are similar to those reported by LeBaron (1992) and Sentana and Wadhwani (1992), suggesting that the volatility-serial correlation relationship is not likely to be induced by the microstructure specifics of a particular market. More recently, Huang, Liu, Rhee, and Zhang (2009) document significantly negative (positive) correlations between realized idiosyncratic volatility in the previous month and stock returns in the following month when lagged stock returns are positive (negative). This finding suggests that stock returns following a period of high volatility are more likely to revert.

A possible link between trading volume and volatility is mostly related to a "mixture of distribution" or "information flow" hypothesis, introduced by Clark (1973). This hypothesis posits a joint dependence of returns and volume on an underlying information flow variable. Since there is a wide consensus that the trading volume is highly positively autocorrelated, one of the implications of this theory is that the stock return volatility should also be positively related to the lagged trading volume. Lamourex and Lastrapes (1990) find strong evidence of the trading volume positively affecting the variance for a sample of common stocks traded on the US market. Andersen (1996) develops an empirical return volatility-volume model based on a microstructure framework. Lee and Rui (2002) report a positive feedback relationship between the trading volume and volatility on the US, UK, and Japanese stock markets. Similar results are reported by Gerlach, Chen, Lin, and Huang (2006) for selected samples of Asian and European stock markets.

The documented volatility-volume and volatility-autocorrelation relations are particularly important in the context of this study. Together, these findings present an alternative explanation for the reported volume-autocorrelation relation. It is possible that trading volume affects the serial correlation of stock returns not directly, but *indirectly* via volatility, This hypothesis, among others, will be tested in the following sections.

III. Data and Preliminary Analysis

Our data consists of daily data on the closing trading level and volume of nine major developed stock markets: the US, United Kingdom, Germany, Japan, Italy, the Netherlands, Canada, France, and Australia. We also include the Hong Kong stock market which is considered to be the largest and one of the most influential among the emerging stock markets. All data has been obtained from Datastream International. In Table I we list our specific indices, the sample period, and the number of observations for each market after excluding holidays, the trading days with missing observations, and descriptive statistics of the daily close-to-close log returns. All markets exhibit a positive (though statistically insignificant) drift over time. The stock market returns also appear to be slightly negatively skewed, implying that there is a higher probability of observing negative returns. For Canada, the Netherlands, Germany, and Australia the skewness sample estimates are also statistically significant. On the other hand, for all markets the sample estimates of the kurtosis are significantly higher than the one implied by the normal distribution, a finding which is supported by the high values of the Jarque-Bera statistic. Most of the unconditional non-normality seems to be due to leptokurtosis. Some of the stock markets' daily returns also exhibit positive and statistically significant first-order autocorrelation which, however, seems to dissipate rapidly at the higher-order lags, suggesting that the potential reason for this serial autocorrelation is the non-synchronous trading of the index components.

Table I approximately here

Next, we turn to a preliminary analysis of the trading volume series. In this research we define "trading volume" as the total number of shares traded at a particular day. Both earlier (Gallant, Rossi, and Tauchen, 1992) and more recent studies (including, for example, Lee and Rui, 2002) report non-linear trends in the trading volume series. Since we wish to work with stationary data, we follow Lee and Rui (2002) by replacing the raw trading volume v_t by a de-trended one $\left(\widetilde{v}_t\right)$ which is obtained as the estimated residual from the regression

$$v_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \widetilde{v}_t. \tag{1}$$

For all markets we find highly significant non-linear time trends, with the slope coefficients being highly statistically significant. Also based on standard unit root tests, such as the Augmented Dickey-Fuller and Phillips-Perron tests, we conclude that the trading volume series are trend stationary.[1] Thus, following Lee and Rui (2002) for the national stock market indices we shall adopt these de-trended volumes as the basic measure of trading activity in the subsequent analysis. To assess the robustness of our findings, we shall also consider alternative methods of removing low-frequency variations which will be discussed in the following sections.

[1]The results are available from the corresponding author upon request.

IV. Hypotheses and Methodology

In this section we present our hypotheses and discuss the methodology used in our study. We start with the hypotheses development. Then we discuss the methodology employing the semi-nonparametric approach, and we conclude with the parametric model that we use.

A. Hypotheses

Define by r_{t+1} the day t to day $t+1$ close-to-close log-return of a specific stock market index. Also, let v_t and h_t stand for the day t (de-trended) trading volume and the volatility of that particular stock market index, respectively. For the trading volume the following null hypotheses are considered

$$H_1 : \frac{\partial Var(r_{t+1} \,|v_t)}{\partial v_t} = 0; \;\; H_2 : \frac{\partial Cov(r_{t+1}, r_t \,|v_t)}{\partial v_t} = 0.$$

The first hypothesis postulates that the lagged trading volume has no impact on the volatility of the stock market returns. By testing this hypothesis we study the validity of the "information flow" hypothesis which suggests that trading volume might affect the variance of the stock returns. Under H_2 the lagged trading volume is postulated to have no impact on the conditional autocovariance of the stock market returns. By testing this hypothesis we test the class of models which relate the trading volume to the magnitude of the reversals or momentum in the stock returns. This class of models includes the ones proposed by Campbell *et al.* (1993) and Wang (1994) and implies that the lagged trading volume should have a statistically significant impact on the conditional autocovariance and autocorrelation dynamics of the stock returns, and, thus, is an important factor in forecasting whether stock returns will continue or revert during the following trading period.

Next, we formulate hypotheses for the volatility-return reversal relationship. Let h_t be the variance of the stock market returns at time $t+1$, conditional on the information available at time t. We consider the following null hypotheses

$$H_3 : \frac{\partial Cov(r_{t+1}, r_t \,|h_t)}{\partial h_t} = 0.$$

Hypothesis number three postulates that the stock market volatility has no causal effect on the autocovariance of the stock market returns. This hypothesis corresponds to the "feedback trading" model of Sentana and Wadhwani (1992) which relates the magnitude of the stock return reversal to the level of the volatility. For instance, by taking GARCH-type estimates as a proxy for h_t, this test can be interpreted as testing for the presence of a GARCH-in-autocorrelation effect.

B. Semi-nonparametric Analysis

In this subsection we discuss the employed semi-nonparametric approach which requires a minimal set of assumptions, and, thus, reduces the possibility of reaching the wrong conclusions due to possible misspecification of the functional form. Let y be some dependent variable, x be the independent (conditioning) variable, and let $E(\cdot)$ denote the expectation operator. We consider the following decomposition of y

$$y = m(x) + \epsilon, \quad E(\epsilon \,|x) = 0, \tag{2}$$

with $m(x)$ being (by definition) the conditional expectation of y given x. For instance, y can be the return of a specific stock market index and x can be the corresponding lagged trading volume. Then, by testing the null hypothesis that $\frac{\partial m(x)}{\partial x} = 0$, for some or all x, or

$E\left(\frac{\partial m(x)}{\partial x}\right) = 0$ we test for the presence of a causal effect between trading volume and stock market returns.

Clearly, a correct specification of $m(\cdot)$ plays a crucial role, where ignoring potential non-linear relations between stock returns, volume, and volatility may affect our test results.[2] In order to estimate $m(\cdot)$ we use a Flexible Fourier Form (FFF) series approximation as proposed by Gallant (1981). This Fourier Flexible Form approach was used, among others, by Andersen and Bollerslev (1997) and Martens, Chang, and Taylor (2002) in modeling intraday seasonality in stock market volatility, and Linton and Perron (2003) in estimating stock market risk premium. Within this framework the conditional moment $m(\cdot)$ is approximated by $m_{M,\theta}(\cdot)$, given by

$$m_{M,\theta}(x) = a + bx + cx^2 + \sum\nolimits_{\ell=1}^{\frac{M}{2}} (\varphi_\ell \cos(\ell x) + \phi_\ell \sin(\ell x)), \tag{3}$$

where M is the total number of trigonometric expansion terms to be chosen, and $\theta \equiv (a, b, c, \varphi_1, ..., \varphi_M, \phi_1, ..., \phi_M)'$ is the vector of parameters which can be estimated via Ordinary Least Squares. Under appropriate regularity conditions, including $M = M_n \to \infty$ as $n \to \infty$, with n the sample size, this approach allows for consistent estimation of $m(\cdot)$, assuming that it belongs to a large class of functions, see Gallant (1982).

This method, see also Linton and Perron (2003), can easily be extended to more complex moment based estimators: for instance, the conditional variance of the stock market returns can be estimated via a two-step procedure. First, the conditional expectation of the stock market returns is estimated within the FFF framework. Next, the squared deviations from the conditional mean are calculated and used as the dependent variable to estimate the

[2] In particular, Linton and Perron(2003) report the relation between stock market returns and volatility being significantly non-linear.

conditional variance. A similar approach can be used to estimate more complex moments, such as the first-order conditional autocovariance, *etc.* For instance, one can consistently estimate the dynamics of the conditional first-order autocorrelation coefficient by estimating the conditional variance and the first order autocovariance of the stock returns, which might provide a valuable insight into the role of the trading volume and the volatility in the dynamics of stock return reversals/momentum over time.

A number of issues should be kept in mind while applying a FFF series approximation. First, as pointed out by Gallant (1981), the conditioning variable x should be restricted to lie between $(0, 2\pi)$ (see also Pagan and Ullah, 1994). When the conditioning variable is the detrended volume $\widetilde{v}$, we replace it by $x = 2\pi\frac{\exp(\widetilde{v})}{1+\exp(\widetilde{v})}$, that is, we apply a simple logistic transformation to the detrended volume. When the conditioning variable is the volatility h we replace it by $x = 2\pi\frac{h\cdot 10^3}{1+h\cdot 10^3}$. A second issue concerns the choice of the truncation window M. Unfortunately, there is no clear-cut rule of how to choose the number of expansion terms. Andrews (1991) finds that $M = M_n$ can be of the order of magnitude between $O(n^{1/3})$ and $O(n^{1/5})$. Obviously, this is not too helpful, even if we would know what the "optimal" order of expansion should be, since it still leaves us with an unknown constant factor. Hence, we choose M_n to be equal to $n^{1/4}$, which leads to a value of M_n equal to eight for most of the indices in our study. In the following sections we shall also test the robustness of our findings to alternative choices of the truncation window.

C. Parametric Analysis

Estimating the conditional moments of the stock returns within the FFF framework provides a straightforward and easy to implement way to study the predictive power of the trading volume and the stock return volatility. Indeed, all issues investigated in this study can be reformulated in terms of restrictions on the dynamics of the conditional moments, and in this context the FFF methodology seems to be a natural way to proceed. But, as is typical for any non-parametric estimator, it suffers from the "curse of dimensionality" requiring quite a lot of observations for *accurate* estimation of flexible functional forms when more regressors are considered at the same time.

Therefore, as support to our parametric analysis, we shall also study the predictive power of the trading volume and volatility within a parametric framework. For each market we estimate the following model

$$r_{t+1} = \mu_0 + \mu_1 v_t + \mu_2 h_t^{0.5} + \rho_t r_t + h_t^{0.5} z_{t+1}, \tag{4}$$

$$\rho_t = \rho_0 + \rho_1 v_t + \rho_2 v_t^2 + \rho_3 h_t^{0.5}, \tag{5}$$

$$\ln(h_t) = \omega + \alpha(|z_t| - E\,|z_t| + \gamma z_t) + \beta \ln(h_{t-1}) + \theta_1 v_t + \theta_2 v_t^2, \tag{6}$$

$$z_{t+1} \overset{iid}{\sim} GED(\eta). \tag{7}$$

In this specification we allow the lagged trading volume v (de-trended, as discussed in the previous sections) to have both a direct and an indirect effect on the expected return of the stock market index. The direct −or "pure" causal− effect of the trading volume is measured by the parameter μ_1 and controls for a volume-return causal effect as reported by Gervais *et al.* (2001) and Baker and Stein (2004). The indirect effect, on the other hand, allows the trading volume to affect the expected stock market returns via the autocorrelation coefficient, as predicted by Campbell *et al.* (1993) and Wang (1994), and is measured by the parameters ρ_1 and ρ_2. In addition, the trading volume is allowed to affect the volatility of the stock market returns via the parameters θ_1 and θ_2, to allow for "information flow" related effects (Clark, 1973). Also, we allow for the impact of the stock market volatility on the autocorrelation as predicted by the "positive feedback trading" model of Sentana and Wadhwani (1992).

We model the volatility as an EGARCH(1,1) process (Nelson, 1991), having as important advantage that it does not require to impose non-negativity constraints on θ_1 and θ_2, and, thus, no *a priori* assumption regarding the sign of the trading volume-volatility relationship is required. Moreover, this model is also reported to yield superior out-of-sample forecasts compared to other models (Pagan and Schwert, 1990).

Model (4)–(7) is flexible enough to allow testing of a number of important models. In particular, versions of the Campbell *et al.* (1993) and Wang (1994) models are obtained by setting $\mu_1, \mu_2, \rho_3, \theta_1$, and θ_2 equal to zero, while by setting μ_1, ρ_1, ρ_2, θ_1, and θ_2 equal to zero this model boils down to a version of the Sentana and Wadhwani (1992) "feedback trading" model. Numerous studies suggest that even after controlling for GARCH effects, stock market returns still exhibit excessive kurtosis and propose to use fat-tailed distributions instead of the Gaussian one, such as the Generalized Error (Nelson, 1991) or Student-t distributions (Diebold, Gunther, and Tai, 1998). In this study z_t is assumed to follow a Generalize Error Distribution (GED) with constant parameter η. For $\eta = 2$ GED boils down to the Normal distribution, while for $\eta < 2$ normalized returns exhibit excessive kurtosis. As a robustness check alternative distributional assumptions will also be considered which will be discussed in the following section.

V. Empirical Findings

In this section we present our testing and estimation results. In the first subsection we present and discuss the results of the semi-nonparametric tests. In the second subsection we compare these results with the results of the supporting parametric analysis.

A. Semi-nonparametric Analysis

In Table II we present the outcomes of testing the hypotheses $H_1 - H_3$, using the semi-nonparametric approach. In the upper panel we present the p-values of the joint Wald test for the trading volume. For most of the markets we find strong empirical evidence of the trading volume affecting the variance of the stock market returns, thus, rejecting H_1, a finding which provides some preliminary support for the "information flow" hypothesis. A particularly interesting issue, however, is the impact of the trading volume on the conditional autocovariance of the stock market returns. Surprisingly, only in case of the UK we are able to detect the existence of such a link, while for the rest the null hypothesis H_2 cannot be rejected at any commonly used level of significance. We also compare our findings with the ones based on the alternative measure of the trading volume, the log-volume demeaned by the one-year moving average, as in Campbell *et al.* (1993).[3] No substantial difference was found, with Italy being the only exception, where the effect of the trading volume on stock return variance turns out to be statistically significant. As for the volume-autocovariance link the results, in general, remain unaltered as well. The only noteworthy difference is that with the MA-demeaned volume[4] we find statistically significant links for both the US and

[3]Consistent with their findings the MA demeaned log-volume series (calculated as the log(volume) at time t minus its one year average (from $t = -1$ to $t = -252$)), does not exhibit any drift, while it exhibits a substantial degree of persistence.

[4]The MA-demeaned volume is calculated as log(volume) at time t minus its one year average (from $t = -1$ to $t = -252$).

the UK, while for the rest of the markets the null still cannot be rejected.

Table III approximately here

The weak evidence of the volume-autocovariance link comes in sharp contrast with the numerous studies which report that using the lagged trading volume as an additional filter improves the performance of the contrarian/momentum based investment strategies (see, for instance, Conrad, *et al.*, 1994, among others). Combined with our findings, these results suggest that, though the trading volume may have a significant impact on the magnitude of the stock return reversal, the link between the former and the latter seems to be *indirect*, rather than direct, as suggested by Campbell *et al.* (1993) and Wang (1994). Such an indirect link between the trading volume and the stock return can occur via a volatility-autocorrelation relationship, and, therefore, we turn to the analysis of the stock market volatility and its role in the stock market return dynamics.

In the lower panel of Table II we report the p-values for the joint Wald test for the volatility related hypothesis. For the majority of the markets in our sample we find that the volatility has a significant impact on the conditional autocovariance of the stock market returns. In other words, the probability of observing momentum or reversal appears to be different during turbulent and tranquil periods, a finding which appears to be consistent with the predictions of the Sentana and Wadhwani (1992) "feedback trading" model. As with the trading volume we compare our results with those based on the alternative measure of the stock market volatility. We run the same test for the volatility proxy implied by the PARCH(1,1) model. Introduced by Ding, Granger, and Engle (1993), this model nests a number of linear GARCH-type models by turning the power coefficient of the volatility into an additional parameter which has to be estimated along with the other parameters.

We also try different numbers of the higher order terms by expanding and reducing the window length of M_n. The results remain virtually the same, supporting the robustness of our findings.

While having an advantage of combining both the parametric and nonparametric features, statistical inference on the FFF coefficients should be conducted with care since their asymptotic distribution depends on the approximation order and the way the latter has been chosen (Gallant and Souza, 1991). To bypass this difficulty, following Ivaldi, Ladoux, Ossard, and Simioni (1996), in addition to p-values based on an asymptotic approximation, we also construct confidence intervals for the estimated Wald statistics by performing a bootstrap. For each conditional moment we generate 2000 samples by randomly drawing with replacement the dependent variable (the raw return for the conditional mean, the conditionally demeaned squared return for the variance, etc.), and the conditioning variable (the volume or the volatility measure). For each sample we calculate the value of the Wald statistic and by that procedure we create the empirical distribution of the latter under the null that no relation between the trading volume/volatility and the conditional moments exists. The resulting p-values are presented (next to the ones based on the asymptotic approximation) in the upper panel of Table II for the hypotheses $H_1 - H_2$ and in the lower panel of Table II for the hypothesis H_3. Interestingly, an overall impression is that for all the tests under consideration the critical values implied by the bootstrap procedure are somewhat lower than the standard χ^2 based ones. However, we do not find any substantial dispersion based on either of the two approaches. The only exception are France and Germany, where in case of using the bootstrap-based critical values the link between the return autocovariance and the lagged trading volume turns out to be statistically significant.

To summarize our semi-nonparametric based findings, the results suggest that

a The lagged trading volume significantly affects the volatility of the stock market returns, a finding which is consistent with the "information flow" hypothesis.

b The stock market volatility significantly affects the autocovariance of the stock market returns, supporting the "feedback trading" hypothesis of Sentana and Wadhwani (1992).

c Some limited evidence of the lagged trading volume affecting the autocovariance of the stock market returns has been found, consistent with the predictions of the Campbell *et al.* (1993) and Wang (1994) models.

These findings suggest that for the purpose of further analysis it seems reasonable to separate the potential impact of the trading volume on the dynamics of the stock market returns from the effects of the stock market volatility on the latter. We investigate this in terms of our supporting parametric analysis.

B. Parametric Analysis

In this subsection we study the role of the trading volume and the volatility in the stock returns dynamics within the parametric framework of model (4)–(7). Maximum likelihood estimates of the mean and variance dynamics are presented in Tables III and IV, respectively. For all the markets the conditional variance of the stock market returns exhibit a high degree of persistence, consistent with other related studies. Also, for all the markets the estimate of θ_1, the parameter quantifying the effect of volume on the volatility, is significantly negative. This result suggests that volatility is negatively correlated with the lagged stock market returns, a finding, that can be attributed to the "leverage effect" (Christie, 1982). For all the markets the estimate of η, quantifying the shape of the distribution, is significantly smaller than 2, indicating that even after controlling for GARCH effects the returns still reflect some leptokurtosis.

Turning next to the analysis of the impact of the trading volume and volatility on the stock return dynamics, a number of interesting findings can be mentioned. First, the trading volume does seem to provide some information regarding the direction of the stock market returns, a finding which also supports the results of Chen, Firth, and Rui (2001) with the coefficient μ_1, measuring the return to volume sensitivity, being both statistically and economically significant for five out of the ten markets in our sample. However, the impact of the lagged trading volume on the expected stock market returns does not seem to have any consistent pattern. While for the US, UK, and the Netherlands an increase in trading volume seems to lead to a subsequent decline in the stock market value, a finding which is consistent with predictions of the Baker and Stein (2004) model, for other markets, such as Italy and Germany, the impact of the trading volume on the expected stock market returns shows an opposite sign, which is more consistent with the "visibility" hypothesis of Gervais *et al.* (2001). As for the GARCH-in-mean coefficients, in general, a positive sign of μ_2, the return to volatility sensitivity, is consistent with a risk-return trade-off, but only in case of the US market the stock market volatility has a statistically significant power to forecast future stock returns.

Tables III and IV approximately here

Next, we study the impact of the trading volume and the volatility on the autocorrelation between the stock market returns (hypotheses H_2 and H_3). Supporting the results of the FFF based analysis, the evidence of the trading volume having any *direct* effect on the autocorrelation of the stock market returns as in the Campbell *et al.* (1993) and Wang (1994) models is very weak. Though for some markets, consistent with the above mentioned model (Campbell *et al.*, 1993) the estimate of ρ_1, quantifying the autocorrelation sensitivity to the trading volume, shows a negative sign, it still lacks statistical significance, with France being the only exception. Turning next to the impact of the stock market volatility on the autocorrelation dynamics, we find that in contrast to the trading volume the "GARCH-in-autocorrelation" effect is both statistically and economically significant for the majority of the stock markets in our sample. More specifically, consistent with the predictions of Sentana and Wadhwani (1992), an increase in the stock market volatility increases the likelihood of observing reversals in the stock market returns, with the estimate of ρ_3, quantifying the correlation sensitivity to the volatility, being negative and statistically significant. However, the lagged trading volume seems to have an *indirect* effect on the magnitude of the stock market return reversal via the stock market volatility. For the majority of stock markets, consistent with the results of FFF based tests, we find that the lagged trading volume significantly affects the stock market volatility. More specifically, an increase in the trading volume seems to lead to a higher market volatility, consistent with models which relate the trading volume to the information flow. Combining these results, our findings suggest that in the dynamics of the stock market return reversal mechanism the trading volume plays a secondary, although important, role, while the leading source of changes in the stock market return autocorrelation seems to be the stock market volatility.

Figure 1 approximately here

To provide some visual impression on the dynamics of the stock market return reversal and volatility, we plot the conditional autocorrelation ρ_t and the conditional volatility h_t implied by the parametric model discussed above. We present the results for the three largest developed markets, namely the US, UK, and Japan, and for the Hong-Kong stock exchange, which is considered to be the largest among the emerging stock markets in Figure 1. A general impression is that, though in our model specification the trading volume was allowed to have both a direct and an indirect (volatility) effect on the autocorrelation dynamics, its direct effect appears to be negligible compared to the indirect one via the volatility, a finding which supports the results of both the FFF based and parametric analysis. The impact of the volatility on the autocorrelation dynamics is especially pronounced in case of the US and UK markets, where the former is virtually the mirror image of the latter. A number of interesting observations arises from the analysis of the autocorrelation histogram. First, it appears that the major share of the autocorrelation distribution mass lies in the positive range. This finding is consistent with numerous studies reporting daily and intradaily returns, exhibiting an *unconditional* positive serial correlation. It also appears to be negatively skewed, which can be due to both a statistically and an economically significant leverage effect in the volatility dynamics. However, taking into account both the direct effect of the positive feedback trading strategies and the indirect effect of trading volume via the volatility, we find changes, not only in the magnitude, but also in the sign of the stock market return autocorrelation. For instance, taking a look at the dynamics of the US and UK stock market serial correlation, it appears that, starting from the middle of 1997, the latter gradually turns from being moderately positive to substantially negative with peaks around 1999-2000, a finding which can be attributed to the collapse of the "dot.com" bubble. There is also an additional peak around 2002, which is more pronounced for the US market, and which can be attributed to the series of corporate scandals around that period, followed by sharp declines in the stock market value on the one hand and high market turbulence on the other hand. For the Hong-Kong stock market the dynamics of the serial correlation is characterized by a substantially negative serial correlation and a high volatility around the period of mid 1997-mid 1998, that is, the period of a severe currency and stock market crisis, known as the "Asian Flu." The conditional autocorrelation of the Japanese stock market, on the other hand, as well as the variance of the latter, appears to be highly volatile during the whole time-span of our study. Overall, these findings suggest the importance of accounting both for feedback trading and volume-"information flow" related effects in the dynamics of the stock market returns.

We test our model specification using the approach proposed by Diebold *et al.* (1998). They show that if the density is correctly specified then the integral transforms should follow *iid* U(0,1) distribution. Based on the results of the Kolmogorov-Smirnov test the null hypothesis of correct model specification cannot be rejected for nine out of ten markets, with Germany being the only exception where the null hypothesis is rejected at the 10% significance level. As a robustness check we re-estimate our parametric model with the same mean and variance equations but this time with the Generalized Student t-distributed errors as in Bollerslev *et al.* (1994). This distribution nests both the Generalized Error and Student-t distributions as special cases and, thus, makes our parametric model more flexible. Overall, the estimation results remain similar to the ones reported in Tables III and IV.[5]

VI. Out-of-sample Performance

The findings reported in the previous section emphasize the importance of accounting for both the lagged trading volume and volatility while modeling the dynamics of stock market returns. A natural question that arises is whether the trading volume and "feedback trading" models provide a superior out-of-sample forecasting performance compared to a model which does not take into account any of these effects. This question is of particular interest to practitioners who would be interested to know whether and how the information contained

[5] The results are available upon request.

in the trading volume and volatility can be exploited in predicting future behavior of the stock markets. To investigate this we consider the following three models.

a) *Generalized model,* i.e., model (4)–(7), accounting for both volatility and lagged trading volume effects.

b) *Trading volume effects,* a restricted version of the generalized model, obtained by setting the parameters μ_2 in (4) and ρ_3 in (5) equal to zero. This model still takes into account trading volume effects both in the drift parameter, as discussed by Gervais *et al.* (2001) and Baker and Stein (2004), and in the dynamics of the serial correlation, as suggested by Campbell *et al.* (1993).

c) *Volatility effects,* obtained by setting the parameters μ_1, ρ_1, ρ_2, θ_1, and θ_2 in (4)–(7) equal to zero. This model is a version of the "feedback trading" model of Sentana and Wadhwani (1992), which allows for GARCH-in-mean effects and time variations in the serial correlation parameter due to time variations in volatility.

Predictive power of each of these three models is compared to the out-of-sample performance of a benchmark model. This benchmark model is obtained by setting the parameters μ_1, μ_2, ρ_0, ρ_1, ρ_2, ρ_3, θ_1, and θ_2 in (4)–(7) equal to zero, with no trading volume or volatility effects allowed.

As first comparison we use the Root Mean Squared Error (RMSE) criterion. The RMSE is based on the (expected) difference between the actual and predicted returns. However, one might argue that it is the sign of the return rather than its magnitude which matters (Granger and Pesaran, 2000; Danilov and Magnus, 2004). Therefore, we also study the ability of the three models discussed above to predict the sign of stock market return by using the hit-rate test, proposed by Pesaran and Timmermann (1992). Let r and $\hat{r}$ be the actual and predicted returns, respectively. Let z be a random variable equal to a product of r and $\hat{r}$. If a model has no predictive power (the null hypothesis) then r and $\hat{r}$ will be independent. This, in turn, implies that $P(z > 0)$, the "hit-rate," is equal to

$$P(r > 0) \cdot P(\hat{r} > 0) + (1 - P(r > 0)) \cdot (1 - P(\hat{r} > 0)) \tag{8}$$

the "benchmark hit-rate." Pesaran and Timmermann (1992) show that under the null hypothesis the difference between the sample analogue of $P\,(z > 0)$ and (8) is asymptotically normally distributed (after appropriate scaling).

We now proceed as follows. For each market we start with estimating the model exploiting the first three years of data. Using the model estimates we generate one-day-ahead forecasts for the next 22 trading days (approximately one trading month). Next, we add these observations to our sample and re-estimate the model. Using new estimates we generate one-day-ahead forecasts for the next trading month, and so on. A similar strategy, although for annual frequency data, has been used by Pesaran and Timmermann (1994) and Danilov and Magnus (2004).

The results are reported in Table V. For each market we report the sample estimates of the RMSE (Panel A) and the "hit-rate" criterion (Panel B). The RMSE of each model is compared to the RMSE of the benchmark model, with the corresponding t-statistics reported in parentheses. Similarly, we compare the estimated "hit-rates" with the "benchmark hit-rates," with the corresponding t-statistics reported in parentheses in Panel B (for these t-statistics, see also Pesaran and Timmerman, 1992, or Franses, 2003).

Table V approximately here

We start with comparing the out-of-sample performance of the models based on the RMSE criterion. Our findings suggest that neither the volume, nor the volatility, nor the generalized model outperform the benchmark model, with the $t-$statistics being insignificant for all but two markets. The only exception is Japan where the RMSE of both the volatility and the generalized models is significantly lower than the benchmark model. On the other hand, in case of the Australian stock market we find the benchmark model outperforming the generalized model at the 10% significance level. Thus, in general, we find no evidence that taking into account volume or volatility effects leads to superior point forecasts of the stock market returns, at least, at a daily frequency.

However, a different picture unfolds when we examine the results of the "hit-rate" test. For each market and for each of the there models we report the estimated "hit-rate," i.e., the chance of correctly predicting the sign of the stock market return, conditioning on the past trading volume, past volatility, or both (depending on the model). The estimated "hit-rate" is compared to the "benchmark hit-rate," following Pesaran and Timmermann (1992), with the corresponding $z-$statistics reported in parentheses. Our results suggest that incorporating volume or volatility effects into the stock market returns dynamics leads to significantly more accurate sign forecasts. In particular, the model which allows for trading volume effects in the drift and serial correlation parameters significantly outperforms the benchmark model in case of the UK, Japanese, Canadian, and German stock markets. The "feedback trading" model, which allows for the time-varying volatility in the drift and the serial correlation parameters, yields superior forecasts in case of the Canadian and Japanese markets. Finally, the generalized model, which augments a variance equation with the lagged trading volume and which allows for both the trading volume and volatility in the drift and serial correlation parameters, significantly outperforms a benchmark model in case of Japan, Canada, the Netherlands, and Hong-Kong.

Overall, we find that, while not leading to any significant improvement of the point forecasts in terms of the RMSE, taking into account the lagged trading volume and volatility leads to more accurate sign forecasts. While the RMSE and the "hit-rate" criterion lead to different conclusions regarding the out-of-sample performance of the models, the dispersion between the results is quite intuitive and is likely to be related to the noisy nature of the daily frequency data. In fact, as argued by Granger and Pesaran (2000), investors will be more interested in predicting the direction of change in security prices rather than the magnitude of the change itself. Moreover, our findings suggest that even despite the noisy nature of the daily stock market returns, the lagged trading volume and volatility still contain valuable information regarding the future value of stock markets, thus, contradicting the notion of semi-strong market efficiency.

VII. Summary and Conclusions

In this paper we study the role of the trading volume and the volatility in the time-series dynamics of aggregate national stock markets indices. Our analysis uses both parametric and semi-nonparametric (Flexible Fourier Form) estimation, which makes our findings robust to potential model specification errors.

Our key findings are as follows. First, consistent with previous studies, we find strong evidence of the lagged trading volume affecting the variance of the stock market returns. More specifically, an increase in the trading volume leads to an increase in the stock market variance during the subsequent trading period, a finding which is consistent with the "information flow" hypothesis. Secondly, we find that the stock market return autocorrelation is inversely related to the volatility, a finding which supports the"feedback trading" theory of Sentana and Wadhwani (1992). Third, although the trading volume has a dircet impact on the expected returns, no negative relation between the lagged trading volume and the autocorrelation, as suggested by Campbell *et al.* (1993) model, has been found. Combining these three findings together, our results suggest that the profitability of volume-filter based contrarian strategies, as reported by Conrad, Hameed, and Niden (1994), can be explained by the combination of the "information flow" and "feedback trading" models, but might not be explained by the trading volume-autocorrelation class of models, such as the Campbell *et al.* (1993) and Wang (1994) models. In terms of out-of-sample forecasting, we find that taking into account the lagged trading volume and volatility leads to more accurate sign forecasts, implying that the lagged trading volume and volatility contain valuable information regarding the future value of stock markets, and, thus, contradicting the notion of semi-strong market efficiency.

Our results suggest a number of interesting directions for further research. First, our results seem to indicate that the dominant factor that governs the stock return reversal dynamics is the stock market volatility and not the trading volume. Thus, it seems reasonable to compare the profitability of the contrarian strategies based on the volatility-filters with those based on the trading volume filters. One way to proceed will be to use a volatility/volume weighted version of the zero-investment strategy, proposed by Lo and MacKinlay (1990). Second, it would be interesting to make a distinction between the informative and the non-informative trading periods by looking at the share of the medium size trades during a particular trading period, following Barclay and Warner (1993), who report that informed traders are concentrated in the medium size category. If informed trades are indeed characterized by the medium size, the volume-price relationship during days with a high share of the medium-size trades may differ from ones when this share is low. Finally, it would be interesting to study the intraday dynamics of the price discovery process. Previous studies report both the trading volume and volatility to follow a “U-shape,” which in the context of our study would suggest that the price reversals are more likely to be observed close to the opening or the end of the trading session.

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Tables and Figures

Table I
Descriptive statistics of daily market returns

Country	US	UK	Canada	Japan	Italy
Market Index	S&P 500	FTSE 100	TSX	TOPIX	DS Index
Sample Period	01/91-12/2005	06/88-12/2005	01/91-12/2005	01/91-12/2005	01/91-12/2005
No obs.	3782	4451	3777	3708	3790
Mean	0.0004	0.0003	0.0003	0.0002	0.0003
St.Dev	0.01	0.011	0.009	0.012	0.013
Skewness	-0.09	-0.12	-0.71*	0.06	-0.16
Kurtosis	6.88**	6.15**	10.44**	5.95**	5.81**
$\rho_{t,t-1}$	-0.002	0.019	0.11**	0.086**	0.059**
J-B stat.	2376.1**	1855.9**	9054.63**	1349.9**	1264.7**
Country	Netherlands	Hong-Kong	Germany	France	Australia
Market Index	DS Index	Hang-Seng	DS Index	CAC 40	AORD
Sample Period	02/86-12/2005	01/91-12/2003	06/88-12/2005	01/92-12/2005	03/00-12/2005
No obs	4995	3504	4431	3311	1444
Mean	0.0002	0.0004	0.0003	0.0002	0.0003
St.Dev	0.01	0.017	0.011	0.014	0.007
Skewness	-0.49**	-0.015	-0.66**	-0.089	-0.93**
Kurtosis	10.16**	12.3**	10.12**	5.46**	10.55**
$\rho_{t,t-1}$	0.01	0.034*	0.053**	0.016	-0.015
J-B stat.	9681.6**	12609.9**	9702.4**	836.6**	3639.4**

This Table provides a brief description of the stock market indices used in this study and reports the descriptive statistics of daily market returns. For the markets where the data for the stock market composite was not available at Datastream we use the Datastream (DS) index instead. $\rho_{t,t-1}$ denotes a sample estimate of the serial correlation. J-B stat. denotes the value of Jarque-Berra statistic. $^{**(*)}$ denotes significance at 10 (5)% level.

Table II
Fourier Flexible Form analysis

Panel A. Trading volume related hypotheses

H	US	UK	Canada	Japan	Italy
$\frac{\partial Var(r_{t+1}\|v_t)}{\partial v_t} = 0$	0.000/0.000	0.000/0.000	0.48/0.33	0.37/0.27	0.25/0.19
$\frac{\partial Cov(r_{t+1},r_t\|v_t)}{\partial v_t} = 0$	0.35/0.11	0.002/0.02	0.86/0.22	0.85/0.59	0.98/0.93
	Netherlands	Hong-Kong	Germany	France	Australia
$\frac{\partial Var(r_{t+1}\|v_t)}{\partial v_t} = 0$	0.000/0.01	0.004/0.03	0.000/0.002	0.000/0.005	0.89/0.18
$\frac{\partial Cov(r_{t+1},r_t\|v_t)}{\partial v_t} = 0$	0.36/0.24	0.84/0.63	0.33/0.03	0.89/0.03	0.96/0.83

Panel B. Volatility related hypotheses

H	US	UK	Canada	Japan	Italy
$\frac{\partial Cov(r_{t+1},r_t\|h_t)}{\partial h_t} = 0$	0.000/0.000	0.04/0.07	0.27/0.05	0.003/0.72	0.000/0.01
	Netherlands	Hong-Kong	Germany	France	Australia
$\frac{\partial Cov(r_{t+1},r_t\|h_t)}{\partial h_t} = 0$	0.000/0.01	0.000/0.003	0.000/0.003	0.16/0.004	0.03/0.05

This Table reports the results of Flexible Fourier Form analysis. For each market we test the hypotheses H_1 to H_3 as discussed in Section IV. The hypotheses are formulated in the "H" named column, where v_t and h_t denote detrended trading volume and volatility, respectively. The numbers reported are the asymptotic (at the LHS) and bootstrap-based (at the RHS) p-values of the Wald tests corresponding to each null hypothesis.

Table III
Trading volume and volatility-mean dynamics

	US	UK	Canada	Japan	Italy
μ_0	-0.0008^{**} (0.0004)	-0.0003 (0.0004)	0.0004 (0.0003)	-0.0012^{**} (0.0006)	$-6 \cdot 10^{-5}$ (0.00045)
μ_1	-0.0015^{**} (0.0005)	-0.0011^{**} (0.0004)	0.0002 (0.0003)	0.0004 (0.0005)	0.0007^{**} (0.0003)
μ_2	0.14^{**} (0.05)	0.07 (0.052)	0.0021 (0.045)	0.09 (0.056)	0.04 (0.045)
ρ_0	0.155^{**} (0.05)	0.01 (0.043)	0.32^{**} (0.038)	0.27^{**} (0.06)	0.19^{**} (0.049)
ρ_1	0.023 (0.07)	0.021 (0.043)	-0.006 (0.056)	-0.003 (0.045)	-0.034 (0.036)
ρ_2	0.039 (0.08)	-0.015 (0.045)	-0.061 (0.084)	0.024 (0.049)	0.0035 (0.037)
ρ_3	-14.63^{**} (4.49)	-7.31^{**} (4.14)	-19.16^{**} (3.97)	-15.26^{**} (4.37)	-9.71^{**} (3.55)

	Netherlands	Hong-Kong	Germany	France	Australia
μ_0	0.0004 (0.0003)	0.0005 (0.0006)	0.0002 (0.0004)	-0.0009 (0.0007)	0.0003 (0.0005)
μ_1	-0.0004^{**} (0.0002)	-0.0006 (0.0004)	0.0004^{**} (0.00013)	-0.0007 (0.00049)	0.0001 (0.0005)
μ_2	0.013 (0.039)	-0.016 (0.052)	0.043 (0.042)	0.097 (0.064)	0.012 (0.095)
ρ_0	0.11^{**} (0.031)	0.22^{**} (0.039)	0.102^{**} (0.038)	0.041 (0.056)	0.098 (0.077)
ρ_1	0.021 (0.033)	-0.031 (0.034)	-0.028 (0.018)	-0.096^{**} (0.05)	0.038^{**} (0.091)
ρ_2	0.0012 (0.0087)	0.079^{**} (0.038)	0.011 (0.016)	0.009 (0.068)	-0.058 (0.12)
ρ_3	-8.21^{**} (2.75)	-10.99^{**} (2.2)	-6.07^{**} (3.14)	-1.55 (3.92)	-11.98 (11.05)

This Table reports the Maximum Likelihood estimates of the mean equation of the model as formulated in Section IV, equations (4) and (5). Asymptotic standard errors are reported in parentheses. *(**) denotes significance at 10 (5) percent level.

Table IV
Trading volume and volatility-volatility dynamics

	US	UK	Canada	Japan	Italy
ω	-0.225^{**}	-0.165^{**}	-0.122^{**}	-0.348^{**}	-0.16^{**}
	(0.039)	(0.032)	(0.026)	(0.063)	(0.036)
α	0.113^{**}	0.114^{**}	0.146^{**}	0.187^{**}	0.165^{**}
	(0.014)	(0.014)	(0.014)	(0.021)	(0.015)
β	0.976^{**}	0.983^{**}	0.988^{**}	0.961^{**}	0.983^{**}
	(0.004)	(0.003)	(0.0026)	(0.007)	(0.004)
γ	-0.09^{**}	-0.058^{**}	-0.051^{**}	-0.099^{**}	-0.048^{**}
	(0.009)	(0.008)	(0.01)	(0.012)	(0.0086)
θ_1	0.032^{**}	0.017^{**}	0.014	0.03^{**}	0.0002^{**}
	(0.012)	(0.008)	(0.013)	(0.015)	(0.058)
θ_2	0.031	0.032^{**}	0.036	-0.0064	0.0091
	(0.023)	(0.013)	(0.031)	(0.026)	(0.0069)
η	1.48^{**}	1.72^{**}	1.44^{**}	1.43^{**}	1.49^{**}
	(0.038)	(0.04)	(0.03)	(0.04)	(0.039)
Log-ld	12534.4	14785.52	13031.36	11432.54	11627.99

	Netherlands	Hong-Kong	Germany	France	Australia
ω	-0.18^{**}	-0.153^{**}	-0.192^{**}	-0.126^{**}	-0.341^{**}
	(0.029)	(0.04)	(0.03)	(0.033)	(0.098)
α	0.157^{**}	0.134^{**}	0.124^{**}	0.116^{**}	0.07^{**}
	(0.015)	(0.017)	(0.013)	(0.014)	(0.021)
β	0.981^{**}	0.982^{**}	0.98^{**}	0.986^{**}	0.967^{**}
	(0.003)	(0.004)	(0.0034)	(0.004)	(0.008)
γ	-0.056^{**}	-0.065^{**}	-0.06^{**}	-0.061^{**}	-0.142^{**}
	(0.007)	(0.0097)	(0.009)	(0.0088)	(0.017)
θ_1	0.022^{**}	0.012^{**}	0.0031	-0.003	0.073^{**}
	(0.006)	(0.0060	(0.0025)	(0.007)	(0.035)
θ_2	0.0044	0.0068	0.0054^{**}	0.008	0.063
	(0.0034)	(0.0077)	(0.0027)	(0.018)	(0.068)
η	1.49^{**}	1.36^{**}	1.38^{**}	1.74^{**}	1.56^{**}
	(0.027)	(0.03)	(0.018)	(0.061)	(0.058)
Log-ld	16728.42	10010.31	14385.4	9869.57	5344.01

This Table reports the Maximum Likelihood estimates of the variance equation of the model as formulated in Section IV, equation (6). Asymptotic standard errors are reported in parentheses. *(**) denotes significance at 10 (5) percent level.

Table V
Trading volume and volatility-out-of-sample performance

Panel A. RMSE criterion

Market	USA	UK	Canada	Japan	Italy
Volume effects	1.0947 (0.733)	1.0503 (0.843)	0.9521 (1.219)	1.209 (−1.125)	1.2948 (1.052)
Volatility effects	1.0930 (0.926)	1.0501 (0.062)	0.946 (0.589)	1.201 (−3.991**)	1.2966 (0.741)
Generalized model	1.1038 (1.031)	1.0507 (0.696)	0.9474 (0.735)	1.202 (−3.578**)	1.2977 (0.712)

Market	Netherlands	Hong-Kong	Germany	France	Australia
Volume effects	1.0757 (−0.104)	1.6923 (0.136)	1.1297 (−0.136)	1.4505 (0.816)	0.5104 (1.2)
Volatility effects	1.08 (1.431)	1.7087 (−1.574)	1.1357 (1.593)	1.4565 (1.36)	0.5101 (0.629)
Generalized model	1.0801 (1.266)	1.7272 (−1.416)	1.1399 (1.631)	1.4554 (1.271)	0.5114 (1.849*)

Panel B. "Hit-rate" criterion

Country	USA	UK	Canada	Japan	Italy
Volume effects	52.98 (1.034)	52.36 (1.85*)	55.29 (4.833**)	53.23 (3.83**)	51.17 (0.804)
Volatility effects	51.57 (−1.494)	51.15 (−0.034)	54.92 (4.206**)	54.44 (4.867**)	49.72 (−0.723)
Generalized model	52.49 (0.114)	51.48 (0.602)	54.79 (3.991**)	54.14 (4.566**)	50.08 (−0.349)

Market	Netherlands	Hong-Kong	Germany	France	Australia
Volume effects	53.51 (0.645)	50.13 (−0.304)	53.37 (2.743**)	49.45 (−1.03)	55.6 (−1.117)
Volatility effects	53.86 (1.572	50.44 (0.199)	52.55 (0.988)	48.91 (−2.247**)	54.02 (0.168)
Generalized model	54.01 (2.062**)	51.12 (1.028)	53.8 (3.17**)	49.81 (0.797)	53.02 (−1.432)

This Table reports the results of the out-of-sample performance as described in Section VI. For each market and for each model we report the Root Mean Squared Error (Panel A) and the "hit-rate" (Panel B), measured in percentage points. The RMSEs and "hit-rates" are compared to the benchmark model with the corresponding $t-$ and z-statistics reported in parentheses. The benchmark model is outperformed in terms of RMSE ("hit-rate") if the corresponding $t(z)-$ statistic is significantly negative (positive).

Figure 1. Some conditional autocorrelations and volatilities.