# An Analysis of Causality in the Relationship between Analysts' Forecast Revisions and Market Prices: The European Experience

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Abstract: The information provided by equity analysts to the market has been one of the most heavily researched areas in finance over the 30 years. One important question highlighted in this research has been the extent to which the information provided by sell-side analysts is useful to the market, especially given the pressures to which the analysts are subjected that can cause biases in the information that they provide. In this paper we attempt to shed some light on the extent of the information provided by the analysts by examining the direction of the causation between the revisions in the analysts' earnings forecast and the movement in stock prices. We find in the major European markets that the analysts are largely price followers with their earnings revisions being heavily influenced by recent price movements whereas the feedback from earnings revisions to price movements is minimal

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The role of financial markets is to set prices based on the interpretation by the participants of the available information. One important group in this price setting process is the equity analysts who perform a key intermediary role in collecting and interpreting information and then passing on their assessment to the wider community in such forms as earnings forecasts and stock recommendations. This information provided by the analysts becomes an important input into the investment decision making process of both institutions and individual investors. Therefore, analysts are in a position to influence the prices of securities within markets and represent an important cog in making these markets efficient. For decades now, we have seen an expanding volume of evidence, which questions not only the efficiency of equity markets but also the contribution made by analysts towards efficient pricing within these markets. There is little question that the analysts have an impact on markets but there is a question as to whether they perform to the best of their abilities, especially as they would appear be subject to a number of influences which might bias the quality of the information that they provide (Jegadeesh et al, 2004)

The focus of this paper is on the extent to which the analyst influences market prices and equally on the extent to which market prices influence the analysts. In a truly efficient market, the prices existing at any point in time would represent the best available summary of all the information available in the market. Given this is the case, it may well be that the analysts when determining the information that they are going to release to the market, do so with one eye on trends in market prices which may reflect information either that is not available to them or that they have failed to fully incorporate into their forecasts. The economic value of the role that analysts perform within markets is largely dependent on them providing new and timely information to markets.

In an attempt to provide some interesting insights into the economic role of the financial analysts, we address the vexing question of causation: does the information provided by the analysts lead the movements in market prices or is it that the movements in market prices that influence the information provided by analysts. There is only limited evidence on this issue even within the US markets and almost no direct evidence elsewhere (Ramnath et al., 2008). In this paper, we extend the amount of available evidence by evaluating the causation between changes in the consensus earning forecast by analysts and movements in stock prices across several major European markets and regions within these markets.

Our major finding is that for the overall European markets there is clear evidence to support that it is the movement in prices that heavily influences the earnings forecast by analysts with there being little or no feedback from earnings forecasts revisions back to future prices. This same finding also applies to each of the countries and regions within Europe that is included in our data set and thus questions the extent of the information contained in these forecasts.

In section 1 of the paper we discuss a selection of the available evidence relevant to the question that we are addressing. The data utilised in this study and the methods that we employ are outlined in Section 2. We go on in Section 3 to report and discuss our major findings while we provide a brief summary of the paper in Section 4.

## I. Literature

Studies that have addressed the information provided by analysts date back over 30 years while we have more than a 100 years of research on the behaviour of stock prices over time. For a decade or more after Fama (1970) categorised market efficient, the popular view was that stock prices in the major equity markets were efficiently priced (Jensen, 1978) with analysts being presumed to be a contributing factor towards this efficiency. However in more recent times, even the most devoted followers of market efficiency have begun to question its validity in the face of difficult-to-explain, documented anomalies such as post announcement drift (Foster et al, 1984), price momentum (Jegadeesh and Titman (1993), and the value premium (Lakonishok et al, 1994). The implication of these three types of anomalies is that stock prices underreact to the release of new information, trend and then reach a level where they exceed fair value (Lee and Swaminathan, 2000).

The question remains as to what contribution analysts make to this pricing process? The initial studies of analyst forecasts were quick to identify that their consensus earnings forecasts were overly optimistic (Brown, 1995; Dreman and Berry, 1995) and to question whether they were any more accurate than those that could be obtained from naïve forecasting approaches (Fried and Givoly, 1982; Bird et al, 2000)[1]. Numerous studies have attempted to provide explanations for these findings with contributing factors proving to be internal pressures placed on analysts to generate turnover and maintain corporate clients, the need to

[1] It is true that the optimism in analysts' forecasts would seem to have disappeared under the guidance of corporate management now more interested in ensuring that their company met or beat the consensus earnings forecast number. Although the accuracy of the earnings forecasts improved at this time, it did not mean that the analysts were under any less pressure in formulating their forecasts nor that these forecasts have greater information content.

keep corporate management happy as they are an important source of analyst information, and a number of behavioural factors that impact on decision-making such as the natural human bent towards being overly optimistic.

The metric used in this study to gauge the information provided by analysts is the revision of their consensus earnings forecasts. One insight that we gain from the literature relevant to these revisions is that analyst tend to initially underreact to new information (Ramnath, 2002). It is significant that analysts would appear to contribute to the underreaction that has been found to apply to investors more generally. The other important insight that we gain from prior research is the tendency for analysts to herd in that they will play "follow the leader" in revising their forecasts in a particular direction. This herding behaviour is largely a consequence of behavioural and economic pressures which result in the perceived rewards from being close to the consensus figure outweighing the perceived costs.

The implications of these phenomena for the behaviour of the individual analyst is that he has a tendency to be slow in adjusting his earnings forecast to incorporate new information and may made several revisions before fully impounding the available information. Further, the herding means that the process for incorporating the full information into the consensus forecast will be somewhat tortuous with one analyst revising, then another and so on. The consequence being that trends are created in earnings forecast revisions that mirror the strong momentum that has been found to exist in prices.

With both revisions in consensus earnings forecasts and revision in stock prices following similar trends, the natural question to ask is which of the two is the leader in the process. There is important evidence to suggest that the drift process relating to the release of new information would be slower in the absence of analysts (Hong et al, 2000) but this does not necessary mean that the analysts are leaders in the process but rather that they exist in sufficiently large numbers to speed up what otherwise would be an even slower adjustment process.

We turn in the next section to outline the methods that we employ and the data on which we depend to address this issue of causation.

## Data and Methodology

### 2.1 The Data

Our sample includes 7990 firms from the following 15 European markets: The United Kingdom, France, Austria, Belgium, Greece, Ireland, Italy, The Netherlands, Portugal, Spain, Denmark, Finland, Norway and Sweden. We examined the larger European markets separately (UK, France and Germany) but grouped the remaining countries into the “Other Europe” region and the Scandinavian countries. The analysis was conducted over a sample period ranging from January 1989 to December 2007, using return data provided by GMO UK, and data on sell-side analyst’s earnings forecasts provided by I\B\E\S. Given the focus of the article, we concentrated our attention on two variables:

- *Accumulated excess returns*: computed as the ratio between the absolute return of each stock over a six-month period and the geometric average of the returns across all stocks in the market considered over the same six-months;
- *6-month analyst’s EPS forecast revisions*:

$$Forecast\_\mathrm{Re}visions_{i,t} = \sum_{j=0}^{6} \frac{EST_{i,t-j} - EST_{i,t-j-1}}{EST_{i,t-j-1}}$$

The indicator, expressed as a percentage variation, is given in month *t* by the analysts’ consensus (median) FY1 earnings forecast for firm i in month *t-j* ($EST_{i,t-j}$) minus the same consensus (median) *FY1* estimate in month *t-j-1* ($EST_{i,t-j-1}$). The difference is then divided by the median *FY1* estimate in month *t-j-1* ($EST_{i,t-j-1}$) in order to scale the criterion, with *j* lagged up to 6 months (length of the formation period minus one).

In Table I we provide statistics on the main characteristics of the two variables in terms of their median, standard deviation, min and max values as well as the total number of stocks for each country/region.

**Insert Table I here.**

The analysis has been conducted not only by countries/regions but also by market capitalisations; in each month, we rank the stocks in the European area by their market cap and we divide them in three equal clusters: small, medium and large cap. We then select just the two extreme clusters (European Small and Large Caps).

### 2.2 The Methodology

As already stated, the purpose of this article is to analyse the existence across stocks of a lead-lag effect between excess returns and the revisions in the analyst's consensus EPS forecast. The relationship between these two variables is investigated by applying the following three tests in order to examine:

a. The *existence* of a causal relationship between excess returns and revisions in analyst forecasts. For this purpose, we computed the frequency of both exogenous causation and contemporaneous feedback existing between the variables considered by using a Granger [1969] causality test[2];
b. The *sign* (positive or negative) of the relation existing between the variables[3]. This task is achieved by simulating in period *t* a 1-unit positive shock (impulse) generated in one variable (say excess returns) and visualising the resulting response(s) of another variable (say changes in analyst forecasts) from period *t+1* onwards;
c. The *magnitude* of causation[4], obtained by attributing back the appropriate proportion of total variation (in the residuals) in one variable (say excess returns) induced originally by shocks in other variables.

A detailed description of the methodology is to be found in the Appendix.

As a preliminary to conducting this analysis we test for stationarity in the data series for each stock. For this purpose we used the Augmented Dickey and Fuller test (hereafter ADF)[5] which considers the case where the residuals are not white noise. Through a visual analysis of

[2] This test consists of regressing an endogenous covariance stationary $i^{th}$ variable $y_{i,t}$ on the past realizations of all the independent *j* variables $y_{j,t-p}$ (see Appendix B for more details on the Granger test).
[3] The computation and plotting of an impulse-response function is a practical way to visually illustrate the behaviour of the variables considered in response to various shocks. In this paper, we adopt the Choleski decomposition in order to control for any contemporaneous feedback running either ways between FCF, CSR and corporate performance measures. After simulating a 1-unit shock in the (assumed) leading variable, we track the responses of the variables following in the order of causation for 10 periods. The result is a methodology able to disentangle the extent of leading and consequent lag effects.
[4] Once we determined the history of the relation between the variables through the impulse-response functions, we proceed with an analysis of the magnitude of the responses that take place in the 10 periods after the initial shock is simulated. The magnitude is calculated by first decomposing the variance of the residuals of the forecasting errors and then attributing this variance back to variable that caused it (see the appendix B for more details on the calculation).
[5] Dickey and Fuller (1979)

the series, we decided to use an ADF estimated with an intercept and a constant term putting aside the case of a deterministic trend. Therefore, the test involves estimating the equation:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{k} \beta_i \Delta y_{t-i+1} + \varepsilon_t \qquad (1)$$

where: $\gamma = -(1 - \sum_{ii=1}^{k} a_{ii})$

$$\beta_i = -\sum_{r=1}^{k} a_r$$

As stated by Dickey and Fuller, the purpose in adding the terms $\Delta y_{t-i+1}$ is to allow for an ARMA error process. The null hypothesis is $H_0$: $\gamma = 0$ (the series contains a unit root) and $[y_t]$ is said to be stationary if one can reject $H_0$. After conducting this analysis, we excluded all stocks for which we could not reject $H_0$ in order to ensure that we did not draw any erroneous conclusion in those cases where the data series was non-stationary.

## 3. Results

### 3.1 The Granger causality test

We applied the Granger causality test to all the stationary series and computed the percentage of the times when the returns Granger cause the forecasts, and vice versa, for all the markets and capitalization clusters. In order to throw light on the extent to which the leading variable (as indicated in Table II) influences or explains the behaviour of the other variable, we compute across all stocks, in each cluster considered, the average adjusted $R^2$ obtained from the following two autoregressive processes:

a. Univariate VAR: the return (forecasts) is the dependent variable and the lagged values of returns (or forecasts) are independent;

b. Bivariate VAR: the return (forecasts) is the dependent variable and the lagged values of both returns and forecasts are the independent variables.

Perhaps more importantly we also report in parenthesis in Table II the causality percentages on both variables. These percentages are the result of counting the number of stocks where the causality is significant at least at the 1% level. Of course, there are instances where this significance works in both directions and the percentage of occasions where this occurs is reported in the last row.

**Insert Table II here**

First we will discuss the Adjusted-$R^2$ in the case of both the univariate and bivariate analysis which tell us a very similar story at both the aggregate Europe level and for each of the country/regions. From the univariate analysis, it is clear that there is serial-correlation in the excess returns which is not a surprising finding given the ample evidence on the profitability of momentum investing across most markets including the European markets. However, the finding is universal that past earnings revisions do not explain future earnings revisions which is a somewhat surprising finding given the evidence to suggest that there is a fair amount of herding behaviour by analysts in revising their earnings forecasts (Welch, 2000). The increment in the Adjusted-$R^2$ when the second explanatory variable is introduced provides some insights into the question of causation. In almost all markets, the increase in the Adjusted-$R^2$ when adding the other variable (e.g. lagged excess returns [forecast revisions] when the dependent variable is forecast revisions [excess returns]) is relatively small and of similar magnitude. The only obvious exception to this being in Scandinavia where the addition of excess returns explains much more of the variability in earnings forecast revisions than when earnings revisions are added to explain excess returns.

We see a similar, but not quite identical, story when we examine the number of instances where at the stock level, it can be shown that excess returns (forecast revisions) has a significant impact on forecast revisions (excess returns). At the aggregate European level, and in the case of the UK and Other Europe, the percentages prove to be about equal which means that it is difficult to tell a causation story. The instances where the direction would seem to run in both directions are limited to between 10 and 16% of stocks in these three cases which also would seem to deny the existence of a feedback loop. In the case of France and Germany, there are many more cases where excess returns lead forecast revisions (approximately 60%) than vice versa (approximately 40%) whereas in the case of Scandinavia the proportions are the other way around with more instances where it is the forecast revisions which lead excess returns.

### 3.2 Further tests

The available evidence on causation commonly does not go beyond conducting a Granger test (Forbes and Skerratt, 1992), but the results obtained with a Granger test tell us more about the percentage of instances when one variable significantly causes the other, but little or nothing about the sign and magnitude of this effect. A more interesting investigation could be to identify empirical regularities as a result of an examination of the informative and predictive content of the dynamic interaction among variables as represented by either the *direction* of the response of a variable to the independent variables used in the system or the *magnitude* of the impact of one variable on the other variables. For this reason, we first simulate in period *t* a 1-unit positive shock (impulse) generated in one variable (say, excess returns) and then visualise the resulting response(s) of another variable (forecast revisions) from period *t+1* onwards. After observing the direction of the relationship, we can then decompose the forecast error variance (of the residual) in each autoregression in order to quantify also the magnitude (relevance) of the response of the variable to the shocks induced in the others.

*Impulse Response Function and variance Decomposition*

The last step in our paper is to plot the impulse-response function in order to provide further evidence on the sign and the timing of the adjustment in the returns and/or forecasts in the two cases of causal priority. In Figure I, we graph two subplots for each country/region, and level of capitalisation: in the upper left-hand (right-hand) panel we illustrate the response of excess returns (forecast) to a shock only in the forecast (excess returns), while in the lower left-hand (right-hand) panel we illustrate the variance decomposition of these same relationships In order to provide greater clarity we also provide corresponding figures for these decompositions in Table III for all countries.

The results are all but identical for each of the country/regions. In every case, with the exception of France, there is a positive relationship between a shock to the excess return and the revision in analyst forecasts suggesting that positive (negative) momentum in the price is likely to result in an upward (downward) revision in the consensus analyst earnings forecast. In contrast the information from the instant response function suggests a negative relationship in all cases. However, the direction of the relationship is of little consequence without it being of economic significance. The variance decomposition illustrated in Figure 1 and reported in Table III clearly indicates that much of the variation in forecasts revisions are explained by prior price movements whereas there is a much weaker relationship between excess returns and prior forecasts revisions.

The conclusion that we draw from an analysis of the impulse response function and the variance decomposition are much more definite that what we can draw from the Granger causality analysis. The clear indication being that the analysts as a group when revising their forecasts are heavily influenced by the recent price history of the company's stock. This is consistent with previous evidence that a preference for "winners" (positive momentum stocks) is a consistent bias in the recommendations made by analysts (Azzi et al, 2006). One might assume that this bias is more applicable to small cap stocks which are subject to less in-depth analysis via the analysts community but our findings suggest that this is not the case as the momentum-chasing behaviour of the analysts seems to apply fairly equally to the large cap and the small cap stocks.

## 4. Conclusions

Numerous articles have concentrated their attention on the information provided by analysts with many investigating the impact that this information has on market prices. However, little evidence exists relating to the causality between analysts' information and stock price movements. In this paper, after ascertaining the degree of stationarity in the variables used, we employed an autoregressive process with monthly data to analyse this issue of causality within many countries/regions in Europe.

The use of a Granger test to determine the extent to which the lagged values of the variables cause each other provides somewhat mixed evidence. However when we extend the analysis to include the instant response function and variance decomposition, the one clear indication that we get is that analyst are heavily influenced by a stock's recent price movements when revising their earnings forecasts. In contrast the influence that these revisions have, at least at the consensus level, on future price movements is much more diminished and somewhat surprisingly negative.

This paper has provided some useful insights into the economic contribution of European analysts. In general the results have not been all that encouraging in that analysts would seem to provide information that the market perceives to not be of much incremental value over and above that which is already reflected in past price movements. Indeed, whatever evidence that there is suggests that the incremental information provided in the forecasts may be negative in value in most of the countries regions. This evidence is fairly consistent with previous evidence on the performance of financial analysts (Azzi et al, 2006) and suggests that further research is required to determine what is driving these results

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## Table I: Descriptive Statistics

The table shows over the period 1989 to 2007 for the entire sample (Europe) and also each country/region, the number of stocks in our sample and also the descriptive statistics of the distributions of the excess returns and the analyst's EPS forecast revisions.

| Excess Returns | Europe | Uk | France | Germany | Scandinavia | Others |
|---|---|---|---|---|---|---|
| Mean | -0.0001 | 0.000 | 0.000 | 0.000 | -0.001 | 0.000 |
| Median | -0.002 | -0.002 | -0.003 | -0.001 | -0.001 | -0.002 |
| Std Dev | 0.149 | 0.146 | 0.147 | 0.160 | 0.125 | 0.142 |
| Min | -0.446 | -0.441 | -0.395 | -0.469 | -0.403 | -0.435 |
| Max | 0.471 | 0.469 | 0.385 | 0.515 | 0.325 | 0.458 |
| Num obs. | 7990 | 2883 | 1020 | 1050 | 1285 | 1752 |

| Forecast Revisions | Europe | Uk | France | Germany | Scandinavia | Others |
|---|---|---|---|---|---|---|
| Mean | -0.001 | -0.001 | 0.000 | -0.002 | 0.001 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Std Dev | 0.214 | 0.110 | 0.300 | 0.350 | 0.542 | 0.472 |
| Min | -0.995 | -0.487 | -1.083 | -1.800 | -2.471 | -2.036 |
| Max | 0.923 | 0.435 | 1.051 | 1.138 | 2.679 | 2.238 |
| Num obs. | 7990 | 2883 | 1020 | 1050 | 1285 | 1752 |

# Table II

The table shows the results of a Granger test on bivariate vectors of autoregression on the stationary series of the Excess Returns (ER) and Forecast Revisions. In Panel A (B), we document the relation between the two variables in terms of the increase in the adjusted $R^2$ from the univariate (e.g. $ER_t$ on $ER_{t-1}$) to bivariate (e.g. $ER_t$ on both $ER_{t-1}$ and $ForecastRevisions_{t-1}$) autoregression. In the same tables we also report the percentages of Granger causality as well as the significance level, computed across all stocks in the European market. In the right side of the table we also added an additional column documenting the frequency of contemporaneous feedback existing between the variables in order to highlight the relevance of controlling for simultaneous impact of the two variables considered on each other. We also split the analysis at the level of each country/region.

| | | | | | | |
|---|---|---|---|---|---|---|
| | *Dependent Variable (Europe)* | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 24.3% | 27.8% | --- | 0.034 [49%] | 14.6% |
| | Forecast Revisions | 0.6% | 5.1% | 0.037 [51%] | --- | |
| | | | | | | |
| | | | | | | |
| | *Dependent Variable (UK)* | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 22.2% | 27.0% | --- | 0.026 [51%] | 16.1% |
| | Forecast Revisions | 0.9% | 5.7% | 0.041 [48%] | --- | |
| | | | | | | |
| | | | | | | |
| | *Dependent Variable (France)* | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 27.3% | 29.8% | --- | 0.038 [41%] | 10.0% |
| | Forecast Revisions | 0.4% | 3.6% | 0.052 [58%] | --- | |
| | | | | | | |
| | *Dependent Variable (Germany)* | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 27.0% | 31.5% | --- | 0.029 [42%] | 11.0% |
| | Forecast Revisions | 0.8% | 5.1% | 0.023 [57%] | --- | |
| | | | | | | |
| | *Dependent Variable (Scandinavia)* | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 26.9% | 28.4% | --- | 0.029 [58%] | 0.0% |
| | Forecast Revisions | 1.7% | 8.7% | 0.033 [42%] | --- | |

| | Dependent Variable (Others) | Adjusted-$R^2$ | | p-value [% causation] | | Simultaneous Feedback |
|---|---|---|---|---|---|---|
| | | univariate | bivariate | Excess Returns | Forecast | |
| | Excess Returns | 24.2% | 27.6% | --- | 0.035 [49%] | 11.9% |
| | Forecast Revisions | 0.5% | 4.3% | 0.042 [51%] | --- | |

# Table III

## Forecast Error Varian Decomposition by Countries

In this table we document the decreasing percentage value of the forecast error variance decompositions corresponding to each response function of Excess Returns (Forecast Revisions) over the following 10 lags to a standard 1-sigma shock in the error term of the Forecast Revisions (Excess Returns). These figures are documented for each country/region over the sample period 1989 to 2007.

| | Forecast Error Variance Decomposition (FEVD) | | | | |
|---|---|---|---|---|---|
| | UK | France | Germany | Scand. | Others |
| Lag | Response of FCST to shock in ER | | | | |
| 1 | 0.663 | 0.646 | 0.608 | 0.655 | 0.671 |
| 2 | 0.148 | 0.171 | 0.157 | 0.168 | 0.157 |
| 3 | 0.031 | 0.042 | 0.040 | 0.045 | 0.035 |
| 4 | 0.007 | 0.010 | 0.010 | 0.012 | 0.007 |
| 5 | 0.001 | 0.002 | 0.002 | 0.003 | 0.002 |
| 6 | 0.000 | 0.001 | 0.001 | 0.001 | 0.000 |
| 7 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 8 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 9 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 10 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

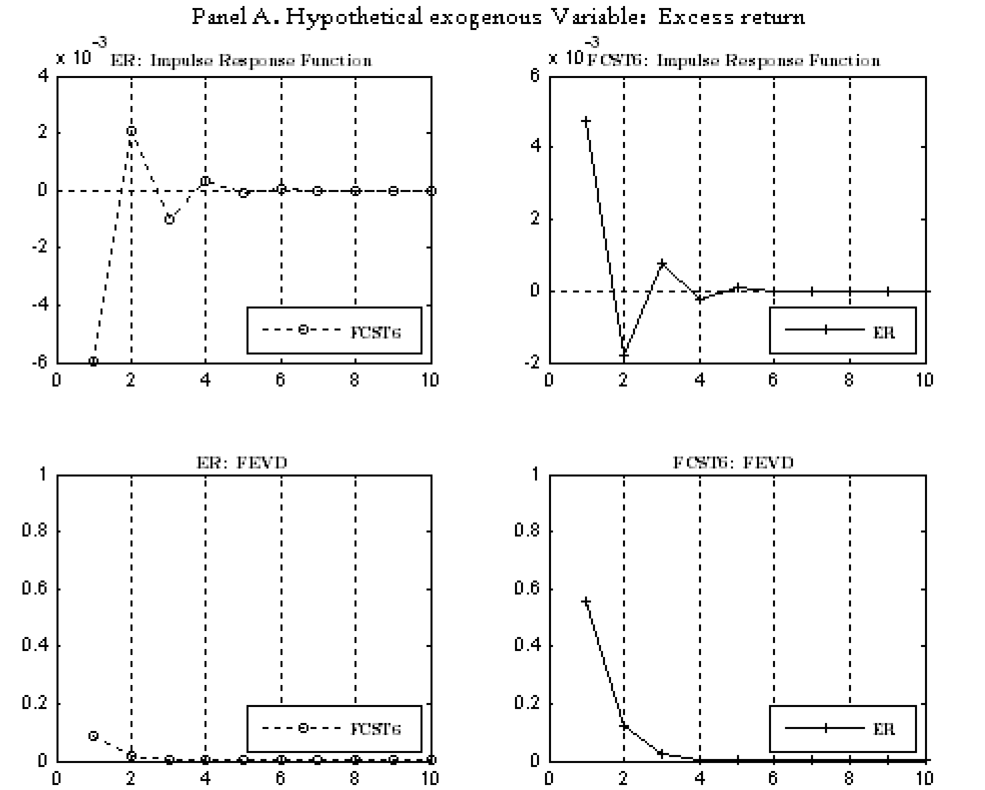
| | Forecast Error Variance Decomposition (FEVD) | | | | |
|---|---|---|---|---|---|
| | UK | France | Germany | Scand. | Others |
| Lag | Response of ER to shock in FCST | | | | |
| 1 | 0.265 | 0.255 | 0.221 | 0.365 | 0.159 |
| 2 | 0.015 | 0.016 | 0.014 | 0.021 | 0.015 |
| 3 | 0.003 | 0.004 | 0.002 | 0.004 | 0.002 |
| 4 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 |
| 5 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 7 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 8 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 9 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 10 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

# Figure I

## Impulse-Response Function across Different Countries/Regions

The figure shows the pattern of the impulse-response functions obtained with the *Choleski decomposition* and applied to the bivariate autoregressive processes in each country/region. We split each subplot (market) in two panels: the upper panel is the response of one variable to a shock in the other variable in the autoregression. The lower panel illustrates the forecast error variance decompositions corresponding to each response function. The shock is the standard 1-sigma change in the error term of the VAR models.

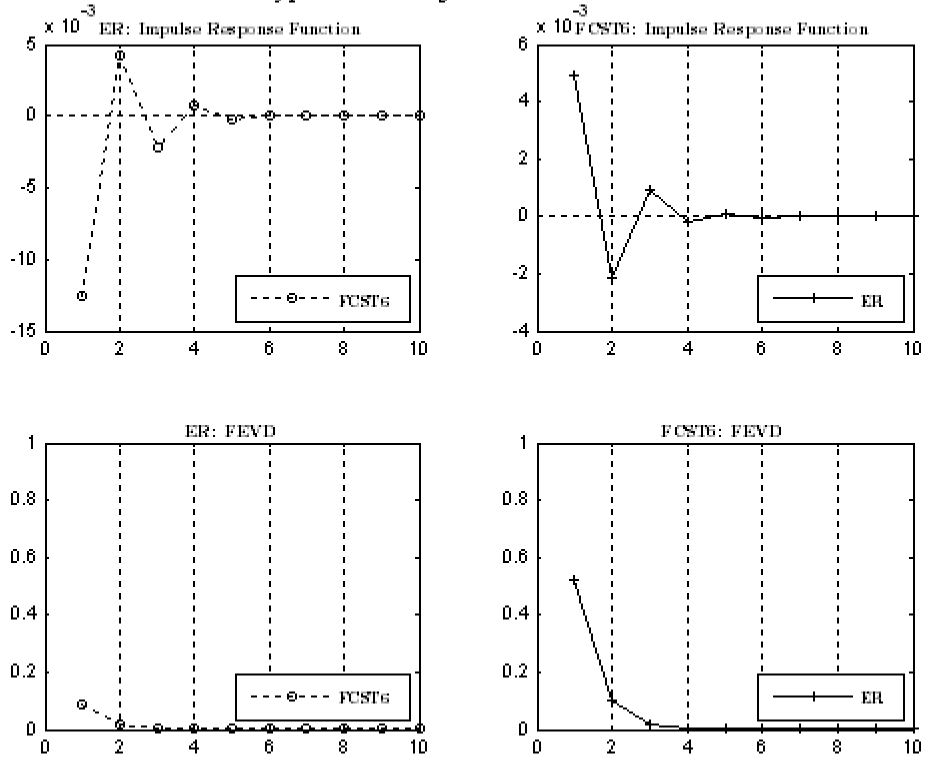
## Europe




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## UK

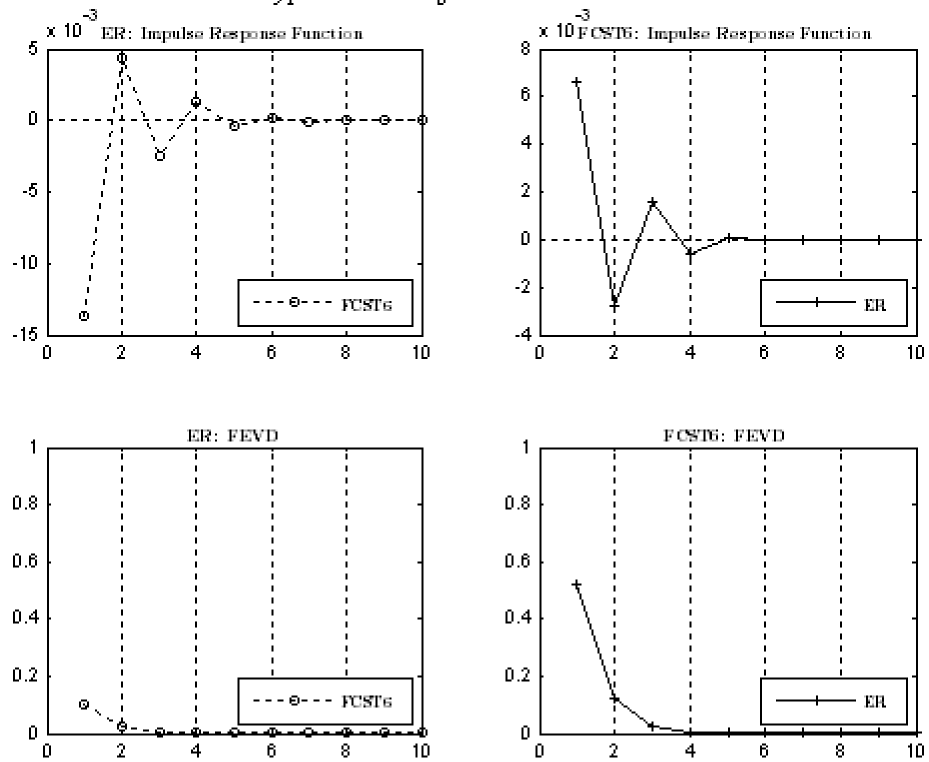
Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## Germany

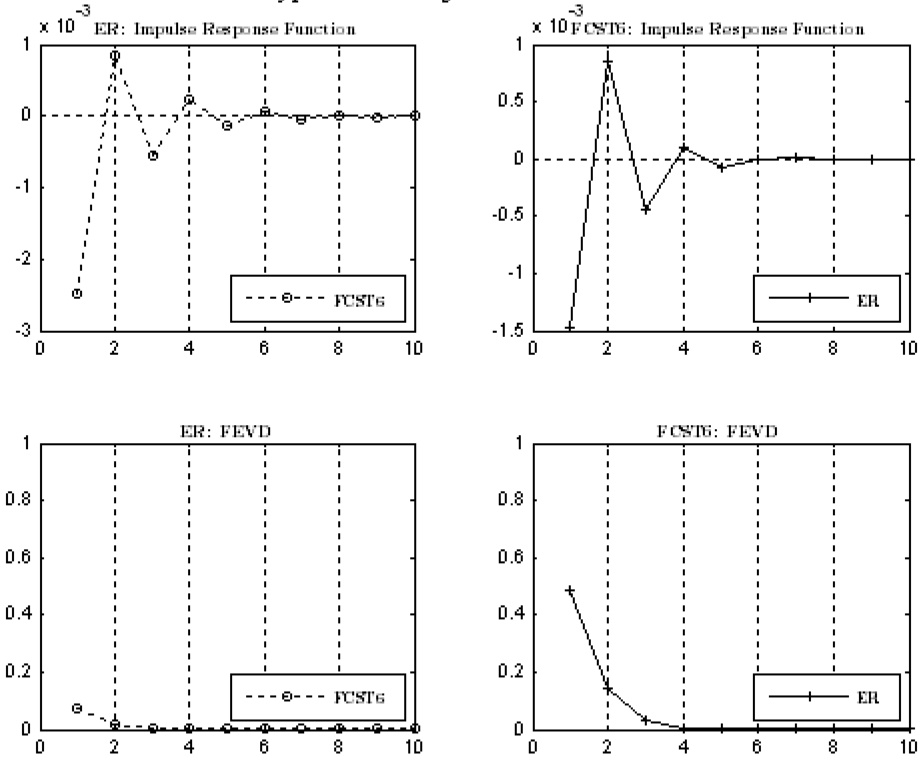
Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## France

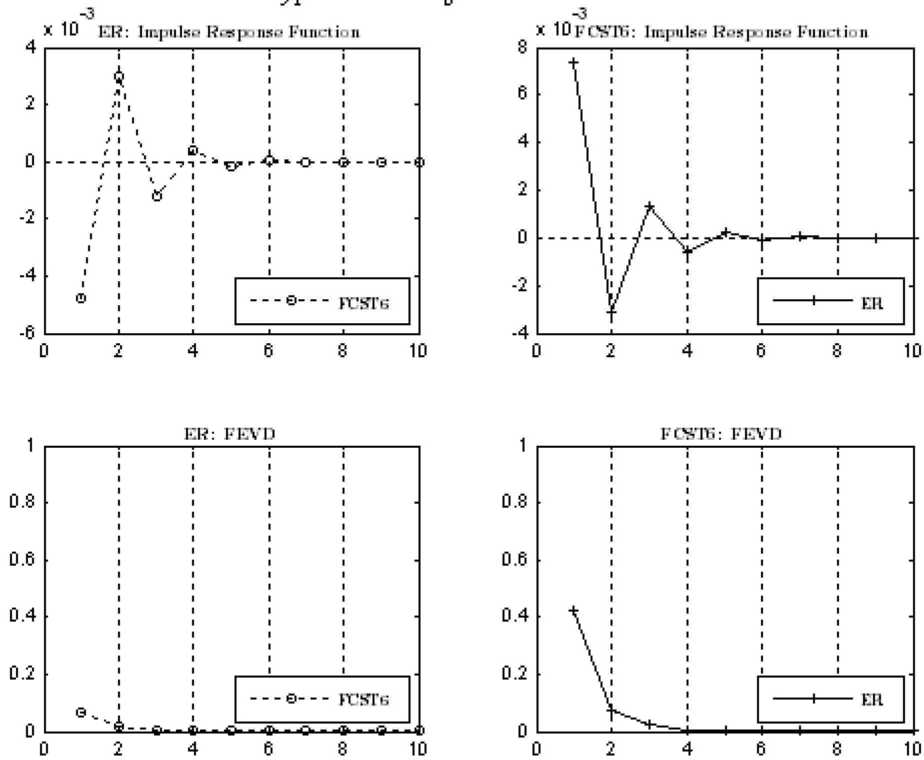
Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## Scandinavia

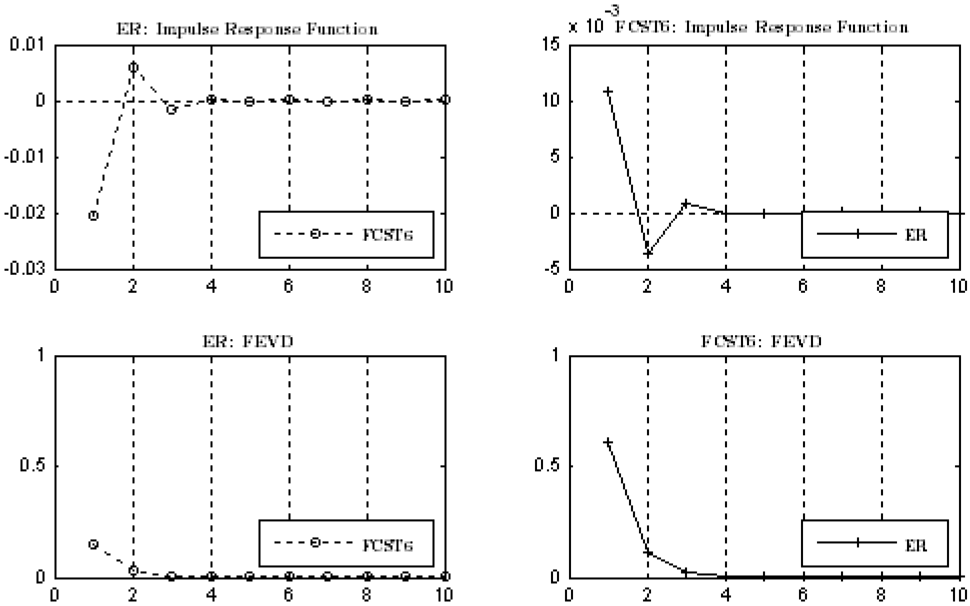
Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## European Small Cap

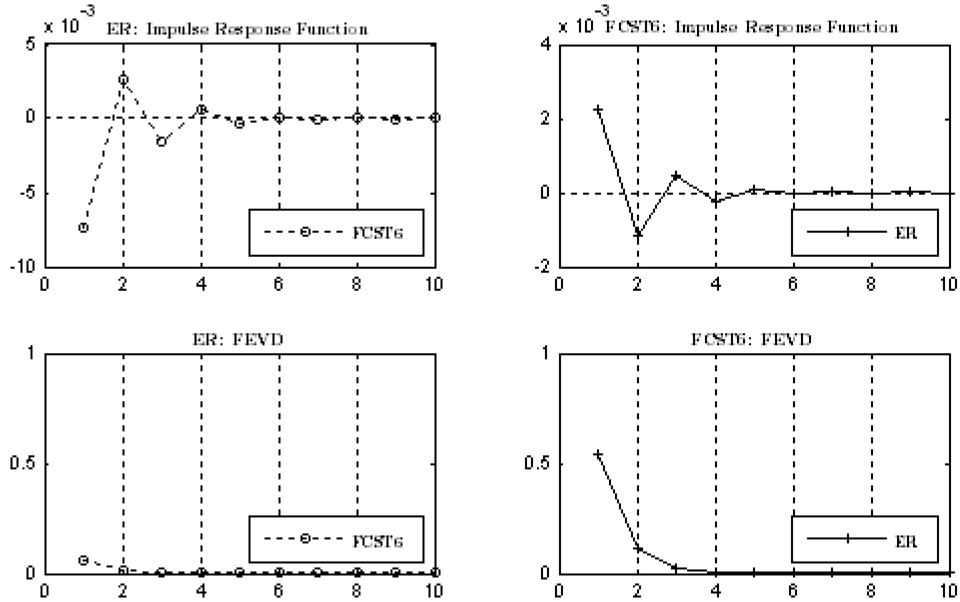
Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## European Large Cap

Panel A. Hypothetical exogenous Variable: Excess return




* All responses are within 5 (95) percent confidence interval (10,000 bootstrapped residuals)

## APPENDIX

The bi-variate VAR used in our analysis consists of regressing an endogenous covariance-stationary variable $y_{i,t}$ on past realizations of all the independent variables ($y_{j,t-p}$, for $j$=1, and 2, in our analysis). In this case, $y_{i,t}$ can be compactly expressed as[6]:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} \beta^1_{11} & \beta^1_{12} \\ \beta^1_{21} & \beta^1_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{1}$$

where the coefficient $\beta^p_{i,j}$ represents the effect of a change in the $j^{th}$ variable at time $t$-$p$ on the $i^{th}$ variable at time $t$. Econometric tests of whether a particular observed series $y_{j,t-p}$ causes (or *Granger-causes*) $y_{i,t}$ can be based on an OLS estimation of the coefficients $\beta^p_{i,j}$. In the case of just one lag ($p$ = 1) and $T$ observations, we conduct an *F-test* of the null hypothesis:

$$H_0 : \beta^1_{i,j} = 0 \qquad \forall\, i \neq j \tag{2}$$

If the $F$-statistic is grater than the 95% critical value for an $F(p,\ T\text{-}2p\text{-}1)$ distribution, then we reject $H_0$, and conclude that $y_{j,t-p}$ helps in forecasting (or is causally prior to) $y_{i,t}$. This clearly does not imply that the series $y_{j,t-p}$ *causes* $y_{i,t}$ to move up or down.
If we want to examine not only whether one variable(s) leads (in the sense of being causally prior to) other(s) variable(s), but also the direction and magnitude of the causality, we need to compute the impulse-response function and decompose the forecast error variance of the dependent variables.
In the case of the IRF, formally we estimate the model:

$$\frac{\partial\, \hat{\mathrm{E}}(\mathbf{y}_{i,t} \mid y_{j,t-p}, \mathbf{x}_{\mathrm{t-p-1}})}{\partial y_{j,t-p}} = \mathbf{\Theta}_p \tag{3}$$

where $\mathbf{\Theta}_{\mathrm{p}}$, called *impact multiplier*, represents the impact of a shock hitting the $j^{th}$ variable of the system at time $t$-$p$ on the $i^{th}$ variable of the system at time *t, holding all the other innovations constant in the other period*s. It can be used to visualise the effect of (1-unit) shocks on the time path of the dependent variables investigated. As already mentioned in the paper, by choosing a particular recursive ordering of the variables with the Choleski method, we are implicitly investigating the direction of the leading effect of one variable, the first in the order, on the others (those that appear later in the order). Ordering the variables is crucial, but more crucial is the theoretical dynamics of the group of variables used in our analysis. Indeed, if the variance-covariance matrix of the shocks is positive definite (and symmetric), our ordering for the three variables implies that the vector of residual ($e_{i,t}$) is related to a set of mutually orthogonal structural shocks ($\varepsilon_{t-p}$) determined with the Choleski factorization, which implies the existence of a lower triangular matrix **C** such that $y_t$ can be represented as a function of orthogonalised innovations ($\varepsilon_i$).
The result is that the innovation in one equation (e.g. $y_1$) affects -but is not affected contemporaneously by the other variable (e.g. $y_2$)[7]. For instance, the Granger causality of $y_1$ on $y_2$ can be expressed as follows:

[6] The selection of the appropriate lag length for the independent variables in the VAR is based on different criteria. We used the Likelihood Ratio, the Final Prediction Error, the Akaike, Schwartz and Hannan-Quinn Information criteria. In most of the cases, the length returned by the different criteria is 1 lag (year). The results of these tests are available on request from the authors.

$$\begin{cases} \mathbf{e}_{1,t} = \boldsymbol{\varepsilon}_{1,t} \\ \mathbf{e}_{2,t} = c_{21}\boldsymbol{\varepsilon}_{1,t} + \boldsymbol{\varepsilon}_{2,t} \end{cases} \tag{4}$$

In this particular case, $y_1$ is said to be "causally-prior" to $y_2$.
Finally, in addition to the impulse-response function we also document the forecast error variance decomposition (FEVD) obtained by deriving the error in forecasting variable $y$ $t$-steps ahead into the future. As previously demonstrated by Lee (1992), the variance ($Var$) of such forecasting error can also be expressed as:

$$Var(y_{t+i} - \overline{y}_{t+i}) = \mathbf{\Phi}_0\mathbf{I}\mathbf{\Phi}_0' + \mathbf{\Phi}_1\mathbf{I}\mathbf{\Phi}_1' + ... + \mathbf{\Phi}_i\mathbf{I}\mathbf{\Phi}_i' \tag{5}$$

where $\mathbf{I}$ is the identity matrix of rank $m$ (in our case $m$ equals 3), $\mathbf{\Phi}$ is a nonsingular matrix such that $\mathbf{\Sigma}^{-1} = \mathbf{\Phi}'\mathbf{\Phi}$, and $\mathbf{\Sigma}$ is the symmetric positive definite variance matrix of the shocks in the structural VAR.
The previous formula permits to compute the share of the total variance attributable to the variance of each shock, when shocks are orthogonal to each other (as the covariance terms are zero given the orthogonality property of the shocks). In this way, we can assign the variance of each element in the series $y_t$ to sources in elements of $\varepsilon_i$, given that $\varepsilon_i$ are serially and contemporaneously uncorrelated. It follows that the FEVD can be expressed as:

$$\sum_{i=0}^{s-1}\mathbf{\Phi}_{s,ij}^2 \Big/ \sum_{j=1}^{m}\sum_{i=0}^{s-1}\mathbf{\Phi}_{s,ij}^2 \tag{6}$$

In equation (6), the numerator represents the proportion of forecast error variance in the $t$-step ahead forecast of the dependent variable $y_i$ explained by the shock in the independent variable $y_j$.

[7] In the particular case of a bi-variate VAR, it is necessary to impose 2 ([n$^2$-n]/2) restrictions (all the elements above the principal diagonal are set to be zero) on the model in order to identify the system (necessary but not sufficient condition to an exact identification of the structural VAR).