A common factor analysis for the US and the German stock markets during overlapping trading hours

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Abstract

The purpose of this study is to investigate the short- and long-run relationships between the US and the German stock markets during overlapping trading hours. We employ the framework of a bivariate common factor model for our empirical analysis to establish a permanent-stationary decomposition of the two major indices (the Deutsche Aktienindex (DAX) for Germany and the Dow Jones Industrial Average (DJIA) for the US). Based on a novel high-frequency data set for 2003 we are able to compute various measures to identify the fundamental dependencies between the two indices. Our findings can be summarized as follows: (1) we reveal a significant cointegration relationship between the DAX and the DJIA and identify a common trend shared by both stock indices; (2) we find that the DJIA contributes up to 95% to the total innovation of the common factor, clearly demonstrating the dominant role played by the US market during overlapping trading hours; (3) we show that both markets adjust within minutes to a system-wide shock and to shocks coming from either direction; and (4) analyzing the relevance of each individual factor component we verify that the DJIA is in fact the main driving force in the transatlantic system of stock indices.

Keywords: Stock Market Cointegration, High-frequency Data, Permanent-Transitory Decomposition

JEL Classification: C32, G15

1 Introduction

Over the last three decades, the financial world has undergone a profound change. While national financial markets were largely isolated until the beginning of the 1970s, the stock market crash in October 1987 and recently the events of September 11, 2001 have shown how inter-connected securities markets have become over time. Regularly, three broad driving forces behind this process are identified in the literature. The first is connected with the gradual abolition of trade barriers, deregulation, and market liberalization as well as policy coordination to establish economic ties which imply a strong integration in the goods market and consecutively the co-movement of output, earnings/dividends, and stock prices. The second is related to the dissemination of floating exchange rate systems, to global investor entities, and to multiple international stock listings fostering a worldwide repercussion of shocks. And, the third driving force is linked with technological advancements in communication and trading systems leading to an efficient information sharing and thus a facilitation of the transmission of news and innovations.

The purpose of this contribution is to analyze the long- and short-run interrelationship between national stock markets. While the literature in this area of empirical finance and financial economics is rather heterogenous, we specifically seek to bring together two strands of this literature to provide new insights into the information processing mechanism of stock markets during overlapping trading hours. The first line of research, dating back at least to the contributions of Taylor and Tonks (1989), Jeon and Chiang (1991), Kasa (1992), and Richards (1995), seeks to identify empirically cointegration relationships between national stock markets. More recent studies in this vein include Knif and Pynnönen (1999), Dickinson (2000), Chen, Firth and Rui (2002), Bessler and Yang (2003), Eberts

(2003), Yang, Min and Li (2003), and Westermann (2003). As may be expected, the results brought forward are not unanimous. Some papers find evidence in favor of cointegration, notably Kasa (1992) and Bessler and Yang (2003), while others (e.g. Richards, 1995 and Westermann, 2003) fail to reject the hypothesis of a stable common stochastic trend among the stock market indices but find evidence of weak predictability or common serial correlation. The data used for the various studies differ markedly with respect to their sampling frequency, the time spans covered and the number of indices scrutinized. Important from our point of view is the fact that the lowest sampling frequency used in the previous cited studies is daily data.

The second strand of literature comes from the field of market microstructure analysis and is closely connected with the work of Hasbrouck (1995). Its purpose is to identify the driving forces of a price discovery process for a security linked by arbitrage conditions. Various extensions and applications of this approach are discussed in several contributions published in a special issue of the Journal of Financial Markets Volume 5, 2002. A closely related contribution to this literature turned out to be the paper by Gonzalo and Granger (1995) which can also be used to measure the relative importance of the contributions to price discovery in financial markets. An important branch of this literature using the Hasbrouck and/or Gonzalo-Granger methodology is the analysis of cross-listed shares traded on different (national and international) exchanges. For a recent contribution see e.g. Grammig, Melvin and Schlag (2005).

While the basic idea of our study is in the spirit of Kasa (1992), it differs from it and the existing literature in various respects. The most obvious difference is our focus on the US and the German stock markets during overlapping trading hours such that activity in one market may simultaneously influence, and respond to, same-day activity in the other market. We feel that this provides the most natural environment to identify a common stochastic trend driving the two markets while both have a chance to react on news arrivals instantaneously (probably to a different degree). Consequently, we rely on high-frequency intraday data of the major stock market indices in either country for our empirical analysis. Our approach comprises generalized impulse response and forecast error variance analyses, as well as permanent-transitory decompositions, which were put forward by Hasbrouck (1995) and Gonzalo and Granger (1995). A subsequent application of three different information revealing techniques seeks to identify the fundamental dependencies between the two indices under study. Papers that have applied these methods in a similar fashion in the context of stock market interaction are Cheung and Lai (1999), Phylaktis and Ravazzolo (2002), and Yang et al. (2003). Yet, these authors mainly focus on emerging market linkages or stock markets within Europe and only consider daily or even monthly data. Hence, our study is the first to analyze the interrelation of the US and German stock markets by using high-frequency data and asking: what, if any, are the possible leadership effects that the US and German stock markets have over each other during overlapping trading hours and if (economic) news is first aggregated in the US and then transferred to the German stock market.

The remainder of the paper is organized in the following manner. In section 2 we describe the data and consider particular institutional features of the two markets. Section 3 is devoted to an outline of the methodology employed in our analysis. Section 4 presents and discusses the empirical results and section 5 concludes.

2 Institutional Background and Data

The stock indices included in our study are the Dow Jones Industrial Average (DJIA) and the Deutsche Aktienindex (DAX).[1] Market participants, the financial media, and the literature usually refer to the DJIA when judging the overall performance of the US stock market. The DAX is the obvious German analogue to the DJIA - and not only in this respect. In fact, both indices comprise 30 of the highest capitalized and most traded domestic companies (see Table 1).

- *Table 1 on Trading Hours, Market Cap., and Trading Value* -

The study is based on high-frequency intraday data for the year 2003 in which country specific bank holidays are omitted from both series. More explicitly, we create a sample running from March 13, 2003 to December 31, 2003 to neutralize uncertainties underlying the stock markets worldwide due to the Iraqi crisis. As Table 1 shows, the common trading time overlap begins at 2:30pm GMT but varies in its closing time. On November 03, 2003 Frankfurt's trading hours were curtailed by 2.5 hours, mainly due to low trading volume during the late evening hours. Therefore, we focus on the main trading-time overlap of Deutsche Boerse and the New York Stock Exchange, ranging from 2:30pm GMT to 4:30pm GMT. To base our further analysis on conventional grounds, we transform both index series by taking natural logarithms.

Stock prices and indices respond very quickly to new information. High-frequency data thence provides useful insights into market dynamics. As mentioned by Grammig et al. (2005), there may be one-way causalities which exist among

[1] The DJIA data was obtained from Olsen & Associates and the DAX data from the KKMDB (Karlsruher Kapitalmarkt Datenbank).

the variables at a shorter sampling interval that cannot be identified at a lower frequency. On the other hand, increasing the frequency to an arbitrary level is also counterfactual. Indices especially face infrequent trading problems since they contain also less liquid stocks. Hence, we regard minute by minute data as the best way to cope with the trade-off between the issues of contemporaneous correlation and non-trading. Tests based on lower sampling frequencies (two minutes up to five minutes) showed qualitatively similar results but higher contemporaneous correlation.
Considering minute by minute data, together with our data range chosen provides us with $T = 20628$ observations in our sample. Interpreting statistical tests from the classical perspective to a sample of this size is likely to indicate statistical significance for values that won't be statistical significant otherwise. Since there is no general approach to tackle this issue and many analyses of high-frequency data are often conducted using conventional significance levels (e.g. Harris, McInish and Wood, 2002 and Grammig et al., 2005), we provide p-values - where appropriate. Reasoning along a similar line of the classical perspective, Shiller and Perron (1985) conclude that as the number of observations increases, the power of a test ought to be very high even though the data come from a relatively short sample period. That means one should think of the power of a test as depending more on the span of the data than on the number of observations. As our sample period (almost ten months) is relatively large compared to similar studies of high-frequency data (e.g. Grammig et al., 2005 who have a span of three months), we consider our sample period to be long enough to prevent the power of our tests being biased by too many observations.

Closely connected to the previously mentioned problem of stock indices facing infrequent trading is the so-called stale-quote-problem, which is for both indices one of the main institutional features that must be considered (see e.g. Lin, Engle and Ito, 1994). Since both stock exchanges try to publish the opening quote as early as possible right after trading starts, the indices may not reflect all relevant information available at that time. In fact, we found for both indices that relevant information was lacking at the beginning of the trading day (i.e. opening quotes which differed only marginally from the previous day's closing quote) for a relative large fraction of our sample period. To get robust results, we follow similar studies, in particular Baur and Jung (2006), and tested for several opening-proxies. We find that omitting the first 10 minutes of trading on the New York's stock exchange is most suitable for overcoming this negative feature. Hence, we chose 2:40pm GMT as the beginning of the common trading time overlap. Alternatively, continuously traded future (index) data is often used to circumvent the stale-quote-problem (see e.g. Roope and Zurbruegg, 2002). However, since the DJIA and the DAX usually receive more attention when it comes to monitoring transatlantic stock market linkages we take the exchange's spot index.

Our analysis could also be accomplished by following Kasa (1992) and converting national stock price indices into a common currency (Euro or U.S. dollars) or even deflating them by using CPI- or GDP-deflators. Yet, we are interested in the pure leadership effect of one national stock market over its transatlantic counterpart and thus base our analysis on nominal data in local currencies. Converting either the US or the German stock price index into a common currency could distort our findings because it implicitly assumes that the exchange rate evolution is stationary. To check if such a conversion implies additional effects, we tested for a unit root in the Euro/USD exchange rate and strongly failed to reject the null-hypothesis. Also, expressing both stock equity index in real terms would hide a possible leadership effect by either excluding the US or the German inflation; apart from that, deflating our high-frequency data by CPI- or GDP-deflators is not feasible since these deflators are based on lower sampling (monthly or quarterly) frequencies.

3 Methodology

3.1 Common stochastic trend representation

Given the nature of and the empirical evidence that financial markets tend to move together, it seems only natural from a statistical point of view that stock markets consist of a common factor and an individual transitory component which captures country specific innovations. Let us thus propose that each stock market index $y_{i,t}$ $(i = 1, .., N)$ evolves according to a random walk plus noise model, i.e.:

$$y_{i,t} = f_t + \eta_{i,t}, \quad \text{with} \quad f_t = f_{t-1} + \xi_t, \tag{1}$$

where $\{\xi_t\}$ is a white-noise process and $\eta_{i,t}$ is a well-defined zero-mean covariance-stationary random disturbance.

Recursively substituting in (1) for $f_{t-1}, ..., f_1$ and assuming $f_0 = 0$ for ease of notation yields:

$$y_{i,t} = \sum_{s=1}^{t} \xi_s + \eta_{i,t}. \tag{2}$$

The individual sequences $y_{i,t}$ share a common factor, i.e. the stochastic trend $\sum_{s=1}^{t} \xi_s$ of cumulated random information arrivals, but they differ from each other by the stock market specific transitory disturbance $\eta_{i,t}$. By explicitly modeling stock indices in such a way we implicitly assume that new information emanating from economic fundamentals is aggregated in the equity markets.

To capture the joint evolution of the stock market indices, we extend our univariate random walk plus noise model (2) to a multivariate version of the Beveridge-Nelson (1981) decomposition. In particular, we consider the polynomial factorization $C(L) = C(1) + (1 - L)C^*(L)$, where $C^*(L) = \sum_{j=0}^{\infty} C_j^* L^j$ is "absolutely summable in matrix norm" and $C_j^* = -\sum_{l=j+1}^{\infty} C_l \; \forall \; j \geq 0$. Defining Y_t and ε_t as the N-dimensional versions of the time series vectors $\{y_{i,t}\}$ and $\{\xi_t\}$, respectively, then leads to:

$$Y_t = C(1) \sum_{s=1}^{t} \varepsilon_s + \eta_t, \qquad (3)$$

where ε_t is white-noise with $E(\varepsilon_t \varepsilon_t') = \Omega$ being positive definite ($\Omega = \{\omega_{i,j} \; \forall i, j = 1, 2, ..., N\}$) and $\eta_t = C^*(L)\varepsilon_t$. Hence, the system of stock market indices depends on a non-stationary (permanent) component $C(1) \sum_{s=1}^{t} \varepsilon_s$, where $C(1)$ represents the long-run impact matrix of a disturbance on each of the variables in the system, as well as a covariance stationary (transitory) component η_t.

If $C(1)$ has full rank then the permanent part of equation (3) is only a linear combination of N random walks and no stationary part exists. However, if $C(1)$ is of rank $k = N - r$, then this implies the presence of r stationary components, i.e. cointegrating vectors β, and the existence of k common trends (i.e. random walks with serially uncorrelated increments) which drive the cointegrated system (Stock and Watson, 1988). Using Johansen's (1991) notation we obtain equation (3) as:

$$Y_t = \beta_{\perp} \varphi' \sum_{s=1}^{t} \varepsilon_s + \eta_t, \qquad (4)$$

where $\beta' C(1) = 0$, $C(1)\alpha = 0$, $\varphi' \alpha = 0$, $\beta_{\perp}' \beta = 0$, and $\varphi' \varepsilon_t$ is the common stochastic trend component innovation.[2] Applying the Granger representation theorem

[2] $\varphi' \sum_{s=1}^{t} \varepsilon_s$ is the Stock and Watson common stochastic trend component.

(Engle and Granger, 1987) this multivariate process may also be represented by the following vector error correction model (VECM):

$$\Delta Y_t \;=\; \alpha\beta' Y_t + \sum_{p=1}^{P-1} \Gamma_p \Delta Y_{t-p} + \varepsilon_t. \tag{5}$$

3.2 Detection of leadership effects

Assuming only one common trend in the system of stock indices raises the question to what extend different markets have leadership effects over each other, i.e. how the individual information content relates to the common long-run factor. In this respect, the studies by Hasbrouck (1995) and Gonzalo and Granger (1995) supply qualified techniques for which the work by Kasa (1992) shall be used as a benchmark.

Kasa's measure

Kasa (1992) starts to derive the basic idea of the relative independence of each national stock market from the common stochastic trend by specifying the state space formulation of equation (4):

$$Y_t \;=\; \beta_\perp(\beta'_\perp\beta_\perp)^{-1}\beta'_\perp Y_t + \beta(\beta'\beta)^{-1}\beta' Y_t, \tag{6}$$

where the first part on the right hand side of equation (6) reads as the permanent and the second part as the stationary component.

Kasa (1992) arranges the orthogonal complements of the permanent component to define the common factor as a weighted average of the variables under consideration, i.e. $(\beta'_\perp\beta_\perp)^{-1}\beta'_\perp Y_t$ with loading vector $\beta_\perp$. To attach an economic meaning to this decomposition, Kasa normalizes the vector of factor loadings such that the weights of the variables in the common factor sum to unity. As he points out, the relative importance of each market to the trend is the same as the relative importance of the trend to each market (except for a normalization factor). We therefore calculate the relative importance of each variable to the common trend from the factor loadings $\beta_\perp$. Considering a bivariate system of variables, we compute our measure in the sense of Kasa by first solving simultaneously the orthogonality condition $\beta'_\perp\beta = 0$ and $\iota'\beta_\perp = 1$, where ι is a vector of ones, and then correcting for the normalization issue. Thus, Kasa's measure ($K_{1,2}$) can be characterized as:

$$K_1 = 1 - \frac{\beta_2}{\beta_2 - \beta_1}, \quad K_2 = 1 - \frac{\beta_1}{\beta_1 - \beta_2}, \tag{7}$$

where $\beta = (\beta_1, \beta_2)'$.

In contrast to the common-trend-representation by Stock and Watson (1988), Kasa's common stochastic trend will no longer be a pure random walk. Any short-run dynamics that are orthogonal to the cointegration relation (the long-run dynamics) might be included in the common trend. Needless to say, isolating a group of transitory shocks from their permanent counterparts is somewhat controversial when not applying any additional identification restrictions (e.g. motivated by economic theory).

Hasbrouck's measure

The Hasbrouck (1995) methodology of measuring the contribution of each market to the overall variance of the system essentially boils down to a variance decomposition of the common factor. Central to the argumentation is the factor component (common to all markets, i.e. the stochastic trend) of which the elements represent the new information arrival that is permanently impounded. Taking into account that all the variables have the same long-run impact (i.e. the same common trend) the rows of C(1) in equation (4) are identical. Equation

(4) then becomes:

$$Y_t = \iota c \sum_{s=1}^{t} \varepsilon_s + \eta_t, \tag{8}$$

where c is the common row vector of $C(1)$. The variance of the common factor innovations can be decomposed into components attributable to the ith variable and its relative contribution is defined as:

$$H_i = \frac{([cM_{ii}])^2}{c\Omega c'}, \tag{9}$$

where a Cholesky factorization of the form $\Omega = MM'$ (with M as a lower triangualar matrix) is typically used to tackle the issue of contemporaneous correlation among the innovations. Unfortunately, different conclusions can be obtained by alternative rotations of the variables. Thus, one can only compute a range of measures to establish upper and lower bounds such that the effect of any common factor is attributed to the variable that comes first in the system. Nevertheless, one should be careful with the tempting idea that the upper bound of Hasbrouck's measure can always be attributed to the variable ordered first. In fact, Hasbrouck (2002) shows that a maximum (upper) bound can be obtained from the variable ordered last. It is thus necessary to rotate the variables and check for upper and lower bounds.

Usually, Hasbrouck's measure is estimated using the Vector Moving Average (VMA) form of the cointegrated variables. As Martens (1998) shows, the common row vector c is, up to a scale factor, orthogonal to the vector of adjustment coefficients α in a bivariate VECM-system. Consequently, the information measures only depend on the adjustment coefficients and the covariance matrix of the cointegrated system. More precisely, the orthogonal complement to the vector of adjustment coefficients are obtained by solving simultaneously $\alpha'_{\perp}\alpha = 0$ and

$\iota'\alpha_\perp = 1$, where ι is again a vector of ones. Hasbrouck's measure ($H_{1,2}$) can then be written (depending on the order of the variables) as:

$$\begin{aligned} H_1 &= \frac{[\alpha_{\perp,1}M_{11} + \alpha_{\perp,2}M_{21}]^2}{[\alpha_{\perp,1}\Omega_{11}\alpha_{\perp,1} + \alpha_{\perp,2}\Omega_{21}\alpha_{\perp,1} + \alpha_{\perp,1}\Omega_{12}\alpha_{\perp,2} + \alpha_{\perp,2}\Omega_{22}\alpha_{\perp,2}]}, \\ H_2 &= \frac{[\alpha_{\perp,2}M_{22}]^2}{[\alpha_{\perp,1}\Omega_{11}\alpha_{\perp,1} + \alpha_{\perp,2}\Omega_{21}\alpha_{\perp,1} + \alpha_{\perp,1}\Omega_{12}\alpha_{\perp,2} + \alpha_{\perp,2}\Omega_{22}\alpha_{\perp,2}]}, \end{aligned} \tag{10}$$

where $\alpha_\perp = (\alpha_{\perp,1}, \alpha_{\perp,2})'$.

Gonzalo-Granger measure

In comparison to Kasa (1992) and Hasbrouck (1995), Gonzalo and Grangers' (1995) analysis supplies an additive separable form of the system of cointegrated variables in a more concrete manner. The basic idea is to decompose the cointegrated system into a permanent component f_t (the common factor) and a transitory component $\widetilde{Y}_t$:

$$Y_t = A_1 f_t + \widetilde{Y}_t, \tag{11}$$

where A_1 represents a factor loading matrix. By using the identifying restrictions that f_t is a linear combination of Y_t and that the transitory component $\widetilde{Y}_t$ does not Granger-cause Y_t in the long-run (see Gonzalo and Granger, 1995, definition 1), the dynamics above can be decomposed as:

$$Y_t = \beta_\perp(\alpha'_\perp\beta_\perp)^{-1}\alpha'_\perp Y_t + \alpha(\beta'\alpha)^{-1}\beta' Y_t. \tag{12}$$

That is to say, since f_t is given as $\alpha'_\perp Y_t$ the elements of $\alpha_\perp$ are the common factor weights of the variables driving the cointegrated system. More precisely, Gonzalo and Granger (1995) show that in a N-variable system with r cointegrating restrictions the relevant vectors of common factor weights are given by the eigenvectors corresponding to the $N-r$ smallest eigenvalues (determined in a reduced rank regression and generalized eigenvalue problem similar to those of Johansen, 1988, 1991). Once $\alpha_\perp$ has been normalized so that its elements sum to unity, it measures the fraction of system innovations attributable to each variable. In a bivariate system, the Gonzalo-Granger measure ($G_{1,2}$) is tantamount to:

$$G_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \quad G_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}, \tag{13}$$

where $\alpha = (\alpha_1, \alpha_2)'$.

As Gonzalo and Granger (1995) point out, the random walk part of their common factor corresponds indeed to the common trend of the Stock-Watson decomposition. However, their common factor as such differs from the Stock-Watson definition of a common trend because the changes in f_t are serially correlated. Nevertheless, the appealing feature of Gonzalo and Grangers' approach is the definition of the common factors as a linear combination of observations, and the simple separation of the transitory component by having only temporary effects on Y_t.

Connection between the three approaches of information dominance

At first glance, especially the Gonzalo-Granger and Hasbrouck's measures seem to be competing approaches to detect leadership effects in cointegrated security markets. The provision of bounds by Hasbrouck (1995) versus the precise estimate derived from the Gonzalo-Granger methodology is one of the most obvious differences. Hasbrouck gauges variable i's innovation ε_i to the total variance of the common trend innovations. He defines the permanent component as a combination of current as well as lagged variables of interest, since the common stochastic trend is (and the transitory components are) driven by current and lagged innovations ε_t. This I(1)-process is, however, still a random walk by definition. On the other hand, Gonzalo and Granger (1995) measure the impact of ε_i on the innovation in the common factor and their permanent component only comprises current values of y_t. Any non-stationary process could thus form the permanent component in the Gonzalo-Granger decomposition (as is the case in Kasa's decomposition) and might be forecastable, in which case a reasonable interpretation would fail (Hasbrouck, 2002); obviously, this is somewhat controversial. Nevertheless, the two methodologies are indirectly related to each other via the Gonzalo-Granger factor loadings which directly feed into the calculation of Hasbrouck's measure. This can be best seen in a bivariate system in which the vector of factor loadings is broken down to the common row vector c of equation (8) and is therefore equivalent (up to a scale factor) to the orthogonal complement of the vector of adjustment coefficients.

Furthermore, Escribano and Peña (1994) give an intuitive way of looking at the connection between Gonzalo and Grangers' decompostion and the decomposition provided by Kasa. Subtracting equation (12) from equation (6) gives:

$$\beta_\perp(\beta_\perp'\beta_\perp)^{-1}\beta_\perp' Y_t = \beta_\perp(\alpha_\perp'\beta_\perp)^{-1}\alpha_\perp' Y_t + (\beta(\beta'\beta)^{-1} - \alpha(\beta'\alpha)^{-1})\beta' Y_t. \tag{14}$$

Premultiplying by $\alpha_\perp'$ or $\beta_\perp'$ delivers either the common factor of the Gonzalo-Granger decomposition in terms of Kasa, i.e.:

$$\alpha_\perp' Y_t = \alpha_\perp'\beta_\perp(\beta_\perp'\beta_\perp)^{-1}\beta_\perp' Y_t - \alpha_\perp'\beta(\beta'\beta)^{-1}\beta' Y_t, \tag{15}$$

or that of Kasa in terms of the Gonzalo-Granger approach:

$$\beta_\perp' Y_t = \beta_\perp'\beta_\perp(\alpha_\perp'\beta_\perp)^{-1}\alpha_\perp' Y_t - \beta_\perp'\alpha(\beta'\alpha)^{-1}\beta' Y_t. \tag{16}$$

It is clear from the above specifications that the common factors are not only simple mutual linear combinations but, as stated above, they also differ in defining the common factor. In the Gonzalo-Granger decomposition, the long-term dynamic is eliminated in a manner that shocks to the common factor have only a temporary effect on Y_t. Kasa (1992), on the other hand, allows for "transitoriness" in the permanent component, i.e. any short-run dynamics that are orthogonal to the cointegrating relation are included in the common trend.

3.3 Speed of incorporating new information

Tightly connected to the detection of leadership effects is the nature of the long-run structure. We employ the persistence profile developed in Pesaran and Shin (1996) to analyze the time profile of the long-run impacts of a shock to the cointegrated system. Specifically, Pesaran and Shin cast up the impact of a system-wide shock as a difference between the conditional variances of the j-step- and the $(j-1)$-step-ahead forecast, scaled by the difference between these measures on impact:

$$\begin{aligned}\psi_Z(j) &= \frac{Var(\zeta_{t+j}|\mathcal{I}_{t-1}) - Var(\zeta_{t+j-1}|\mathcal{I}_{t-1})}{Var(\zeta_t|\mathcal{I}_{t-1}) - Var(\zeta_{t-1})} \\ &= \frac{\beta' B_j \Omega B_j' \beta}{\beta' \Omega \beta}, \qquad \text{for} \quad j = 0, 1, 2, ..., \end{aligned} \tag{17}$$

where $Var(\zeta_{t+j}|\mathcal{I}_{t-1})$ is the conditional variance of the equilibrium relation $\zeta_{t+j} = \beta' X_{t+j}$ given the information set $\mathcal{I}_{t-1}$ at time $t-1$, and $B_j = \sum_{l=0}^{j} C_l$ as well as $\psi_Z(0) = 1$ on impact. The persistence profile will be unique in the case of just one cointegrating relation and does not require prior orthogonalization of the shocks (e.g. by a Cholesky factorization); it is thus invariant to the ordering of the variables in the model. Moreover, the profile provides valuable information of the speed with which the effects of a system-wide shock eventually disappear as the system returns to its steady state, even though such a shock may have lasting effects on each individual variable. As the speed of adjustment to the (new) equilibrium indicates how strong the variables are cointegrated, cointegration analysis can also be interpreted as a test on the limiting value of the persistence profile being zero as the forecast-horizon j tends to infinity (Pesaran and Shin, 1996).

We further investigate the dynamic effects of a variable-specific shock on each of the other variables. Based on the Wold representation of equation (5), Pesaran and Shin (1998) develop a (scaled) generalized impulse response function (IRF) of the VECM-variables ΔY_{t+j} to a one-standard-error shock in first differences which is again invariant to the ordering in the system. It is given by:

$$\psi_{\Delta Y,i}(j) \quad = \quad \frac{C_j \Omega}{\sqrt{\omega_{ii}}} e_i, \qquad \text{for} \quad j = 0, 1, 2, ..., \tag{18}$$

where e_i is a $(n \times 1)$ selection vector with its ith element equal to one and zeros elsewhere. A generalization in terms of an integrated form of (18) is obtained by:

$$\psi_{Y,i}(j) \quad = \quad \frac{B_j \Omega}{\sqrt{\omega_{ii}}} e_i, \qquad \text{for} \quad j = 0, 1, 2, ..., \tag{19}$$

where e_i, C_j and B_j as before. This generalized IRF (19) gives further insight into the dynamic interactions between the level-series, i.e. whether shocks to the ith variable only affect the ith variable or if they strike predominantly other variables in the model.

3.4 Testing hypotheses on the common factor

To gauge the nature of the common permanent trend, we identify the common factor components by applying the permanent-transitory decomposition of Gonzalo and Granger (1995). Furthermore, we test which variable is the driving force in the system, i.e. whether information revealed on one market contributes mainly to the permanent component. The latter hypothesis can be tested by using the Gonzalo-Granger likelihood ratio test to analyze the relevance of each individual factor component. This hypothesis on $\alpha_\perp$ is formulated as:

$$H_0 : \alpha_\perp = G\theta, \tag{20}$$

where G is a $(N \times m)$ restriction matrix on $\alpha_\perp$ with m as the number of freely estimated coefficients of the common factor and θ is the $(m \times (N-r))$ matrix of restricted coefficient estimates. In particular, Gonzalo and Granger (1995) estimate θ as the m eigenvectors associated with the m smallest eigenvalues ($\lambda_i' s$) of the following generalized eigenvalue problem:

$$(\lambda G' S_{00} G - G' S_{01} S_{11}^{-1} S_{10} G)\theta = 0, \tag{21}$$

in which S_{jl} ($j, l \epsilon \{0,1\}$) are the residual product matrices of the Johansen (1988, 1991) technique. The likelihood ratio test statistic is then given by:

$$-T \sum_{i=r+1}^{N} ln \frac{(1-\tilde{\lambda}_{i+m-N})}{(1-\hat{\lambda}_i)} \quad \sim \chi^2_{(N-r)\times(N-m)}, \tag{22}$$

which is χ^2 distributed with $(N-r)\times(N-m)$ degrees of freedom, and where $\hat{\lambda}_i$ and $\tilde{\lambda}_{i+m-N}$ represent the solution to the unrestricted and restricted (equation (21)) eigenvalue problems, respectively.

4 Empirical Results

4.1 Preliminary analysis

The subsequent analysis was conducted using Gauss software and programs written by the authors. Although many standard software packages offer pre-programmed procedures for the kind of analysis undertaken here, they do not allow for the special data handling necessary in our case. To avoid spurious results in our analysis caused by overnight influences, we carefully adjusted the starting point for the data on each day in such a way that lagged values would not be taken from the previous trading day.

Keeping the interrelatedness of the two stock market series in mind, we started our empirical analysis by testing for the presence of a single unit root. Since financial series are generally considered to move according to a stochastic trend, we apply the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979,1981) with a constant but without a linear time trend in order to assess the order of integration of DAX or DJIA, respectively. Both ADF-regressions are conducted on the levels and on first differences. To determine the optimal lag length, we employ a general-to-specific modeling strategy.

- *Table 2 on ADF-Test* -

Table 2 reports the ADF-test results for $I(1)$ versus $I(0)$. For every stock index series, the null-hypothesis of a unit root is not rejected at any conventional significance, whereas the null of non-stationary first differences is rejected at the 0.01%-level.

To test for one common stochastic trend in the underlying system of the DAX- and DJIA-indices we apply the reduced rank regression proposed by Johansen (1988, 1991). This procedure (being robust to non-normal innovations and GARCH effects, see e.g. Cheung and Lai, 1993, as well as Lee and Tse, 1996) has the advantage of incorporating all that matters in the context of our goal to determine common trends and information dominance into the well-known maximum likelihood framework by simply specifying an autoregressive process with white-noise error terms. In practice, the cointegration rank is best chosen by applying both test-procedures ($\lambda_{trace} = -T \sum_{i=r+1}^{N} ln(1 - \hat{\lambda}_i)$ and $\lambda_{maxeig} = -Tln(1 - \hat{\lambda}_{r+1})$) proposed in Johansen (1988, 1991) along with the eigenvalues ($\hat{\lambda}_i^{\prime}s$) themselves. As is well known, the λ_{maxeig}-statistic tends to have more power than the λ_{trace}-statistic in the presence of unevenly distributed (either very large or very small) eigenvalues whereas the opposite is true when the eigenvalues are uniformly distributed. Both test statistics are non-normally distributed with critical values given in MacKinnon, Haug and Michelis (1999). The cointegration test is conducted by restricting the constant to lie in the cointegration space, thus assuming that there is no deterministic trend in stock markets. Moreover, the optimal lag length is determined by applying the Schwarz information criterion; a general-to-specific modeling strategy leads to similar results with the presence of cointegration being robust to the number of lags.

- *Table 3 on Cointegration-Test* -

According to Table 3, we do not fail to reject the null hypothesis of no cointegration among the two stock indices at the 0.02%-level. In other words, there exists a common trend which affects both stock markets significantly.

Finally, we assess the model adequacy by checking the VECM-residuals for contemporaneous correlation, non-normality, and autocorrelation, which are depicted together with some descriptive statistics in Table 4. We cannot detect any contemporaneous correlation in the innovations and also cannot reject the null-hypothesis of no autocorrelation at any significance level.

- *Table 4 on Error Diagnostics* -

4.2 Information dominance

Virtually all results of our analysis of information dominance are obtained on the basis of the estimation results from the reduced rank regression. We adopt the bootstrap method for cointegrated systems developed by Li and Maddala (1997) to overcome the shortcoming that the precision of our estimates cannot be assessed analytically. We choose to bootstrap from the estimated residuals of the VECM in order not to distort the dynamic structure of our model (see Sapp, 2000 for further details on bootstrapping dependent variables in a dynamic framework). Using estimated parameters and initial values, we create a new set of system variables (with the same number of observations as in the original data) by drawing independently observations with replacement from the innovations. Based upon the generated data, the common trend relationship and the subsequent assessments are re-estimated. This process is then repeated 1000 times and the standard errors are calculated from the empirical distribution.

Table 5 assembles our estimates for the various information measures which are perhaps not surprising - the US stock market exhibits strong leadership effects over its German counterpart.

- *Table 5 on Information Measures* -

According to Hasbrouck's measure, the DJIA contributes 95% to the total innovation of the common factor, whereas the DAX merely attains a level of five percent on average. This means that the permanent shocks emanate predominantly from the US market, or put differently, the DJIA has a leading role in impounding new information. Moreover, the bounds of Hasbrouck's measure are close together (due to the small contemporaneous correlation of the innovations) which strengthens our findings. Gonzalo-Grangers' method displays the same outcome. The US market enters with almost 90% percent into the common long memory component and thus affirms our hypothesis that (economic) news is first aggregated in the US and then transferred to the German stock market during overlapping trading hours. These results are strengthened by considering Kasa's measure which assesses the relative importance of each market to the common trend. The US market is relative important to the common trend (the DJIA determines the common factor by 61%) while the DAX-weight in the common factor is 39%.

In a next step, we examine the persistence profile and generalized impulse responses following Pesaran and Shin (1996, 1998) to gain further insight into the structure of shocks impacting the system of stock markets. After a system-wide shock, the equilibrium relationship between the US and German stock markets adjusts very quickly, i.e. within the first five to ten minutes (Figure 1, where the bootstrapped 95%-confidence bands are also shown). However, such an impact exhibits long persistence such that the pre-shock state is only restored after approximately 40 days which is in line with other studies on the persistence of shocks to a cointegrated system of stock markets (e.g. Yang et al., 2003).

- *Figure 1 on Persistence Profile* -

Figure 2 and 3 depict the generalized impulse responses to one-standard-error shocks (along with the bootstrapped 95%-confidence bands) of the adjustment- and level-equations, respectively. The findings from the generalized impulse responses of Figure 2 provide further support that the two markets react very quickly (in less than five minutes) to shocks coming from either direction, although a shock emanating from the same direction has a stronger effect on the own market on impact. Moreover, as the plots in Figure 3 show, a DAX innovation affects Frankfurt's stock market more than its US counterpart whereas a DJIA innovation has a greater effect on the US market on impact. However, such a shock to New York's stock index exerts a bigger impact on the DAX in the long-run compared to the long-run effect of a DAX-shock on the US index. The greater long-run impact of DJIA innovations on the German stock market supports our findings that shocks emanating from the US market have a broad or permanent effect on the German stock market while a DAX shock is only transitory in the long-run.

- Figure 2 and 3 on IRF -

Given the information to what extend the individual information content relates to the common long-run factor, a probably more illuminating way to gain further understanding of the trend across markets is to compare plots of the actual series versus its permanent component. If stock price changes represent predominantly innovations to the long-rung factor, both series will be closely aligned, whereas the permanent component series and the actual index series should deviate from each other if transitory disturbances are relatively important to the market. Figure 4 shows the Gonzalo and Grangers' (1995) permanent component of the two stock indices superimposed on the actual series. As the relative magnitudes of the Gonzalo-Granger measure suggest, the fit is best for the DJIA (note: although the scaling of Panel (a) and (b) in Figure 4 is different, the number and the span of intervals is the same).

- Figure 4 on Permanent Component vs. Actual Series -

Turning to the permanent-transitory decomposition of our multivariate random walk plus noise model it can be seen from Table 6 (feedback parameters) that deviations from the equilibrium relation do not appear to be significant in the case of the DJIA (α_1 receives a p-value of 0.19) whereas they are significant for the DAX for which α_2 receives a p-value of 0.06. Hence, one could conclude that $\alpha = (0,1)'$, i.e. the common factor could be assumed to be a multiple of the DJIA and the permanent component could be written as:

$$f_t = (1,0) \begin{pmatrix} DJIA_t \\ DAX_t \end{pmatrix}. \tag{23}$$

This means that, ceteris paribus, any innovation in the DAX is going to affect the German and the US stock markets only via the transitory component. This is exactly the conclusion we inferred from the generalized IRFs of Figure 3 where a DAX shock seems to have only transitory effects in the long-run.

- *Table 6 on Permanent Component Estimation and Hypothesis Testing* -

To assess more thoroughly the role of the national stock markets as a source of price relevant information, we test the null-hypotheses (in the sense of Gonzalo and Granger, 1995) that either stock index is the only variable driving the whole system in the long-run. For the null-hypothesis that e.g. the US stock market is in fact responsible for revealing 100% of the common factor this means:

$$H_0 : \alpha_\perp = G\theta, \quad \text{with} \quad G = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \tag{24}$$

Table 6 lists also the χ^2-test statistic and p-value for these null-hypotheses. We cannot reject the null-hypothesis $H_{0,a}$ that the US stock market only contributes to the revelation of the common factor (p-value=0.19). However, we don't fail to reject $H_{0,b}$ that the German market drives the system and obtain a χ^2-test statistic of 15.5 with a p-value smaller than 0.0001. Thus, our presumptions that the DAX introduces only transitory components and that the common factor seems to be a multiple of the DJIA variable are justified.

5 Concluding Remarks

This paper provides an empirical analysis of the common factor driving the intraday movements of the DAX and the DJIA during overlapping trading hours. Based on minute-by-minute data set spanning from March to December 2003 we estimated a bivariate common factor model for the two indices. By explicitly modeling the two stock indices we implicitly assumed that news on economic fundamentals is aggregated in either equity market and that therefore both stock indices are linked by a common trend of cumulated random information arrivals. We computed various measures of information leadership and found that the DJIA is the predominant source of price relevant information flowing into the transatlantic system of stock indices. While the measure by Kasa attributes a weight of 61% for the DJIA in the common factor, the measures by Hasbrouck as well as Gonzalo and Granger demonstrate that the DJIA contributes up to 95% to the total innovation of the common factor. Moreover, our impulse response analyses show that both stock markets adjust very quickly (in less than five minutes) to shocks emanating from either the US or the German side but that DJIA innovations have a greater long-run impact on the German stock market whereas DAX shocks are transitory in the long-run. This observation is further strengthened by our permanent-transitory decomposition. It clearly emerges from our hypothesis testing that the US stock index is the main variable driving the bivariate system during overlapping trading hours. Any innovations in the German stock index affect both markets only via the transitory component. Hence, our analysis implies that (economic) news is first incorporated in the US and then transferred to the German stock market.

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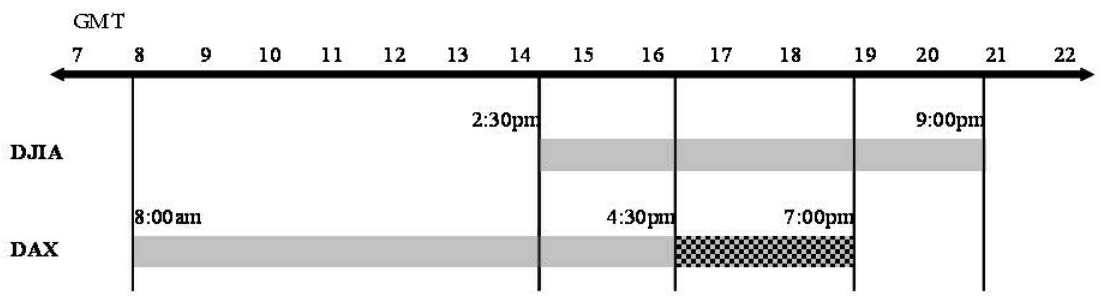
Appendix

Table 1

Table 1: Trading Hours, Market Capitalization, and Trading Value in 2003



Market	*Index Capitalization*[1]	*5% Market Value*[2]	*5% Trading Value*[2]	*No. of 5% Domestic Companies*
DJIA / NYSE	22.2	58.6	41.5	92
DAX / Deutsche Boerse	63.5	67.0	85.3	36

[1]Percent of total market capitalization (Dec. 2003).

[2]Market concentration (in %) of 5% of the largest companies by market capitalization and trading value compared with total domestic market capitalization and trading value, respectively.

Source: Datastream, World Federation of Stock Exchanges, and authors' calculations.

Table 2

Table 2: Unit root test of stock index series

Estimated equation: $\Delta y_{i,t} = a_0 + \gamma y_{i,t-1} + \sum_{p=1}^{P} b_p \Delta y_{t-p} + \varepsilon_t$

$\tau(\gamma)$	***DJIA***	***DAX***
	P=1	*P=5*
log index-level	-2.21	-3.31
	[0.2028]	[0.0144]
log index-return	-96.55	-59.01
	[<0.0001]	[<0.0001]

Note: $\tau(\gamma)$ is the $t - statistic$ of the estimate of γ. P-values in squared brackets according to MacKinnon (1996).
Lag-length P based on general-to-specific modeling strategy.

Source: authors' calculations.

Table 3

Table 3: Johansen test results

Estimated equation: $\Delta Y_t = \alpha(\beta' Y_t + c) + \sum_{p=1}^{P-1} \Gamma_p \Delta Y_{t-p} + \varepsilon_t$

	P=8		
H_0	λ_{trace}	λ_{maxeig}	*Eigenvalue*
$r = 0$	24.92	21.46	0.001136
	[<0.0001]	[0.0002]	
$r \leq 1$	3.45	3.45	0.000183
	[0.9985]	[0.9796]	

Note: λ_{trace} is the Johansen's trace and λ_{maxeig} is the Johansen'smaximum lambda test. P-values in squared brackets according to MacKinnon et al. (1999).

Lag-length P chosen according to Schwarz information criterion.

Source: authors' calculations.

Table 4

Table 4: Error Term Diagnostics

Contemporaneous correlation		
	DJIA	***DAX***
DJIA	1	
DAX	0.0716	1

	Mean	Std.Dev.	Skewness	Excess Kurtosis	LB-Q(15)
DJIA	0.0038	0.3487	0.0143	6.3638	6.88
DAX	0.0034	0.7872	0.0660	8.5245	10.89

Note: Ljung-Box Q-test distributed as a $\chi^2(15)$. ***:=sign. at 1%; **:=sign. at 5%; *:=sign. at 10%

Source: authors' calculations.

Table 5

Table 5: Information dominance

	DJIA	***DAX***
Kasa's measure		
	0.6112	0.3888
	[0.0267]	[0.0408]
Hasbrouk's measure		
average	0.9510	0.0490
	[0.0021]	[0.0405]
bounds	0.9061 , 0.9959	0.0939 , 0.0041
	[0.0051] , [0.0002]	[0.0404] , [0.0452]
Gonzalo-Grangers' measure		
	0.8724	0.1276
	[0.0029]	[0.0199]

Note: P-values in squared brackets based on bootstrapped standard errors.

Source: authors' calculations.

Table 6

Table 6: Common permanent component estimation and hypothesis testing

	DJIA	***DAX***
Feedback parameters		
$\alpha = (\alpha_1, \alpha_2)'$	0.0036	-0.0246
	[0.1942]	[0.0605]
Hypothesis testing	$H_{0,a}$	$H_{0,b}$
Q_{GG}	1.6920	15.5001
	[0.1934]	[<0.0001]

Permanent-transitory decomposition (Gonzalo and Granger, 1995)

$$\begin{pmatrix} Y_{DJIA_t} \\ Y_{DAX_t} \end{pmatrix} = \begin{pmatrix} 0.3321 \\ 0.2936 \end{pmatrix} f_t + \begin{pmatrix} -3,8140 \\ 26,0601 \end{pmatrix} z_t$$

where

$$f_t = 2.6670 Y_{DJIA,t} + 0.3902 Y_{DAX,t}$$

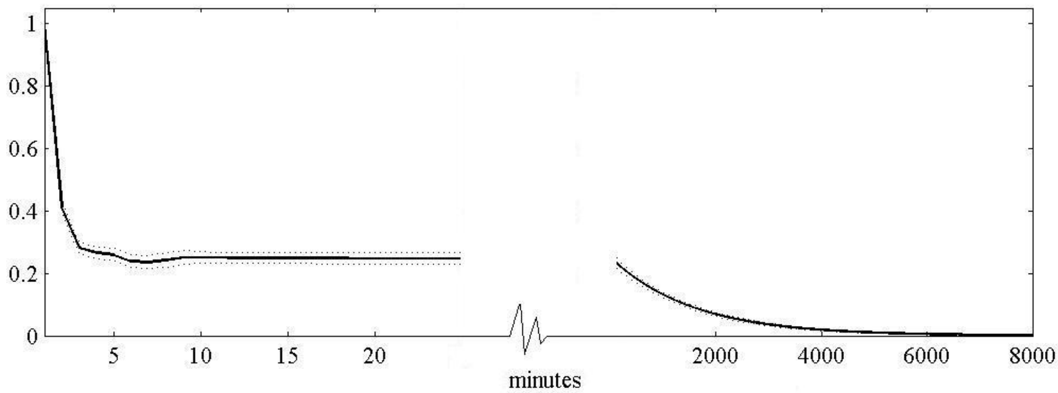
$$z_t = -0.0490 Y_{DJIA,t} + 0.0312 Y_{DAX,t}$$

Note: Q_{GG} is the $\chi^2(1)$-distributed test statistic of Gonzalo and Grangers'likelihood ratio test on common factor weights with one degree of freedom.
P-values in squared brackets (based on bootstrapped standard errors).

Source: authors' calculations.

Figure 1

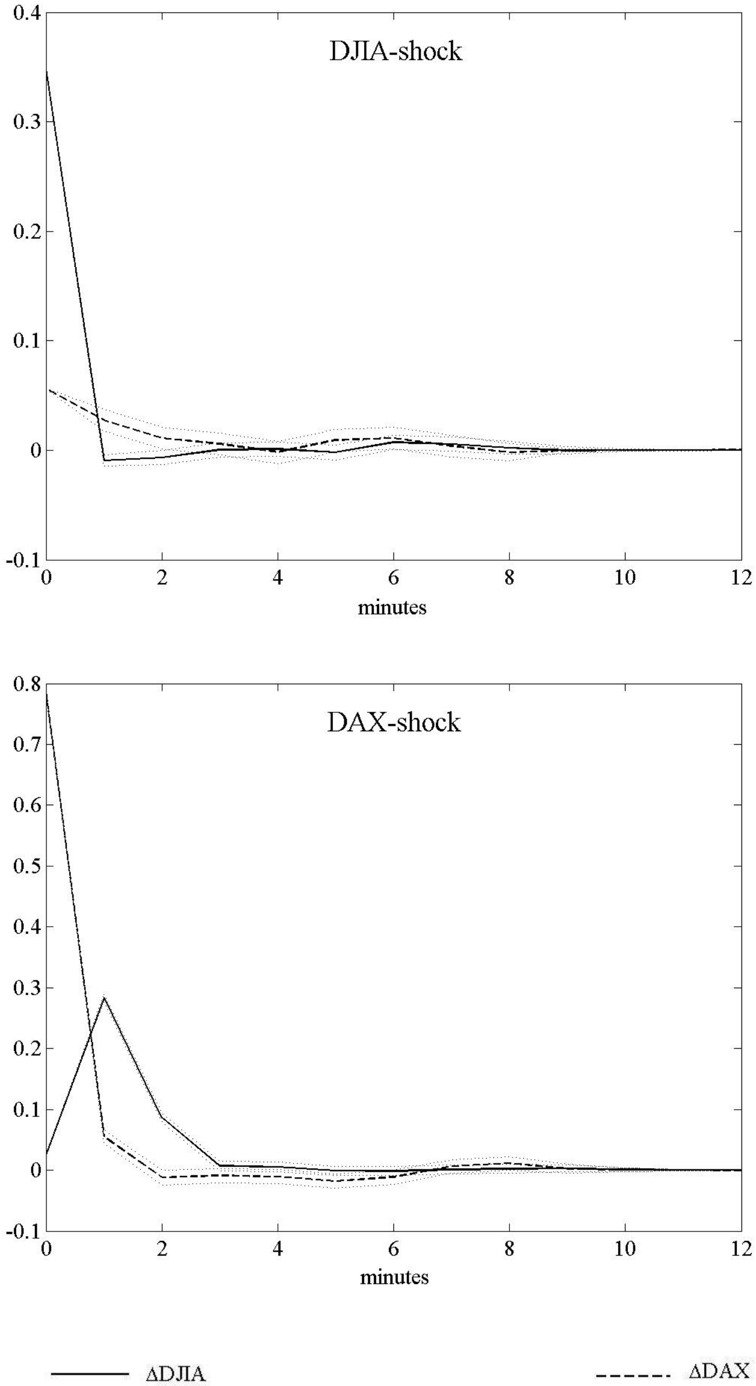
Figure 1: Persistence profile of a one-standard-error shock



Source: authors' calculations.

Figure 2

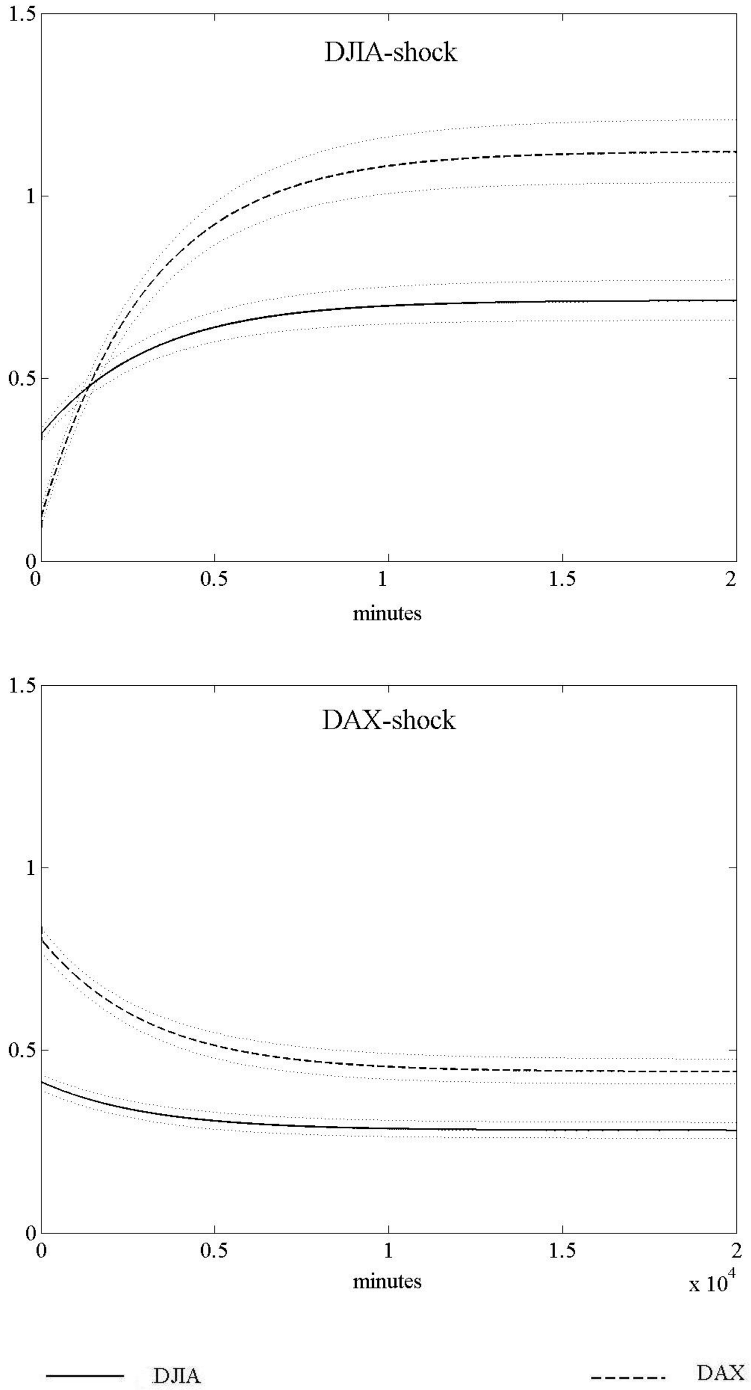
Figure 2: Effects of a one-standard-error shock to adjustment equations



Source: authors' calculations.

Figure 3

Figure 3: Effects of a one-standard-error shock to level equations

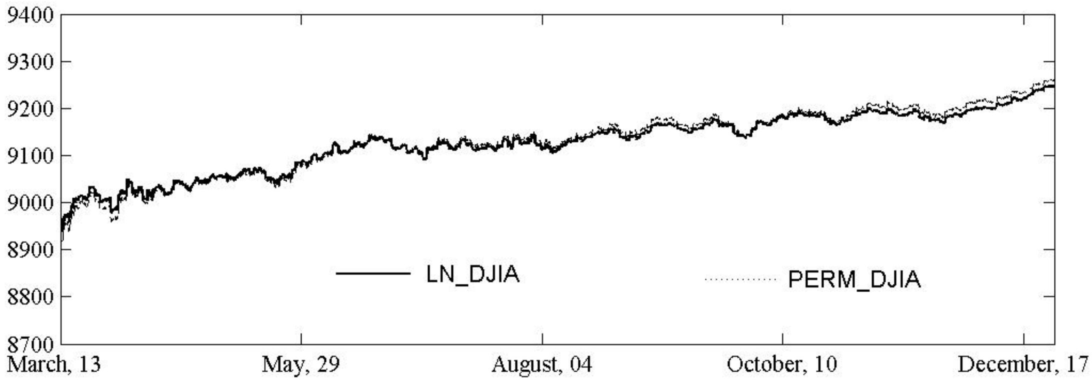


Source: authors' calculations.

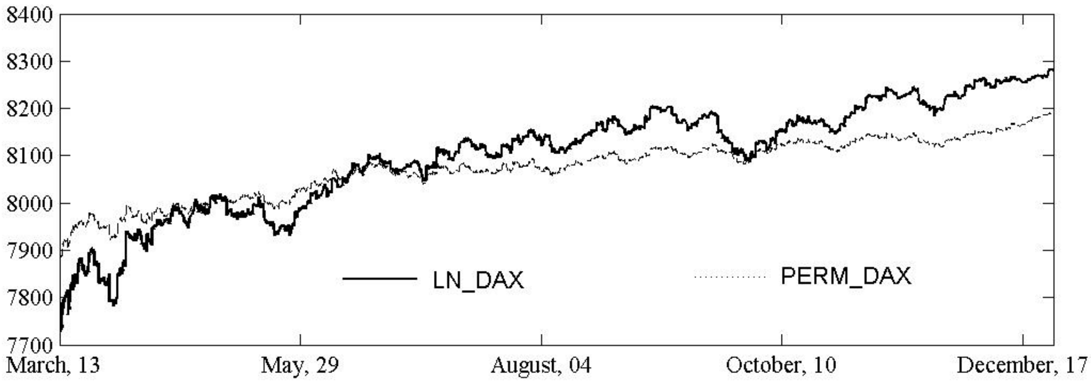
Figure 4

Figure 4: Permanent component vs. actual series

(a): Permanent component imposed on DJIA



(b): Permanent component imposed on DAX



Note: PERM_DJIA $= 0.3321 f_t$ and PERM_DAX $= 0.2936 f_t$, where $f_t = 2.6670 Y_{DJIA,t} + 0.3902 Y_{DAX,t}$.

Source: authors' calculations.