Kiel Institute for World Economics

Duesternbrooker Weg 120
24105 Kiel (Germany)

Kiel Working Paper No. 1235

Sources of Predictability of European Stock Markets for High-Technology Firms

by

Christian Pierdzioch and Andrea Schertler

January 2005

Sources of Predictability of European Stock Markets for High-Technology Firms

January 2005

Christian Pierdzioch and Andrea Schertler

Kiel Institute for World Economics, Duesternbrooker Weg 120, 24100 Kiel, Germany

---

Abstract
We study return predictability of stock indexes of blue chip firms and smaller high-technology firms in Germany, France, and the United Kingdom during the second half of the 1990s. We measure return predictability in terms of first-order autocorrelation coefficients, and find evidence for return predictability of stock indexes of smaller high-technology firms, but no evidence for return predictability of stock indexes of blue chip firms. Our findings suggest that a leading candidate for explaining the economic sources of return predictability of stock indexes of smaller high-technology firms is transaction costs.

Keywords: Stock markets; Return predictability; High-technology firms

JEL classification: G14, N24

Address:

Kiel Institute for World Economics	Telephone: +49 431 8814 269 (or 496)
Duesternbrooker Weg 120	Telefax: +49 431 8814 500
24105 Kiel	E-Mail: c.pierdzioch@ifw.uni-kiel.de
Germany	or a.schertler@ifw.uni-kiel.de

Acknowledgements:

Financial support from the European Commission: DG Research in cooperation with DG ECFIN and DG ESTAT (Contract No. SCS8-CT-2004-502642) is gratefully acknowledged. We thank participants of the first research meeting of the FINPROP consortium for helpful comments. The usual disclaimer applies.

1. Introduction

In an integrating world economy, new and revolutionary products form the basis of the international competitiveness of firms, industries, and entire economies. New and revolutionary products are often not developed by established large and financially strong firms, but by young and highly innovative firms. Such high-technology firms undertake extremely risky investment projects. Because of the innovative nature of the high-technology firms' investment projects, investors often find it difficult to collect comprehensive and reliable information concerning the business prospects of high-technology firms. As a result, high-technology firms have limited access to regular stock markets, markets for bank credits, and markets for other forms of external financing important to financing their research and development activities (see Berger and Udell 1998, Harhoff 1998, Hall 2002, Westhead 1997, to mention just a few).

In an attempt to remedy this problem, many European stock exchanges established special stock markets for smaller high-technology firms in the second half of the 1990s.[1] The establishment of these markets was intended to give young and innovative high-technology firms access to well-structured and sufficiently liquid capital markets. The creation of special stock market segments on which high-technology firms can issue their shares should, in principle, help to lower market-entry costs for such firms. At the same time, indexes composed of stocks traded on special stock markets for high-technology firms should lower information costs for investors.

A condition that must be satisfied in order to ensure that investors' scarce investment funds are optimally allocated among the most productive investment projects available in an economy is that stock markets are efficient in the sense of the efficient market hypothesis. This hypothesis rests on the assumption that the information set used by agents to form their rational forecasts of future expected returns contains all the information relevant to the pricing of financial securities. A financial market is called weakly efficient if this set of information incorporates all the information already embedded in past returns (Fama 1970). Hence, in a weakly efficient financial market, returns are not predictable in the sense that it is

---

[1] The listing requirements of these stock market segments have been less restrictive than the listing requirements of official markets.

not possible to forecast returns on a particular day by using returns observed on a previous day, implying that there should be no autocorrelation in stock market returns.

Empirical studies of stock market efficiency are legion, but only a few authors have empirically studied the efficiency of Europe's stock markets for high-technology firms.[2] This is a serious shortcoming of the earlier empirical literature because market efficiency is particularly important as regards stock markets for high-technology firms. For many investors, efficient stock markets for high-technology firms are an ideal, and often the only platform for collecting, processing, and aggregating dispersed information about high-technology firms at low costs.[3] At the same time, the bubble-like phenomena of the late 1990s stimulated many commentators to discuss whether stock markets for high-technology firms worked rather inefficiently. Our empirical analysis should help to inform this discussion of the efficiency of Europe's stock markets for high-technology firms.

We studied the efficiency of Europe's stock markets for high-technology firms by analyzing the predictability of daily continuously compounded returns of indexes of smaller high-technology firms in France, Germany, and the United Kingdom. Studying stock markets in these three countries is of particular interest because all of them developed a particular segment for high-technology firms in the second half of the 1990s, and because these countries differ with respect to their financial market structure. According to the study by Beck and Levine (2002), the United Kingdom is a leading market-based economy, while France and Germany are both bank-based economies.

In order to analyze predictability of stock index returns, we estimated a time-varying parameter model. The model we estimated is similar to the models that have recently been used by Rockinger and Urga (2000, 2001) and Zalewska-Mitura and Hall (1999) to study return predictability. We estimated a time-varying parameter model because Europe's stock markets for high-technology firms are new markets that were established only in the 1990s. As a result, a time-varying

2 For recent surveys of the empirical literature on the efficient markets hypothesis, see Fama (1991) and Cochrane (1999). For recent evidence on the efficiency of the German stock market for smaller high-technology firms, the so-called Neuer Markt, see Bohl and Reitz (2004).

3 In addition, efficient stock markets for high-technology firms are important for the development of other financial market segments such as venture capital markets (e.g., Black and Gilson 1998, Bascha and Walz 2001).

parameter model is likely to yield interesting insights into the working and evolution of these markets. Specifically, our model renders it possible to study (i) whether there was predictability in returns of Europe's stock markets for high-technology firms, (ii) whether return predictability changed over time, and (iii) whether similar patterns of return predictability can be detected across European stock markets for high-technology firms. Our main finding is that the returns of European stock indexes of high-technology firms, as measured by the first-order autocorrelation coefficients, were predictable. This positive autocorrelation of returns is consistent with empirical results that, beginning with Cowles and Jones (1937), have been reported in numerous contributions to the empirical finance literature. We found that, despite the significant changes in the structure of European stock markets for high-technology firms that took place in the 1990s, the positive first-order autocorrelation coefficient was remarkably stable over time.

What were the sources of the return predictability of European stock indexes of high-technology firms? To answer this question one has to take into account that return predictability is a necessary but a by no means sufficient condition for market inefficiency. A number of competing explanations for return predictability have been developed in the finance literature (see Mech 1993, Lo and MacKinlay 1990, Shiller 1984, Conrad and Kaul 1988, to mention just a few). In order to trace out the likely sources of return predictability of European stock indexes of high-technology firms, we adopted a three-step approach.

In the first step, we estimated a time-varying parameter model to study the return predictability of stock indexes of European blue-chip firms. The results of this estimation gave us a useful benchmark for studying the return predictability of stock market indexes of high-technology firms. We found that, in sharp contrast to the returns for high-technology firms, returns for blue-chip firms are not predictable. This result indicates that features specific to European stock markets for high-technology firms, but not to the stock markets for blue-chip firms must have been responsible for return predictability. Among these features are the relatively high costs of collecting information about high-technology firms and the resulting relatively high transaction costs in stock markets for high-technology firms.

Consequently, in the second step, we estimated models that render it possible to shed light on the likely sources of return predictability of Europe's stock markets for high-technology firms. We concentrated on examining the contribution of two factors to return predictability: noise trading and transaction costs. Noise trading in the form of so-called positive feedback trading has been suggested in a recent empirical study by Bohl and Reitz (2004) as a source of the return predictability of one of the European stock market indexes for high-technology firms that we also study: the German Neuer Markt. To take their argument into account, we followed Sentana and Whadwani (1992) and estimated an empirical model that allows the relevance of the positive feedback trading hypothesis to be studied. We found that, during phases of very high stock market volatility, feedback trading may account for the differences between Europe’s stock markets for high-technology firms and markets for blue-chip firms with regard to return predictability. However, we also found that positive feedback trading is unlikely to account for the persistent and positive autocorrelation in the returns of stock market indexes for high-technology technology firms that we found in our empirical analysis.

Therefore, in the third step, we studied whether transaction costs may account for the return predictability of Europe’s stock markets indexes for high-technology firms. We focused on transaction costs because transaction costs should in general be high if the collection of dispersed information about the firms listed on a stock market is relatively costly. With regard to blue-chip firms, the costs of collecting and processing information are relatively low because the business strategies of these firms are well known to investors. With regard to high-technology firms, however, the costs of collecting and processing information are relatively high. The reason for this is that many firms listed on Europe’s stock markets for high-technology firms operated in the information and communication industry. The growth of this industry gained momentum only in the 1990s. Thus, investors had hardly experience in evaluating the business strategies of Europe’s high-technology firms. As a result, they had to expend time and resources to develop strategies to collect and process information, and these expenses raise transaction costs (Merton 1987). Moreover, in an environment in which investors have to learn how to evaluate business strategies of high-technology firms, problems of moral hazard are likely to be severe. In such an environment, transaction costs, defined as costs of collecting and processing information, inhibit arbitrage, and this implies that stock prices reflect information only partially (Grossman and Stiglitz 1980). The result is a delay in the transmission of new information into stock prices and, in consequence, return predictability.

To study whether transaction costs were a source of return predictability, we estimated empirical models that were developed by Mech (1993) and Ogden (1997). We found evidence supporting their models. Results indicate that transaction costs at least partially account for the return predictability of indexes of European stock markets for high-technology firms. This result, of course, does not rule out that other factors like, for example, positive feedback trading also gave rise to return predictability. However, while we found, consistent with positive feedback trading, an "overshooting" of returns to the arrival of new information, we also found that positive feedback trading alone cannot account for the return predictability. Our result add a new and interesting facet to the discussion on the sources of the (in-)efficiency of Europe's stock markets for high-technology firms.

We organize the remainder of this paper as follows. In Section 2, we describe the time-varying parameter model we used to study return predictability. We also describe the data we used in our empirical study, and we report our estimation results. In Section 3, we study the sources of return predictability. We report that transaction costs are likely to be an important source of return predictability in returns of European stock market indexes for high-technology firms. In Section 4, we summarize our main results and offer some concluding remarks.

2. Testing for Return Predictability

To study return predictability, we used a time-varying parameter model. A model with time-varying parameters renders it possible to keep track of the evolution of European stock markets for high-technology firms in the 1990s. These markets were beleaguered by bubble-like phenomena in the second half of the 1990s. The significant run-up and later crash of stock prices led to substantial reorganizations of these markets over time. The stock market bubble and the ensuing reorganization of markets are likely to be sources of instability of time-invariant parameters in a conventional regression model.

2.1 The Data

In order to study whether financial market structure and the technology-orientation of firms matter for predictability of stock market returns, we used various daily stock market indexes for France, Germany, and the United Kingdom.

As blue-chip indexes, we used the *DAX30,* the *CAC40,* and the *FTSE100*. The DAX30 is an index based on the 30 largest German firms officially listed on the Frankfurt Stock Exchange. The CAC40 is a benchmark index based on a selection of 40 stocks of the Premier Marché and structured so as to reflect the full range of equities traded on Euronext Paris. The FTSE100 is an index based on a selection of 100 stocks of the Main Market of the London Stock Exchange.

As high-technology indexes, we used the *Nemax50,* the *Nouveau Marché Index,* and the *TechMark100*. The Nemax50 is composed of the 50 largest high-technology firms of the Neuer Markt. Listing requirements of the Neuer Markt were less restrictive than of the official market. The Nouveau Marché index is composed of all French securities listed on the Nouveau Marché. It is intended to be a market segment which meets the needs of fast-growing young high-technology firms seeking capital to finance expansion. As in the case of the German stock market, the listing requirements of the Nouveau Marché are less restrictive than the listing requirements of the Premier Marché. The TechMark100 is composed of medium and small techMARK™ firms. It is a special segment of the Main Market and is one of the world's leading markets for shares of firms at the forefront of innovative technology.

In order to get the ball rolling, Figure 1 graphs the stock market indexes for the period January 1, 1998 to January 31, 2002. The indexes were rescaled to assume the value 100 on January 1, 1998. The figure begins in 1998, and so did our empirical analysis, because the Neuer Markt and the Nouveau Marché were founded only in 1997 and 1996, respectively. The figure ends in January 2002 because nothing spectacular happened to share prices since then.

— Insert Figure 1 about here. —

The figure shows that the indexes of high-technology firms increased substantially, while the indexes of blue chips did not. The indexes of high-technology firms show similar behavior over time. However, the Nemax50 jumped substantially in the beginning of 1998, while the Techmark100 and the Nouveau Marché indexes did not. In the second half of the 1990s, the Nemax50 reached a maximum of about 850 basis points, the Nouveau Marché index reached a maximum of about 750, and the Techmark100 reached a maximum of only 600.

— Insert Table 1 about here. —

Table 1 offers summary statistics of continuously compounded returns. In all cases, the mean of the returns is almost zero, the skewness of the unconditional returns distribution is slightly negative, and the unconditional returns distribution is leptokurtic, i.e., its kurtosis exceeds that of the normal distribution. Thus, the unconditional returns distribution has “fat tails.” There is also evidence for a significantly positive first-order autocorrelation coefficient. The autocorrelation coefficients of orders larger than one are in general very small. There is also strong evidence for autocorrelation in the squared returns, implying the presence of volatility clustering and GARCH effects. All in all, Table 1 highlights that the summary statistics of returns closely resemble the summary statistics and “stylized facts” of other financial market data (Lux and Marchesi 2000).

Table 2 summarizes the results of tests for stability of parameters in regressions of returns on a constant and on lagged returns. These results indicate that in many cases the constant in such regressions is not stable over time. We found evidence for structural shifts in the constant in the case of the Nemax50, the Nouveau Marché, and the Techmark100. Changes in the constant capture the significant ups and downs of stock prices for high-technology firms in the 1990s. The results further indicate that the parameter of lagged returns was relatively stable over time. There is some evidence for structural breaks in the parameter of lagged returns in the case of the Nouveau Marché, the CAC40, and the FTSE100 at a marginal significance level of 10%.

Taken together, the results suggest that return predictability was relatively stable over time. However, it could be the case that, given that the European stock market segments for high-technology firms were established only in the 1990s, the efficiency of these markets and, hence, the return predictability might have gradually changed over time. In order to capture such gradual changes, we used a time-varying parameter model that provides a maximum amount of flexibility in tests for changes in predictability over time.

— Insert Table 2 about here. —

2.2 The Empirical Model

To measure return predictability, we used a time-varying parameter model similar to the models that Zalewska-Mitura and Hall (1999) and Rockinger and Urga (2000, 2001) have recently developed. The time-varying parameter model we estimated has the following form:

$$R_t = \beta_{0,t} + \beta_{1,t} R_{t-1} + u_t, \qquad u_t \sim i.i.d. N(0, h_t), \tag{1}$$

$$\beta_{m,t} = \beta_{m,t-1} + v_{m,t}\,, \qquad\qquad v_{m,t} \sim i.i.d.N(0, \sigma^2_{m,v})\,, \tag{2}$$

$$h_t = \omega + \eta_1 u^2_{t-1} + \eta_2 h_{t-1}\,, \tag{3}$$

where $m = \{0,1\}$.[4] Equation (1) stipulates that stock market returns, R_t, are equal to a time-varying intercept, $\beta_{0,t}$, plus a time-varying slope coefficient, $\beta_{1,t}$, times lagged returns plus a stochastic disturbance term. Equation (2) implies that the time-varying intercept and slope coefficients follow random-walk processes. Hence, the only source of variation in $\beta_{0,t}$ and $\beta_{1,t}$ is due to the variance of the respective stochastic disturbance terms, $v_{0,t}$ and $v_{1,t}$. The stochastic disturbance terms, u_t and $v_{m,t}$, are independently normally distributed and are uncorrelated with each other, $E(u_t v_{m,t}) = 0$. Equation (3) implies that the stochastic disturbance term in Equation (1) follows a GARCH(1,1) process. This allows the "fat tails" property of the distributions of returns commonly found in high-frequency financial market data to be taken into account (see also Table 1).

2.3 Empirical Evidence

The results of estimating the model described in Section 2.2 are given in Table 3.[5] A visual representation of the results is given in Figure 2 for Germany, Figure 3 for France, and in Figure 4 for the United Kingdom.[6] In the first rows of these figures, we plot the respective stock market indexes. In the second rows, we plot the intercept coefficient, $\beta_{0,t}$. In the third rows, we plot the first-order autocorrelation coefficient, $\beta_{1,t}$. In the fourth rows, we plot the estimated

---

4 Harvey (1992) and Kim and Nelson (2000) provide detailed descriptions of the Kalman filter approach. To estimate the model, we used the algorithm proposed by Harvey, Ruiz, and Sentana (1992). We used Gauss 3.6 to implement the Kalman filter approach. Further, we used the computer programs described in Kim and Nelson (2000).

5 Because the sampling distribution of the parameters is nonstandard, care must be taken when conducting tests for significance (see Harvey 1992, page 236). If the point estimate of a parameter is zero, then the corresponding coefficient, $\beta_{i,t}$, is a constant, and conventional statistical theory can be used to conduct tests for significance. If the point estimate of a parameter is nonzero, then the corresponding coefficient, $\beta_{i,t}$, varies and its significance can be graphically analyzed.

6 When using the Kalman filter approach, one can either use the filtered or the smoothed estimates of the model's coefficients to measure the predictability of returns. The difference between the two lies in the information set one uses (Kim and Nelson 2000). Filtered estimates are based on information available up to period *t*. Smoothed estimates are based on all available information in the entire sample. We report filtered estimates because, in any given period t, a stock market participant can only use information up to time *t* for making inferences about the time-varying predictability of returns.

conditional variance of returns implied by the GARCH model. In the first column, we plot results for indexes of stock markets of blue-chip firms and in the second column we plot results for indexes of stock markets of high-technology firms.

— Insert Table 3 about here. —

With regard to the intercept coefficient, $\beta_{0,t}$, we found that this coefficient is relatively stable and insignificant as regards the indexes of stock markets for blue-chip firms as compared to the indexes of stock markets for high-technology firms. The intercept coefficient of the model we estimated for indexes of stock markets for high-technology firms shows a peak around the time of the tremendous upswing of stock prices in these markets that took place in 1999/2000. This indicates that the variation in the coefficient, $\beta_{0,t}$, captures time variation in expected returns, implying that serial correlation in high-technology markets is not (entirely) due to time variation in expected returns. The intercept coefficient is largest in the case of the Nemax50.

— Insert Figures 2 to 4 about here. —

With regard to the first-order autocorrelation coefficient, $\beta_{1,t}$, we found that this coefficient is insignificant as regards the stock markets for blue-chip firms. As regards stock markets for high-technology firms, we found significantly positive first-order autocorrelation coefficients in all three markets. While the first-order autocorrelation coefficient of the Nemax50 was remarkably stable over time, there are fluctuations in the first-order autocorrelation coefficients of the Nouveau Marché and the Techmark100. Notwithstanding, a main result is that the first-order autocorrelation coefficients and, thus, the predictability of Europe’s stock markets for high-technology firms was surprisingly stable over time.

From the results summarized in Figures 2 to 4, we draw two conclusions. First, because there is no evidence for return predictability of indexes of blue-chip firms, the return predictability of indexes of European stock markets for high-technology firms must have been caused by factors specific to the high-technology industry in Europe. Second, because of the stability of return predictability over time in the case of high-technology firms, predictability was not mainly caused by rapid changes in market sentiment or changes in conditions which characterized European stock markets in the 1990s. For example, as we will argue in more detail in Section 3, it is unlikely that return predictability in the case of high-technology firms was entirely due to investor sentiment and, e.g., feedback trading.

With regard to the estimated conditional variance, we found that, in all markets, conditional variance is highly persistent. This can be seen be adding the ARCH coefficient, η_1, and the GARCH coefficient, η_2. As in many other empirical studies of daily financial market time series, the sum of these coefficients is close to, but strictly smaller than, unity. As one would have expected, the conditional variance is always larger in the case of the stock markets for high-technology firms than in the case of blue-chip firms.

3. Explaining the Predictability of Stock Returns

In this section, we discuss two factors that might have caused the predictability in returns of indexes of European stock markets for high-technology firms. We start by analyzing whether noise trading has caused return predictability. Shiller (1984), Sentana and Whadwani (1992), and others have suggested noise trading as a source of return predictability. In a recent empirical study, Bohl and Reitz (2004) have studied noise trading as a source of the predictability of the Nemax50. We then proceed and study whether transaction costs explain the return predictability of European stock markets indexes for high-technology firms. Transaction costs as a source of return predictability have been studied, for example, by Mech (1993), Ogden (1997), Lesmond et al. (1999), and others. We focus on noise trading and on transaction costs as sources of return predictability to trace out whether return predictability was mainly caused by recurrent changes in market sentiment or by structural features specific of Europe’s stock markets for high-technology firms.

3.1 Noise Trading and Return Predictability

Noise traders are agents who behave “irrationally” in the sense that their investment decisions are not entirely determined by economic fundamentals. If a sufficiently large proportion of all traders acting in a stock market behaves as noise traders, then stock prices can, at least temporarily, deviate from economic fundamentals (DeLong et al. 1990). This deviation of stock prices from economic fundamentals can imply autocorrelation and, hence, return predictability. Specifically, return predictability can arise if noise traders follow so-called feedback trading strategies (Cutler et al. 1991). Positive feedback trading involves buying stocks when prices have risen and selling stocks when prices have fallen. Negative feedback trading, in contrast, requires just the opposite: buying stocks when prices have fallen and selling stocks when prices have risen. Positive feedback trading should result in negative autocorrelation of returns because it gives rise to a short-run overreaction of stock market prices.

The theoretical model we used to analyze the implications of feedback trading for return predictability is based on Shiller (1984) and Sentana and Whadwani (1992). Their models rest on the assumption that two different groups of traders populate a stock market. The first group of agents is called “smart money” traders because their demand for stocks is governed by risk-return considerations:

$$Q_{1,t} = (E_{t-1}R_t - \alpha) / \mu_t \, , \tag{4}$$

where $Q_{1,t}$ denotes the proportion of smart money traders in the market, α denotes the return at which the demand for stocks by smart money traders is zero, and μ_t is the risk premium for holding stocks. If only smart money traders were active in the stock market then $Q_{1,t}$ would equal one and stocks would be priced according to Merton’s (1980) Capital Asset Pricing Model.

The second group of agents is feedback traders. Their demand for stocks can be described by the following equation:

$$Q_{2,t} = \gamma R_{t-1} \, , \tag{5}$$

where $Q_{2,t}$ denotes the proportion of feedback traders in the market. If $\gamma > 0$, then feedback traders adhere to a positive feedback trading strategy, i.e., they buy (sell) stocks when the prices of stocks have risen (fallen). If, in contrast, $\gamma < 0$, feedback traders follow a negative feedback trading strategy, i.e,. they buy (sell) stocks when the prices of stocks have fallen (risen).

Upon invoking the assumption of rational expectations, $R_t = E_{t-1}R_t + \varepsilon_t$, and the condition for stock market equilibrium, $Q_{1,t} + Q_{2,t} = 1$, one obtains the following difference equation:

$$R_t = \alpha + \mu_t - \gamma \mu_{t1,t} R_{t-1} + \varepsilon_t \, , \tag{6}$$

where ε_t denotes a stochastic disturbance term with mean zero and conditional variance h_t^2. We assume a normal distribution for the disturbance term. We also assume that the dynamics of the conditional variance of the disturbance term can be described by means of a GARCH(1,1) process.[7] Upon defining $\mu_t = \rho h_t^2$ and using a linear approximation of the risk premium, $\gamma\mu_t = \gamma_0 + \gamma_1 h_t^2$, one obtains the following equation:

$$R_t = \alpha + \rho h_t^2 - (\gamma_0 + \gamma_1 h_t^2) R_{t-1} + \varepsilon_t . \tag{7}$$

This equation shows that if feedback trading is at the root of return predictability then there should be a close link between the conditional variance and the first-order autocorrelation of stock returns. Specifically, in the case of positive (negative) feedback trading, $\gamma > 0$ ($\gamma < 0$), first-order autocorrelation of stock returns should turn negative (positive) if the conditional variance of stock returns is high.

We summarize the estimation results for the feedback-trader GARCH model in Table 4. Results indicate that the coefficients that capture the interaction of autocorrelation of returns and the conditional variance are not significant with regards to blue-chip firm indexes, but are significant with regard to European stock markets indexes for high-technology firms. This result suggests that feedback trading may have been one of the factors specific to high-technology firms that caused the predictability of index returns in these markets.

— Insert Table 4 about here. —

However, before jumping to premature conclusions, one has to take into account that the time-varying parameter model of Section 2 implies *positive* autocorrelation of the returns of European indexes of high-technology firms. According to the model advocated by Shiller (1984), positive autocorrelation of returns would be consistent with *negative* feedback trading. In contrast, the results of the feedback-trader GARCH model imply, because $\gamma_1 < 0$, *positive* feedback trading.

— Insert Figure 5 about here. —

To reconcile these seemingly conflicting results, we plot in Figure 5 the estimated conditional autocorrelation coefficient, $\gamma_0 + \gamma_1 h_t^2$, implied by the feedback-trader GARCH model. It can be seen that the conditional autocorrelation coefficient was negative only on a limited number of days during which stock

---

[7] We also estimated a model that allows possible asymmetries in conditional variance to be taken into account. The results turned out to be very similar to those of the GARCH model. Therefore, we present the results the for simple GARCH model.

market volatility was extremely high. Specifically, the estimated conditional autocorrelation coefficients turned negative mainly at the time at which the decline in stock prices on Europe's stock markets for high-technology firms began. For most of the time, however, the conditional autocorrelation coefficient implied by the feedback-trader GARCH model is, in line with the results implied by the time-varying parameter model, *positive*. From this we conclude that positive feedback trading was a dominant source of return predictability only on particular days. Hence, positive feedback trading does not explain the positive "base level" of the autocorrelation of Europe's stock markets for high-technology firms.

3.2 Transaction Costs and Return Predictability

We proceeded with our analysis by studying whether transaction costs explain the return predictability in Europe's stock markets for high-technology firms. To this end, we used a model developed by Mech (1993). Mech's model is based on the insight that if transaction costs are an important source of return predictability, then stock prices should adjust rapidly to new information in periods when price changes are large relative to transaction costs. Mech's starting point is the following partial-adjustment model:

$$\log P_t = \log P_{t-1} + \lambda_t \left(\log V_t - \log P_{t-1} \right), \tag{8}$$

where P_t is the price of a portfolio of stocks (i.e., the stock market index), V_t is the "best" estimate of the price of this portfolio, $\lambda_t \geq 0$ is the speed of price adjustment, which is allowed to vary over time. In each period, the prices of some of the stocks adjust to their "best" estimate, while others do not. As a result, portfolio value adjusts partially to its time-varying "best" estimates. If $\lambda_t = 0$ then the price of a portfolio of stocks does not change in period t. Thus, new information is not priced in this case. In contrast, if $\lambda_t = 1$ then new information is fully reflected in stock prices and, therefore, in the price of a portfolio of stocks. If $\lambda_t \geq 1$, then arrival of new information induces a change in the prices of stocks and, in consequence, in the price of a portfolio consisting of these stocks that exceeds the price change indicated by the "best" estimate.

First differencing of equation (8) implies

$$R_t = \phi_t R_{t-1} + \lambda_t R_t^*, \tag{9}$$

where $\phi_t = (\lambda_t / \lambda_{t-1}) - \lambda_t$ and R_t^* is the "best" estimate of the continuously-compounded returns of a portfolio of stocks. Thus, the observed return in period t is a combination of initial adjustment to new information, $\lambda_t R_t^*$, and continuing adjustment to old information, $\phi_t R_{t-1}$. If information that was new in the previous period was fully included in all stock prices and, thus, returns in the previous period, i.e., if $\lambda_{t-1} = 1$, then there were no further adjustment to old information because then $\phi_t = 0$.

The coefficient measuring the speed of adjustment, λ_t, is allowed to vary over time. Specifically, Mech (1993) has assumed that it is a function of the magnitude of absolute observed returns: The larger absolute observed returns are, the less important transaction costs should be, the faster stock prices should adjust, and, as a result, the larger the adjustment coefficient should be. A larger adjustment coefficient, in turn, implies a faster and more complete adjustment of stock prices to new information, implying that return predictability of a portfolio of stocks should become insignificant. Distinguishing between high and low absolute returns, the coefficient of the speed of adjustment can be specified as $\lambda_t = c_{\lambda 0} + c_{\lambda 1} D_t$, where $D_t = 0$ if absolute returns are below the median value of returns, and $D_t = 1$ if returns are above the median value of returns.

Estimation of Mech's (1993) model requires definition of a "best" estimate of the continuously compounded return of a portfolio of stocks. The choice of an instrument for this best estimate is not an easy task. Mech has used a large-firm portfolio as an instrument in his analysis. This reflects his assumption that transaction costs should be smaller for large firms than for small firms. In our analysis, we used returns on stock indexes of blue-chip firms because we found that returns of these indexes were not predictable. This suggests that these indexes adjusted instantaneously when new information arrived at the market. Specifically, we assumed $R_t^* = a_1 + a_2 R_t^{**}$, where R_t^{**} denotes the return on indexes of blue-chip firms.

Upon using the definition of R_t^*, the definition of λ_t, and equation (9), one obtains the following model that can be used to test whether transaction costs explain return predictability:

$$
\begin{aligned}
R_t = {} & b_{00} + b_{01} D_t + \\
& b_{10} R_{t-1} + b_{11} D_{t-1} R_{t-1} + b_{12} D_t R_{t-1} + b_{13} D_t D_{t-1} R_{t-1} + . \\
& b_{20} R_t^{**} + b_{21} D_t R_t^{**} + u_t
\end{aligned}
\tag{10}
$$

The coefficient b_{10} should be positive in the case of positive autocorrelation. The coefficient b_{12} should be positive because high transaction costs imply that yesterday's returns unfold a positive effect on today's returns if there are large returns today. The reason for this is that, due to the assumed partial-adjustment model, information that arrived in the market in period *t*-1 has not been fully reflected in yesterday's returns. The coefficient b_{11} should be negative because the coefficient b_{10} is the average autocorrelation for large and for small absolute returns. However, if transaction costs matter for returns dynamics, than the coefficient b_{10} overestimates autocorrelation in the case of large returns. The negative sign of the coefficient b_{11} should correct for this overestimation. In a similar vein, the coefficient b_{13} should be negative because the coefficient b_{12} is the average autocorrelation for large and for small absolute returns observed in period *t*-1. The coefficient b_{20} should be positive if our "best" estimate of the continuously compounded returns contains valuable information for stock markets for high-technology firms. Finally, the coefficient b_{21} should be positive because, in the case of large returns, a larger proportion of the information captured by our "best" estimate of the continuously compounded returns is incorporated in the returns of our indexes of stock markets for high-technology firms.

As indicated by estimation results presented in Table 5, all our coefficients have the expected signs, although some of the coefficients are not significant. In particular, b_{11} is never significant. Thus, in the case of high absolute returns in period *t-1*, returns in the period *t-1* do not help in predicting today's return. The coefficient b_{13} is significantly different from zero and negative for the Nouveau Marché, but not for the Nemax50 and the Techmark100. This implies that, with regard to the Nouveau Marché, when absolute returns in period *t* and period *t-1* are high, returns of the period *t-1* help predicting today's return. The coefficients b_{12} and b_{21} are significantly different from zero, and they are positive for all European stock markets for high-technology firms. The result that the coefficients b_{10} and b_{20} are small relative to the coefficients b_{12} and b_{21} indicates that stock prices adjusted much faster on days of large returns.[8]

---

8 As an alternative measure of R_t^* we used returns on the NASDAQ in order to check the robustness of our results with respect to the choice of the "best" estimate of continuously compounded returns. Results are in general in line with the results reported in Table 5. Regarding the NEMAX50 and the Techmark100, the significance of the estimated coefficients is similar to that of the coefficients reported in Table 5. Regarding the Nouveau Marché, however, the coefficient b_{20} is insignificant and the coefficient b_{21} is significant, implying that NASDAQ returns had only an impact on returns if returns were large. Results are not reported here but are available from the authors upon request.

The fact that some of the coefficients of the model given in Equation (10) are not significantly different from zero should not be interpreted as evidence against the hypothesis that transaction costs were an important source of return predictability. The reason for this is that when interpreting the significance of the coefficients of our regression model, one has to take into account that our regression model contains regressors that are highly correlated. In particular, the regressors $D_{t-1}R_{t-1}$, $D_t R_{t-1}$, and $D_t D_{t-1} R_{t-1}$ are highly correlated. As shown by the regression results summarized in Table 5, some of the coefficients of these regressors are not statistically significant. However, the results of Wald tests for *joint* insignificance of these coefficients are highly significant.

— Insert Table 5 about here. —

We conclude that transaction costs were important for the dynamics of returns of European indexes stock markets for high-technology firms. Because the model fits best in the case of the Nemax50 and the Nouveau Marché, we further conclude that it is likely that transaction costs were more important in the German and in French segment for high-technology firms than in the British segment for high-technology firms. This result corroborates the conventional wisdom that the Techmark100 was more liquid and less beleaguered by problems due to, for example, the asymmetric distribution of information among investors and firms than the Nemax50 and the Nouveau Marché.

3.3 Overshooting of Returns

It is interesting to note that the coefficient b_{21} in Mech's model exceeds unity. One can think of at least two explanations for this result. The first explanation for the result $b_{21} > 1$ is that our model may not capture all of the industry-specific characteristics of the high-technology sector. Specifically, our "best" estimate of continuously compounded returns, which we assumed to be given by returns on a stock market index of blue-chip firms, may not capture all developments in the high-technology sector. The second explanation for the result $b_{21} > 1$ is that an overshooting in price adjustment to new information was characteristic of returns of European stock indexes for high-technology firms. Such an overshooting would be consistent with positive feedback trading on Europe's stock markets for high-technology firms.

To examine the first explanation more closely, we used a regression suggested by Ogden (1997). To this end, we regressed the returns in Europe's stock markets indexes for high-technology firms on contemporaneous and lagged returns on the corresponding indexes of blue-chip firms:

$$R_t = a_0 + \sum_{k=0}^{K} a_{i,k} R_{t-k}^{**} + u_t , \qquad (11)$$

where we assumed $K = 20$ in order to ensure that the regression captures all 'old' common information contained in the current returns of the indexes for blue chip firms. The regression results are summarized in Panel A of Table 6. As one would have expected, the magnitude and significance of the coefficients $a_{i,k}$ in this regression is in general an inverse function of the lag parameter *k*. Further, the magnitudes of the coefficients of determination (adjusted for degrees of freedom) of the regressions clearly reveal that indexes of blue-chip firms did not reflect all industry-specific information relevant to movements in the indexes of high-technology firms. Notwithstanding, "market wide" information that gave rise to movements in the indexes of blue-chip firms was to a substantial extent reflected in movements in the indexes of high-technology firms.

— Insert Table 6 about here. —

We then used the regression results to compute the ratios $\sum_{k=0}^{k*} a_{i,k} \Big/ \sum_{k=0}^{K} a_{i,k}$, with $k* \leq K$. These ratios can be interpreted as estimates of the fraction of stocks in indexes of high-technology firms that have, by time t, incorporated information also incorporated in indexes of blue-chip firms that arrived between time $t - k*$ and time t. The ratios given in Panel B of Table 6 show that the indexes of Europe's stock markets for high-technology firms incorporated between 45% (Nouveau Marché) and 70% (Neuer Markt) of the information incorporated on the same day in indexes of blue-chip firms. After five trading days, the indexes of Europe's stock markets for high-technology firms incorporated between 85% (Nouveau Marché) and 94% (Techmark100) of the information also incorporated in indexes of blue-chip firms. From this, we conclude that most "market-wide" information embedded in indexes of blue-chip firms was, with a delay of a few days, also embedded in Europe's stock market indexes of high-technology firms. Thus, while our "best" estimate of continuously compounded returns, R_t^{**}, certainly did not reflect all of the industry-specific characteristics of the high-technology sector, the information flow reflected in movements of R_t^{**} was also highly relevant for movements of R_t.

The second explanation for the result $b_{21} > 1$ is that an overshooting in price adjustment to new information was characteristic of the returns of European stock indexes for high-technology firms. Such an overshooting would be consistent with positive feedback trading. For example, one could argue that, consistent with the empirical evidence reported by Bohl and Reitz (2004), feedback trading gained in importance when transaction costs were relatively unimportant, i.e., on days of exceptionally large returns. This argument implies that transaction costs were a key structural factor that gave rise to a positive and persistent “base level” of predictability, and that feedback trading arose whenever large transaction costs were relatively unimportant for the position-taking of feedback traders in European stock markets for high-technology firms. On a theoretical basis, this argument could be motivated by pointing to theoretical results derived by Balduzzi et al. (1995) and others. They have developed a model in which trading thresholds exist at which positive feedback traders’ sell or buy orders are automatically executed. They have shown that, when traders anticipate the impact of these orders on return dynamics, stock price volatility tends to be high in the neighborhood of a trading threshold. Thus, in the neighborhood of a trading threshold, returns tend to be large and, in consequence, transaction costs tend to be relatively unimportant. As a result, transaction costs account for the “base level” of returns predictability and positive feedback trading accounts for return predictability in times of high stock market volatility.

Alternatively, one could argue that the importance of transaction costs was due to the fact that both informed traders and liquidity traders (Black 1986) acted in Europe’s stock markets for high-technology firms. In the theoretical literature on noise trading, a conventional assumption is that liquidity traders often trade, and that they trade at disequilibrium prices that do not embed the latest information. For example, in the model developed by De Long et al. (1990), liquidity traders act as positive feedback traders. Informed traders, in contrast, trade when the wedge between the actual stock price and the full-information equilibrium stock price is sufficiently large. The key point is that the exact meaning of “sufficiently large” may depend on the magnitude of transaction costs. Thus, as has also been emphasized by Ogden (1997), when transaction costs are of a nonnegligible magnitude, the interaction of liquidity traders and informed traders may imply that information is fully reflected in stock prices only after a delay because informed traders wait longer before they step into the market, implying return predictability.

In order to study further the relative importance of transaction costs and positive feedback trading for the positive and persistent predictability of returns of indexes of Europe's stock markets for high-technology firms, we split up our sample into a pre-crash sample and a post-crash sample. We then estimated Equation (10) for the pre-crash and the post-crash sample. In order to study the pre-crash and post-crash period, we estimated Equation (10) for pre-crash period 1/1/1998-3/20/2000 and for the post-crash period 3/21/2000-2/4/2002. We found that splitting up the sample into a pre-crash and a post-crash sample does not affect the significance of the coefficients. Thus, with regard to significance of coefficients, the results for the two sample periods are similar to the results reported in Table 5 and are, therefore, not reported.

— Insert Figure 6 about here.—

One interesting difference between the sample periods, however, is that the overshooting coefficient, b_{21}, is smaller than one in the pre-crash sample, and larger than one in the post-crash sample (Figure 6). Given that return predictability was prevalent during both sample periods, one would expect to observe overshooting in both sample periods if positive feedback trading was a major source of the return predictability. Thus, we conclude that, although positive feedback trading helps to explain the return predictability in periods of high stock-market volatility, it was not the only source of the return predictability. Transaction costs, in contrast, do account for the positive and persistent return predictability of indexes for European stock markets for high-technology firms in both sample periods.

4. Summary and Concluding Remarks

We have analyzed the return predictability of various European stock market indexes of blue-chip firms and of high-technology firms. In particular, we have analyzed the DAX30 and the Nemax50 from Germany, the CAC40 and the Nouveau Marché from France, and the FTSE100 and the Techmark100 from the United Kingdom. We have found strong evidence for return predictability of European indexes of stock markets for high-technology firms by measuring predictability in terms of the first-order autocorrelation coefficient of returns. We have found that the first-order autocorrelation coefficient was persistently positive in the case of returns of indexes of high-technology firms. There was no evidence for autocorrelation and, thus, return predictability of indexes of blue-chip firms. Interestingly, we have found that return predictability of indexes of stock markets for high-technology firms changed only slightly during the 1990s. Moreover, we have found strong similarities between Europe's stock markets for high-technology firms. Yet, there are also some interesting differences, for example, with regard to autocorrelation fluctuations over time. Specifically, while the autocorrelation coefficient of the Nemax50 did not change in times of high share prices, those of the Nouveau Marché and the Techmark100 did.

We have proceeded by analyzing potential sources for the predictability in returns of Europe's stock markets for high-technology firms. We have focused on two potential sources of return predictability: positive feedback trading and transaction costs. Our results indicate that positive feedback trading contributed to return predictability during phases of high stock market volatility. However, positive feedback trading alone cannot explain the persistent and positive return predictability of European stock markets indexes of high-technology firms in the 1990s.

We also have found that transaction costs are likely to be an important source of the positive "base level" of return autocorrelation in Europe's stock markets for high-technology firms. Our empirical results suggest that it took time for stock prices of high-technology firms to fully embed new information that arrived at the market. Specifically, we have found that on days of large returns, stock prices of high-technology firms tend to adjust faster than on days of small returns. This finding indicates that transaction costs were of minor importance for return dynamics on days of large returns, but of major importance for returns on days of small returns. Interestingly, we have found, in the case of stock markets for high-technology firms, evidence for an overshooting of prices in response to the arrival of new information. Thus, the specific way in which new information was processed in these markets may have been a main source of return predictability.

Overshooting of stock prices raises the question of whether regulations in general and listing requirements in particular gave rise to the return predictability of indexes of European stock markets for high-technology firms by lowering the effectiveness of information processing. While listing requirements might explain the return predictability of the Nemax50 and the Nouveau Marché, they do not help in explaining the return predictability of the Techmark100. The reason for this is that this index is part of the Main Market at London Stock Exchange. Of course, this does not rule out the possibility that regulations of primary markets may help in explaining the return predictability in Europe's stock markets for high-technology firms. Analyzing this possibility is left to future research. Our study sets the stage for such research.

References

Andrews, Donald W. K. and Werner Ploberger (1994). Optimal Tests When a Nuisance Parameter is Present Only Under the Alternative. Econometrica 62: 1383–1414.

Black, B.S., and R.J. Gilson (1998). Venture Capital and the Structure of Capital Markets: Banks versus Stock Markets. Journal of Financial Economics 47(3): 243–277.

Balduzzi, P., G. Bertola, and S. Foresi (1995). Asset Price Dynamics and Infrequent Feedback Trades. Journal of Finance 50: 1747–1766.

Bascha, A., and U. Walz (2001). Convertible Securities and Optimal Exit Decisions in Venture Capital Finance. Journal of Corporate Finance 7: 285–306.

Beck, T., and R. Levine (2002). Industry Growth and Capital Allocation: Does Having a Market- or Bank-Based System Matter? NBER Working Paper 8982. Cambridge, Mass..

Berger, A.N., and G.F. Udell (1998). The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle. Journal of Business and Finance 22: 613–673.

Black, F. (1986). Noise. Journal of Finance 41: 529–543.

Bohl, M.T. and S. Reitz (2004). Do Positive Feedback Traders Act in Germany's Neuer Markt? Quarterly Review of Economics and Finance (forthcoming).

Cochrane, J.H. (1999). New Facts in Finance. Economic Perspective. Federal Reserve Bank of Chicago: 36–58.

Conrad, J. and G. Kaul (1988). Time Variation in Expected Returns. Journal of Business 61: 893–920.

Cowles, A. and H.E. Jones (1937). Some a Posteriori Probabilities in Stock Market Action. Econometrica 5: 280–294.

Cutler, D.M., Poterba, J.M., and L.H. Summers (1991). Speculative Dynamics. Review of Economic Studies 58: 529–546.

DeLong, J.B, A. Shleifer, Summers, L.H., and R.J. Waldmann (1990). Noise Trader Risk in Financial Markets. Journal of Political Economy 98: 73–738.

Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of U.K. inflation. Econometrica 50: 987–1008.

Fama, E.F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance 25: 383–417.

Fama, E.F. (1991). Efficient Capital Markets: II. Journal of Finance XLVI, 1575–1617.

Grossman, S.J. and J.E. Stiglitz (1980). On the Impossibility of Informationally Efficient Markets. American Economic Review 70: 393–408.

Hall, B.H. (2002). The Financing of Research and Development. Oxford Review of Economic Policy 18: 35–51.

Hansen, B. E. (1997). Approximate Asymptotic P-Values for Structural Change Tests. Journal of Business and Economic Statistic 15: 60–67.

Harhoff, D. (1998). Are there Financing Constraints for R&D and Investment in German Manufacturing Firms? Annales D'Économie et de Statistique 49/50: 421–456.

Harvey, A.C., (1992). Forecasting, Structural Time Series Models and the Kalman Filter. Cambridge University Press, New York.

Harvey, A.C., E. Ruiz, and E. Sentana (1992). Unobserved Component Time Series Models With ARCH Disturbances. Journal of Econometrics 52: 129–157.

Kim, C.J. and C.R. Nelson (2000). State-Space Models with Regime Switching. MIT-Press, Cambridge, Mass.

Mech, T.S. (1993). Portfolio Return Autocorrelation. Journal of Financial Economics 34: 307–344.

Merton, R.C. (1980). On Estimating the Expected Return on the Market. Journal of Financial Economics 8: 323–361.

Merton, R.C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. Journal of Finance 42: 28–30.

Lesmond, D.A., J.P. Ogden, and C. Trzcinka (1999). A New Estimate of Transaction Costs. Review of Financial Studies 12: 1113–1141.

Lo, A.W. and A.C. MacKinlay (1990). An Econometric Analysis of Nonsynchronous Trading. Journal of Econometrics 45: 181–211.

Lux, T. and M. Marchesi (2000). Volatility Clustering in Financial Markets: A Micro-Simulation of Interacting Agents. International Journal of Theoretical and Applied Finance 3: 675–702.

Ogden, J.P. (1997). Empirical Analysis of Three Explanations for the Positive Autocorrelation of Short-Horizon Stock Index Returns. Review of Quantitative Finance and Accounting 9: 203–217.

Rockinger, M. and G. Urga (2000). The Evolution of Stock Markets in Transition Economies. Journal of Comparative Economics 28: 456–472.

Rockinger, M. and G. Urga (2001). A Time-Varying Parameter Model to Test for Predictability and Integration in the Stock Markets of Transition Economies. Journal of Business and Economics Statistics 19: 73–84.

Sentana, E. and S. Whadwani (1992). Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data. Economic Journal 102: 415–425.

Shiller, R.J. (1984). Stock Prices and Social Dynamics. Brookings Papers on Economic Activity 2: 457–498.

Westhead, S. (1997). Financial Constraints on the Growth of High Technology Small Firms in the United Kingdom. Applied Financial Economics 7: 197–201.

Zalewska-Mitura, A. and S.G. Hall (1999). Examining the First Stages of Market Performance: A Test of Evolving Market Efficiency. Economics Letters 64, 1–12.

Table 1 — Summary Statistics of Returns

Index	DAX30	Nemax50	CAC40	NOUV	FTSE100	Tech100
Mean	0.01	0.01	0.04	0.01	0.00	0.04
Median	0.02	0.00	0.02	0.01	0.00	0.18
Maximum	6.43	12.28	5.55	16.70	4.35	9.64
Minimum	-8.87	-9.71	-7.68	-12.85	-5.89	-9.13
Std. Dev.	1.63	2.71	1.48	2.37	1.24	2.11
Skewness	-0.34	- 0.04	-0.25	-0.37	-0.16	-0.36
Kurtosis	4.82	4.26	4.47	4.47	3.94	5.32
AR(1)	0.04	0.12	0.04	0.22	0.05	0.24
AR(2)	-0.06	0.03	-0.05	0.07	-0.12	0.06
AR(3)	-0.01	-0.00	-0.04	-0.01	-0.06	0.01
AR(4)	0.09	0.12	0.02	0.15	0.00	0.02
AR(5)	0.00	0.02	-0.00	0.07	-0.02	-0.01
Q-statistic	1.40	16.03 ***	1.77	51.32 ***	2.48	60.08 ***
LM-ARCH(1)	6.48 **	29.96 ***	9.75 ***	98.35 ***	24.30 ***	39.61 ***
LM-ARCH(2)	40.16 ***	42.21 ***	23.73 ***	152.89 ***	48.00 ***	66.72 ***
JB	166.82 ***	70.65 ***	105.72 ***	1304.61 ***	43.88 ***	261.23 ***

Note: The table gives summary statistics of continuously compounded daily returns. Returns were computed as $R_t = 100 \times [\log(index_t) - \log(index_{t-1})]$, where $index_t$ denotes the stock market index and *log* denotes the natural logarithm. *AR*(*i*), *i*=1,…,4 denotes the coefficients of autocorrelation of order *i*. The *Q*-statistic denotes the Box-Lung statistic for autocorrelation of first-order. *LM-ARCH*(*i*) denotes Engle’s (1982) Lagrange multiplier test for autocorrelation of order *i* in squared returns. The Jarque-Bera (*JB*) test is a test for normality of the unconditional returns distribution. *** (**) denotes significance at the one (five) percent level. The sample period is 1998/1/1 to 2002/2/4.

Table 2 — Tests for Stability of Regression Coefficients

	Andrews-Quandt test		Andrews-Ploberger test	
	test	p-value	test	p-value
		DAX30		
Constant	4.058	0.366	0.739	0.294
AR(1) coef.	2.932	0.568	0.552	0.402
Both coefs.	7.686	0.230	0.314	0.626
		Nemax50		
Constant	17.807	0.001***	5.448	<0.000***
AR(1) coef.	0.942	1.000	0.121	0.970
Both coefs.	20.808	0.001***	6.799	0.002***
		CAC40		
Constant	5.749	0.179	1.457	0.104*
AR(1) coef.	6.868	0.109*	1.578	0.089*
Both coefs.	14.602	0.013**	4.552	0.012**
		Nouveau Marché		
Constant	18.520	<0.000***	4.945	0.001***
AR(1) coef.	7.870	0.070*	0.514	0.430
Both coefs.	21.695	0.001***	6.299	0.003***
		FTSE100		
Constant	1.923	0.805	0.421	0.509
AR(1) coef.	7.156	0.096*	1.117	0.166
Both coefs.	7.157	0.278	1.722	0.243
		Tech100		
Constant	13.608	0.005***	3.375	0.009*
AR(1) coef.	6.103	0.154	0.978	0.203
Both coefs.	15.853	0.008***	5.074	0.008*

Note: For a description of the tests for stability of the coefficients in a regression of returns on a constant and lagged returns, see Andrews and Ploberger (1994) and Hansen (1997). *** (**,*) denotes significance at the one (five, ten) percent level. The sample period is 1998/1/1 to 2002/2/4.

Table 3 — Estimation Results for the Time-Varying Parameter Model

	DAX30	NEMAX50	CAC40	NOUVEAU	FTSE100	TECH100
Variance Beta_0	0.0026	0.0103	0.0037	0.0057	-0.0014	0.0113
Standard deviation	*0.0031*	*0.006*	*0.0032*	*0.0071*	*0.0026*	0.0056
Variance Beta_1	0.0000	0.0000	0.0034	0.0051	-0.0047	0.0044
Standard deviation	*0.0074*	*0.0032*	*0.0029*	*0.0041*	*0.0024*	0.0033
Constant	0.0724	0.223	0.0681	0.0346	0.0798	0.0283
Standard deviation	*0.0268*	*0.0848*	*0.0275*	*0.0116*	*0.0297*	0.0039
ARCH coefficient	0.0866	0.1149	0.0638	0.152	0.0916	0.0975
Standard deviation	*0.0162*	*0.0221*	*0.0143*	*0.0193*	*0.0213*	0.0122
GARCH coefficient	0.8859	0.8575	0.9041	0.848	0.8542	0.9019
Standard deviation	*0.0207*	*0.0279*	*0.022*	*0.0193*	*0.0353*	0.0141
Iterations	31	17	19	34	28	17
Log likelihood function	-1962.28	-2496.45	-1887.75	2145.23	-1690.45	-2103.26

Note: This table reports the results of estimating the time-varying parameter model described in Section 2.2 by maximum likelihood.

Table 4 — Testing for Feedback Trading

	DAX30	NEMAX50	CAC40	NOUVEAU	FTSE100	TECHM100
Bc	-0.0312	-0.1960	-0.0667	0.0399	-0.0919	0.2002
t-statistic	*-0.3336*	*-1.4257*	*-0.5441*	*0.9452*	*-0.8039*	3.4349***
Bd	0.0418	0.0446	0.07195	0.0014	0.0868	-0.0251
t-statistic	*1.0791*	*2.0967***	*1.1187*	*0.1531*	*1.0464*	-1.6166
Vc	0.0737	0.2473	0.0687	0.0302	0.0773	0.0317
t-statistic	*2.8659****	*2.0312***	*2.2705***	*1.8572***	1.8862*	1.8130
ARCH coefficient	0.8828	0.8484	0.9046	0.8225	0.8604	0.8866
t-statistic	*41.7959****	*21.1765****	*36.9273****	*21.6943****	*18.0399****	46.0433***
GARCH coefficient	0.08888	0.1199	0.0637	0.2015	0.0879	0.1154
t-statistic	*4.6192****	*3.7790****	*4.0279****	*4.0218****	*2.9761****	5.3911***
Gamma0	0.0103	0.2728	0.0767	0.3533	0.1307	0.3095
t-statistic	*0.2024*	*4.9290****	*1.2136*	*7.8351****	*1.7078**	6.7699***
Gamma1	0.0046	-0.0151	-0.0122	-0.0079	-0.0422	-0.0099
t-statistic	*0.3838*	*-3.1821****	*-0.5229*	*-3.9420****	*-1.0330*	-1.9966***
Iterations	22	48	28	44	26	27
Log likelihood function	-953.29	-1476.52	-882.35	-1119.63	-693.11	-1132.71

Note: This table reports the results of estimating the feedback-trader GARCH model described in Section 3.1 by maximum likelihood. t-statistics based on Newey-West standard errors are given below coefficients. *** (**,*) denotes significance at the one (five, ten) percent level.

Table 5 — The Role of Transaction Costs

		Expected signs	Nemax50	Nouveau Marché	Techmark 100
C	b_{00}	+/-	-0.015 (-0.46)	0.017 (0.83)	0.094^{***} (4.40)
D_t	b_{01}	+/-	0.189^{*} (1.76)	0.050 (0.46)	-0.029 (-0.35)
R_{t-1}	b_{10}	+/-	0.097 (1.64)	0.116^{**} (2.02)	0.050 (1.00)
$D_{t-1}R_{t-1}$	b_{11}	-	-0.086 (-1.41)	-0.079 (-1.35)	-0.024 (-0.47)
$D_t R_{t-1}$	b_{12}	+	0.363^{**} (2.34)	0.890^{***} (3.44)	0.399^{*} (1.84)
$D_t D_{t-1} R_{t-1}$	b_{13}	-	-0.259 (-1.60)	-0.646^{**} (-2.44)	-0.131 (-0.60)
R_t^{**}	b_{20}	+	0.257^{***} (8.07)	0.095^{***} (5.05)	0.268^{***} (10.80)
$D_t R_t^{**}$	b_{21}	+	1.137^{***} (18.86)	1.083^{***} (15.31)	1.110^{***} (17.70)
Number of observations			1059	1059	1059
Adjusted R-squared			0.580	0.452	0.585
DW statistic			1.96	2.17	1.98
Wald statistic			9.17**	14.31***	10.53**

Note: This table reports regression results for Mech's (1993) model of transaction costs in stock markets. See Section 3.2 for details. White heteroskedasticity-consistent t-statistics are reported in parentheses. *** (**,*) denotes significance at the one (five, ten) percent level. DW denotes the Durbin-Watson statistic for first-order autocorrelation in regression residuals. The Wald statistic gives the results of a Wald test for joint insignificance of the coefficients b_{11}, b_{12}, and b_{13}. The sample period is 1998/1/1 to 2002/2/4.

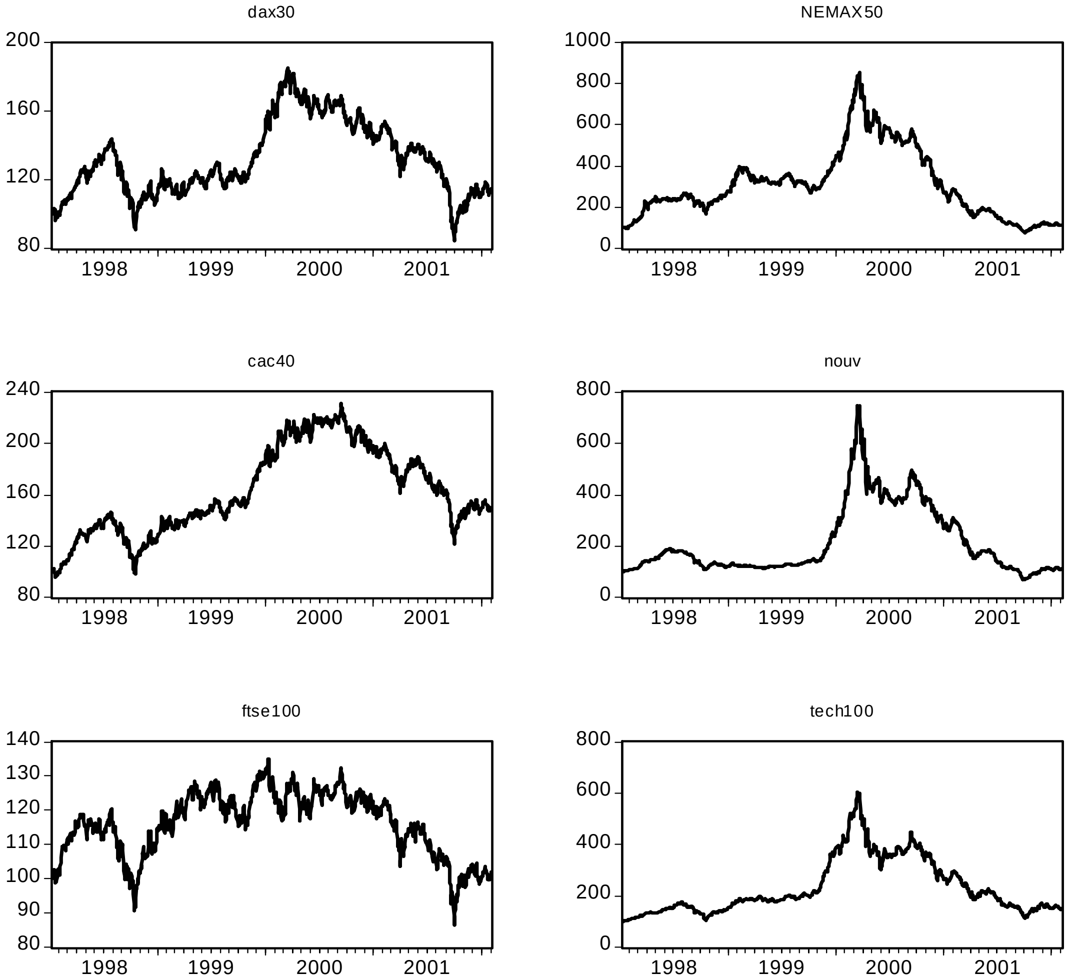
Table 6 — The Information Content of Returns on Blue Chips for Returns on High-Technology Firms

PANEL A						
	NEMAX50	t-stat	NOUV	t-stat	TECH100	t-stat
Constant	-0.02	-0.29	-0.08	-1.17	0.03	0.49
R	1.17	23.52***	0.88	12.47***	1.16	21.10***
R**(-1)	0.08	2.43**	0.35	8.16***	0.26	7.00***
R** (-2)	0.07	1.98**	0.18	4.00***	0.06	1.59
R** (-3)	0.00	-0.05	0.06	1.24	0.09	2.11**
R** (-4)	0.08	2.34**	0.10	2.84***	0.09	2.60***
R** (-5)	0.10	2.52**	0.11	2.02**	0.03	0.84
R** (-6)	0.07	1.84*	0.09	1.94*	0.05	1.28
R** (-7)	0.02	0.53	0.10	2.40**	0.05	1.16
R** (-8)	0.03	0.68	0.08	1.57	0.00	0.07
R** (-9)	0.06	1.52	0.07	1.75*	-0.02	-0.47
R** (-10)	-0.01	-0.35	-0.05	-1.24	0.02	0.41
R** (-11)	-0.02	-0.58	0.06	1.46	-0.03	-0.69
R** (-12)	0.05	1.37	0.03	0.87	0.04	1.05
R** (-13)	0.09	2.53**	0.03	0.67	0.05	1.25
R** (-14)	-0.02	-0.43	-0.06	-1.46	-0.03	-0.72
R** (-15)	0.11	2.65***	0.01	0.19	0.04	1.06
R** (-16)	0.05	1.44	0.07	1.54	0.06	1.74*
R** (-17)	-0.04	-1.33	0.01	0.34	0.02	0.60
R** (-18)	0.03	0.76	0.03	0.67	0.06	1.37
R** (-19)	0.00	-0.03	0.04	1.04	-0.01	-0.37
R** (-20)	-0.01	-0.30	0.01	0.25	-0.04	-1.06
Adj. R^2	0.51		0.37		0.48	

PANEL B			
	NEMAX50	NOUV	TECH100
lag 0	0.70	0.45	0.64
lag 1	0.75	0.63	0.79
lag 2	0.79	0.72	0.83
lag 3	0.79	0.75	0.88
lag 4	0.84	0.80	0.93
lag 5	0.90	0.85	0.94

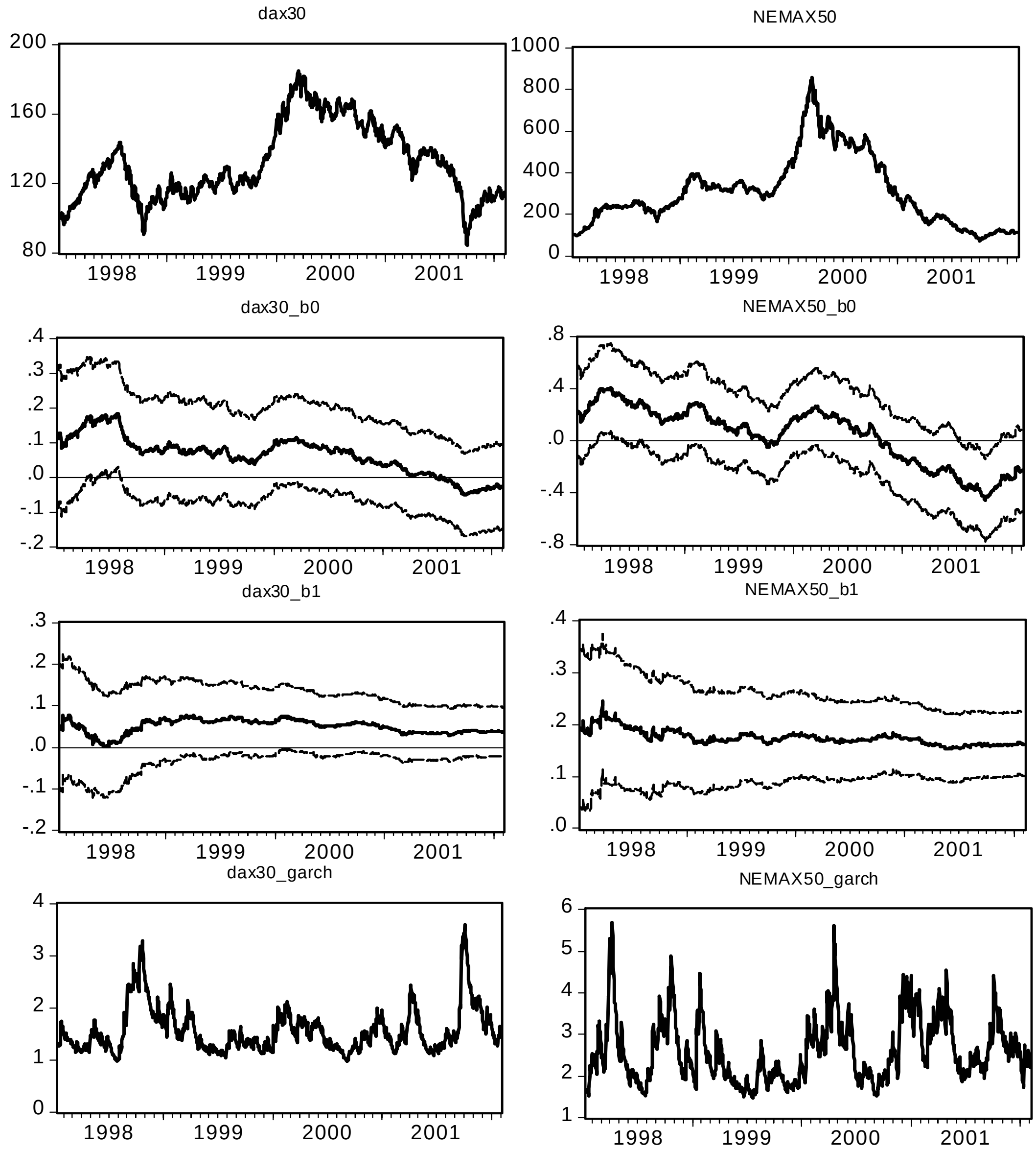
Note: In Panel A, this table reports results of estimating the regression model $R_t = a_0 + \sum_{k=0}^{K} a_{i,k} R^{**}_{t-k} + u_t$, where R** denotes returns on an index of blue-chip firms. Newey-West standard errors were used to compute t-statistics. In Panel B, this table reports the ratios $\sum_{k=0}^{k^*} a_{i,k} \Big/ \sum_{k=0}^{K} a_{i,k}$. See Section 3.3 for details. The sample period is 1998/1/1 to 2002/2/4.

Figure 1 — Stock Market Indexes in Europe (1998:01 – 2002:02)



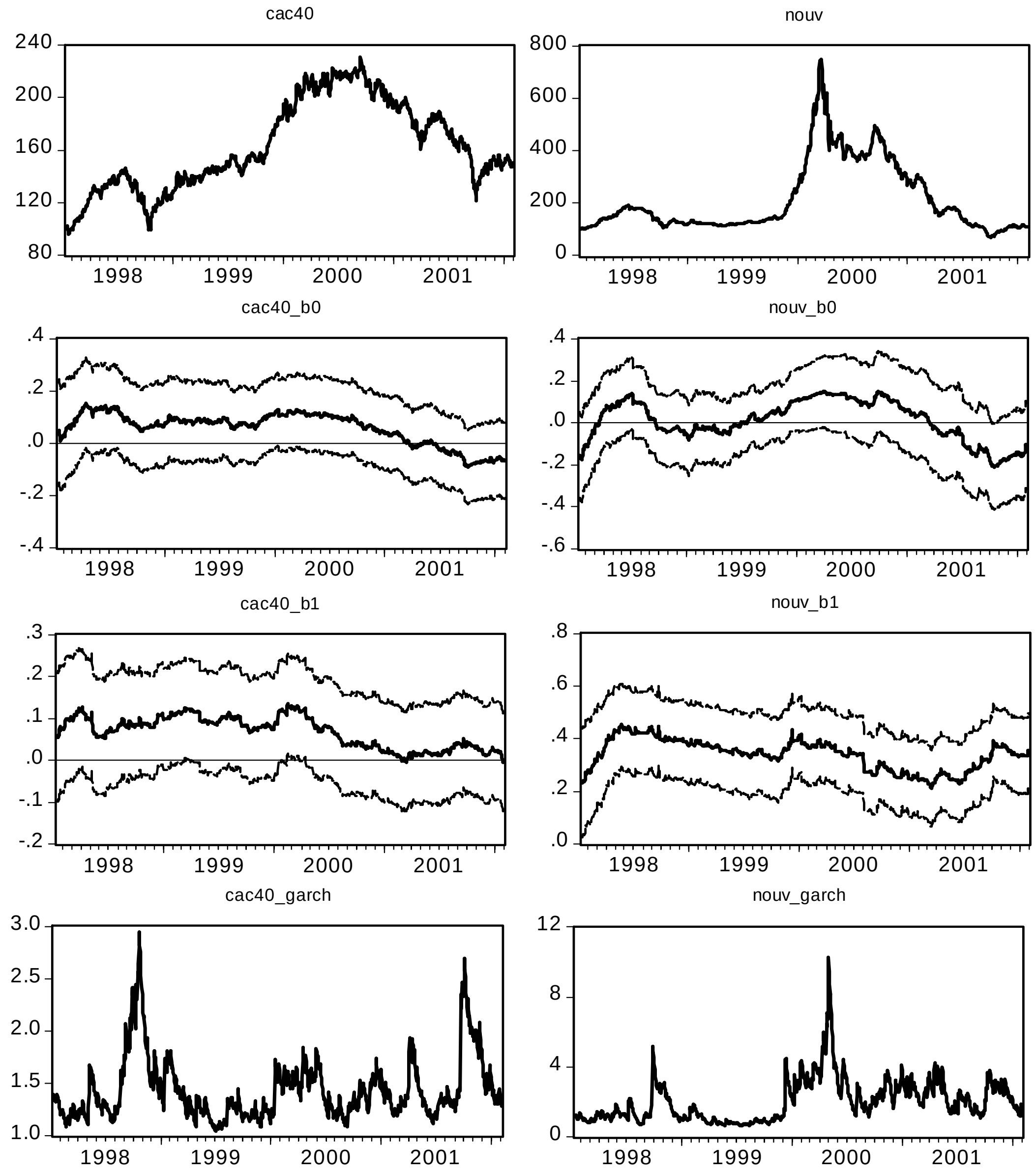
Note: Daily data were taken from Thompson Financial Datastream.

Figure 2 — Stock Market Index and Time-Varying Return Predictability in Germany (1998:01 – 2002:02)



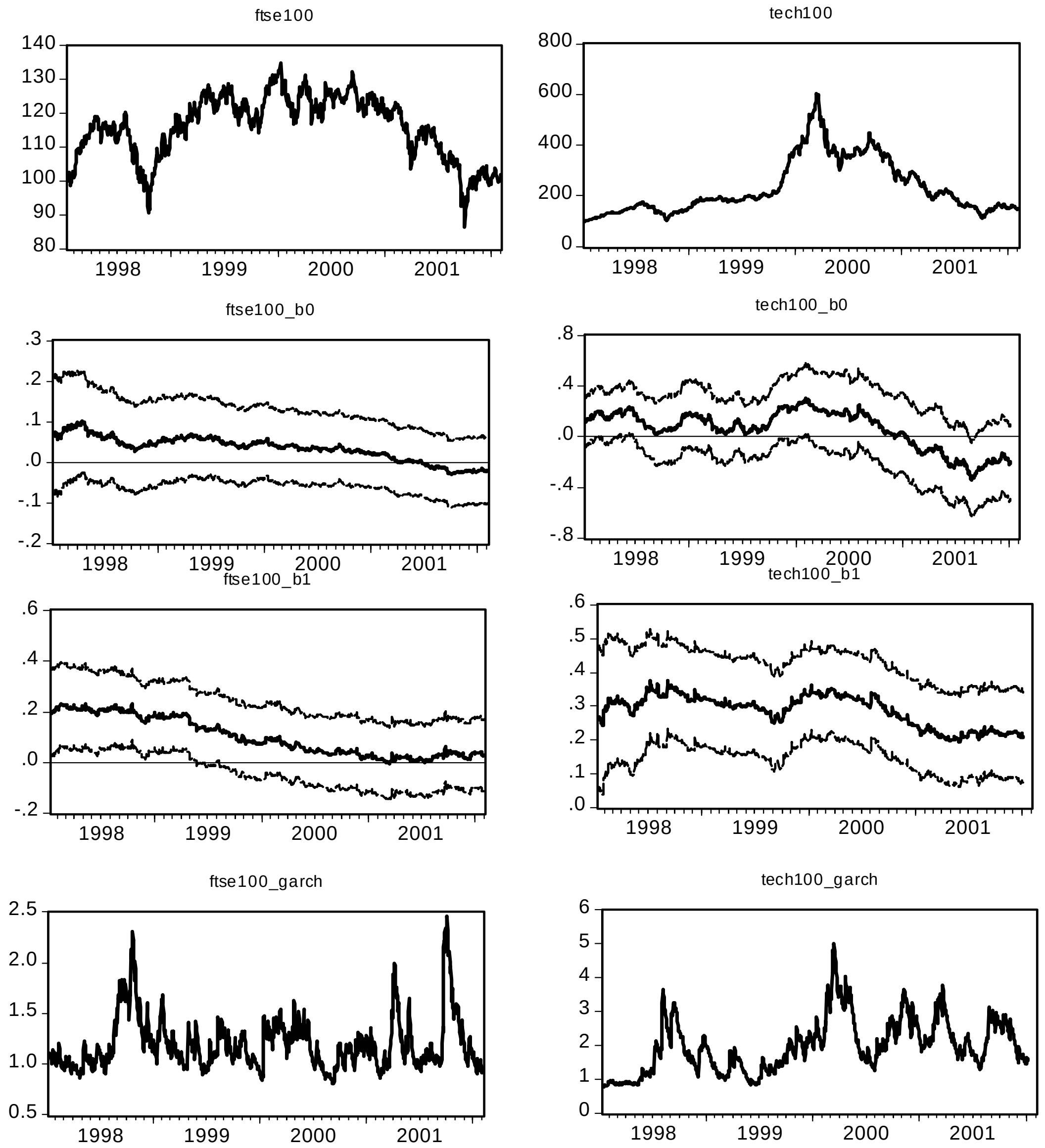
Note: _b0 denotes the coefficient $\beta_{0,t}$. _b1 denotes the coefficient $\beta_{1,t}$. The time paths of these coefficients are shown together with the corresponding confidence bands ($\pm 2 \times$ standard deviations). The coefficient $\beta_{1,t}$ captures the time-varying return predictability. Returns were computed as $R_t = 100 \times [\log(index_t) - \log(index_{t-1})]$, where $index_t$ denotes the stock market index. _GARCH denotes the conditional variance of stock index returns. The graphs show filtered estimates of $\beta_{0,t}$ and $\beta_{1,t}$.

Figure 3 — Stock Market Index and Time-Varying Return Predictability in France (1998:01 – 2002:02)



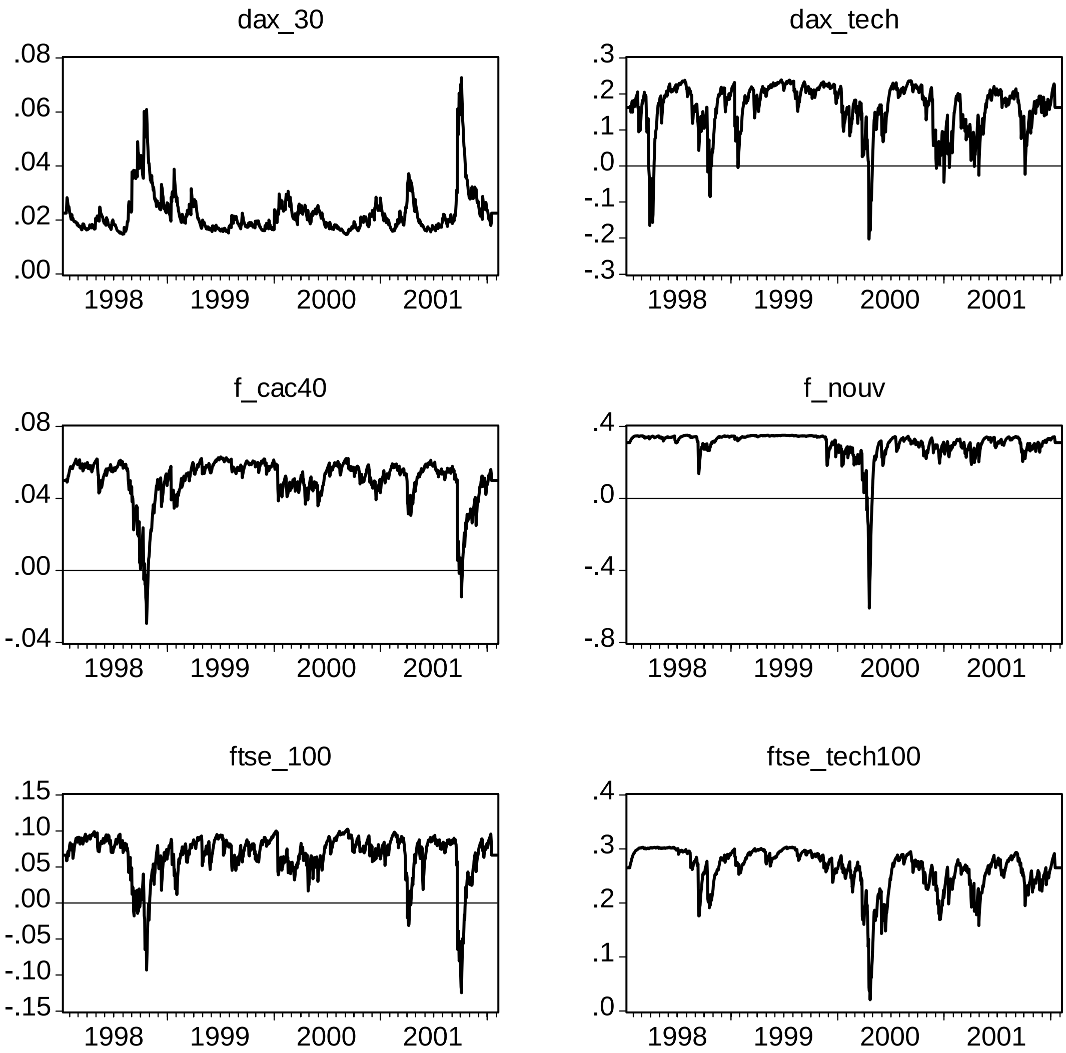
Note: See Figure 2.

Figure 4 — Stock Market Index and Time-Varying Return Predictability in the United Kingdom (1998:01 – 2002:02)



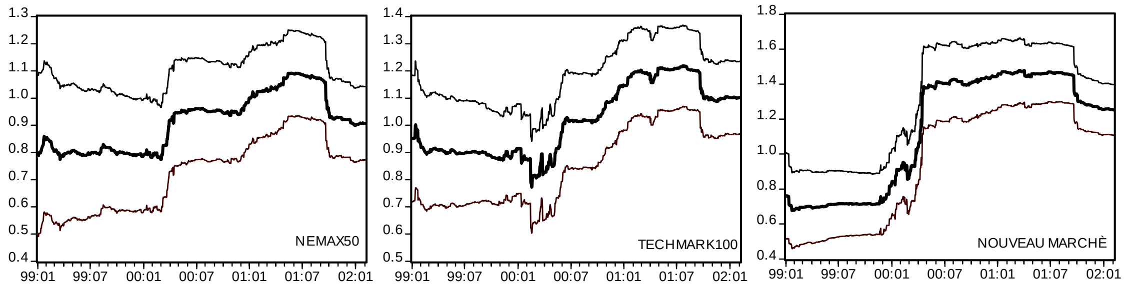
Note: See Figure 2.

Figure 5 — Results for a Feedback-Trading ARCH(1,1) Model



Note: This graphs show the estimated conditional correlation coefficients, $\gamma_0 + \gamma_1 h_t^2$, of the feedback-trader GARCH model described in Section 3.1

Figure 6 — Overshooting of returns in the pre-crash and the post-crash period



Note: This figure shows the evolution of the coefficient b_{21} of Equation (10) over time. The graphed results were obtained by recursive estimation of Equation (10) using ordinary least squares. Thin lines denote 95% confidence bands.