Did the Bundesbank React to Stock Price Movements?

Martin T. Bohl
(European University Viadrina)

Pierre L. Siklos
(Wilfrid Laurier University Waterloo)

Thomas Werner
(Deutsche Bundesbank)

Discussion paper 14/03
Economic Research Centre
of the Deutsche Bundesbank

June 2003

Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431, fax +49 69 5601071

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax No. +49 69 9566-3077

ISBN 3–935821–64–6

Abstract

In this paper, we investigate the relationship between stock returns and short-term interest rates. Identification of the stock return-interest rate relation is solved by using a new technique that relies on the heteroskedasticity of shocks to stock market returns. We suggest some improvements to the identification technique and its justification, as well as providing some new findings. In particular, we ask whether the Bundesbank, prior to the European Central Bank taking responsibility for monetary policy in 1999, reacted systematically to stock price movements. In contrast to the results for the US, our empirical findings for the 1985 – 1998 period show a positive, but statistically insignificant, parameter for the relationship between German stock returns and short-term interest rates at the daily frequency. The same result is found at the monthly frequency. Nevertheless, the confidence bands are wide enough that we cannot entirely exclude the possibility of a reaction at lower frequencies. The results are extremely robust to alternative methods used to identify changes in heteroskedasticity. The evidence is, therefore, inconsistent with the hypothesis of a systematic reaction of the Bundesbank to every wiggle in German stock prices. Both the historical and institutional evidence are supportive of this conclusion.

Zusammenfassung

In diesem Diskussionspapier untersuchen wir den Zusammenhang zwischen Aktienkursveränderungen und Veränderungen der kurzfristigen Zinssätze. Die ökonometrische Identifikation dieses Zusammenhangs erfolgt mit Hilfe eines neuen Verfahrens, das die Heteroskedastie von Aktienkursveränderungen ausnutzt. Wir schlagen einige Verbesserungen und Rechtfertigungen zu diesem Verfahren vor und liefern neue empirische Befunde. Im Vordergrund der Betrachtungen steht die Frage, ob die Bundesbank vor der Übernahme der geldpolitischen Entscheidungen durch die Europäische Zentralbank im Jahre 1999 systematisch auf Veränderungen der Aktienkurse reagiert hat. Im Unterschied zu den verfügbaren Ergebnissen für die Vereinigten Staaten von Amerika, finden wir auf Basis von Tagesdaten zwar einen positiven, aber statistisch nicht signifikanten Parameter für die Reaktion des kurzfristigen Zinssatzes auf Änderungen des Aktienkurses. Auf der Grundlage von Monatsdaten ist der Parameter ebenfalls positiv und statistisch insignifikant. Die Konfidenzintervalle sind aber sehr breit, so dass eine Reaktion auf der niedrigeren Frequenz nicht völlig ausgeschlossen werden kann. Die empirischen Resultate sind sehr robust gegenüber unterschiedlichen Modellspezifikationen. Die empirische Evidenz widerspricht somit der These einer systematischen Reaktion der Bundesbank auf jede Bewegung am Aktienmarkt, was durch die historischen und institutionellen Gegebenheiten gestützt wird.

Contents

Did the Bundesbank React to Stock Price Movements?*

1. Introduction

Econometrics has made great strides in identifying the reactions of the monetary authorities to economic developments from data that simultaneously reflects the behavior of agents in the economy. Nevertheless, it is also becoming apparent that reaction function estimates might inaccurately identify central bankers' preferences. One reason is that other factors that a central bank might react to are omitted from the reaction function, most notably developments in asset markets. In addition, there is a lack of recognition that there are pressures on the central bank to react to high frequency movements in asset prices in particular.

Rigobon (2002), and Rigobon and Sack (2003), offer a solution to the identification problem. An important feature of the Rigobon-Sack approach is that it relies on high frequency data (viz., daily observations) and, in particular, on an identification procedure that exploits the heteroskedasticity of shocks to stock market returns to identify regimes when the central bank reacts to stock market developments. Using daily US data over the 1985 – 1999 period, Rigobon and Sack (2003) conclude that rising stock prices drive short-term interest rates in the same direction, suggestive of a systematic reaction of the Federal Reserve to stock price movements.

The behavior of stock prices in recent years, together with the growing relative importance of financial wealth more generally, has re-ignited a debate about the role asset prices ought to play in monetary policy decisions. This is not the first time, of course, that

* The research for this paper was partly conducted while the first two authors were visiting the research centre of the Deutsche Bundesbank. Both authors like to thank the Deutsche Bundesbank for their hospitality and financial support, Heinz Herrmann and Roberto Rigobon for comments on an earlier draft. Siklos also thanks the SSHRCC for financial support. Previous versions of this paper were presented at the Oesterreichische Nationalbank, Vienna, the Universidade Nova de Lisboa, Lisbon, Queensland University of

the impact of asset prices on the conduct of monetary policy, especially stock prices, has become an important topic of debate. For example, in 1987, the Federal Reserve, was given credit for stemming the perceived negative macroeconomic effects of the stock market crash of that year. Further impetus for this debate comes from the increased visibility and importance over the past several years given to the stock market's role in the monetary transmission process (Chami, Cosimano, and Fullenkamp, 1999; Mishkin, 2001). Even in the European context, while stock markets are thought to pay a less prominent role than in the US, their importance is rising quickly suggesting that the gap between the two continents in this respect is narrowing (Goodhart and Hofmann, 2001; European Central Bank, 2002).

It has been popular to interpret monetary policy decisions by framing them around some monetary policy rule, namely a Taylor rule. Such rules have also been found to adequately describe the behavior of the Bundesbank (Clarida, Gali, and Gertler (1998), but see Faust, Rogers, and Wright (2001)). Nevertheless, there is as yet little consensus about whether central banks react to something other than to inflation and output and criticisms have also been levelled at the manner in which existing reaction functions have been estimated (see below). As a result, one branch of the literature asks whether, in addition to an inflation and an output gap, a term representing stock price movements should also be included (e.g., Bernanke and Gertler, 1999, 2001; Cecchetti, Genberg, Lipsky, and Wadhwani, 2000; Bullard and Schaling, 2002; Gilchrist and Leahy, 2002). A possible drawback with such an approach is that it relies on data typically sampled at the quarterly frequency. Hence, the potential reaction of central banks and money markets to occasionally large day-to-day shocks emanating from the stock market is diminished when lower frequency data are used.

Technology, La Trobe University, the Norges Bank, and the Deutsche Bundesbank. The views in this paper are those of the authors and do not necessarily represent those of the Deutsche Bundesbank.

On the other hand, one ought to consider whether it is at all advisable for central banks to react to rapidly rising stock price movements, especially as they might be accused of displaying myopic behavior (e.g., Siklos 1999, 2002).[1] Therefore, any reaction might be muted or implemented over a longer period of time thereby becoming apparent only in monthly or even quarterly data. A deeper question is whether it is even appropriate at all for a central bank to react to asset prices. Thus, while inflation and output developments affect everyone in society the same is not true of asset prices. A counter-argument is that if developments in asset prices signal financial instability this may have repercussions economy-wide.

The rising volatility of asset prices, such as stock prices, seems to have been associated with a diminution of volatility in business cycle movements. It is possible that this too is partly the result of central banks that have systematically responded to stock price movements. Yet, there are few empirical studies that have estimated the size of this response (and none for countries outside the US) owing to a serious identification problem. The problem stems from the fact that while monetary policy might react to stock prices, money markets are also supposed to anticipate future developments in monetary policy. In other words, the stock price-interest rate relationship involves endogenous variables. Moreover, conventional methods, such as instrumental variables approaches, are unable to satisfactorily correct the endogeneity problem because of the near non-existence of instruments highly correlated with asset prices but uncorrelated with interest rate movements.[2]

The aim of the paper then is twofold. First, we provide empirical evidence on the stock price-interest rate link using German data covering a sample when the Bundesbank

[1] Indeed it is this kind of consideration that led Alan Greenspan (2002) to remark that "…nothing short of a sharp increase in short-term rates … is sufficient to check a nascent [stock market] bubble". Since monetary policy displays a tendency for interest rate smoothing (e.g, Goodhart, 1999; Sack and Wieland, 1999), a reflection of the natural caution of central bankers, this might suggest that central banks should not respond to day-to-day fluctuations in asset prices.

was solely responsible for the conduct of monetary policy in Germany, namely February 1, 1985 to December 30, 1998. As one of the world's most successful central bank in terms of controlling inflation, it has long practised monetary policy in a highly pragmatic fashion that has involved monitoring all key economic indicators around a policy of monetary targeting (Deutsche Bundesbank, 1999).[3] In addition, we provide a brief discussion suggesting that the theoretical motivation linking stock prices to monetary policy is varied though a common thread is the concern that a central bank might express over the volatility of stock returns. Nevertheless, institutional differences suggest that the Bundesbank in particular, unlike its US counterpart, might be less inclined to react to stock market developments.

Second, we modify Rigobon and Sack's (2003) testing strategy in a number of ways. In particular, we use different methods to identify volatility regimes. Whereas Rigobon and Sack (2003) rely on a thirty-day rolling variance of the residuals from a VAR, and recognize that this is an ad hoc procedure, we instead posit a Markov switching process to identify different volatility regimes. In addition, we implement a bootstrapping procedure to calculate the standard error of the parameter of interest that recognizes the fat tailed nature of asset prices instead of the normality assumption made by Rigobon and Sack (2003). Finally, our VARs capture the potential spillovers of stock market developments in the US. Hence, even if the German stock market, per se, has a limited impact on German monetary policy it is conceivable that stock market developments in the US, where stocks play an increasingly important role in the transmission process, may indirectly influence Bundesbank actions.

The paper proceeds as follows. In section 2, we discuss the relationship between stock price developments and monetary policy. The identification technique is outlined in

[2] There are strong theoretical reasons to link stock prices and interest rates or inflation. Space constraints prevent a full discussion. See, however, Sellin (2001) for a recent survey.

section 3. Section 4 contains the empirical results, and section 5 concludes with a summary and suggestions for future research.

2. Monetary Policy and the Stock Market

A popular view of the determination of stock prices is that they reflect expectations of future cash flows. Another important strand of the literature views stocks as a hedge against inflation. Hence, stock returns may be viewed as a forward-looking variable and there is empirical evidence that associates the stance of monetary policy, notably monetary expansions, with stock market performance (e.g., Thorbecke, 1997). Nevertheless, the evidence for the G7 countries, suggests that the forecasting properties of asset prices is rather poor (Stock and Watson, 2001).

Important contributions by Allen and Gale (2000, 2002) suggest that since stocks and real estate are often purchased with borrowed funds, there exists an incentive for borrowers to shift risk to lenders who may not be able to observe the underlying riskiness of the investments made by the borrowers. This produces an agency problem. Consequently, they show that, as bank credit expands, asset prices react more strongly than in the discounted expected payoff scenario. Hence, asset price volatility provides an indication of the consequences of too rapid bank credit expansion. Of course, if bank credit expands too quickly the central bank is duty bound to react by raising interest rates. Nowhere is this view likely to be as strongly held as in the Bundesbank.

In a multi-country setting, Allen and Gale (2000, 2002) also show that relatively more asset price inflation in one country can, if asset price volatilities differ, actually exacerbate a fall in asset prices in another country. As such, interlinkages in asset price markets can matter a great deal. Therefore, there may be good reasons for policy makers in

[3] More recently, it has become fashionable to interpret the monetary targeting regime of the Bundesbank as being consistent with a form of inflation targeting (e.g., see Bernanke and Mihov, 1997).

one country to be concerned with asset price developments in other countries. Obviously, stock market developments in the US would serve as the benchmark.

There is empirical evidence that stock market volatility is not immune to monetary policy. For example, Bomfin (2002) concludes that, for the US, stock market volatility is “abnormally” high around days the FOMC meets. Therefore, in principle, it seems sensible to suggest that higher stock market volatility is suggestive of a central bank reacting to stock market developments. Nevertheless, it is clear that the link between stock returns and an interest rate instrument, heavily influenced by central bank actions, is an endogenous one. That is, while the stock market may be attempting to anticipate the future stance of monetary policy it is also clear that the central bank may itself react to current stock market volatility via the interest rate instrument. As the foregoing suggests, volatility, at least at the theoretical level, is the device that offers a link between asset price movements and may motivate interest rates reactions by the central bank. To the extent that higher stock returns are associated with more volatile returns, and the former is perceived by the central bank as presaging higher future inflation, a central bank reaction is warranted. The difficulty is that not all such developments signal higher future inflation. The potential then for a central bank to react to stock returns, their volatility, or both, need not be unambiguous.

Therefore, whereas Rigobon and Sack (2003) presume that the Federal Reserve raises interest rates in response to higher stock market returns, the theoretical literature has decidedly mixed views on the subject. For example, Bernanke and Gertler (2001) suggest that an inflation targeting policy ought to stabilize inflation and output even when stock markets are volatile so that there is no benefit in responding to asset prices. Cecchetti, Genberg, Lipsky, and Wadhwani’s (2000) simulations reveal that explicit reaction to asset price movements in a Taylor-type rule can, under certain circumstances (e.g., a shift in the risk premium), assist the monetary authorities in reducing output volatility.

Nevertheless, an overwhelming feature of much of the literature is the focus on the reactions of the stock market to central bank actions and less so on the question of whether the central bank itself responds to stock market developments. Indeed, there is a rich literature that addresses the former issue (e.g., Smets (1997) and Giammarino (1998) and references therein). Yet, the emphasis in the literature that addresses the reaction of central banks to asset prices has tended to focus on whether it is desirable or even possible for the monetary authority to prevent stock market bubbles (e.g., Filardo, 2001) with the literature deeply divided on the practicability of such a policy. Bordo and Jeanne (2002) argue forcefully that there is little to be gained from trying to anticipate the coming of a bubble. Instead, they advocate the monitoring of indicators of financial stress since they believe these are better suited to uncovering hints of the types of credit crunches that generally follow a rapid drop in asset prices.

There is also relatively little discussion in the literature about the potential conflict between a central bank responsible for maintaining low and stable inflation rates while showing concern for output developments, both slow moving and persistent aggregates, and a central bank that attempts to respond to data produced at high frequency. Siklos (1999) refers to a central bank that responds too often as one that suffers from "tunnel vision". The quest to understand the implications of high frequency data for the conduct of monetary policy reveals that policy makers are asking: since information is supplied by the market apparently more frequently, should this necessarily elicit more frequent responses? Why should central bankers care about, say, daily fluctuations in the exchange rate, interest rates or stock prices, if these are unlikely to have permanent economic effects or threaten the success of their stated policy objectives?

There are a couple of reasons for the resulting tensions between taking the long view on policy questions and the need to be seen as responding to frequent shocks which may, or may not, have lasting consequences for the economy. First, central banks are also viewed as the guardians of the stability of the financial system and, as such, may be expected to react to news that might influence financial markets. Second, interest by central banks in high frequency information resides in the fear that one small event, whether "rational" or not, can trigger a financial crisis and, thus, threaten the stability of the financial system (e.g., the "irrational exuberance" statement made by Alan Greenspan in December 1996). Therefore, policy makers worry that the probability that one small event can have disastrous consequences for the stability of the financial system is sufficiently high to warrant the monitoring and response to high frequency data.

The discussion in this section shows that, to the best of our knowledge, no single theoretical model in the literature fully addresses the relationship between stock market behavior and monetary policy. Moreover, the connection to stock market volatility is heavily dependent on views about how stock prices are determined. Nevertheless, Allen and Gale (2002) show that the agency problem discussed above implies that a link exists between asset prices and bank credit. The possibility of stock market bubbles, and their prevention, is therefore tied to monetary policy actions. In other words, the volatility of asset prices can play a central role in influencing interest rate determination. Rigobon and Sack's (2003) procedure relies precisely on this feature to identify the central bank's potential reaction of interest rates to stock prices.

At an institutional level, there are also grounds for scepticism about the potential for interest rate reactions initiated by the central bank to stock market developments. First, as noted above, central banks are viewed as acting cautiously as reflected by the widespread belief that they smooth interest rates. Second, central banks make decisions at regular intervals only (every two weeks in the case of the Bundesbank) and, unlike the Federal funds market, there was less scope for the Bundesbank to react to daily developments in money or bond markets.

3. Identifying Policy Reactions to Stock Prices via Heteroskedasticity

Rigobon and Sack's (2003) technique to identify the reaction of monetary policy to stock price movements relies on the heteroskedasticity in interest rate and stock returns over time (see also Rigobon, 2002). The motivation behind of their identification technique is similar to the one used to solve the identification problem in the standard example of supply and demand curves. When shocks produce greater volatility in the stock market, the covariance between interest rates and stock returns is assumed to rise and this implies a positive link between interest rates and stock prices, the *a priori* sign predicted from such a relationship. The increase in the volatility of stock market shocks thus serves the role of an instrument, since the higher covariance between interest rates and stock prices is a reflection of the greater responsiveness of monetary policy to the stock market that permits identification of a reaction function of the central bank to asset price movements. However, as noted earlier, the relationship between the central bank's policy instrument and stock prices is a simultaneous one and more structure is required to disentangle the sources of correlation between the two series.

Consider the same dynamic structural equations as in Rigobon and Sack (2003):

$$i_t = \beta s_t + \theta x_t + \gamma z_t + \varepsilon_t \tag{1}$$

$$s_t = \alpha i_t + \phi x_t + z_t + \eta_t, \tag{2}$$

where i_t denotes the short-term interest rate and s_t the stock return. x_t is a vector containing lags of i_t and s_t, as well as other observable macroeconomic shocks. The variable z_t summarizes unobservable shocks that may affect stock returns and the interest rate. The inclusion of z_t completes the specification of the model and rules out factors that could also explain the covariance between monetary policy actions and the stock return.

Equation (1) is the monetary policy reaction function, and is the focus of this paper, (2) is the stock market reaction function, and the policy shock variable ε_t is orthogonal to the stock market shocks η_t. Note that reaction function (1) could be interpreted as a version of the conventional Taylor rule augmented by the stock returns variable. However, as the identification procedure relies primarily on high frequency data, there are no obvious counterparts to the inflation and output gap terms. Hence, at best, (1) may be viewed as a restricted version of a conventional monetary policy reaction function.[4] As noted above, central banks may be accused of reacting too frequently to stock market developments while seemingly ignoring other economic developments. Hence, it may also be sensible to estimate versions of (1) and (2) at a lower frequency, say monthly, as any central bank reactions to stock market prices may become more apparent at such frequencies, especially for a central bank that is cautious.

If the parameter α is different from zero, equation (1) cannot be estimated via OLS since the parameter of interest, β, is a biased estimate of the reaction of the short-term interest rates to stock price changes owing to the simultaneity problem discussed above. Moreover, z_t is unobservable which further contributes to a bias in OLS estimates of β. Indeed, what can be estimated is a reduced form written as:

$$\begin{pmatrix} i_t \\ s_t \end{pmatrix} = \Phi\, x_t + \begin{pmatrix} v_t^i \\ v_t^s \end{pmatrix}. \tag{3}$$

The residuals in equation (3) are as follows:

$$v_t^i = \frac{1}{1-\alpha\beta}\left[(\beta+\gamma)z_t + \beta\eta_t + \varepsilon_t\right] \tag{4}$$

$$v_t^s = \frac{1}{1-\alpha\beta}\left[(1+\alpha\gamma)z_t + \eta_t + \alpha\varepsilon_t\right] \tag{5}$$

[4] Needless to say, one could argue that a central bank may very well have a daily reaction function in addition to a monthly or quarterly policy rule. In this sense, (1) can be likened to the reaction implicit in a

and the covariance matrix of the reduced form residuals is:

$$\Omega = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} (\beta+\gamma)^2\sigma_z^2 + \beta^2\sigma_\eta^2 + \sigma_\varepsilon^2 & (1+\alpha\gamma)(\beta+\gamma)\sigma_z^2 + \beta\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 \\ . & (1+\alpha\gamma)^2\sigma_z^2 + \sigma_\eta^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix}. \tag{6}$$

The covariance matrix provides only three moments (the variance of i_t, the variance of s_t, and the covariance between i_t and s_t) but there are three unknown coefficients, namely α, β and γ, as well as three unknown variances σ_z^2, σ_η^2 and σ_ε^2. If the covariance does not remain constant, a shift to a regime with a different covariance matrix provides three new equations as well three new unknown parameters, namely σ_z^2, σ_η^2 and σ_ε^2. However, imposing additional assumptions to the variances of the shock process, such as assuming that ε_t is homoskedastic, ensures an identification of the system.[5] Hence, three additional equations are generated when there is a shift in the covariance matrix. Identification in this case then requires three volatility regimes.

As shown in Rigobon and Sack (2003) and also in Rigobon (2002) the β parameter must solve the following system of equations:

$$\theta = (\Delta\Omega_{21,12} - \beta\Delta\Omega_{21,12})/(\Delta\Omega_{21,11} - \beta\Delta\Omega_{21,12}), \tag{7}$$

$$\theta = (\Delta\Omega_{31,12} - \beta\Delta\Omega_{31,22})/(\Delta\Omega_{31,11} - \beta\Delta\Omega_{31,12}). \tag{8}$$

This is a system of equations with two unknowns (θ, β) and is, therefore, just identified when there are three volatility regimes. Each additional regime requires another equation of the same type in which case the system becomes over-identified. In this case it is possible to estimate it via GMM.

monetary conditions index that can be computed, and has been by a number of central banks, at the daily frequency. See Siklos (2000), and references therein.

[5] Additionally, the coefficients α, β and γ are treated as stable across the covariance regimes, an assumption often invoked in the reaction function literature. The empirical evidence to be presented below justifies such an assumption, at least for the data and sample employed here.

The terms in (7) and (8) represent elements that produce changes in the covariance matrices from regimes $i=1$ to regimes $i=2,3$. These can be identified with the help of the covariance matrix under each regime $i=1,2,3$ written as:

$$\Omega_i = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} (\beta+\gamma)^2\sigma_{i,z}^2 + \beta^2\sigma_{i,\eta}^2 + \sigma_\varepsilon^2 & (1+\alpha\gamma)(\beta+\gamma)\sigma_{i,z}^2 + \beta\sigma_{i,\eta}^2 + \alpha\sigma_\varepsilon^2 \\ . & (1+\alpha\gamma)^2\sigma_{i,z}^2 + \sigma_{i,\eta}^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix}. \qquad (9)$$

Moreover, defining the change of the covariance matrix from regime $i=1$ to regime $i=2$ as $\Delta\Omega_{21} = \Omega_2 - \Omega_1$ and, equivalently, the change of the covariance matrix from regime $i=1$ to regime $i=3$ as $\Delta\Omega_{31} = \Omega_3 - \Omega_1$ equation (9) implies for $j=2,3$:

$$\Delta\Omega_{j1} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} (\beta+\gamma)^2\Delta\sigma_{j1,z}^2 + \beta^2\Delta\sigma_{j1,\eta}^2 & (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma_{i,z}^2 + \beta\sigma_{i,\eta}^2 + \alpha\sigma_\varepsilon^2 \\ . & (1+\alpha\gamma)^2\sigma_{i,z}^2 + \sigma_{i,\eta}^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix}, \qquad (10)$$

where $\Delta\sigma_{j1,z}^2 = \sigma_{j,z}^2 - \sigma_{1,z}^2$ and $\Delta\sigma_{j1,\eta}^2 = \sigma_{j,\eta}^2 - \sigma_{1,\eta}^2$. Hence, $\Delta\Omega_{j1,kl}$ in equations (7) and (8) is the element k and l in matrix $j=2,3$.[6]

4. Empirical Evidence

Our empirical investigation relies on daily data covering the period from February 1, 1985 to December 30, 1998. The sample is motivated by institutional and historical considerations. Beginning in February 1985 the Bundesbank's operating procedure changed and relied primarily on repurchase agreements instead of discount and Lombard rates to influence money market rates. Our sample ends when the European Central Bank took over the responsibility of monetary policy from the Bundesbank on January 1, 1999.

The time series used in our study are the daily returns on the Deutsche Aktienindex (Dax) at the close of trading day, s_t, the change in the three months money market rate as the German short-term interest rate, Δi_t. The control variables in the vector x_t are changes

[6] For further details on the solution of the identification problem see the appendix in Rigobon and Sack (2001) and Rigobon (2002).

in the US three months Treasury bill yield (secondary market rate), Δi_t^{US}, the returns on the US Dow Jones index, again at the close of trading, dow_t, the rate of change in the spot DM-US-$ exchange rate, ξ_t, and the rate of change in world market oil price, oil_t. Stock returns and oil price inflation are evaluated in first log differences of the levels.

Data were obtained from FRED II (research.stlouisfed.org/fred2/), Datastream, and the Bundesbank. In computing rates of change no special adjustments were made for weekends and holidays (alternative specifications were examined and these did not impact the conclusions). Therefore, we omitted from the data set all non-overlapping daily observations prior to computing daily rates of change in all variables, where relevant. This yielded a total of 3365 observations.[7] In addition to the daily time series we provide empirical evidence for the monthly frequency. The monthly time series are averages of daily data.

To obtain some stylised facts about the relationship between stock returns, the short-term interest rate, and stock market volatility, we estimate the rolling six months correlation coefficients and the corresponding standard deviations of the stock returns. As seen in Figure 1a, periods of consecutive negative and positive correlation coefficients exist and this outcome is comparable to the findings of Rigobon and Sack (2003, Figure 3) who used US data. However, in Rigobon and Sack's case there seems to be a relatively close relationship between the correlation coefficients and stock market volatility, while for Germany periods of high (low) volatility and positive (negative) correlation are less pronounced. It should be noted that Figure 1 relies on the first difference of interest rates and not their levels as in Rigobon and Sack (2003).[8]

---

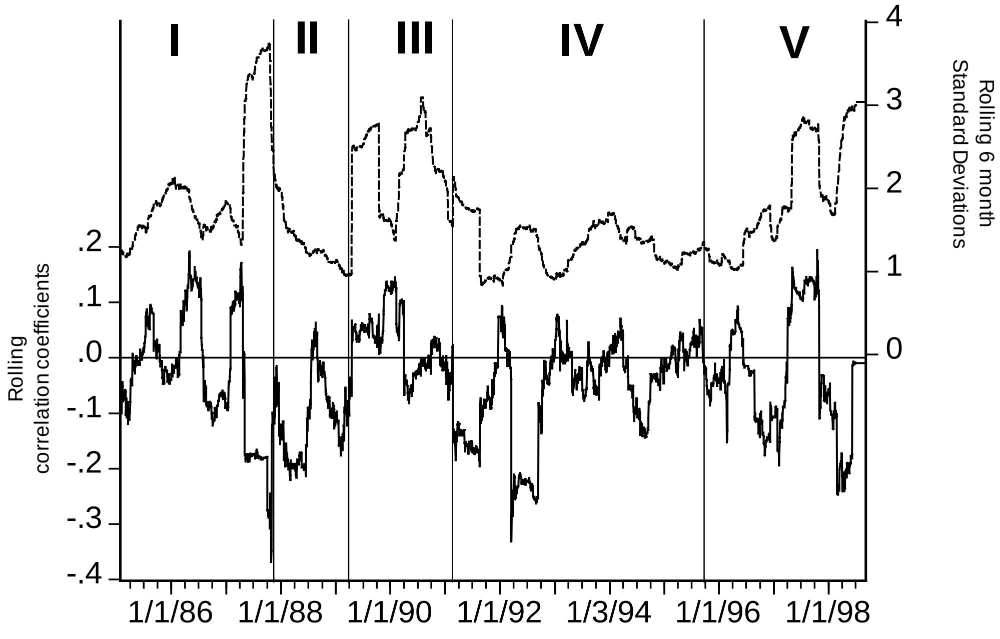
[7] If we ignore holidays, the potential number of observations over the sample considered is shown in parenthesis: s (3476), dow (3516), ξ (3483), oil (3629), and i^{US} (3478).

[8] As noted earlier the identification technique used here relies on the volatility of stock returns. However, one could instead rely on the volatility of interest rates to identify the relevant regimes. It seems unlikely that the results would be qualitatively different (results not shown).

Turning to monthly data, as shown in Figure 1b, the relationship is broadly the same as in the case of daily data except that the correlations can be much higher (in absolute values), and this is especially notable at times of large swings in the standard deviations of returns. The resort to a lower frequency does reduce the heteroskedasticity in the data but it is unclear that it destroys the underlying correlations that are highlighted by the identification technique used here. The vertical bars in Figure 1a and 1b define the boundaries that separate high from low volatility periods based on a Markov regime switching model (see below). Generally, the Markov switching approach's choice for high versus low volatility regimes is not vastly different from that based on the rolling standard deviation measure and the one used by Rigobon and Sack (2003).

Figure 1: Rolling Correlation Coefficients and Standard Deviations

Figure 1a: Daily Data



The first stage of the estimation process involves obtaining the residuals from a vector autoregression (VAR) of the reduced form (3):

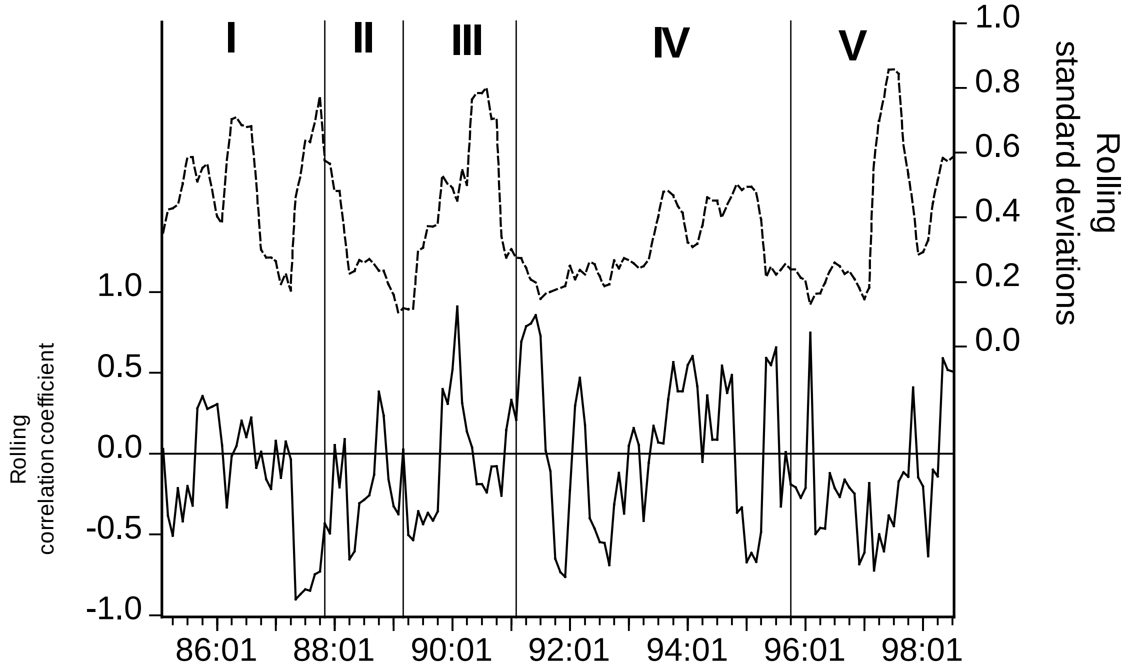
$$x_t = \left(\Delta i_t, s_t \mid \Delta i_{t-i-1}, s_{t-i-1}, dow_{t-i}, \Delta i_{t-i}^{US}, oil_{t-i}, \xi_{t-i}\right)', \quad i = 0,1,\ldots,5, \tag{11}$$

where Δi_t and s_t have been previously defined and we include five lags for each of Δi_t and s_t, and conditioned on the contemporaneous and five lags in dow_t, ξ_t, Δi_t^{US}, and oil_t as exogenous variables. It is not immediately clear whether i_t is stationary. Indeed, it is common to first difference interest rate time series to induce stationarity (a unit root test confirms this result). We follow this standard approach to the treatment of the interest rate time series although first differencing of the nominal interest rate series may be objected to on theoretical grounds. In any event, our conclusions are unaffected by this choice (results for i_t in levels are available on request). It should also be noted that the simple correlation between Δi_t and s_t is considerably higher in absolute terms than when interest rates in levels are used (– 0.018).[9]

[9] The simple correlation between i and s is – 0.018 while the correlation between Δi and s is – 0.083. A potential drawback of the level specification is that it may result in the appearance of a zero correlation between the variables of interest even if there exists a structural relationship between these same series. In contrast, the first difference specification can preserve the underlying structural relationship that might exist between interest rates and stock returns.

Figure 1: Rolling Correlation Coefficients and Standard Deviations (Continued)

Figure 1b: Monthly Data



Note: In Panel 1a and 1b, the dashed line is the rolling standard deviation of the Dax using a six-month window. The solid line is the rolling correlation coefficient between the daily rate of change in the Dax and the change in the three months German money market rate. The vertical lines identify high versus low volatility regimes. These are numbered I to V. In the case of daily data, the regimes are dated as follows: November 16, 1987, March 20, 1989, February 18, 1991 and September 25, 1995. For monthly data the dates are: November 1987, March 1989, February 1991 and October 1995.

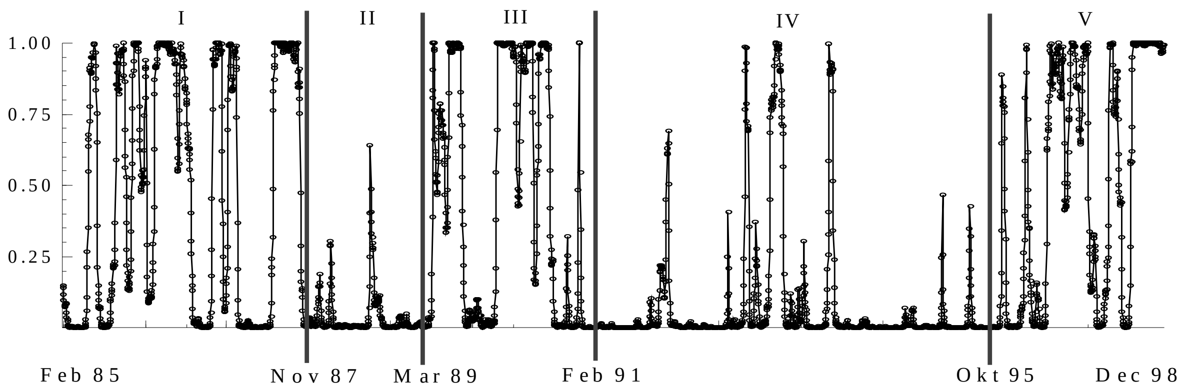
As Rigobon and Sack (2003) point out, it is important to control for observable macroeconomic shocks. While they resort to the use of forecast errors based on monthly releases of five economic indicators, we prefer to assume that the arrival of such shocks is more frequent and better proxied by daily data. In addition, since it is very likely that money and stock market developments in the US will have a significant impact on German interest rates and stock market returns we add the rate of change in the Dow index as an exogenous variable, as well as a short-term US interest rate. Oil prices are also added as a means of controlling for exogenous aggregate supply shocks on the stock market while the exchange rate variable (again, in rates of change) also reflects potential indirect inflationary influences via their pass-through effects on domestic prices and, consequently, may also exogenously impact domestic stock prices.

Regimes are identified, first, by examining the residuals from the stock return equation in the VAR. Next, we use a Markov switching model to extract the regimes. The Markov switching approach is arguably the most popular class of models used to detect regime switches using non-observable variables. Details about the Markov switching model are contained in Appendix A1.[10] While the univariate Markov-switching model suggests that there are two states, namely one displaying high volatility the other low volatility, this need not imply that the regimes identified in this manner are the same. The technique is merely used to permit the subdivision of the sample into periods that appear to display different time series characteristics. Moreover, as we shall see below, the chosen regimes can be linked with important historical events.

Figure 2 plots the probabilities of being in the high volatility regime, while the vertical lines delineate the high from low volatility regimes. Hence, regimes I, III, and V are considered to be high volatility regimes. Recall that the estimation procedure requires that at least three volatility regimes be identified. Some of the regime switches occur around dates that appear imminently reasonable based on the historical experience. For example, the first regime change occurs around the 1987 stock market crash. The second date occurs around the time of the collapse of Communism in Eastern Europe and the publication of the Delors Report setting out the process for European Monetary Union.

[10] The GAUSS programs are available at www.wlu.ca/~wwwsbe/faculty/psiklos/research.htm. The GAUSS programs are adapted from the ones developed by Rigobon who makes them available at http://web.mit.edu/rigobon/www/research.html#workinprogress. The program for the Markov switching routine is explained in Appendix A1.

Figure 2: Smoothed Probabilities of High Volatility Regimes



Note: The line in this graph shows the probability of being in a high volatility regime. The probabilities are bases on a Markov switching model described in Appendix A1. The vertical lines identify the chosen dates for the high and low volatility regimes required for the identification procedure used in the paper. Hence, regimes I, II, and V, are high volatility regimes while regimes II and IV are the low volatility regimes.

It is perhaps more difficult to pinpoint the main economic events that might be associated with the switches in early 1991 and the fall of 1995. Nevertheless, the dissolution of the Soviet Union and the BCCI scandal figure prominently as events that took place in 1991, while the Kobe earthquake and the collapse of Barings took place in 1995. Clearly, a drawback with the Markov switching approach is that it presumes that high or low volatility regimes are all the same when this need not be the case. It is conceivable, for example, that regimes V and I are fundamentally different since one occurred after reunification while the other did not.

In order to guard against the possibility of spurious regime dating we experimented with three other alternatives.[11] First, we considered the possibility that negative and

[11] We also considered the possibility of a sixth regime, between February 1991 and October 1995, assumed to be in the high volatility state (see Figure 2) but our conclusions are unaffected. In addition, we varied by several days the date of the exact location of volatility regime shifts with no impact on the conclusions.

positive shocks in the basic VAR should be treated separately in using the Markov switching technique to locate the timing of regime shifts. Second, we also experimented with a bivariate Markov switching model.[12] Third, we examined the unit root properties of the commercial paper-call money spread, a popular indicator of financial system stress, and found that we could not reject the null of an asymmetric unit root. Estimating the threshold consistently we then defined regimes switches according to whether error corrections were positive or negative. Both the regime switching dates and the overall conclusions of this study were largely unaffected by the method used to locate the timing of volatility regimes. Hence, we report only results based on the standard Markov switching model as our results are very robust to the dating of regime switches.

Turning to monthly data, the identification of regimes via the Markov switching model did not produce as many clear-cut regime switches. However, visual examination of Figure 1b suggests that the regime dating based on daily data can usefully serve to identify regime changes at the monthly frequency. Hence, with the exception of the regime switch in 1989, assumed to occur nine months later than for daily data, the dating of regimes is the same at both frequencies.

Table 1 reports our estimation results. The second column contains the point estimates of the reaction parameter, β, for all regimes and for all regimes without one regime. These estimates are used for a test of constancy of β over the regimes. For the daily time series the point estimate of β is positive and very small, $\hat{\beta} = 0.000005$. The bootstrapped p-value for the null hypothesis $H_0 : \beta = 0$ is 0.795 for the one-sided test with the alternative hypothesis $\beta > 0$. Hence, the null hypothesis clearly cannot be rejected.[13] We also computed a bootstrapped confidence interval and this yielded a range of

[12] Under this approach four states are permitted (two each dependent on the mean and the variance). These were estimated using the MSVAR package written by Hans-Martin Krolzig. The results for this model are relegated to an appendix but, in any event, our conclusions are unchanged.
[13] Details on the bootstrap method for computing the p-values can be found in Appendix A2.

[$-$.009100; 0.00518]. Hence, it is difficult to find any support for a reaction to stock market returns at the daily frequency.

For the monthly data the parameter of interest is also positive and statistically insignificant with a p-value of 0.22. It should be noted that the value of the point estimate $\hat{\beta} = 0.0233$ is considerably larger than in the case of daily time series.[14] In addition, the bootstrapped confidence interval yielded a range of [$-$.9974; 1.8825]. The rather wide confidence interval makes it difficult to rule out entirely a response by the Bundesbank to stock returns.

[14] The point estimate when the interest rate enters in levels is – 0.2534 with a p-value of 0.82). While the null that $\beta = 0$ clearly cannot be rejected, the point estimate is considerably larger than the one shown in Table 1.

Table 1: Estimation Results for Daily and Monthly Time Series

Regimes	$\hat{\beta}$	$\Delta\hat{\beta}$	H_0	p-value
		Daily Data		
All	0.000005		$\beta = 0$	0.79
All without I	0.001670	– 0.001664	$\Delta\beta = 0$	0.61
All without II	– 0.000794	0.000799	$\Delta\beta = 0$	0.72
All without III	0.003997	– 0.003991	$\Delta\beta = 0$	0.48
All without IV	– 0.003994	0.003999	$\Delta\beta = 0$	0.47
All without V	– 0.000283	0.000288	$\Delta\beta = 0$	0.35
		Monthly Data		
All	0.0233		$\beta = 0$	0.22
All without I	– 0.0484	0.0717	$\Delta\beta = 0$	0.32
All without II	– 0.0704	0.0937	$\Delta\beta = 0$	0.44
All without III	0.0230	0.0002	$\Delta\beta = 0$	0.82
All without IV	0.0255	– 0.0021	$\Delta\beta = 0$	0.78
All without V	0.0234	– 0.0001	$\Delta\beta = 0$	0.88

Note: $\hat{\beta}$ denotes the estimated parameter of interest relating the change in short-term interest rates and stock returns. For details on the estimation procedure and the data see Section 3 and 4, respectively. The one-sided p-values are bootstrapped where a description can be found in Appendix A2. Regimes I to V are defined in Figure 2.

To provide a check for robustness we have performed a test on changes in β by excluding successively a different regime. This test of constancy is possible because we have five regimes and three regimes are enough for identification. This allows us to use a test for over-identifying restrictions (Rigobon and Sack, 2003). The results are reported in the third column of Table 1 and are identified as the test of the null hypothesis $H_0 : \Delta\beta = 0$. The β does not change if a regime is excluded from the estimation procedure, that is, $H_0 : \Delta\beta = 0$. The results are shown in the fifth column. For both the daily and the monthly data we cannot reject constancy over the regimes.

Although our findings differ somewhat from those in Rigobon and Sack (2003), there are some common elements. First, we find that the point estimates of the reaction of interest rates to stock returns are robust across regimes. Second, there is a positive, though largely insignificant, effect on interest rates from stock returns. The differences with the empirical evidence reported in Rigobon and Sack (2003) are, however, worthy of discussion. Our point estimates of β in (1) based on daily data are considerably smaller that theirs. Hence, at the daily frequency, short-term money market rates did not respond to Dax returns. However, the impact is considerably larger at the monthly frequency with a 1 % rise in the Dax resulting in a 2.33 basis point rise in the short-term interest rate.

Notwithstanding open questions with the interpretation of β as a policy reaction of the Bundesbank to the stock market, we view our results as suggesting that the German central bank did not respond to every wiggle in stock returns. However, it is somewhat less clear whether the Bundesbank reacted to stock market developments at longer horizons than at the daily frequency. This might reflect the Bundesbank's pragmatic approach to monetary policy (Deutsche Bundesbank, 1995) as well as differences in the implementation of monetary policy in the US versus Germany mentioned earlier.

5. Summary and Conclusions

The nature of the relationship between asset price movements and monetary policy is currently a hotly debated topic in macroeconomics. Even though this aspect of the monetary transmission mechanism seems to be of importance for the conduct of monetary policy, little empirical evidence is available that estimates the relationship between asset price movements and monetary policy measures. This paper provides new empirical findings on the role of stock price movements on interest rates using data from Germany over the 1985 – 1998 period when the Bundesbank, as one of the most influential of central banks in Europe, was responsible for monetary policy. We ask whether the Bundesbank reacted to stock prices to gain additional insights into central bank behavior.

The relevant empirical evidence is difficult to obtain because of an identification problem that cannot be adequately solved with conventional methods such as instrumental variables. Rigobon and Sack (2003) and Rigobon (2002) put forward a new identification technique based on the heteroskedasticity of shocks to stock returns and find that the Federal Reserve reacted to positive stock price movements by raising interest rates, and vice-versa. We also implement what we believe are improvements to their approach and consider the experience of the Bundesbank. Its institutional structure and monetary policy strategy serves as the inspiration for the European Central Bank.

Our empirical results show that, for daily data, interest rates did not respond to stock returns. When using monthly observations, the estimated coefficients are considerably larger but remain statistically insignificant. However, given the wide confidence interval at the monthly frequency the possibility that the Bundesbank might have reacted to stock market developments at lower frequencies cannot be ruled out entirely. These results stand in contrast with the US evidence provided by Rigobon and Sack. While it is possible that our estimation approach provides one reason for the discrepancy between the German and US evidence, though we rely on the same identification technique as the one developed by both authors, we believe that the theoretical rationale linking central bank reactions to asset prices is not yet sufficiently well-developed to provide definite guidance on the question.

Other differences between our approach and the one in Rigobon and Sack include the fact that our VAR uses daily data to provide control for exogenous influences on both interest rates and stock returns unlike Rigobon and Sack who relied on variables available at the monthly frequency. It is also possible that the institutional structure of the Bundesbank and the German stock market may have led to a different response to stock market movements than at the Federal Reserve. In particular, the 1987 stock market crash dwarfs by a considerable margin all other events that raises the volatility in US stock returns, whereas the German stock market experienced three such shocks over the sample considered. As a result, whereas more than 90 % of the US sample used by Rigobon and Sack (2003) is concentrated around the 1987 period, only 20 % of our sample makes up this regime.[15] As Rigobon and Sack point out, while it is difficult to assign all of the weight of the reaction coefficient to central bank policies, we believe our results are consistent with a central bank that does not suffer from tunnel vision but instead waits for an accumulation of evidence about stock returns before changing interest rates.

[15] It is also possible that such features of the data explain why the Fed might have reacted to stock prices while the Bundesbank did not since the threat to expected inflation from stock market performance may simply have not been the same for Germany as it was for the US. We are grateful to Roberto Rigobon for pointing out this possibility to us.

References

Allen, Franklin and Douglas Gale (2000), Bubbles and Crashes, *Economic Journal* 110, 236 – 55.

Allen, Franklin and Douglas Gale (2002), Asset Price Bubbles and Monetary Policy, in *Financial Crises and Global Governance*, Proceedings of a Conference held at the London School of Economics, October (forthcoming).

Bernanke, Ben S. and Mark Gertler (2001), Should Central Banks Respond to Movements in Asset Prices? *American Economic Review Paper and Proceedings* 91, 253 – 7.

Bernanke, Ben S. and Mark Gertler (1999), Monetary Policy and Asset Price Volatility, *Federal Reserve Bank of Kansas City Economic Review* 84, 17 – 52.

Bernanke, Ben S. and Ilian Mihov (1997), What Does the Bundesbank Target? *European Economic Review* 41, 1025 – 53.

Bomfin, Antulio N. (2002), Pre-Announcement Effects, News, and Volatility: Monetary Policy and the Stock Market, *Journal of Banking and Finance* 27, 133 – 51.

Bordo, Michael D., and O. Jeanne (2002), “Asset Price Reversals, Economic Instability, and Monetary Policy”, working paper, Rutgers University.

Bullard, James B. and Eric Schalling (2002), Why the Fed Should Ignore the Stock Market, *Federal Reserve Bank of St. Louis Economic Review* , 35 – 41.

Cecchetti, Stephan, Hans Genberg, John Lipsky, and Sushil Wadhwani (2000), Asset Prices and Central Bank Policy, Geneva Reports on the World Economy, No. 2 London: Centre for Economic Policy Research.

Chami, Ralph, Thomas F. Cosimano, and Connel Fullenkamp (1999), The Stock Market Channel of Monetary Policy, IMF Working Paper 99/22.

Clarida, Richard, Jordi Gali, and Mark Gertler (1998), “Monetary Policy Rules in Practice: Some International Evidence”, *European Economic Review* 42, 1033 – 67.

Davidson, A. C. and Hinkley, D. V. (1997): Bootstrap Methods and their Application, (Cambridge: Cambridge University Press).

Deutsche Bundesbank (1999), Fifty Years of the Deutsche Mark (Oxford: Oxford University Press).

Deutsche Bundesbank (1995), *The Monetary Policy of the Bundesbank* (Frankfurt: Deutsche Bundesbank), October.

European Central Bank (2002), The Stock Market and Monetary Policy, ECB Monthly Bulletin, February.

Faust, John, John H. Rogers, and J. H. Wright (2001), An Empirical Comparison of Bundesbank and ECB Monetary Policy, International Finance Discussion Papers 705, August.

Filardo, Andrew J. (2001), Should Monetary Policy Respond to Asset Price Bubbles? Some Experimental Results, Working Paper 01-04, Federal Reserve Bank of Kansas City, July.

Giammarino (1998), Central Bank Policy, Inflation and Stock Prices, in Information in Financial Asset Prices, Proceedings of a Conference held at the Bank of Canada, May 1998 (Ottawa, ON: Bank of Canada), 141 – 62.

Gilchrist, Simon and John V. Leahy (2002), Monetary Policy and Asset Prices, *Journal of Monetary Economics* 49, 75 – 97.

Goodhart, Charles A. E. (1999), Central Bankers and Uncertainty, *Bank of England Quarterly Bulletin* 39, 102 – 14.

Goodhart, Charles A. E., and Boris Hofmann (2001), “Asset Prices, Financial Conditions, and the Transmission of Monetary Policy”, Paper Prepared for the Conference ‘Asset Prices, Exchange Rates, and Monetary Policy’, Stanford, February.

Greenspan, Alan (2002), Economic Volatility, Remarks by Chairman Alan Greenspan at a Symposium Sponsored by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming, 30 August, available at www.federalreserve.gov.

Hamilton, James D. (1994): Time Series Analysis (Princeton: Princeton University Press).

Mishkin, Frederic S. (2001), The Transmission Mechanism and the Role of Asset Prices in Monetary Policy, NBER Working Paper No. 8617.

Rigobon, Roberto (2002), Identification through Heteroskedasticity, Sloan School of Management Working Paper.

Rigobon, Roberto and Brian Sack (2003), Measuring the Reaction of Monetary Policy to the Stock Market, *Quarterly Journal of Economics* 118, 639 – 69.

Sack, Brian and Volker Wieland (1999), Interest-Rate Smoothing and Optimal Monetary Policy: A Review of Recent Empirical Evidence, Working Paper, Board of Governors of the Federal Reserve System.

Sellin, Peter (2001), Monetary Policy and the Stock Market, *Journal of Economic Surveys* 15, 491 – 541.

Siklos, Pierre L. (2002), *The Changing Face of Central Banking: Evolutionary Trends Since World War II* (Cambridge: Cambridge University Press).

Siklos, Pierre L. (2000), Is the MCI a Useful Signal of Monetary Conditions? An Empirical Investigation, *International Finance* 3.

Siklos, Pierre L. (1999), Pitfalls and Opportunities for Central Banks in A World of High Frequency Data, in Information in Financial Asset Prices (Ottawa: Bank of Canada, 1999), 331 – 69.

Smets, Frank (1997), Financial Asset Prices and Monetary Policy: Theory and Evidence, BIS Working Paper 47, September.

Stock, James H. and Mark W. Watson (2001), Forecasting Output and Inflation: The Role of Asset Prices, NBER Working Paper No. 8180.

Thorbecke, Willem (1997), On Stock Market Returns and Monetary Policy, *Journal of Finance* 52, 635 – 54.

Appendix

A1. Classifying Volatility Regimes with Markov Switching Models

To classify the volatility regimes on which the identification procedure is based we use an univariate Markov switching model (Hamilton, 1994). We suppose the existence of two unobservable states $i = 1,2$ and a Markov chain the with transition matrix:

$$\mathbf{P} = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix}. \tag{A1}$$

The transition matrix governs the process. For example, p_{11} is the probability that state 1 is followed by state 1. The analysed variable y_t, in our case the residual of the stock return equation in the VAR, is modelled as:

$$y_t - \mu_i = \varepsilon_{t,i}\,, \tag{A2}$$

where $Var(\varepsilon_{t\,i}) = \sigma_i$. The only difference between the two regimes are the mean and the volatility. This model can be estimated with maximum likelihood and the (smoothed) probabilities for the regimes are a result of the filtering method developed by Hamilton. For more details about the estimation procedure see Hamilton (1994) Chapter 22. The computations are performed by using the Ox package written by Hans-Martin Krolzig.

As an alternative we also identified volatility regimes via a bivariate Markov switching model where μ in equation A2 above is a vector of variables consisting of the change in the interest rate and stock returns. In this manner we can permit four separate regimes to exist in which either the volatility of interest rate changes or stock returns is high or low or both are high or low. The results using this procedure are shown below and may be directly compared with the ones provided in Table 1. The results below confirm the statistically insignificant reaction of the Bundesbank to stock returns reported in the text.

Table A1: Estimation Results Using a Bivariate Markov Switching Model

Regime	Standard Deviation		Covariance	Number of Observations
Daily Data	Δi	s		
1(high-high)	0.1076	1.9688	0.0188	210
2(low-high)	0.0138	2.2488	– 0.0073	424
3(low-low)	0.0045	0.8659	– 0.0002	1346
4(high-low)	0.0293	0.8331	– 0.0042	1374
$\hat{\beta} = -0.00057$, p-value 0.93, confidence interval (– 0.00147, 0.00041) (95 %)				
Monthly Data	Δi	s		
1(high-high)	0.1001	0.3037	– 0.0011	6
2(low-high)	0.0041	0.0842	– 3.6016	29
3(low-low)	0.0072	0.2235	– 1.6415	99
4(high-low)	0.0125	0.2187	– 0.0015	29
$\hat{\beta} = -0.00127$, p-value 0.52, confidence interval (– 0.001869, 0.00297) (95 %)				

A2. Bootstrap Method for Computing p-Values

In general, a statistical hypothesis test compares a test statistic t with the distribution $t(F)$, where F is the (theoretical) distribution of the data under the null hypothesis. If the distribution of the data is not known it is possible to use the empirical distribution $\hat{F}$ of the data. This can be done by resampling with replacement from the data, or in our case from the residuals of the VAR. If we do this for $R = 199$ bootstrap samples we can calculate R times the test statistic $(t_1^*, \cdots, t_R^*)$ and can compare this empirical distribution with the actual test statistic $\hat{t}$. The p-value is:

$$p = \frac{1 + \#(t_r^* \geq \hat{t})}{R + 1}, \tag{A3}$$

where #(A) denotes the number of cases in which the condition A is fulfilled (see, for example, Davidson and Hinkley, 1997).

However, in most cases a studentized bootstrap provides more stable test statistics. The basic idea is to transform the test statistic similar to the way known from standard *t*-test:

$$Z_r^* = \frac{t_r^* - \hat{t}}{\sqrt{V_r^*}}. \tag{A4}$$

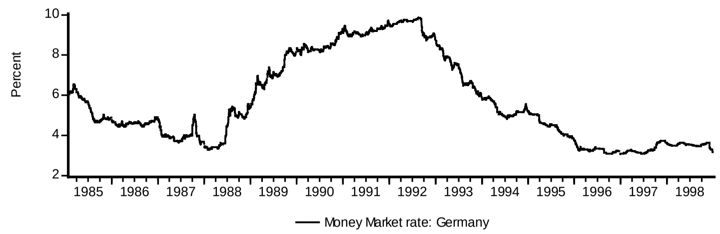
In this expression t_r^* is the r-th bootstrap test statistic and V_r^* the corresponding variance. We calculate the variance by using a double bootstrap. We resample from the r-th bootstrap sample $m = 25$ times and compute the variance for the corresponding values of the test statistic. To calculate the p-value it is only necessary to compare the Z_r^* values with $z_0 = (\hat{t} - t_0)/\sqrt{V}$ (t_0 is the value of the test statistic under the null hypothesis) in the same way as described above.

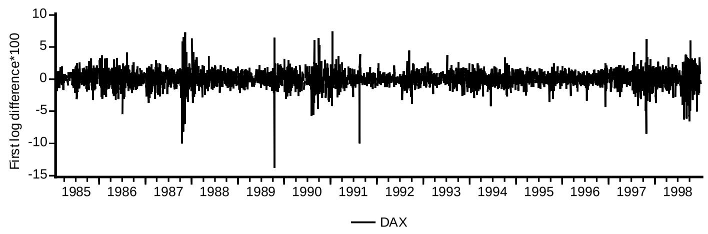
Table A2: Results for Daily and Monthly Time Series with the Interest Rate in Levels

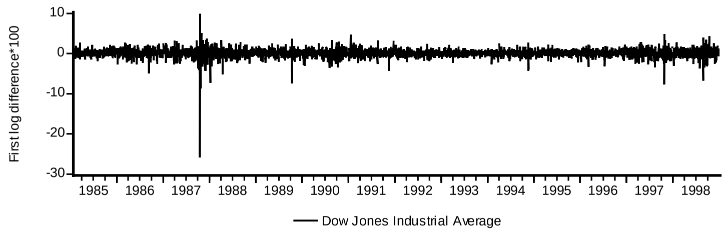
Regimes	$\hat{\beta}$	$\Delta\hat{\beta}$	H_0	p-value
		Daily Data		
All	0.00038		$\beta = 0$	0.64
All without I	0.00183	– 0.00144	$\Delta\beta = 0$	0.65
All without II	– 0.00030	0.00068	$\Delta\beta = 0$	0.79
All without III	0.00386	– 0.00348	$\Delta\beta = 0$	0.53
All without IV	– 0.00309	0.00347	$\Delta\beta = 0$	0.58
All without V	0.00010	0.00028	$\Delta\beta = 0$	0.32
		Monthly Data		
All	– 0.2534		$\beta = 0$	0.82
All without I	– 0.2405	– 0.0128	$\Delta\beta = 0$	0.99
All without II	– 0.2298	– 0.0235	$\Delta\beta = 0$	0.81
All without III	– 0.2448	– 0.0085	$\Delta\beta = 0$	0.84
All without IV	– 0.2958	0.0423	$\Delta\beta = 0$	0.75
All without V	– 0.2532	– 0.0001	$\Delta\beta = 0$	0.89

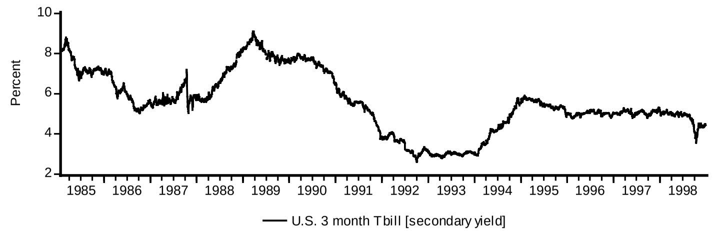
Note: The results are based on using interest rates in levels. For comparison and explanations see Table 1. The 95 % (bootstrap) confidence interval for the daily data is [– 0.01265; 0.00693] and the 95 % (bootstrap) confidence interval for the monthly data is [– 1.7873; 0.4918].

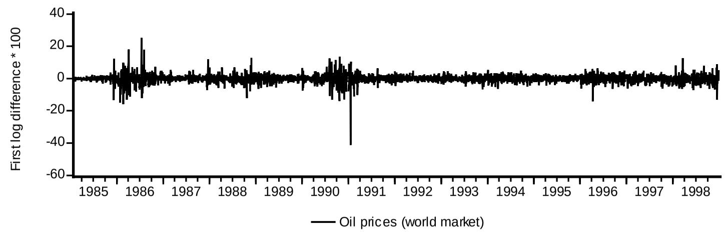
A3. Plots of the Raw Data

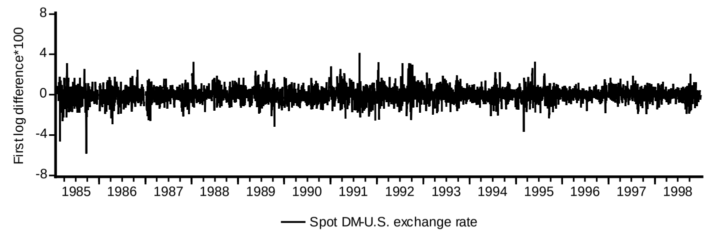






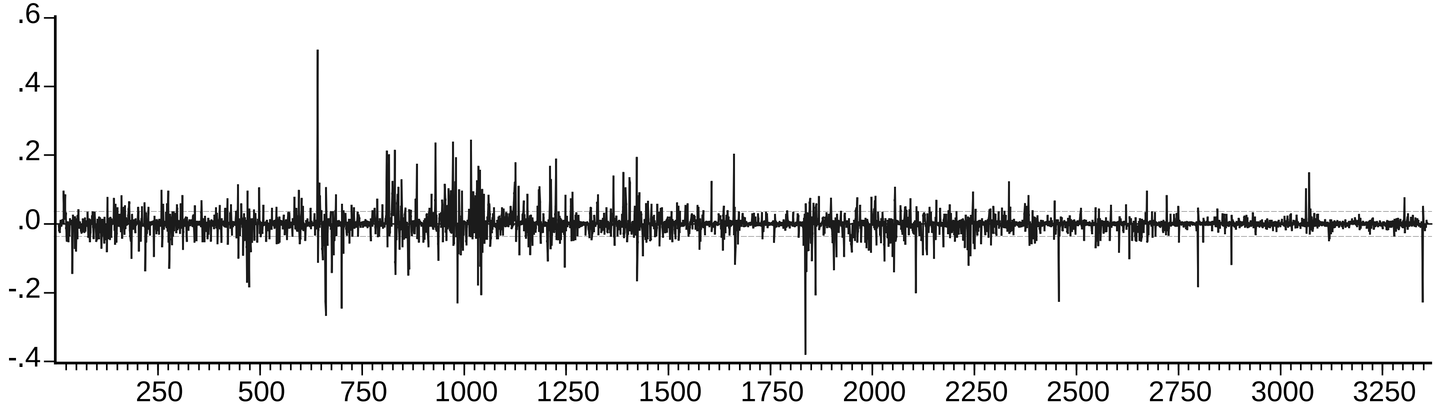




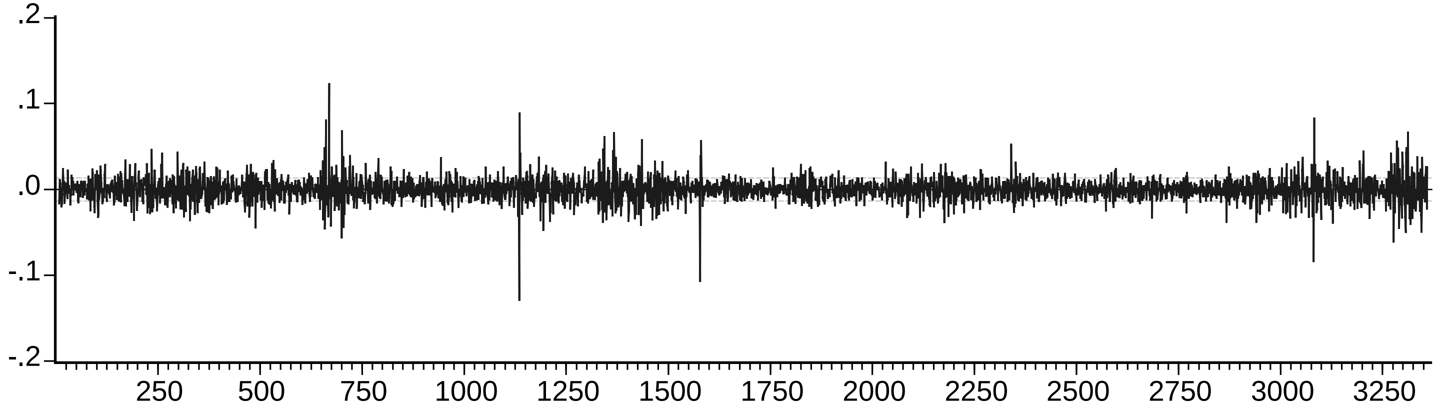


A4. Residuals from the VAR

SHORT Residuals



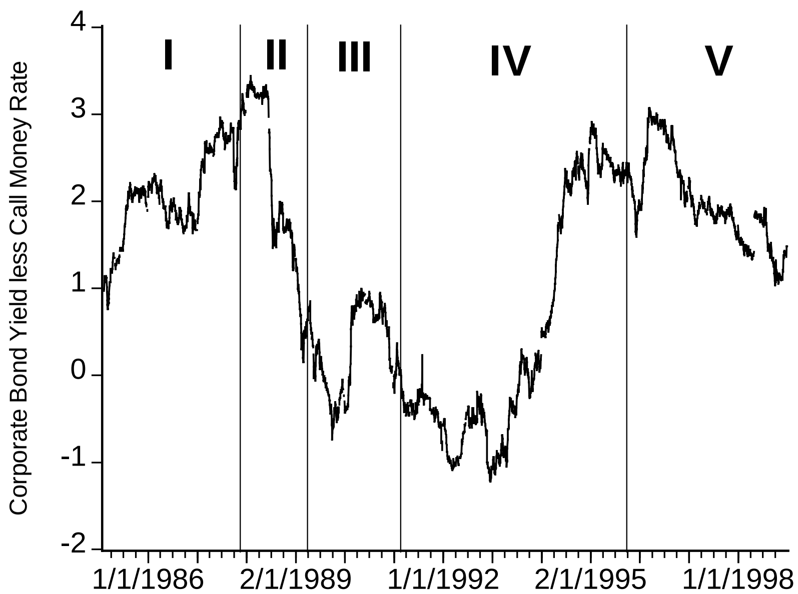
DAX_Returns Residuals



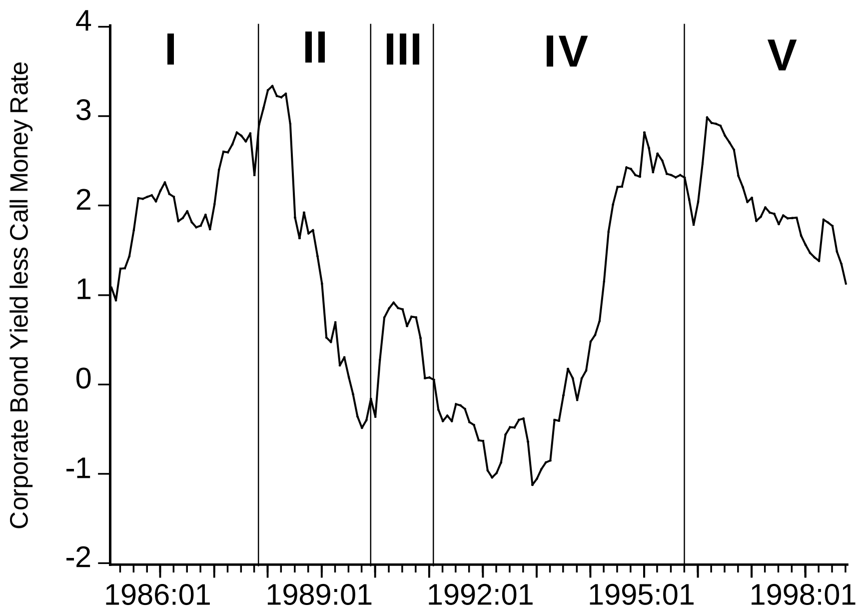
Note: The plot shows the residuals from VAR as specified in (3) in the order shown above with dow_t, Δi_t^{US} , oil_t, ξ_t as exogenous variables with a contemporaneous term and 5 lags. Observation numbers are shown on the horizontal axis.

A5. The Corporate – Call Money Spread

(A) Daily Frequency

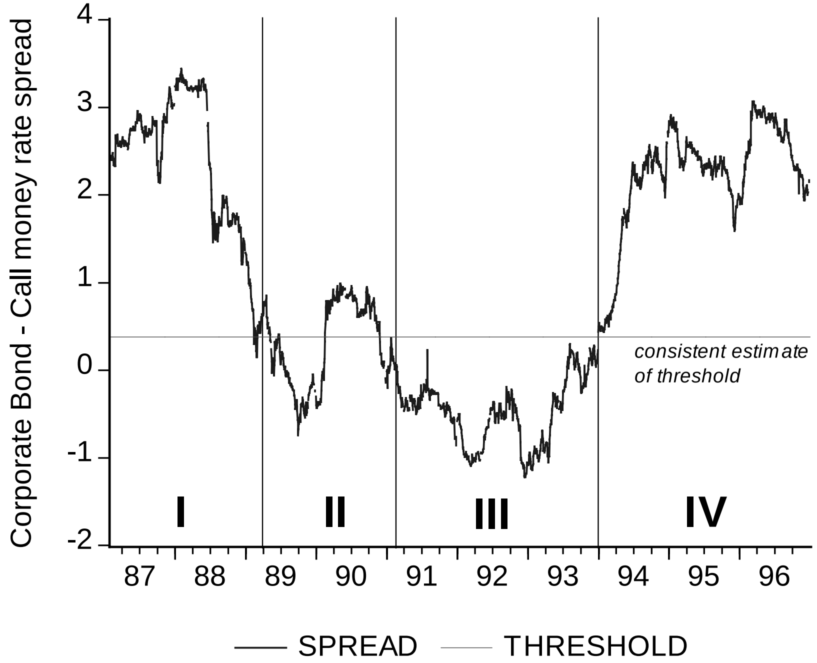


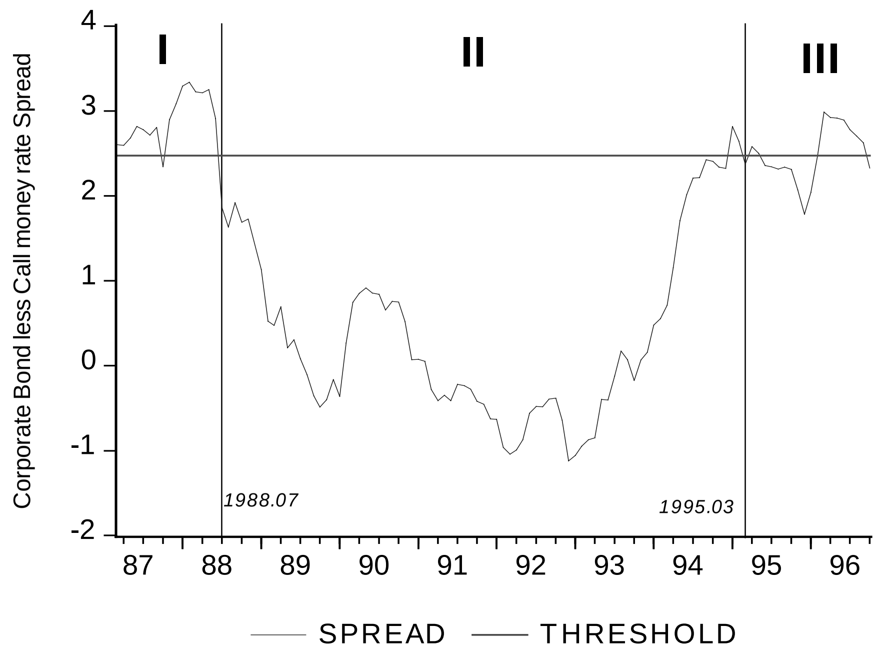
(B) Monthly Frequency



A6. Identifying Regimes: Asymmetric Unit Root Tests

A. Daily Frequency





The following papers have been published since 2002:

January	2002	Rent indices for housing in West Germany 1985 to 1998	Johannes Hoffmann Claudia Kurz
January	2002	Short-Term Capital, Economic Transform-ation, and EU Accession	Claudia M. Buch Lusine Lusinyan
January	2002	Fiscal Foundation of Convergence to European Union inLászló Halpern Pre-Accession Transition Countries	Judit Neményi
January	2002	Testing for Competition Among German Banks	Hannah S. Hempell
January	2002	The stable long-run CAPM and the cross-section of expected returns	Jeong-Ryeol Kim
February	2002	Pitfalls in the European Enlargement Process – Financial Instability and Real Divergence	Helmut Wagner
February	2002	The Empirical Performance of Option Based Densities of Foreign Exchange	Ben R. Craig Joachim G. Keller
February	2002	Evaluating Density Forecasts with an Application to Stock Market Returns	Gabriela de Raaij Burkhard Raunig
February	2002	Estimating Bilateral Exposures in the German Interbank Market: Is there a Danger of Contagion?	Christian Upper Andreas Worms
February	2002	The long-term sustainability of public finance in Germany – an analysis based on generational accounting	Bernhard Manzke

March	2002	The pass-through from market interest rates to bank lending rates in Germany	Mark A. Weth
April	2002	Dependencies between European stock markets when price changes are unusually large	Sebastian T. Schich
May	2002	Analysing Divisia Aggregates for the Euro Area	Hans-Eggert Reimers
May	2002	Price rigidity, the mark-up and the dynamics of the current account	Giovanni Lombardo
June	2002	An Examination of the Relationship Between Firm Size, Growth, and Liquidity in the Neuer Markt	Julie Ann Elston
June	2002	Monetary Transmission in the New Economy: Accelerated Depreciation, Transmission Channels and the Speed of Adjustment	Ulf von Kalckreuth Jürgen Schröder
June	2002	Central Bank Intervention and Exchange Rate Expectations – Evidence from the Daily DM/US-Dollar Exchange Rate	Stefan Reitz
June	2002	Monetary indicators and policy rules in the P-star model	Karl-Heinz Tödter
July	2002	Real currency appreciation in accession countries: Balassa-Samuelson and investment demand	Christoph Fischer
August	2002	The Eurosystem’s Standing Facilities in a General Equilibrium Model of the European Interbank Market	Jens Tapking

August	2002	Imperfect Competition, Monetary Policy and Welfare in a Currency Area	Giovanni Lombardo
August	2002	Monetary and fiscal policy rules in a model with capital accumulation and potentially non-superneutral money	Leopold von Thadden
September	2002	Dynamic Q-investment functions for Germany using panel balance sheet data and a new algorithm for the capital stock at replacement values	Andreas Behr Egon Bellgardt
October	2002	Tail Wags Dog? Time-Varying Information Shares in the Bund Market	Christian Upper Thomas Werner
October	2002	Time Variation in the Tail Behaviour of Bund Futures Returns	Thomas Werner Christian Upper
November	2002	Bootstrapping Autoregressions with Conditional Heteroskedasticity of Unknown Form	Sílvia Gonçalves Lutz Kilian
November	2002	Cost-Push Shocks and Monetary Policy in Open Economies	Alan Sutherland
November	2002	Further Evidence On The Relationship Between Firm Investment And Financial Status	Robert S. Chirinko Ulf von Kalckreuth
November	2002	Genetic Learning as an Explanation of Stylized Facts of Foreign Exchange Markets	Thomas Lux Sascha Schornstein
December	2002	Wechselkurszielzonen, wirtschaftlicher Aufholprozess und endogene Realignmentrisiken *	Karin Radeck

***** Available in German only.

December	2002	Optimal factor taxation under wage bargaining – a dynamic perspective	Erkki Koskela Leopold von Thadden
January	2003	Testing mean-variance efficiency in CAPM with possibly non-gaussian errors: an exact simulation-based approach	Marie-Claude Beaul Jean-Marie Dufour Lynda Khalaf
January	2003	Finite-sample distributions of self-normalized sums	Jeong-Ryeol Kim
January	2003	The stock return-inflation puzzle and the asymmetric causality in stock returns, inflation and real activity	Jeong-Ryeol Kim
February	2003	Multiple equilibrium overnight rates in a dynamic interbank market game	Jens Tapking
February	2003	A comparison of dynamic panel data estimators: Monte Carlo evidence and an application to the investment function	Andreas Behr
March	2003	A Vectorautoregressive Investment Model (VIM) And Monetary Policy Transmission: Panel Evidence From German Firms	Joerg Breitung Robert S. Chirinko Ulf von Kalckreuth
March	2003	The international integration of money markets in the central and east European accession countries: deviations from covered interest parity, capital controls and inefficien-Cies in the financial sector	Sabine Herrmann Axel Jochem
March	2003	The international integration of foreign exchange markets in the central and east European accession countries: speculative efficiency, transaction costs and exchange rate premiums	Sabine Herrmann Axel Jochem

March	2003	Determinants of German FDI: New Evidence from Micro-Data	Claudia Buch Jörn Kleinert Farid Toubal
March	2003	On the Stability of Different Financial Systems	Falko Fecht
April	2003	Determinants of German Foreign Direct Investment in Latin American and Asian Emerging Markets in the 1990s	Torsten Wezel
June	2003	Active monetary policy, passive fiscal policy and the value of public debt: some further monetarist arithmetic	Leopold von Thadden
June	2003	Bidder Behavior in Repo Auctions without Minimum Bid Rate: Evidence from the Bundesbank	Tobias Linzert Dieter Nautz Jörg Breitung
June	2003	Did the Bundesbank React to Stock Price Movements?	Martin T. Bohl Pierre L. Siklos Thomas Werner

Visiting researcher at the Deutsche Bundesbank

The Deutsche Bundesbank in Frankfurt is looking for a visiting researcher. Visitors should prepare a research project during their stay at the Bundesbank. Candidates must hold a Ph D and be engaged in the field of either macroeconomics and monetary economics, financial markets or international economics. Proposed research projects should be from these fields. The visiting term will be from 3 to 6 months. Salary is commensurate with experience.

Applicants are requested to send a CV, copies of recent papers, letters of reference and a proposal for a research project to:

Deutsche Bundesbank
Personalabteilung
Wilhelm-Epstein-Str. 14

D - 60431 Frankfurt
GERMANY