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Investing in European Stock Markets for High-Technology Firms

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Abstract:

We used a recursive modeling approach to study whether investors could, in real time, have used information on the comovement of stock markets to forecast stock returns in European stock markets for high-technology firms. We used weekly data on returns in the Neuer Markt, the Nouveau Marché, the Alternative Investment Market, and the NASDAQ. We found substantial changes over time in the usefulness of the inter-European and cross-Atlantic comovement of stock markets for predicting stock returns. We also studied how monitoring the comovement of stock markets would have affected the performance of simple trading rules and investor's market-timing skills.

Keywords: Recursive modeling approach; Comovement of returns; High-technology firms

JEL Classification: B22, C32, E24

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1. Introduction

At the end of the 1990s, advances made in high-technology sectors like the IT sector and the bio-sciences sector were in the focus of the mass media and investors. Investors were strongly interested in investing in high-technology firms that needed capital to finance their expansion. As a result, European stock exchanges founded new stock markets for high-technology firms. In Frankfurt, Paris, and London important marketplaces for trading stocks in European high-technology firms were established.

A key problem of investors who planned to invest in the new European stock markets for high-technology firms was that little was known about these markets and the firms listed in these markets. Because these markets were new, investors knew little about how these markets processed information and how they reacted to news. Moreover, because many high-technology firms operated in completely new technological fields, investors had hardly any experience in assessing the growth prospects for firms listed on European stock markets for high-technology firms. As a result, investors' beliefs concerning the bright growth prospects of particular high-technology firms resulted in the bubble-like phenomena that were a characteristic feature of stock markets for high-technology firms in the late 1990s.

In general, there was no empirical evidence available that could have guided investors in determining the key driving factors of stock returns in the new European stock markets for high-technology firms. Even worse, the potential for portfolio diversification across markets was limited because European stock markets for high-technology firms witnessed a non-negligible degree of comovement at the end of the 1990s. This comovement may even indicate that the portfolios held by investors who invested in these markets were vulnerable to the kind of contagion effects and spillovers of market jitters that have been widely studied in the recent literature (Forbes and Rigobon 2002, Hon et al. 2005).

This, however, does not necessarily imply that this comovement was per se bad for investors. In fact, even investors who only invested in their domestic stock market for high-technology firms, rather than in international stock markets, could have benefited from the comovement of stock markets. The reason for this is that the comovement need not reflect only contemporaneous links between stock markets. Rather, the comovement could also indicate that potentially complex lead-lag links between stock markets exist. If this is the case, the comovement of stock markets could imply that investors can use international stock returns to predict returns in their domestic stock market. If the comovement implies predictability of returns, this may even help investors to set up profitable simple trading rules based on the comovement of stock markets.

While many authors have empirically studied the degree and the sources of the international comovement of stock markets (Longin and Solnik 1995, Bekeart and Harvey 1995, Chinn and Forbes 2004, among others), empirical evidence is relatively silent with respect to the comovement of stock markets for high-technology firms. Even less is known about the question whether investors who invested in these stock markets could have taken advantage of the comovement of stock markets for high-technology firms in order to increase the performance of their stock market investments. Therefore, we study whether investors could have used the comovement between European stock markets for high-technology firms to increase the performance of their investments. To the best of our knowledge, our study is the first empirical study to address this question.

In order to conduct our empirical study, we used a recursive modeling approach developed by Pesaran and Timmermann (1995, 2000). A recursive modeling approach implies that, to predict stock returns, investors can only use a set of information that is available in the period of time in which investors have to reach investment decisions. Included in this set of information is the information on the international comovement of stock markets available in the period of time when investment decisions had to be reached. Not included is information on the comovement of stock markets in later periods of time. Thus, a recursive modeling approach renders it possible to explicitly account for the uncertainty concerning the comovement of stock markets that is a crucial aspect of the investors' decision problem in real time.

A recursive modeling approach has two further key advantages. First, a recursive modeling approach renders it possible to trace out potential changes in the comovement of stock markets over time. We deem this to be an important advantage because Hon et al. (2005) have recently reported empirical evidence of structural breaks in the comovement of stock index returns in the information technology and telecommunications sectors. In order to account for structural breaks, we split our dataset into a pre-crash subsample, which covers the time during the stock market bubble, and a post-crash subsample. Second, a recursive modeling approach renders it possible to analyze whether the comovement of stock markets could have been used by investors for the purpose of out-of-sample forecasting of stock returns in real time. A detailed analysis of such forecasting informs about whether investors could have exploited stock return predictability to set up profitable simple trading rules. Thus, our study adds to the recent studies of out-of-sample predictability of stock returns (see inter alia, Breen et al. (1990), Pesaran and Timmermann (1995, 2000), Bossaerts and Hillion (1999), Goyal and Welch (2003), Fong and Yong (2005), and Cooper et al. (2005)).

To study whether investors, in real time, could have exploited the comovement of European stock markets for high-technology firms, we compiled data for three European stock markets for high-technology firms: the Neuer Markt in Germany (founded in 1997), the Nouveau Marché in France (founded in 1996), and the Alternative Investment Market (AIM) in the United Kingdom (founded in 1995). It is interesting to study these markets for at least three reasons. First, empirical evidence regarding the implications of their comovements for the predictability of stock returns in real time is not available. Second, the recent literature on the comovements of stock markets has focused mainly on country-wide stock-market indexes (Ehrmann et al. 2005) that are dominated by large and internationally active firms. The comovement of stock markets for high-technology firms, which are often smaller and domestically operating firms, might be very different from the comovement of stock markets for large and mature firms. Third, the prices of the stocks listed on European stock markets for high-technology firms rallied and crashed in the late 1990s. This led to substantial reorganizations of these markets over time. It should be interesting to analyze whether these reorganizations have had an impact on the comovement of stock markets.

Our estimation results show that the comovement across European stock markets for high-technology firms significantly varied across stock markets and over time. Moreover, the relative usefulness of inter-European comovements as compared to cross-Atlantic comovement with the NASDAQ, the leading U.S. market for high-technology firms, also varied across stock markets and over time. For example, in the pre-crash subsample, we found evidence of comovement of the NASDAQ and the Neuer Markt and the Nouveau Marché, but not of the NASDAQ and the AIM. In the post-crash subsample, by contrast, the comovement of the NASDAQ and the Neuer Markt and the Nouveau Marché lost usefulness, while the comovement of the NASDAQ and the AIM gained in usefulness. Interestingly, we found that only in a few cases would investors have to be able to systematically use the comovement of stock markets for high-technology firms to increase the real-time performance of simple trading rules. Thus, investors could not systematically exploit the comovement of stock markets for high-technology firms to set up trading rules that systematically outperform trading rules that do not account for the comovement of stock markets. Finally, we found that taking information on the comovement of stock markets into consideration when forecasting stock returns does not systematically affect an investor's market-timing skills.

We structure the remainder of our paper as follows. In Section 2, we describe the recursive modeling approach that we used to model how investors may have predicted stock returns in high-technology firms in real time. In Section 3, we describe the dataset we used in our empirical analysis. In Section 4, we report our empirical results. In Section 5, we provide some concluding remarks.

2. The Empirical Model

In order to introduce our recursive approach, we start with a description of how an investor estimates models for predicting stock returns in real time. Then, we describe how an investor selects an optimal forecasting model, how the forecasts implied by the optimal model can be used to set up simple trading rules, and how the performance of these trading rules can be assessed.

2.1 Recursive Forecasting of Stock Returns in Real Time

We considered an investor who must, in each period of time, decide under uncertainty what model is the optimal model for predicting one-step-ahead returns in stock markets for high-technology firms. We assumed that the investor considers a fixed set of macroeconomic and financial variables to be of potential relevance for predicting returns. We assumed that the set of variables considered by the investor contains both domestic macroeconomic and financial variables and returns in foreign stock markets for high-technology firms. Thus, our investor accounts for the real-time comovement of stock markets for high-technology firms when predicting stock returns.

The investor's problem, in each period of time, is that a decision must be reached as to how to combine the then available domestic and foreign variables in an optimal way to predict stock returns. In order to reach a decision, the best the investor can do is to systematically extract the informational content for one-step-ahead stock returns of both the then available domestic and foreign variables. We assumed that the investor uses a recursive modeling approach to this end (Pesaran and Timmermann 1995, 2000). According to the recursive modeling approach, the investor attempts to identify the optimal model for predicting one-step-ahead stock returns by considering, in each period of time, a large number of different models that feature different domestic and foreign variables, where the latter capture the real-time comovement of stock markets for high-technology firms. As time progresses and the investor develops a deeper understanding of the influence of domestic and foreign variables on stock returns, the investor recursively restarts this search for the optimal model. This implies a permanent updating of the optimal forecasting model.

We assumed that the investor identifies the optimal forecasting model by considering, in each period of time, all the possible combinations of variables in the then available information set. Because the information set of the investor contains information on a large number of domestic and foreign variables, the investor must, in each period of time, consider a large number of forecasting models. In order to conduct this search in an efficient manner, the investor only considers linear forecasting models that can be estimated by the ordinary least squares technique. We assumed that all forecasting models include a constant. We also assumed that the investor uses the first 24 observations of the pre-crash and the post-crash subsamples in order to start the recursive modeling approach.

2.2 Model Selection and Trading Rules

Given that the investor considers, in each period of time, a large number of different forecasting models, the investor needs a model-selection criterion with which to identify the optimal forecasting model. We assumed that the investor uses three model-selection criteria to this end: the Adjusted Coefficient of Determination (ACD), the Akaike Information Criterion (AIC, Akaike 1973), and the Bayesian Information Criterion (BIC, Schwarz 1978). These three model-selection criteria have the advantage that an investor can easily compute them in real time. For this reason, they have been widely used in applied research. Moreover, they have the advantage that they were readily available to investors even at the beginning of our sample period. This is important because we must ensure that, in real time, an investor bases investment decisions only on information that was available in the time period in which these decisions had to be reached.

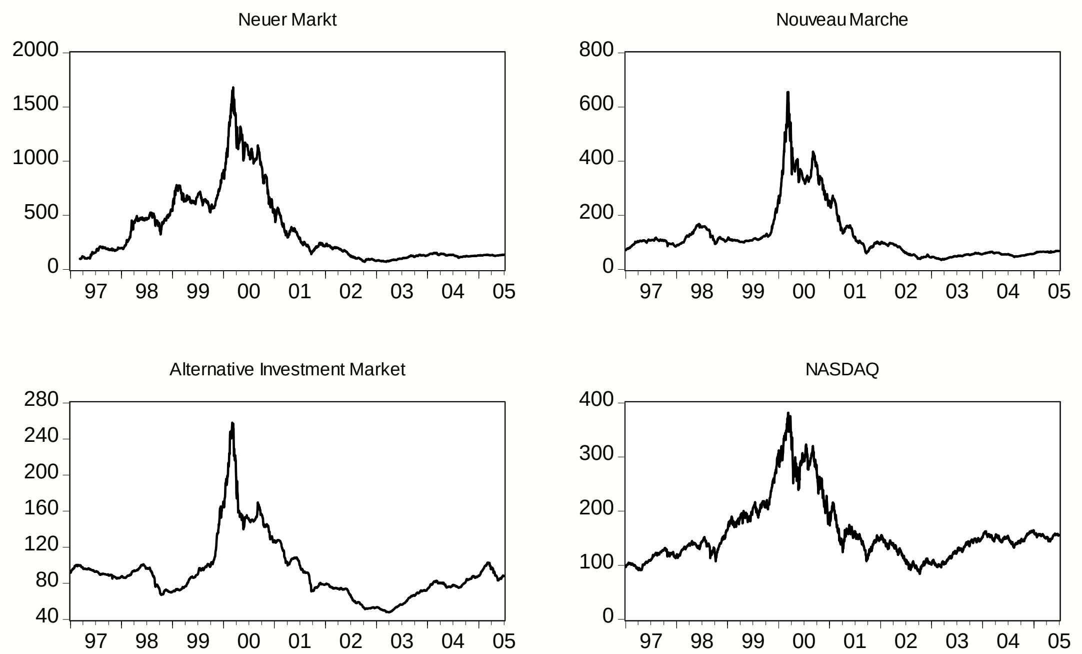
In each period of time, the investor selects a model that maximizes the ACD model-selection criterion, and two models that minimize the AIC and BIC model-selection criteria, respectively. For each model-selection criterion, this gives a sequence of optimal models, and a sequence of optimal one-step-ahead stock-return forecasts. The investor then uses the sequence of stock-return forecasts to set up simple trading rules, one for each model-selection criterion. The trading rules require switching between stocks and bonds, where the decision to switch depends on the stock-return forecast implied by the optimal forecasting model. If the forecast of one-step-ahead stock-returns is positive the investor invests in stocks. If it is negative the investor invests in bonds. Thus, our investor only considers simple switching-rules (see Fong and Yong (2005) for more complex moving-average-based trading rules). We assumed that the investor does not make use of short selling, nor does the investor use leverage when deciding whether to invest in stocks. We also assumed that trading in stocks and bonds involves transaction costs that are (i) constant through time, (ii) the same for buying and selling stocks and bonds, and (iii) proportional to the value of a trade.

Depending on the relative performance of the stock market and the bond market, the financial wealth of the investor changes over time. Pesaran and Timmermann (1995) provide a detailed description of how changes in the investor's financial wealth can be modeled. Changes in financial wealth would be a sufficient measure of the performance of an investor's trading rules if the investor were risk neutral. A risk-averse investor, in contrast, would assess the performance of the trading rules not only by considering financial wealth, but also by inspecting the riskiness of the trading rules. To account for the riskiness of the trading rules, we used the Sharpe ratio (Sharpe 1966), which we computed the Sharpe ratio in two steps. In the first step, we computed excess returns generated by a trading rule by subtracting the riskless short-term interest rate from the return on a trading rule at the end of the pre-crash and the post-crash subsamples. In the second step, we divided the excess returns by the standard deviation of returns implied by a trading rule.

3. The Data

We used weekly data for the sample period January 1, 1997 to June 30, 2005. For this sample period, we plot in Figure 1 the three European stock market indexes that we analyzed and the index for the NASDAQ. We rescale these indexes such that they had the value 100 on March 10, 1997. The overall development of the indexes over time was very similar. For example, they all increased in 1998 and peaked in March 2000. Yet, Figure 1 also reveals interesting differences across the indexes. For example, in 1998, the increase in the index of the Neuer Markt was several times larger than the increase in the indexes of the other two European stock markets for high-technology firms and the NASDAQ. In addition, in March 2000, the Neuer Markt reached a maximum of about 1,600 basis points, followed by the Nouveau Marché, which reached a maximum of about 700 basis points. Both the AIM and the NASDAQ reached much lower levels of 250 and 380 basis points, respectively.

Figure 1:
Stock Market Indexes for High-Technology Firms, 1997:01 – 2005:06



Note: The four indexes were rescaled to assume the value 100 on March 10, 1997.

Returns calculated from indexes for stock markets for high-technology firms were rather volatile, as the mean and standard deviations of returns reported in Table 1 indicate. We calculated returns as weekly continuously compounded returns based on Wednesday quotations. While the Neuer Markt and the NASDAQ yielded positive returns on average, the Nouveau Marché and the AIM yielded negative returns on average. According to the maximum weekly returns, the four indexes yielded returns of almost twelve percent per week in the case of the AIM, and even more than 27 percent in the case of the Neuer Markt. However, according to the minimum weekly returns, investors could lose

Table 1:
Summary Statistics

	Mean	Standard deviation	Minimum	Maximum
		Germany		
Short–term interest rate	3.158	0.844	2.024	5.046
RTB	–0.016	0.182	–0.676	0.621
RGB	–0.036	0.212	–0.566	0.611
TSP	1.468	0.692	–0.122	2.866
RMM	–0.016	0.225	–0.919	1.096
Returns total stock market	0.079	3.557	–14.996	16.461
Returns Neuer Markt	0.078	5.967	–24.017	27.736
		France		
Short–term interest rate	3.173	0.846	2.024	5.046
RTB	–0.018	0.176	–0.676	0.621
RGB	–0.034	0.207	–0.489	0.806
TSP	1.504	0.619	0.040	2.612
RMM	–0.018	0.171	–0.710	0.713
Returns total stock market	0.137	3.234	–12.908	16.550
Returns Nouveau Marché	–0.011	5.396	–41.943	20.934
		United Kingdom		
Short–term interest rate	5.244	1.214	3.281	7.625
RTB	–0.021	0.225	–0.880	0.826
RGB	–0.046	0.225	–0.830	0.454
TSP	–0.091	0.934	–2.678	1.401
RMM	–0.016	0.659	–2.393	3.448
Returns total stock market	0.048	2.425	–10.247	13.344
Returns AIM	–0.010	2.614	–21.428	11.755
Returns NASDAQ	0.105	4.047	–19.066	14.734

Note: RTB denotes the relative three–month interest rate calculated as the interest rate minus the moving average of the preceding twelve weeks. RGB denotes the relative government bond yield calculated as the 10 year government bond rate minus the moving average of the preceding twelve weeks. TSP denotes the term structure calculated as the government bond minus the three–month interest rate. RMM denotes the relative money market rate calculated as the overnight interest rate minus the moving average of the preceding twelve weeks. Returns in total stock markets were calculated from MSCI country price indexes. All returns were calculated as weekly continuously compounded returns based on Wednesday quotations. 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. All data were taken from Thomson Financial Datastream. The sample period is 1997:1 to 2005:6.

significant amounts of money upon investing in stock markets for high-technology firms. The minimum weekly returns were often as low as – 20 percent; in the case of the Nouveau Marché the minimum weekly return was even as low as – 42 percent.

In order to get an impression of how the comovement of stock markets for high-technology firms changed over time, we computed correlations of contemporaneous returns. We also computed correlations of returns with one-week lagged returns in foreign stock markets. Table 2 summarizes the correlations of returns for the pre-crash subsample (1997:1–2000:3) and for the post-crash subsample (2000:4–2005:6). The results illustrate that contemporaneous correlations of returns were relatively high. In most cases, contemporaneous correlations were well above 0.5. The correlations with lagged foreign stock returns were substantially lower than contemporaneous correlations. Nevertheless, in many cases the correlations with lagged foreign stock returns were significantly different from zero. This significance is relevant because it suggests that investors who tried to forecast stock returns in European stock markets for high-technology firms in real time could have used lagged returns in foreign stock markets to forecast domestic stock returns.

There is also evidence that correlations of returns changed from the pre-crash to the post-crash subsample. With regard to the Neuer Markt, correlations with contemporaneous and lagged foreign returns were lower in the pre-crash than in the post-crash subsample. With regard to the Nouveau Marché, correlations with contemporaneous and lagged foreign returns were also very often lower in the pre-crash than in the post-crash sample period. However, cross-subsample differences in return correlations were less pronounced than in the Neuer Markt. It is also interesting to note that, with regard to the AIM, the correlation with contemporaneous and lagged NASDAQ returns did not change much between the two subsample periods.

Table 2:
Correlations of Returns

	Neuer Markt	Nouveau Marché	AIM	NASDAQ
		Pre–crash sample		
Nouveau Marché	0.379			
	(0.000)			
AIM	0.285	0.602		
	(0.001)	(0.000)		
NASDAQ	0.414	0.428	0.426	
	(0.000)	(0.000)	(0.000)	
Neuer Markt (t–1)	0.021	0.084	0.101	–0.051
	(0.803)	(0.326)	(0.237)	(0.547)
Nouveau Marché (t–1)	0.036	0.287	0.263	0.040
	(0.672)	(0.000)	(0.001)	(0.632)
AIM (t–1)	0.029	0.261	0.453	0.125
	(0.730)	(0.001)	(0.000)	(0.128)
NASDAQ (t–1)	0.068	0.054	0.215	0.015
	(0.424)	(0.514)	(0.008)	(0.856)
		Post–crash sample		
Nouveau Marché	0.816			
	(0.000)			
AIM	0.610	0.732		
	(0.000)	(0.000)		
NASDAQ	0.744	0.592	0.438	
	(0.000)	(0.000)	(0.000)	
Neuer Markt (t–1)	0.084	0.205	0.274	0.066
	(0.151)	(0.000)	(0.000)	(0.259)
Nouveau Marché (t–1)	0.062	0.079	0.211	0.056
	(0.287)	(0.179)	(0.000)	(0.343)
AIM (t–1)	0.116	0.128	0.295	0.137
	(0.047)	(0.029)	(0.000)	(0.019)
NASDAQ (t–1)	0.037	0.174	0.250	–0.059
	(0.533)	(0.003)	(0.000)	(0.317)

Note: The table summarizes correlations of continuously compounded weekly 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. The pre–crash (post–crash) subsample is 1997:1–2000:3 (2000:4–2005:6). To indicate the significance of the correlation coefficients, p–values are given in parentheses.

The correlations of returns give a first rough indication of the comovement of stock markets for high-technology firms. They also indicate that the comovement was neither identical across markets nor constant over time. Moreover, European stock markets for high-technology firms showed a substantial comovement with the NASDAQ. Again, this comovement was neither the same for all European stock markets, nor was it constant over time. A key question is, therefore, whether investors could have exploited the comovement of stock markets for high-technology firms to predict stock returns.

When predicting stock returns in real time, investors should not only rely on information on the comovement of stock markets. They should also consider a large number of forecasting variables to be potentially relevant for forecasting stock returns. We assume that investors consider the following variables, summary statistics of which are given in Table 1:

- Investors use the relative three-month interest rate (RTB) to predict returns in stock markets for high-technology firms. We calculated RTB as the three-month interest rate based on Wednesday quotations minus the moving average of the preceding 12 weeks.
- Investors use the relative government bond yield (RGB) to predict returns in stock markets for high-technology firms. We calculated RGB as the 10-year government bond rate based on Wednesday quotations minus the moving average of the preceding 12 weeks.
- Investors base their forecasts of returns in stock markets for high-technology firms on the term spread (TSP). We calculated TSP as the government bond rate minus the three-month interest rate based on Wednesday quotations.
- Investors base their forecasts of returns in stock markets for high-technology firms on the relative money market rate (RMM). We calculated RMM as the overnight interest rate on Wednesday quotations minus the moving average of the preceding 12 weeks. In the case of France, no overnight interest rate was available. Therefore, we used the one-month interest rate.

- Investors use the returns on countrywide stock market indexes to predict returns in stock markets for high-technology firms. We calculated returns on countrywide stock market indexes from MSCI countrywide performance indexes based on Wednesday quotations.

Other authors have used similar variables to analyze the predictability of stock returns (see, for example, Campbell (1987), Chen et al. (1986), Chen (1991), and Rapach et al. (2000)).

4. Empirical Results

We present our empirical results in three steps. In the first step, we report how often domestic and foreign variables were useful for predicting returns in European stock markets for high-technology firms. In the second step, we report how accounting for the comovement of stock markets would have affected the performance of simple trading rules. In the third step, we report the results of tests for market timing.

4.1 Which Variable Helped to Forecast Stock Returns in Real Time?

In Table 3, we report how often the variables that are in the information set of our investor were included in the optimal forecasting models. We report results for the pre-crash and the post-crash subsample. The results illustrate that the relative usefulness of the variables in the information set of investors changed substantially across subsamples. There is also evidence of substantial variation across model-selection criteria. For example, as one would have expected, using the BIC model-selection criteria motivated investors to select parsimonious forecasting models that contain only few variables.

Table 3:
Inclusion of Variables in the Optimal Forecasting Models

	Germany			France			United Kingdom		
	ACD	AIC	BIC	ACD	AIC	BIC	ACD	AIC	BIC
					Pre-crash sample				
RTB	79	67	62	71	61	14	83	70	49
RGB	44	27	23	84	75	8	79	62	33
TSP	31	4	1	20	16	14	74	66	39
RMM	14	10	10	63	59	21	33	1	0
Returns total market	15	11	0	63	48	16	68	29	2
Returns NASDAQ	24	5	2	71	19	0	29	6	5
Returns Neuer Markt	12	0	0	56	50	14	16	0	0
Returns Nouveau Marché	20	19	11	36	8	36	7	2	2
Returns AIM	15	4	2	42	39	31	70	66	67
					Post-crash sample				
RTB	68	62	14	58	14	0	38	17	2
RGB	12	8	0	22	17	3	37	22	13
TSP	83	66	65	81	69	79	86	80	57
RMM	30	0	0	37	1	0	73	22	5
Returns total market	5	0	0	18	7	0	82	37	29
Returns NASDAQ	0	0	0	2	0	0	62	62	62
Returns Neuer Markt	19	0	0	69	61	0	0	0	0
Returns Nouveau Marché	31	6	0	2	0	0	55	10	0
Returns AIM	42	21	20	99	88	21	46	23	11

Note: This table summarizes (in percent) how often variables are included in the optimal forecasting models for one-step-ahead stock returns under the three selection criteria ACD, AIC, and BIC. The pre-crash (post-crash) subsample is 1997:1–2000:3 (2000:4–2005:6).

Our results highlight that the cross-Atlantic comovement of stock markets for high-technology firms underwent substantial changes across subsamples. Our results indicate that information on the cross-Atlantic comovement of stock markets was less useful for forecasting stock returns in the Neuer Markt and the Nouveau Marché in the post-crash than in the pre-crash subsample. The usefulness of NASDAQ returns for forecasting stock returns in the Neuer Markt and the Nouveau Marché was negligible in the post-crash subsample. In sharp contrast, the informational content of NASDAQ returns became more useful for forecasting stock returns in the AIM in the post-crash subsample. In fact, under all model-selection criteria, NASDAQ returns were included in the optimal forecasting model for the AIM in 62% of all forecasting models in the post-crash subsample. Thus, while the cross-Atlantic comovement of stock markets became less useful over time in the case of the Neuer Market and the Nouveau Marché, accounting for cross-Atlantic comovement of stock markets became more useful over time in the case of the AIM.

With regard to the usefulness of the inter-European comovements of stock market returns for forecasting stock returns, we found that stock returns in the AIM were less useful for forecasting stock returns in the Neuer Markt and the Nouveau Marché in the pre-crash than in the post-crash subsample. Thus, with regard to the Neuer Markt and the Nouveau Marché, it seems that returns on the AIM were a substitute for NASDAQ returns in the optimal forecasting models in the post-crash subsample. Further, our results suggest that returns in the Neuer Markt and the Nouveau Marché did not contain much information with respect to subsequent returns in the AIM. Thus, the returns in the AIM were to a large extent disconnected from the returns in other European stock markets for high-technology firms. Rather, the returns in the AIM showed a strong comovement with NASDAQ returns. The relative usefulness of the returns in the Nouveau Marché for forecasting the returns in the Neuer Markt in the pre-crash and in the post-crash subsample depends on the selection criterion being used. The model-selection criterion also plays an important role for the analysis of the relative usefulness of the returns in the Neuer Markt for forecasting the returns in the Nouveau Marché.

Our results further indicate that the usefulness of accounting for the autocorrelation of stock returns has changed over time. We deem this to be an important result because the autocorrelation of stock returns has often been used in the empirical finance literature to measure predictability of stock returns. The usefulness of the autocorrelation of returns is reflected in the inclusion of own lagged stock returns in the optimal forecasting models. The autocorrelation of returns was low in the case of the Neuer Markt, irrespective of the model-selection criterion and the optimal forecasting model being considered. In contrast, autocorrelation of returns was relatively useful for forecasting stock returns in the case of the Nouveau Marché and the AIM in the pre-crash subsample. The relevance of autocorrelation of returns declined substantially in the post-crash subsample. We conclude that the predictability of stock returns, as measured in terms of the autocorrelation of stock returns, has decreased over time in European stock markets for high-technology firms.

The inclusion of domestic variables in the optimal forecasting models depends on the stock market, the sample period, and the model selection criteria being analyzed. The variable RTB was useful for forecasting stock returns in the Neuer Markt in both subsamples. It was also a key variable for forecasting stock returns in the Nouveau Marché and the AIM in the pre-crash subsample but less so in the pre-crash subsample. The variable RGB was more useful for forecasting stock returns in the Neuer Markt, the Nouveau Marché and the AIM in the pre-crash subsample than in the post-crash subsample. The variable TSP was included in the optimal forecasting model of the Neuer Markt and the Nouveau Marché very often only in the post-crash subsample. By contrast, the variable

TSP was included in the optimal forecasting models of the AIM very often in both subsamples. The variable RMM was not included very often in the case of the Neuer Markt, while it was more often included in forecasting models of the Nouveau Marché and the AIM in the pre-crash sample.

4.2 Did Trading Rules Perform Well in Real Time?

A key question is whether accounting for the comovement of stock markets for high-technology firms would have improved the performance of simple trading rules. In order to answer this question, we report in Table 4 the investor's terminal financial wealth implied by the different trading rules. We report results for an investor who neglects transaction costs and for an investor who accounts for transaction costs. We assumed either no transaction costs or transaction costs of 0.1 of a percent for stocks and bonds (see also Pesaran and Timmermann (1995)).

The implications of accounting for the comovement of stock markets for terminal financial wealth are remarkably different across subsamples. As regards the Neuer Markt, the investor would have benefited from including information on the comovement of stock markets in the optimal forecasting model in the pre-crash subsample under the BIC model-selection criterion if transaction costs are neglected. When transaction costs are taken into account, in contrast, it would have been better for the investor, irrespective of the model-selection criterion being used, to neglect information on the comovement of stock markets. In the post-crash subsample, the investor would have been better off if information on the comovement of stock markets had been taken into account, provided transaction costs are assumed to be zero. When transaction costs are high, in contrast, neglecting information on the comovement of stock markets would have been better, in terms of terminal financial wealth, for the investor.

Table 4:
Terminal Financial Wealth

	Transaction costs	ACD		AIC		BIC	
		With…	Without…	With…	Without…	With…	Without…
		…Comovements					
		Neuer Markt					
Pre-crash sample	Zero	467	496	427	451	459	456
	High	362	408	338	379	378	390
Post-crash sample	Zero	31	31	48	46	64	63
	High	16	18	31	31	45	46
		Nouveau Marché					
Pre-crash sample	Zero	539	599	441	594	559	523
	High	365	460	279	429	353	339
Post-crash sample	Zero	64	48	78	36	60	52
	High	23	31	34	25	44	38
		AIM					
Pre-crash sample	Zero	335	324	299	306	310	310
	High	238	245	221	231	212	212
Post-crash sample	Zero	120	118	112	110	114	118
	High	51	61	56	53	59	56

Note: Initial wealth is given by 100 units of money. If the forecast of one-step-ahead stock-returns is positive, the investor invests in stocks. If it is negative the investor invests in bonds. The investor does not make use of short selling, nor does the investor use leverage when deciding whether to invest in stocks. High transaction costs are calibrated as 0.1 of a percent for shares and bonds, respectively. The pre-crash (post-crash) subsample is 1997:1–2000:3 (2000:4–2005:6).

As regards the Nouveau Marché, the results are similar to those for the Neuer Markt. In the pre-crash subsample, accounting for the international comovement of stock returns would have increased the investor's terminal financial wealth under the BIC model-selection criterion, but not under the ACD and AIC model-selection criteria. The results for the post-crash subsample suggest that dropping foreign stock returns from the set of variables considered to be useful for forecasting stock returns in the Nouveau Marché would have decreased the investor's terminal financial wealth. The only exception arises under the ACD criterion when transaction costs are assumed to be high.

The results for the AIM are somewhat different from those for the Neuer Markt and the Nouveau Marché. In terms of terminal financial wealth, it would often have been optimal to neglect information on the international comovement of stock returns. Exceptions are the ACD criterion in the pre-crash subsample when transaction costs are neglected, the AIC criterion in the post-crash sample when transaction costs are neglected, and the BIC criterion in the pre-crash (post-crash) subsample when transaction costs are zero (high).

In Table 5 we report the Sharpe ratios for the investor's trading rules. We report Sharpe ratios for the pre-crash and the post-crash subsample. The results for the Neuer Markt indicate that the Sharpe ratios would have been higher in the pre-crash and the post-crash subsample if information on the international comovement of stock returns had not been considered to be potentially useful for forecasting stock returns.

An investor in the Nouveau Marché who used the ACD and the AIC model-selection criteria would have increased the Sharpe ratios upon neglecting information on the international comovement of stock returns in the pre-crash subsample. In the post-crash-subsample, in contrast, accounting for the international comovement of stock returns would often have increased the Sharpe ratios. This result is interesting because it corroborates our result that, in terms of the investor's terminal financial wealth, the comovement of stock markets became more useful in the post-crash subsample.

Table 5:
Sharpe Ratios

Transaction costs		Pre–crash subsample With…	Pre–crash subsample Without...	Post–crash subsample With...	Post–crash subsample Without...
		…Comovement			
		Neuer Markt			
Zero	ACD	0.235	0.240	–0.178	–0.168
	AIC	0.214	0.217	–0.122	–0.116
	BIC	0.219	0.218	–0.076	–0.071
High	ACD	0.197	0.211	–0.278	–0.240
	AIC	0.180	0.192	–0.198	–0.181
	BIC	0.191	0.195	–0.133	–0.120
		Nouveau Marché			
Zero	ACD	0.308	0.319	–0.074	–0.112
	AIC	0.262	0.303	–0.044	–0.172
	BIC	0.306	0.290	–0.094	–0.113
High	ACD	0.235	0.268	–0.239	–0.178
	AIC	0.179	0.242	–0.193	–0.231
	BIC	0.220	0.209	–0.151	–0.165
		AIM			
Zero	ACD	0.384	0.372	0.102	0.094
	AIC	0.349	0.358	0.061	0.050
	BIC	0.366	0.366	0.079	0.093
High	ACD	0.268	0.279	–0.345	–0.268
	AIC	0.247	0.262	–0.290	–0.295
	BIC	0.236	0.236	–0.274	–0.280

Note: We computed the Sharpe ratio in two steps. In the first step, we computed excess returns generated by a trading rule by subtracting the riskless short–term interest rate from the return on an investment strategy at the end of the investment horizon. In the second step, we divided the excess returns by the standard deviation of returns implied by an investor's trading rule. High transaction costs are calibrated as 0.1 of a percent for shares and bonds, respectively. The pre–crash (post–crash) subsample is 1997:1–2000:3 (2000:4–2005:6).

An investor who invested in the AIM would often have increased the Sharpe ratios upon neglecting information on the international comovement of stock returns in the pre-crash subsample. In the post-crash subsample, in contrast, four out of the six reported Sharpe ratios are higher if information on the international comovement of stock returns is considered to be potentially relevant for forecasting stock returns. Thus, in terms of the Sharpe ratios, an investor who invested in the AIM would have benefited to a much higher extent from accounting for the international comovement of stock markets in the post-crash subsample than from doing so in the pre-crash subsample. The results summarized in Table 3 suggest that this was mainly due to the influence of NASDAQ returns on the returns in the AIM.

4.3 Was Monitoring the International Comovement of Stock Returns Useful for Timing the Market?

In order to analyze the implications of our results for market timing, we used the nonparametric test for market timing developed by Pesaran and Timmermann (1992). Table 6 summarizes the test results. The test results for the Neuer Markt provide no evidence of market timing, irrespective of whether information on the international comovement of stock returns is taken into account. The test results for the Nouveau Marché, in contrast, are significant in the pre-crash subsample, but not in the post-crash subsample. For the AIM, the test results are insignificant in the pre-crash and post-crash subsample for the three model-selection criteria under consideration.

The most interesting result is that evidence of market timing does not depend upon whether an investor considered information on the comovement of stock markets to be of potential relevance for forecasting stock returns. Thus, the comovement of stock markets per se did not improve an investor's market-timing ability. In consequence, if market-timing ability is interpreted as evidence of market inefficiency, the comovement of stock markets per se was not a major source of market inefficiency.

Table 6:
Tests for Market Timing

	ACD		AIC		BIC	
	With…	Without…	With…	Without…	With…	Without…
	…Comovement					
			Neuer Markt			
Pre–crash sample	–1.44	–0.59	–1.47	–0.42	–0.57	0.06
Post–crash sample	0.10	–2.02	–1.35	–1.75	–0.53	–0.66
			Nouveau Marché			
Pre–crash sample	1.29	2.53	2.49	2.94	1.92	2.69
Post–crash sample	–1.15	–0.55	–0.92	–1.90	–0.92	–0.66
			AIM			
Pre–crash sample	1.47	1.26	1.00	1.21	0.68	0.68
Post–crash sample	–1.37	0.02	–1.06	–0.02	–0.51	0.90

Note: This table reports results of nonparametric tests for market timing developed by Pesaran and Timmermann (1992). The Pesaran-Timmermann test is a one-sided test. Positive and significant values of the test indicate market-timing skills. The test has asymptotically a standard normal distribution. The pre-crash (post-crash) subsample is 1997:1–2000:3 (2000:4–2005:6).

5. Concluding Remarks

We analyzed the predictability of returns in European stock markets for high-technology firms. Using a recursive modeling approach, we documented how the usefulness of accounting for the comovement of stock markets for predicting stock returns changed over time. Our results indicate that the optimal forecasting models often include NASDAQ returns for the Neuer Markt and the Nouveau Marché in the pre-crash period, but not in the post-crash period. In the post-crash period, the AIM returns became more useful than NASDAQ returns for forecasting purposes. In contrast, the comovement of NASDAQ returns and the returns in the AIM were more pronounced in the post-crash period than in the pre-crash period. We also analyzed, in terms of investor's terminal financial wealth and in terms of Sharpe's ratio, the implications of changes in the comovement of stock markets for the performance of simple trading rules. These implications varied substantially across model-selection criteria and subsamples. It is, thus, not possible to give a universally applicable, simple answer to the question whether investors should account for information on the comovement of stock markets for high-technology firms when making their investment decisions. Finally, we found that accounting for information on the comovement of stock markets per se does not affect an investor's market-timing skills.

How can our results be interpreted in economic terms? Our results suggest that the answer to this question differs across the pre-crash and the post-crash subsample. Our result that strong cross-Atlantic return links existed between stock markets for high-technology firms in the *pre-crash period* for the Neuer Markt and the Nouveau Marché, but not for the AIM, could be due to the industry composition of the European indexes and the over-evaluation of IT stocks at the end of the 1990s. Such an interpretation of our results would be consistent with the results reported by Hon et al. (2005), who have shown that accounting for industry-specific effects is important for understanding the changes in the international comovement of stock returns that took place around March 2000 and for understanding the relevance of contagion effects.

To illustrate our argument, it is worth noting that of the 340 firms that listed their stocks on the Neuer Markt between 1997 and 2000, 64 percent were operating in either the information and communications industry or in a related industry (Deutsche Börse (various issues)). Of the 160 firms that listed their stocks on the Nouveau Marché between 1996 and 2000, almost 70 percent were operating in this or a related industry (Bourse de Paris (various issues)). In contrast, firms listed on the AIM were less information-technology-oriented than those listed on the Neuer Markt and the Nouveau Marché. Of the 275 firms that listed their stocks on the AIM between 1998 and 2000, only 22 percent were operating in the IT industry or in a related industry (London Stock Exchange (various issues)). Thus, investors' beliefs about the return prospects of the IT industry might have been one reason why we found cross-Atlantic return linkages between the NASDAQ and the Neuer Markt and the Nouveau Marché, but not between the NASDAQ and the AIM in the pre-crash subsample.

The difference between European stock markets for high-technology firms with regard to cross-Atlantic return comovement in the *post-crash subsample* might reflect structural differences between Germany, France, and the United Kingdom. According to a recent study by Beck and Levine (2002), the United Kingdom resembles the United States insofar as it is a leading market-based economy with high stock market capitalization. In contrast, France and Germany are both bank-based economies with comparatively low stock market capitalization. Thus, structural differences may have been one determinant of the relevance of cross-Atlantic comovements in stock returns in stock markets for high-technology firms.

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