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Magnus Andersson

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After finalising the course work I spent the summer of 2001 in an internship at the European Central Bank. During those months, I worked on a project which in the end lead up to the first article in this thesis. The experience in the ECB was very exiting and made me think whether or not to go back to the "real world". As it happened, shortly after that, I got an offer to go back to the Riksbank in a position dealing with financial market analysis in the Monetary Policy department. After long considerations, I accepted, although this meant that the PhD would be postponed for a (considerable) period of time. It turned out I made the right choice, as the boss was great (thanks Javiera) and the division young and dynamic. Apart from the interesting regular work, I was allowed to work on my research projects when time admitted. There are many staff members in the Riksbank which I would like to pay my gratitude to, in particular: Ingvar, Anders L., Gunnar, Titti, Anders E., Jesper, C-F, Östbom, Lena, Malin, Anna and Josef.

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Introduction

This dissertation contains five articles, within various fields of financial economics. The articles in the thesis are the extensions of various analytical projects conducted during the author's positions as an economist in the Financial Market unit in the Riksbank and later on, in the Capital Markets and Financial Structure Division in the European Central Bank. Although the topics of the articles may, at a first glance, look seemingly unrelated to each other, they have one thing in common; they have been produced with the aim of providing useful input to the financial market analysis conducted in the two price stability oriented central banks.

The first article entitled "Evaluating Implied RNDs by Some New Confidence Interval Estimation Techniques" is a joint work together with Magnus Lomakka. Central banks' monetary policy decision is usually based on medium term forecasts of inflation. Typically, central banks also convey the risks they attach to its main scenario. By extracting so-called implied risk-neutral distributions from option prices on stock price indices, interest rates and foreign exchange instruments it is possible to derive the implied probabilities that market participants attach to specific values of the underlying financial asset in the future. Option prices can in this respect provide useful input when central banks gauge the balances of risks attached to its main scenario.

In the early stages of preparing this article, the most widespread approach to extract option-implied densities was a parametric method labeled "double log-normal technique" (DLN hereafter). However, research conducted by the Bank of England argued that the DLN technique had some robustness problems and they put forward the idea of using a nonparametric smoothed implied volatility smile method (SPLINE hereafter) instead.

Inspired by the work conducted by Bank of England, the purpose of the paper is to evaluate the precision of the two estimation techniques by estimating confidence bands for the risk-neutral distributions. The width of the bands is used as the main criterion when determining which of the two estimation techniques to be preferred.

The paper contributes to the existing literature in two main aspects. First, when estimation the confidence bands we take into account the fact that the error terms, measured as the difference between the observed option prices and the theoretical option prices coming out from the two estimation techniques, are not independent neither of option type (call/put) nor of strike price. Second, the bootstrap methods proposed in the paper control for the non-appealing non-normality property of the error structure. The study is applied to equity options on the Swedish stock market (OMX) index.

The DLN and the SPLINE methods require different estimation techniques in order to compute the option-implied density. The DLN method assumes that the functional form of the terminal density of the underlying asset is a mixture of two lognormal densities. Based on this assumption, the option-implied density is then estimated by minimizing the square of the deviation between the observed call/put option prices and the theoretical prices obtained from the lognormal distributions.

The non-parametric SPLINE method explicitly utilizes the relation between option prices and risk-neutral densities which states that the option-implied density can be found by differentiating the option price function twice with respect to the strike prices. The paper employs Malz (1997) suggestion and fits a cubic spline in the implied volatility/delta space.

The results from the bootstrap exercises reveal that the SPLINE method consistently produces tighter confidence bands for the option-implied densities than the DLN method. These results hold for the two different bootstrap methodologies tested; one that groups the error terms based on the historical pattern and a second method that groups error terms with similar strike prices into equally spaced intervals. The bootstrap method based on the former methodology results in confidence bands for the DLN method which are almost five times as wide as the SPLINE counterpart. The difference is somewhat smaller in the latter bootstrap method; the DLN method delivers bands that are approximately four times wider.

For the practitioner, other criteria such as computational efficiency and the rate of convergence should be taken into consideration as well before deciding upon which estimation method to be preferred. The SPLINE method optimization routine always converges and hence the whole pseudo sample is intact when estimating the confidence interval. This differs considerably from the DLN method, where some option implied densities in the pseudo sample have to be omitted in order to avoid spurious-looking[1] confidence intervals. In addition, the SPLINE method also consistently requires less computing time than the DLN method. Thus from a practitioner's point of view there should be little doubt that the SPLINE method is to be preferred.

As a final point, the paper undertakes a case study to show how the confidence bands can be used in practice. It examines if investors changed their perception about the Swedish stock market outlook after the 50 basis point interest rate cut by the ECB and Bank of England on 8 November 2001. The results point to the fact that market participants' outlook did not change significantly as the option implied density estimated after the interest rate cuts fell inside the 95 percent confidence bands extracted just before the events.

[1] These are densities that are not monotonically increasing to the left of the mode and/or not monotonically decreasing to the right of the mode.

The second article entitled "Why does the correlation between stock and bond returns vary over time?" is a joint work together with Elizaveta Krylova and Sami Vähämaa. Stock and government bond markets are closely monitored by policymakers as they embed, among other tings, market participants' economic growth and inflation expectations. As this paper shows, a close monitoring of the observed time-varying correlations between the two assets can offer policymakers, such as central banks, useful complementary information to determine whether the markets are changing their views on inflation, economic activity prospects or if it merely reflects altered risk perceptions.

The purpose of this paper is to examine how inflation, economic growth expectations and perceived stock market uncertainty affect the correlation between stock and bond returns. The empirical analysis is performed using fifteen years of daily data on the US, UK, and German stock and bond returns. These three countries are generally considered among the most important economies and largest financial markets in the world.

The macro economic data consist of twelve-months-ahead forecasts of GDP and inflation obtained from Consensus Economics. To examine the impact of expected stock market uncertainty on the stock-bond return correlation, implied volatilities extracted from broad based stock index options are used.

Two methods are employed to measure the time-varying correlation between stock and bond returns: first, a simple rolling-window sample correlation, and second, a dynamic conditional correlation (DCC) model proposed by Engle (2002). The former has the advantage of being very straightforward to calculate but has the shortcoming that unusually small or large return observations will not gradually diminish over time, but instead lead to jumps in the correlation estimates when these observations fall out of the estimation window. The DCC procedure, although being more computationally complicated, overcomes this negative aspect of the rolling-window measure.

The main contribution of this paper is the focus on the impact of expectations. The use of inflation and economic growth expectations, instead of the actual historical values, is more appealing from a theoretical viewpoint, as stock and bond prices should reflect market participants' expectations of future values of these fundamentals. In addition, this paper extends the literature by jointly examining the impacts of macroeconomic expectations and expected stock market uncertainty on the stock-bond return correlation. Following Connolly et al. (2005), volatility estimates extracted from option prices are used to assess stock market uncertainty. Finally, this paper contributes to the literature by applying recent techniques proposed by Engle (2002) to measure the time-varying correlation between stock and bond returns.

Four interesting features can be noted from the estimations of the time-varying stock-bond correlations. First, the stock-bond return correlations in all three countries are positive, with mean correlation estimates of about 0.12 in the US, about 0.11 in the UK, and about 0.15 in Germany. Second, although the correlations in all three countries are positive on average, it is apparent that the relation between stock and bond returns has been unstable over time, and also prolonged periods of negative correlation can be observed. Third, the estimated stock-bond correlations show a rather similar pattern over time across the three economies, thereby suggesting that some common global factors may determine the time-varying relation between the two main asset classes. Forth, the rolling-window method show signs of being somewhat more erratic compared with the correlations that are produced using the DCC method.

To gauge the impact on stock-bond correlations from the above mentioned candidates, the two measures of the stock-bond correlation are regressed on the expected annual growth rate of consumer prices, expected annual growth rate of real gross domestic product, and implied stock market volatility. Unit root tests indicate that all explanatory variables are stationary, as the null hypothesis of a unit root can be soundly rejected for these time-series.

Overall, the regression results for the United States, United Kingdom, and Germany are very similar. These results strongly indicate that expected inflation is positively related to the correlation between stock and bond returns. The estimated coefficients for expected growth rate of the CPI are positive and statistically significant in four out of six regressions. Since bond prices should be negatively related to inflation expectations, our findings suggest that high inflation expectations have a larger impact on the discount rates than on the expected future dividends, thereby causing a negative relation between stock prices and inflation expectations, and consequently a positive relation between inflation expectations and stock-bond return correlation. Furthermore, the estimated coefficients for implied volatility are negative and statistically significant in all six regression specifications indicating that high stock market uncertainty tends to lead to a decoupling between stock and bond prices. This finding is consistent with the "flight-to-quality" phenomenon, which states that in periods of financial market turmoil investors tend to shift funds from the stock markets to the bond markets (with stock prices declining and bond prices increasing). Finally, the results suggest that stock-bond return correlations are unaffected by economic growth expectations, as none of the six coefficient estimates for GDP appears statistically significant.

The third article entitled "Which News Moves the Euro Area Bond Markets?" is a joint work together with Lars Jul Hansen and Szabolcs Sebestyen. The main purpose of this paper is to examine which ones of the myriads of economic announcements that significantly move the euro area bond markets. Given its inflation mandate, the long-term bond market segment is of particular interest for the ECB as the yields offered on these bonds contain, among other things, the inflation expected to prevail over the maturity of the bond, as perceived by the markets.

Most of the empirical literature within this field has been applied on US data, see Balduzzi et al. (2001) and Andersen et al. (2005). As regards announcement studies applied on the euro area bond markets, the focus in these papers have concerned the impact stemming from US macro announcements. This paper extend earlier studies by exploring the to what extent German, French, Italian and aggregate euro area macroeconomic releases, in addition to the "traditional" US macroeconomic announcements, have a bearing on the euro area bond markets.

To accurately gauge the influence on the euro area bond markets, this paper make use of five-minute intraday prices on German long-term bond futures. The choice of intraday data enables a "cleaner" analysis of market reactions surrounding major market-moving events compared with commonly used daily data, where other news during a trading day may blur instantaneous market reactions to events. It should also be noted that German bond prices can be regarded as providing a fairly sound illustration of interest rate developments for the euro area as a whole over the last couple of years, given the rather small and relatively stable spreads between government bond yields within the euro area since 1999.

To properly capture the news effect from macro releases the paper makes use of a general econometric model, which simultaneously estimates both the level and volatility of intraday returns on German bonds (see eq. 2 and 3 in the paper). A simple semi-parametric model is employed to capture the time-varying feature of intraday return variability. Part of this procedure has been suggested by Andersen et al. (2003, 2005).

The results from the econometric exercise give evidence that US and to some extent euro area and national macro releases exert a significant impact on the returns of long-term German government bonds. Overall, the announcements have a more long-lasting impact on volatility than on the level of bond returns.

US announcements seem to influence German bond returns more than euro area, German, French and Italian macro announcements. There are at least four probable explanations for these findings. First, the US can be perceived as the engine of global growth, which therefore explains its importance for the global financial markets, including the euro area. Second, it may also be argued that business cycles have become more integrated and globalisation therefore has lead to a higher degree of interdependence between economies. Third, US macro data are typically released earlier than equivalent euro area data. Thus, market participants may therefore draw inferences about the euro area economy from the US data releases. In this respect, only euro area releases that cause investors to revise these inferences should lead to market reactions. Fourth, the strong influence of euro area bond yields to US announcements may also be due to the strong observed positive correlations as well as arbitrage relations between US and euro area long-term bond yields (such as interest rate parity).

The fourth article is entitled “Using intraday data to gauge financial market responses to Fed and ECB monetary policy decisions”. The purpose of this paper is to assess bond and stock market reactions in the euro area and the United States following monetary policy decisions by the ECB and the Federal Reserve over a uniform sample period (April 1999 to May 2006). Intraday data are used and the asset price reaction is measured in terms of derived realised volatility measures over five minute intervals. Two different angles are viewed. First, asset price volatility on monetary policy announcements days is compared to the volatility observed on non-announcement days. Second, the volatility pattern when the central bank changes policy rates as opposed when the monetary policy rates are left unchanged is examined. Conditional on these two events, this paper analyze to what extent monetary policy target and path surprises can explain the observed volatility.

The paper reaches three main findings. First, intraday US and euro area stock and bond market volatility strongly increases at the time of the release of monetary policy decisions, and is particularly pronounced for the US financial markets. Second, monetary policy target and path surprises by the ECB both significantly move the euro area financial markets, whereas path surprises by the Fed have on average a larger influence on US bond and stock market volatility compared with the target surprises. Third, the yield response sensitivity for the German bond markets following an ECB monetary policy target surprise is stronger on the occasions when the monetary policy rates have been altered compared with periods when the ECB decided to leave it unchanged.

The fifth article entitled “The market impact of macroeconomic announcements: a learning approach” is a joint work together with J. Ejsing and J. Von Landesberger. This last article builds on the previous two articles that evaluated how “news” (such as macro economic announcements and monetary policy decisions publications) effect intraday asset prices. The methodology used in third and fourth articles, implicitly assume that price reactions to data releases are directly and linearly related to the surprise component embedded in the data releases, the latter usually measured as the difference between actual and expected outcome of the releases. This procedure, however, misses out on one important feature, namely that asset price responses also depend on the quality of the information embedded in the data releases.

The idea in this paper is to view macro announcements as providing noisy signals about the the underlying economic dynamics. Based on this assumption, we use a Baysian learning model to demonstrate that asset price reactions surrounding macro announcements depend on two parts, the surprise component and the “signal to noise” ratio the announcements entail.

The model is applied on two, by the markets, closely monitored categories of data releases - business surveys covering the US manufacturing sector and regional German CPI releases. Intraday data on the US and German long-term bond futures are used to gauge the financial markets impacts from the US and German releases respectively. For the US manufacturing releases, the resulting model-based measure of information content is shown to dominate the standard measure in asset price impact regressions. Moreover, as a robustness check the time-series based measure is shown to co-move positively with an alternative gauge based on dispersion in survey responses.

In the second case study, we show that the muted market impact on pan-German CPI releases is related to the fact that six German federal states (Bundesländer) publish their own estimates, before the aggregate German inflation data are released. In contrast to the previous findings, we uncover systematic asset price responses and show how the learning model handles the stochastic ordering of regional German CPI releases in a simple and consistent way. This suggests that German inflation data do indeed influence asset prices, but via the individual federal state releases, rather than the pan-German inflation release.

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Evaluating implied RNDs by some new confidence interval estimation techniques*,**

Magnus Andersson

Magnus Lomakka

Abstract

This paper evaluates the precision of the parametric double lognormal and the nonparametric smoothing spline method for estimating risk-neutral distributions (RNDs) from observed option prices. By using a bootstrap technique, confidence bands are estimated for the risk-neutral distributions and the width of the confidence bands is used as a criterion when evaluating the precision of the two methods. Previous literature on estimating confidence bands has to a large extent been estimated using Monte Carlo methods. This paper argues that the bootstrap technique is to be preferred due to the non-normality feature of the error structure. Furthermore it is shown that the inclusion of a heteroscedastic error structure improves the precision of the estimated RNDs. Our findings favour the smoothing spline method as it produces tighter confidence bands. In addition, an example of how to apply the estimated confidence bands in practice is also provided.

Keywords: Implied Risk-Neutral distribution, Confidence Intervals, Bootstrap.

JEL classification: C14, G14, E59.

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1. Introduction

Information on financial prices is a valuable tool for policymakers enabling them to gauge market participants' perception of future development of asset prices. For example, forward contracts may in some cases provide a point estimate of expected future asset prices. Using option prices, this methodology has been refined, making it possible to extract a whole probability density function surrounding the expected mean, in which the uncertainty measured by higher moments such as skewness and kurtosis can be quantified. Due to the risk-neutral feature of option pricing models these distributions are classified as risk-neutral distributions (RNDs).

RNDs are widely used within the empirical finance area. For instance, central banks utilise RNDs when performing inflation projections to monitor, not only the development of commodity prices (e.g. oil), but also possible asymmetries in expectations displayed in the estimated RNDs in order to judge uncertainty about future inflation impulses. Market participants also use RNDs as a tool in their investment decisions. For instance, some investors measure the fatness of the tails (the kurtosis) and use this as an indicator of risk-appetite among market participants, reasoning that the fatness tends to be negatively correlated with the degree of risk-appetite.

Two RND estimation techniques have been discerned as standard methods - the nonparametric smoothed implied volatility (SPLINE) method and the parametric double log-normal (DLN) technique. The purpose of this paper is to evaluate the precision of these two methods. This is conducted by estimating confidence bands for the RNDs. We use the width of the bands as the main criterion when determining which RND estimation technique that is to be preferred. Two bootstrap methods are used when estimating the confidence bands, both enabling us to take the non-normality feature of the pricing error into account. Moreover, special attention is given to the impact of heteroscedastic pricing errors as this feature has been overlooked in the literature up until now.

The main finding of the paper is that the SPLINE technique produces more accurate RNDs, since the confidence intervals are more narrow than the DLN counterpart. In addition, the DLN technique produces some computational drawbacks that can be avoided by implementing the SPLINE method.

The paper ends by showing how the estimated confidence bands can be used in practice. In the literature so far, RND densities have been estimated before and slightly after new information has hit the market. By visual inspection between the two RNDs, conclusions have been drawn whether investors' perceptions concerning the uncertainty have changed or not. To give an example, Figure 1 shows two RNDs, estimated from options on the Swedish stock markets, surrounding the September 11 2001 terrorist attacks. The figure suggests a general increase in uncertainty after the attacks as the RND estimated after the terrorist attacks is wider than the RND estimated before the attacks. However, such a procedure does not provide any information as to whether there has been any statistically significant change in the shape of the RNDs. Estimating confidence bands around the RNDs would therefore provide policymakers, such as central banks, with a better indicator on to whether investors' perceptions regarding risk have changed.

This paper is structured as follows: Section 2 examines the theoretical background of RNDs and confidence band estimation. Section 3 discusses how to improve confidence band estimation thereby making them more accurate. The results of the confidence interval estimations are presented in Section 4 together with a case study. Section 5 provides some conclusions.

2. Theoretical background

In this section an overview of the methodology is provided with reference to RND and confidence interval estimation in general. First we derive in some detail how the two RND estimation methods, i.e. how the DLN and the SPLINE technique, are derived. Second a discussion on how confidence bands for RNDs can be estimated is supplied. Third, earlier work on RND confidence interval estimation is presented.

2.1. RND estimation

The starting point of RND estimation methods was a paper by Breeden and Litzenberger (1978), who showed that option-implied densities can be derived from the following relation:

$$q(S_T) = e^{-r\tau} \frac{\partial^2 C(S_T, X, \tau)}{\partial X^2} \tag{1}$$

where $q(S_T)$ is the RND density of the underlying asset at time T, C is the call price function, S is the value of the underlying asset, X is the strike price of the option and τ is the time until expiration of the option. The formula is valid for put option functions as well. Since Breeden and Litzenberger's pioneering work a number of methods have been discussed in the literature - see for example Bliss and Panigirtzoglou (2002). Two methods have now been discerned as standard techniques when estimating RNDs: The double lognormal (DLN) and the smoothed implied volatility smile (SPLINE) methods. The two methods differ as the DLN use a parametric approach while the SPLINE method is non-parametric. The details of the estimation procedure for the two methods are outlined in the following two subsections.

2.1.1 Double Lognormal Method

The Black-Scholes formula involves the assumption that the price of the underlying asset at maturity is lognormally distributed. However, investors generally attach higher probabilities for extreme outcomes than suggested by the Black-Scholes formula. This implies that the terminal RND derived from observed option prices will have "fatter" tails compared with the lognormal distribution. Richey (1990), who examined the impact of non-normal underlying returns densities, found a way to capture this specific characteristic by assuming that the functional form of the terminal density of the underlying asset is a mixture of two or more lognormal densities. In order to minimize the number of parameters to be estimated, a mixture of two lognormal densities (DLN) is employed in this paper. The parameters are estimated by minimizing the square of the deviation between the observed call/put prices and the theoretical prices obtained from lognormal distributions. The prices of European call and put options can be written as:

$$C(S_{T,}X,\tau) = e^{-r\tau}\int_X^{\infty} q(S_T)(S_T - X)dS_T \tag{2}$$

and

$$P(S_{T,}X,\tau) = e^{-r\tau}\int_0^{X} q(S_T)(X - S_T)dS_T \tag{3}$$

The DLN approach assumes that $q(S_T)$ is a weighted sum of two lognormal density functions:

$$q(S_T) = \pi * LnD(\alpha_1, \beta_1; S_T) + (1-\pi) * LnD(\alpha_2, \beta_2; S_T) \tag{4}$$

where two *LnD*:s represent the lognormal densities, α_i and β_i correspond to the mean and the standard deviation of density *i*, and π and (1- π) are the respective weights put on the two densities. Replacing the expression for the density from (4) into the call and put price formulas in

(2) and (3) makes it possible to estimate the theoretical call and put prices, given the parameter vector $\Theta = [\pi, \alpha_1, \alpha_2, \beta_1, \beta_2]$.

Finally, the implied RND can be extracted given the observed option prices and theoretical prices provided by the parameter vector Θ. Moreover, as Bahra (1997) proposed, additional information could be exploited by including the future price as an extra observation in the minimization problem. In absence of arbitrage possibilities, the future price should equal the mean of the RND, which is represented by the last term in equation (5). The estimation is performed using non-linear least squares:

$$\min_{\Theta} = \sum_{i}^{n}[c(X_i,\tau)-\hat{c}_i]^2 + \sum_{i}^{n}[p(X_i,\tau)-\hat{p}_i]^2 +$$

$$[e^{r\tau}S_T - \pi e^{\alpha_1+1/2\beta_1^2} + (1-\pi)e^{\alpha_2+1/2\beta_2^2}]^2 \tag{5}$$

where $\hat{c}_i$ and $\hat{p}_i$ are the observed call and put prices.

2.1.2 Smoothed Implied Volatility Method

The smoothed implied volatility smile method (SPLINE) for estimating RNDs originates from Shimko (1993), and it explicitly utilizes the results of Breeden and Litzenberger (1978). This nonparametric method involves approximating of a function, often a cubic spline, to some discrete observations. Shimko backed out the implied volatility from the Black-Scholes formula, taking the call and put prices of the options as given. A cubic spline was then approximated to the implied volatility observations. Transforming the discrete call/put price observations to a continuum of prices makes it possible to obtain the RND by differentiating the price function twice with respect to the strike price. The cubic spline can be fitted in spaces other than implied volatility/strike price; Bates (1991), for example, discusses fitting in the price/strike space, while Malz (1997) suggests a transformation to the implied volatility/delta space. The delta of call and put prices measures its sensitivity to changes in the underlying asset and hence, transforming the data to the implied volatility/delta space will have the effect that at-the-money options will be less closely grouped together compared with options far away from at-the-money. Thus more shape will be permitted at the center of the PDF than in the tails. The latter approach is implemented by transforming the data from the price/strike space to the implied volatility/delta space. The deltas are obtain by a numerical procedure:

$$\frac{\partial C(S_T, X, \tau)}{\partial S_T} \text{ and } \frac{\partial P(S_T, X, \tau)}{\partial S_T} \tag{6}$$

i.e., the first derivative of the observed call and put prices with respect to the value of the underlying asset. The implied volatility is obtained by backing out the volatility from the Black-Scholes formula taking the price of the option as given using a simple Newton-Raphson approach. A continuous function is then approximated around the discrete observations using a cubic SPLINE.

The smoothness of the SPLINE is controlled by the smoothness penalty parameter λ. A small value of λ will have the effect that the the curvature of the function is minimised whereas a high value on λ has the opposite effect as the function instead puts greater weight on minimizing the sum of the squared errors between the actual observations and the observations obtained from the SPLINE function.

A problem with the SPLINE method is how to choose the value of the smoothing parameter λ. To avoid choosing the value arbitrarily, various methods can be employed. Bliss and Panigirtzoglou (2002) for example, computed the sum of squared errors obtained from the DLN method and choose the λ so that the sum of squared errors from the SPLINE method matched the DLN counterpart. This involved carrying out a line search over the range of possible λ and choosing the value of the smoothing parameter which generated a sum of squared errors which equalled that from the DLN method. We follow the procedure suggested by Bliss and Panigirtzoglou (2002) since it enables a fair comparison of the precision between the two methods.

However, this approach has the disadvantage that one has to rely on the DLN estimation when deciding λ. Therefore, in the practitioner oriented case study, we use another procedure choosing the value of the smoothing parameter by implementing a cross-validation score (CVS) method in line with Craven and Wahba (1979). Using this approach, the problem of choosing the value of the smoothing parameter λ can be solved within the SPLINE method estimation itself, thus overcoming the drawback of using the DLN estimation in deciding the value of λ. The outline of the procedure is as follows:

First, loop over all possible values of λ. In each loop, observations are deleted one by one and a SPLINE function is estimated from the remaining observations. To avoid extrapolating the SPLINE function, the end observations are excluded in the CVS procedure. Second, the squared differences between the deleted observations and the values generated by the SPLINE function are computed (i.e, the cross-validation score). Hence, the CVS can be summarised as:

$$CVS(\lambda) = \sum_{i=1}^{n} (y(i) - g_{\lambda}(t_i))^2 \tag{8}$$

where $y(i)$ is the actual observation and $g_{\lambda}(t_i)$is the smoothing spline estimated from the data pairs excluding $(t_i;y(i))$. Third, the sum of squared errors for each λ is compared, and the smoothing parameter with the smallest sum of squared errors is selected.

The CVS procedure results in a hump-shaped form over the range of λ and for most cases reach a minimum for λ in the range 0.9800-0.9999. This high value of 'optimal' λ is also in line with the results by Bliss and Panigirtzoglou (2002), who test different smoothing parameters when employing RNDs as a forecasting tool.

After choosing the smoothing parameter and estimating the SPLINE function in the implied volatility/delta space, the data are transformed back to the price/strike price space using the Black-Scholes formula. The approximated function outside the observed range of strike prices is estimated by assuming constant implied volatility. The RND is then found by a direct application of the Breeden and Litzenberger (1978) results, see equation (1).

2.2. Confidence intervals

The need to quantify the uncertainty surrounding the estimated RND can be solved by estimating confidence bands. This paper will apply two confidence estimation techniques on both the DLN and SPLINE estimation methods. This enables a direct comparison of which one of the methods that is surrounded with less uncertainty. The confidence bands should thus capture the uncertainty that the two methods give rise to. However, the option prices used as inputs in the RND estimations may not always be correct due to a number of potential sources of error. In general, the most important sources of error are:

- Lack of liquidity for options deep-in-the-money and deep-out-of-the-money might create distortions in the estimations.
- The utilization of settlement prices. If there is no trade in an option during a trading day the settlement price is a theoretical price calculated by the exchange. Therefore, if settlement prices are employed, the sample will most likely include strikes that were not actually traded.

- Too narrow spectrum of strike prices. In most cases there are no observations far from at-the-money. Hence the tails of the RND are totally dependent on the estimation method.
- Pure data errors stemming from erroneous recording of prices.

If the data is distorted, one can not disentangle to what extent the width of the resulting confidence bands is due to the estimation technique itself or if it is caused by the above mentioned sources of errors.

There are some general principals to follow when using option data. For instance, if the estimation is based on settlement prices, there will be quite a large number of non-traded strikes in the data. Hence, in order to better reflect reality, non-traded strikes should be excluded. In addition, if the estimation is based on real time snapshot quotations, the problem of large bid-ask spreads has to be carefully monitored. Using the average of bid and ask quotations might generate fictitious arbitrage opportunities. An inherent problem in all options markets is that a rather narrow spectrum of strikes is actually traded. Therefore excluding strikes on the basis of liquidity considerations may introduce even more uncertainty about the estimated RND. Since there is a vast amount of option price data to be recorded, pure data errors are not unlikely to appear. Screening for theoretical arbitrage opportunities that exceed what could be deemed as reasonable from a transaction cost point of view is one way to reduce the influence of pure data errors. Nevertheless, far from all sources of error can be eliminated, and thus there will always be some uncertainty about the estimated RND. All in all, the uncertainty should be quantified in an appropriate manner. The most straightforward way is probably to define the theoretically correct price and compare it to the observed price (which is the approach used for the DLN technique). The theoretical price should be decided by the model underlying the RND estimation. The pricing error could be extracted by taking the observed price less the theoretical price. Confidence bands can be estimated in several ways, for instance by Monte Carlo simulation or by bootstrap. As discussed later, two new bootstrap procedures will be used in this paper. The first method involves resampling from historical pricing errors (i.e. errors generated from all RND estimation), while the second method involves resampling from current pricing errors (i.e. errors generated from only one RND estimation). The details of the bootstrap procedures are discussed Section 3.1.

2.3. Previous literature on confidence interval estimation and the way to proceed

Earlier work on the uncertainty of estimated RNDs has mainly focused on inflicting some kind of perturbations on either the observed option prices or the estimated parameters and then repeating this procedure until it is possible to extract confidence bands. Söderlind and Svensson (1997) assumed that the correct model was a mixture of lognormal distributions and that the discrepancies between observed prices and theoretical prices were due to random error terms. Thus the sum of squared pricing errors was minimized by non-linear least squares estimation in order to retrieve the parameters of the distribution functions. A heteroscedastic-consistent estimator was implemented to calculate the covariance matrix taking the heteroscedastic price errors into account. Finally, a confidence interval was estimated by applying the delta method. Even though the problem with heteroscedastic price errors was addressed by implementing a heteroscedastic-consistent estimator of the covariance matrix, the asymptotic normality assumption underlying the delta method may lead to underestimation of the width of the confidence bands as the errors tend to be more spread out compared to a normal distribution.

Melick and Thomas (1998) proceeded in the same realm as Söderlind and Svensson, constructing a 95 percent confidence interval for implied RNDs of the Euromark future. The parameters were estimated by constrained maximum likelihood estimation. A Monte Carlo experiment was performed where 500 pseudo-distributions were created from the original RND estimated using the DLN technique. The resulting confidence interval conveyed the message that there was little uncertainty about the estimated RNDs. However, Melick and Thomas also found that the error terms were not likely to be independent. Hence the tight confidence bands might originate from the fact that the normality assumption underlying the Monte Carlo technique was not fulfilled. To avoid imposing any structure on the error terms Melick and Thomas created pseudo samples by drawing with replacement from the available data (bootstrap). The resulting confidence bands were quite wide, thus indicating large uncertainty about the estimated RNDs. As the pseudo samples were drawn with replacement, many pseudo samples had relatively large gaps between strikes, which caused the DLN method to run into some rather serious estimation problems. Furthermore, Melick and Thomas (1998) put a lower bound of 0.02 for the dispersion parameters, thereby avoiding potential problems associated with the optimization procedure. Altogether, the strange-looking confidence bands of the Melick and Thomas (1998) bootstrap simulation are mainly due to estimation problems. Hence, the resulting confidence interval is a poor approximation of the true uncertainty of the implied RND. Melick and Thomas (1998) concluded that estimation problems stemming from relatively large gaps between the strike prices in the data were the main reason for the wide confidence interval.

Söderlind (2000) took a somewhat different approach when estimating the confidence bands of the implied RNDs resulting from the DLN method. By adding error terms to the theoretical option and forward prices implied by the original parameter estimates, 100 simulated data sets were created and utilized to estimate a confidence interval. Söderlind chose two methods to generate the error terms: the first method involved generating pseudo-random numbers from an i.i.d. normal distribution, and in the second method bootstrapped the original data set. The simulated 90 percent confidence intervals of both methods for the underlying contract (short sterling) were found to be very narrow. In the Monte Carlo experiment by Söderlind (2000), the error terms were drawn from an i.i.d. normal distribution with second moment equal to the estimated variance for the corresponding dataset. Thus any heteroscedasticity and/or non-normality of the pricing error distribution was unaccounted for, which might be one reason for the narrow confidence bands. The bootstrap experiment by Söderlind (2000) was conducted in such a manner that the observed error terms were resampled and added to the theoretical prices. This solves one of the problems with the Melick and Thomas (1998) approach, namely, the generation of large gaps between strike prices. However, the problem of heteroscedastic error terms still remained unsolved.

Bliss and Panigirtzoglou (2002) went down yet another road and perturbed the observed option prices rather than the theoretical prices. The simulated prices were attained by adding a uniformly distributed random perturbation of between plus one half and minus one half of the contract's tick size. In the light of the price perturbations the robustness of the DLN and the smoothing spline method were investigated. Bliss and Panigirtzoglou (2002) concluded that there was strong evidence of superior stability of the SPLINE method over the DLN and that the confidence intervals for both methods were sometimes so large that the RND estimates became useless. All in all the DLN was deemed to be inferior to the SPLINE method.

To sum up, earlier work has recognized that the error terms are unlikely to be normally distributed. Still, the Monte Carlo simulations have been conducted under the assumption that the normality assumption for the price errors is valid. Thus, one of the tasks of this article is to check whether the error terms are normally distributed by conducting

Bera-Jarque tests. If the null hypothesis of normality can be rejected, then a non-parametric method will be used to construct the confidence interval, taking the non-normality into account (a thorough description follows in Section 3).

3. Confidence band estimation

The previous literature describing different procedures of how to compute confidence bands, as outlined in Section 2, has a number of drawbacks that could be improved upon. Hence this section is devoted to describing, in detail, how this could be accomplished by employing two different bootstrap techniques. The first bootstrap method employs historical pricing errors, while the second method uses current pricing errors. The former approach has the advantage of capturing the non-normal and heteroscedasticity characteristics of the error terms. On the other hand, the estimated confidence bands will not differ much between different data sets. This disadvantage can be resolved by bootstrapping the current error terms, which motivates including the latter bootstrap method. This approach has its drawbacks as well, since it not fully taking the heteroscedastic property into consideration. Finally, the DLN and SPLINE methods are evaluated and the width of the generated confidence bands is utilized as the primary tool when deciding which one of the two methods to prefer from a precision point of view. The width of the confidence bands is chosen since we believe this measurement is best suited for our purposes when we want to quantify and visualize the uncertainty connected with the RND estimation methods. By estimating RNDs form option prices higher moments such skewness and kurtosis can be extracted. As the skewness measures the asymmetrical feature of investors' attitude toward risk and the kurtosis can gauge the probabilities attached to 'tail-events', practitioners usually carefully monitor these measures. Thus given the importance of these measures confidence bands for the third and fourth moments of the RNDs are also estimated. The width of these confidence bands is used as a secondary evaluation criterion of the two methods.

3.1. Bootstrap from historical errors

The first bootstrap method proposed is much in line with Melick and Thomas (1998), who estimated confidence bands using Monte Carlo simulations of the DLN method. Melick and Thomas (1998) recognized that the error terms were not independent of option type (call/put) or strike price. This is not unique for the data set of Melick and Thomas (German short-term interest rates), but is also present in the Swedish stock market options (OMX) employed in our study. Another non-appealing property of the error structure is the non-normality. Melick and Thomas chose not to take any of these features into consideration in their Monte Carlo simulations. This paper takes the observed dependence into account by utilizing the historical pattern of the error terms, generated by running DLN estimations from January 1991 until October 2002 on options with 30 days until expiration.

To deal with the issue that the strike price range differs over time (when the value of the underlying index varies) the data were grouped by its relative strike price:

$$relative\ strike\ price\left(X\right)=\left(\frac{strike\ price}{future\ price}-1\right) \tag{8}$$

We choose to divide the groups so that sufficiently large number of observations was included in each group.[1] The historical pattern of the DLN error structure and the SPLINE error structure is illustrated in figures 2 and 3. Clearly, both first and second moments vary, not only across strike prices but also depending on option type (call/put). Thus, it seems reasonable to take this dependence into account by grouping the data.

One way to estimate confidence bands is to draw errors for each strike price, assuming normality with zero mean and a variance equal to its corresponding group variance in line with Söderlind (2000). This article tests whether the normality assumption underlying the Monte Carlo approach is valid using the Bera-Jarque test. The test rejects normality, at the five percent significance level, for all groups except one for the DLN case[2] and all groups except one for the SPLINE case.[3] We therefore abstain from assuming normality and instead propose an alternative procedure where the following steps are performed for each pseudo distribution in order to estimate the confidence bands and take the non-normality of the error structure into account:

- Compute the relative strike price for each call and put price.
- For each observation, draw an error term with replacement from its corresponding group (bootstrap within each group).

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[1] This resulted in eight groups with an average of 232 error observations in each group.

[2] These were the groups of puts with relative strike price >= 0.15.

[3] This was the group of calls with relative strike price <=-0.15.

- Add the errors to the theoretical prices in order to get pseudo prices and run the RND estimation.

These steps are repeated 500 times resulting in 500 pseudo RND distributions which are used to extract a 95 percent confidence interval. However in order to apply the bootstrap method one must assume that the pricing errors are identically and independently distributed. By grouping the pricing errors in this manner, we believe that the observed dependence over the range of strike prices is taken into account, i.e. each group consists of pricing errors that are identical distributed. Moreover the bootstrap of historical data makes it less likely that the sampled pricing errors are dependent because of the one month time interval between the estimated data sets. Hence independence is also assumed.

3.2. Bootstrap from current error terms

The second bootstrap experiment is conducted in line with Söderlind (2000), drawing with replacement from the current error terms. The pseudo-samples are created by adding the bootstrapped error terms to the theoretical prices, i.e. as in the bootstrap on historical error terms. As the structure of the error terms differs across strike prices implies that the problem with heteroscedasticity still remains. Thus we improve the approach suggested by Söderlind (2000) and group the error terms in accordance with its characteristics.

The small number of observations in this approach puts an upper restriction on the number of groups since sub-samples with too few observations invalidate the assumptions underlying the bootstrap methodology. To preserve the heteroscedastic characteristics in the resulting confidence bands we group the error terms depending on whether they are in-the-money or not. This will have the effect that when an error term is drawn, for instance, for a call price that is deep in-the-money, the error term will have the characteristics reflecting prices deep in-the-money. [4] As discussed in the appendix, even though in-the-money options are less liquid relative to out-of-the-money options, liquidity should be of enough magnitude to avoid price distortions. The steps of estimating the confidence interval, apart from the error terms on which to base the confidence interval, follow the same steps as described in Section 3.1.

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[4] In order to generate large enough groups with homogenous pricing errors, in-the-money calls are grouped together with in-the-money-puts and out-of-the-money calls are grouped together with out-of-the-money puts.

The bootstrapping method from current error terms requires the pricing errors to be identically and independently distributed. The independence assumption for current error is more problematic compared with that of historical error terms described in the previous section. For instance, some dependence between pricing errors of adjacent strikes may arise perhaps by transactions of a single investor. To examine whether the error terms within each group may be subject to dependence, the correlation coefficients over time for the errors between adjacent strike prices were computed.[5] The results shown in Table 1 reveal that the correlations for the errors using the DLN method in general are positive and small in magnitudes. In addition, the null-hypothesis of zero correlation cannot be rejected on the 5 percent level between the errors within any of the four groups. The error terms from the SPLINE method exhibit both positive and negative correlation without any clear patters. As in the case of the DLN method the correlations are close to zero and the null-hypothesis of zero correlation on the 5 percent level cannot be rejected. The small and insignificant correlations lead us to assume independence between pricing errors.

3.3. Does heteroscedasticity matter?

Both bootstrap approaches above are set up to take the heteroscedastic characteristics of the pricing errors into account. However nothing has been said whether the heteroscedasticity really matters in practice for the estimated confidence bands. In order to shed light on this issue we also estimate confidence intervals without any grouping of the pricing errors, hence enabling us to evaluate the impact heteroscedasticity may have.

4. Results

In this section the results of the confidence band estimation will be described and displayed visually. We measure the width of the confidence bands and conclude that the SPLINE method is to be favoured from a precision point of view, as it results in more narrow confidence bands compared with the DLN method. Furthermore, we also evaluate the impact of heteroscedastic pricing errors. The section ends with a case

[5] Six pair of time series were constructed; 0-3 percent in-the-money calls and puts, 0-3 percent out-of-the-money calls and puts, 6-12 percent deep-out-of-the-money calls and puts. The exact position of the strikes depends on each dataset since underlying asset varies over time. There were to few observations on deep-in-the-money strikes to construct relevant time series.

study showing how estimated confidence intervals can be used for practical purposes.

As mentioned earlier, two different methods of estimating confidence bands are employed: the bootstrap using historical data, and the bootstrap using current data on both the DLN and the SPLINE estimation methods. In order to illustrate how the confidence bands might look like for the different approaches, a randomly chosen data set (trade date: 27 June 2001) has been utilized as the basis for the illustration and the resulting figures can be examined below. The procedure was repeated for a wide number of data sets yielding the same conclusions as those drawn below.

4.1. Bootstrap from historical data

Figures 4A and 4B display the estimated RNDs for the DLN and SPLINE methods, and the confidence intervals based on historical data. As shown in Figure 4A the confidence bands for the DLN method appear to be rather narrow. Nonetheless, the confidence bands are wider than in the Monte Carlo experiments performed by Melick and Thomas (1998), Söderlind and Svensson (1997) and Söderlind (2001). This is likely to be explained by the fact that these experiments did not address the non-normal and heteroscedastic features of the pricing errors.

Moreover, the confidence bands stemming from the SPLINE method are more narrow than the DLN counterparts, see Figure 4B. This is much in line with the results of Bliss and Panigirtzoglou (2002), which state that the SPLINE method is more precise than the DLN method.

4.2. Bootstrap from current data

Figures 4C and 4D show the estimated RNDs for the DLN and SPLINE methods, and the confidence intervals based on current data. The confidence bands for the DLN method are quite narrow compared with the results of Melick and Thomas (1998), see Figure 4C. This is preponderantly due to the fact that Melick and Thomas (1998) resampled the data points rather than the pricing errors and thereby generating psuedodata sets with large gaps between adjacent strikes. On the other hand it appears as the confidence interval is wider than the counterpart of Söderlind (2000). This might be due to the fact that Söderlind (2000) did not consider the problem with heteroscedastic pricing errors. The confidence interval for the SPLINE method seems to be more narrow than for the DLN equivalence, thus again validating the results of Bliss and Panigirtzoglou (2002), see Figure 4D.

To sum up, earlier work on confidence bands estimation that yielded quite narrow confidence bands is problematic since the non-normal and the heteroscedastic features were not addressed. Moreover, the bootstrap experiment conducted by Melick and Thomas (1998) suffered from the inclusion of spurious looking RNDs in the pseudo-sample. Söderlind (2000) addressed all problems but one: the heteroscedastic nature of the pricing errors. The results of this paper indicate that both heteroscedasticity and non-normality of pricing errors should be accounted for in order to, as accurately as possible, quantify the uncertainty of the estimated RNDs. Finally, the SPLINE method seems to be more precise than the DLN method.

4.3. Quantitative results

Thus far, this paper has tentatively suggested that the SPLINE method is more precise than the DLN method since it seems to produce tighter confidence bands. In order to verify this we choose the following procedure: twelve randomly chosen datasets[6] were estimated for the two estimation methods and the two different bootstrap techniques. The mean of the width of the confidence bands was calculated to evaluate the precision of the two methods, see Table 2. This study confirms the tentative suggestion that the SPLINE method is to be preferred from a precision point of view.

Table 2 shows that the SPLINE method consistently produces tighter confidence bands for the RNDs than the DLN method, both for the bootstrap method using historical data and the bootstrap method using current data. The bootstrap on historical data results in confidence bands for the DLN method that are almost five times as wide as the SPLINE counterpart. The difference is somewhat lesser in the bootstrap from current data: the DLN method delivers bands that are approximately four times wider. Furthermore the analyses of the third and the fourth moments display the same feature: i.e. significantly wider confidence intervals for the DLN method regarding both bootstrap approaches.

For the practitioner other criteria such as computational efficiency and the rate of convergence should be taken into consideration as well before deciding upon estimation method. The SPLINE method optimization routine always converges and hence the whole pseudo sample is intact when estimating the confidence interval. This differs considerably from the DLN method, where a great many RNDs in the

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[6] One data set was drawn from a uniform distribution for each year during the period January 1991 - October 2002.

pseudo sample have to be omitted in order to avoid spurious-looking[7] confidence intervals. In addition, the SPLINE method also consistently requires less computing time than the DLN method. Thus from a practitioner's point of view there should be little doubt that the SPLINE method is to be preferred.

A further issue is what bootstrap technique to apply. We generally believe that the bootstrap from current error terms is superior. Estimating confidence bands from historical error terms has the drawback of not being able to capture the specific characteristics of the data set at hand. On the other hand, if only a few strike prices are available, there will be hardly any variation from pseudosample to pseudosample when drawing with replacement, thus invalidating the assumptions underlying the bootstrap methodology. In that case the bootstrap from historical data is to be preferred to the bootstrap from current data.

4.4. Heteroscedasticity does matter

We have argued that the pricing errors in theory should be grouped as they exhibit non-similar features. However, from a more pragmatic point of view, it is also of interest to examine whether the grouping procedure really matters in practice. To examine this we estimated confidence bands for the DLN[8] method without grouping the data and compared these with the confidence bands produced by the grouping procedures. From Table 3 it becomes evident that the inclusion of heteroscedasticity does matter since the confidence bands generally become tighter. Hence inclusion of heteroscedasticity seems to increase the precision of the estimated confidence bands and should therefore be implemented in practice. The impact of heteroscedasticity is especially evident when bootstrapping historical errors where the confidence bands for RNDs, skewness and kurtosis all becomes tighter when grouping the data. For the bootstrap method using current errors grouping, heteroscedasticity also matters yielding tighter confidence bands for RNDs and kurtosis.

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[7] Densities that are not monotonically increasing to the left of the mode and/or not monotonically decreasing to the right of the mode.

[8] We chose the DLN method since it also governs the choice of λ in the SPLINE method in our estimations.

4.5. Case study: Did the ECB and the BoE interest rate reductions on November 8, 2001, alter stock market expectations?

In this section an example is provided of how the estimated confidence bands may be applied as a practical tool in order to quantify whether the perception of risk has changed significantly or not when new information hits the market.

The intention of this exercise is to examine if investors changed their perception, or "true" probabilities, for the future outcome concerning the Swedish stock market after the 50 basis point interest rate cut by the ECB and Bank of England (BoE) on 8 November, 2001. Moreover, if the market's perception towards risk remains unchanged one can interpret the cuts to have been well foreseen by market participants. Hence it is possible by this approach to measure the degree of central bank transparency with respect to the market's risk assessment.

It is important to note that the estimated implied RND derived from observed option prices reflects the market's "true" perception concerning the future density if and only if investors are risk-neutral. This qualification can lead to complications in interpreting the "true" message in RNDs. To illustrate this, suppose an RND is estimated with a stock market index as the underlying asset. If the RND has a negative skewness coefficient (i.e., it is skewed to the left), it is not possible to distinguish the extent to which this reflects a large degree of risk aversion on the part of investors or the extent to which the market attaches a high probability to a sharp downward correction of the stock market.[9] However, if one assumes that the degree of risk aversion over shorter time periods is broadly constant, then changes in RNDs over short periods of time can be interpreted as changes in market expectations concerning higher moments of the value of the underlying asset.

This exercise starts out by estimating an RND and its corresponding confidence band on 8 November, 2001. The RND is estimated on the Swedish OMX index. During this day both the ECB and the BoE cut their interest rates by 50 basis points (ECB at 1.45pm and the BoE at 1.00pm, Central European Time). A second RND was estimated when the markets opened the day after on November 9. By computing the confidence interval around the RND estimated before the cuts and investigating whether the RND estimated after the easening of monetary conditions

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[9] In principal, agents' degree of risk aversion can also be derived from option prices, see Bliss and Panigirtzoglou (2004).

falls within the confidence bands, a sense of whether the subsequent reaction of stock market uncertainty was statistically significant or not can be provided. If the RND estimated after the event were to lie outside the confidence bands this would indicate that the market did significantly change its expectations concerning higher moments of the value of the underlying asset. Although comparisons like these have been made in the literature before, to our knowledge no attempts have been made to quantify whether the changes are statistically significant or not.

In this exercise the confidence bands were estimated by bootstrapping from current data applying the DLN estimation technique.[10] Figure 5 below shows the RND estimated at 10.02 am the day after the decisions together with the 95 percent confidence bands around the RND estimated at 11.06 am on the day of the interest rate cuts. The RND estimated after the interest rate cuts falls inside the 95 percent confidence bands. This can be interpreted as indicating market participants did not significantly alter their view about the uncertainty of the Swedish stock market outlook following the decisions.

5. Conclusions

This paper shows that is important to take the non-normal and the heteroscedastic features of the pricing errors into consideration when computing confidence bands for the estimated RND. Two different statistical methods have been applied: bootstrap from historical pricing errors and bootstrap from current pricing errors. Both methods resulted in less narrow, and perhaps more plausible confidence bands, than earlier work using Monte Carlo simulation have provided. Furthermore, two techniques of estimating RNDs, the SPLINE and the DLN methods, have been implemented in the confidence interval analysis. The SPLINE technique produces more accurate RNDs, since the confidence intervals are more narrow than the DLN counterpart. Another important issue that earlier literature on the subject has failed to address is the heteroscedastic error structure that the data clearly displays. We have shown that heteroscedasticity matters and thus should not be overlooked when estimating confidence bands for RNDs. In addition, the DLN technique produces some computational drawbacks that can be avoided by implementing the SPLINE method. The SPLINE method also requires somewhat less computing time than the DLN method. Finally, estimation

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[10] The DLN method is chosen even though the SPLINE method is to be preferred generally. The reason is that the DLN method generates wider confidence bands and hence better illustrates the task at hand.

of the confidence bands provides an opportunity to deliberate upon whether a shift in the shape of the RND over a short period of time can be attributed to increased perceived uncertainty about the development of the underlying asset.

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Data Appendix

The data used in this study consist of equity options on the Swedish stock market (OMX) index. The options are European style, and in this study options with 30 days to maturity are examined. The data have been downloaded from Reuter during the trading day, thereby avoiding the problems arising from using settlement prices, mentioned in Section 2.1. The average of the bid and ask quotations is used as the price proxy.

The OMX is traded at the Stockholmsbörsen (Stockholm stock exchange) and the contracts mature the fourth Friday of each month. The OMX dataset stretches from January 1991 until October 2002. The options are traded under a rolling schedule which means that there is one contract with 30 days to maturity once a month. The smallest tick size is 0.01.

The option contract has the index as the underlying asset but the future contract matures at the same time as the option, which means that the future could be used as a proxy for the underlying asset.

One possible drawback of the data is that lack of liquidity might distort the results. In order to minimise possible distortions stemming from lack of liquidity we have used options with 30 days to maturity. We have followed recommendations from the data provider (Stockholmsbörsen) as these option contracts usually have good liquidity, not only for options close to at-the-money, but also for strikes deep-in-the-money and deep out-of the-money. By collecting data on open interest we have tried to verify the quality of the data, from a liquidity point of view. The sum of open interest on the first trade date for each month for all available strike price and maturities was obtained from the data providers for the sample from November 1994 until October 2002.[11] There are usually three option contracts traded on the first trading date of the month, the first expiring in about 25 days, the second in about 55 days and the third contract in about 85 days. As we have estimated the confidence bands for options with 30 days to maturity they are not exactly comparable with the 25 days contract. However the data provider confirmed that this five-day miss-match would not significantly change any of the interpretations.

To check the liquidity of the options with shortest maturity in relation to the two other contracts, the sum of the open interest of all strike prices for the 25-days contract together with the sum of the open

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[11] Data on open interest before November 1994 is not available.

interest for the 55 and 85-days contracts were calculated, see Figure 6. Two notable features are evident:

- First, the sum of open interest of the two series clearly moves in tandem.
- Second, the 25-days maturity series most of the time clearly exceeds the 55 – 85 maturity series. This give support for the view that the nearest contract seems to have relatively better liquidity compared with the two contracts with longer horizons.

To examine the liquidity for the options over the range of strike prices, open interest data was divided into four subcategories: in-the-money calls, out-of-the-money calls, in-the-money puts and out-of-the money puts. These categories are identical to the grouping strategy chosen when calculating confidence bands for current data (see Section 3.2). Figures 7 and 8 display the sum of the open interest rates for the four groups. The results suggest the out-of-the-money calls and puts to have better liquidity compared the in-the-money calls and puts, see Table 4. On average, the open interest for out-of-the-money calls are about four times higher then in-the-money calls. Similarly, the open interest for out-the-money put options are about eight times higher than in-the-money puts. Even though in-the-money options are less liquid relative to out-of-the-money options, liquidity is of enough magnitude to avoid price distortions. In addition, the fact that put/call parity in general holds suggests that in-the-money options should also be included so that the resulting confidence bands also reflect the pricing characteristics of in-the-money options.[12]

Further confirming the quality of the data is that the OMX options traded on the Swedish Open Market have a number of market makers which are obliged to give prices for all available contracts and strike prices. Over the sample period we used in this study (1991 – 2002), the number of counterparts have varied between four and eight.

[12] For the observations in which put/call parity does not hold, the deviations are small enough to be explained by transaction costs.

Figures and Tables

Figure 1. RNDs estimated before and after the events of September 11, 2001

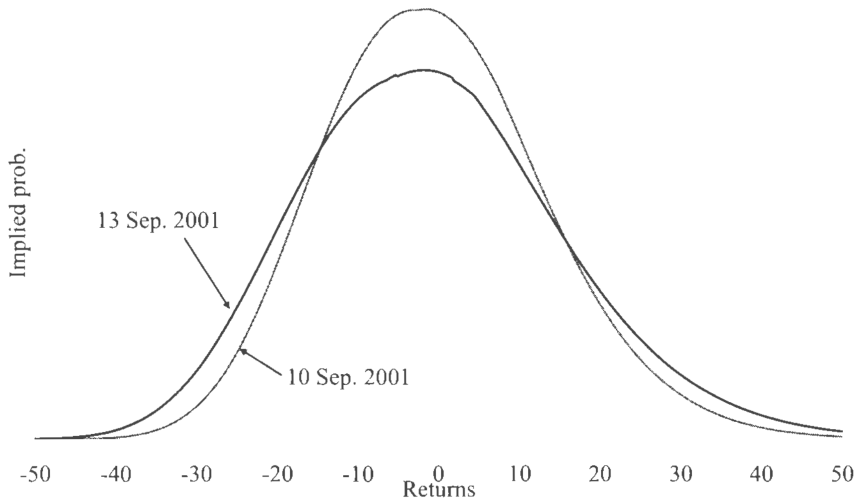
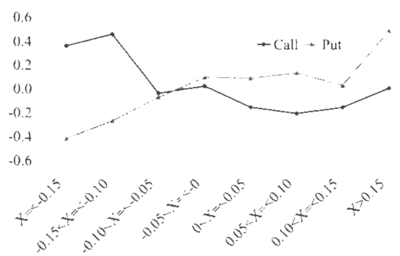


Figure 2. Historical errors, DLN method

A. DLN, average errors grouped according to relative strike price



B. DLN, standard deviations of the errors grouped according to relative strike price

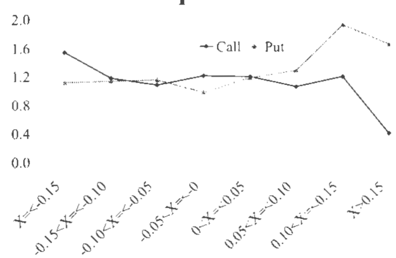
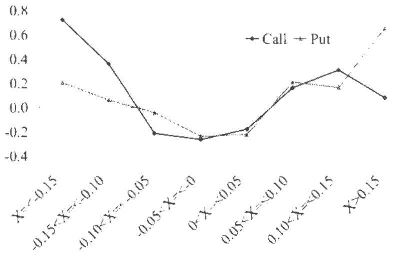


Figure 3. Historical errors, SPLINE method

A. SPLINE, average errors grouped according to relative strike price



B. SPLINE, standard deviations of the errors grouped according to relative strike price

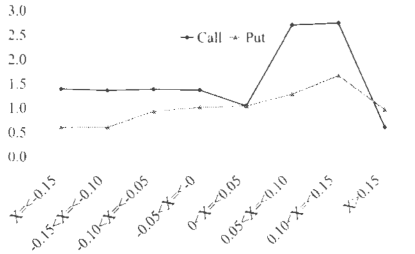
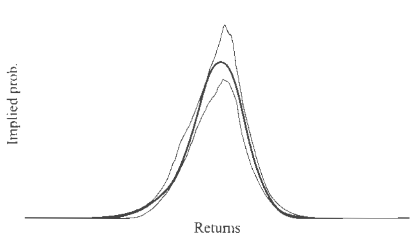
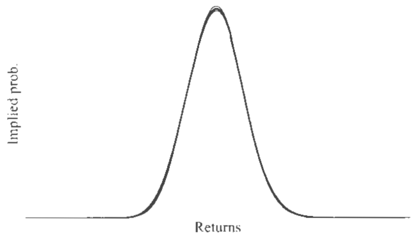


Figure 4. Confidence interval based on OMX options 27 June 2001

A. Bootstrap from historical data, DLN



B. Bootstrap from historical data, SPLINE



C. Bootstrap from current data, DLN

D. Bootstrap from current data, SPLINE

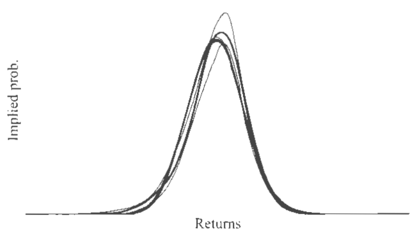


Figure 5. RND and confidence bands

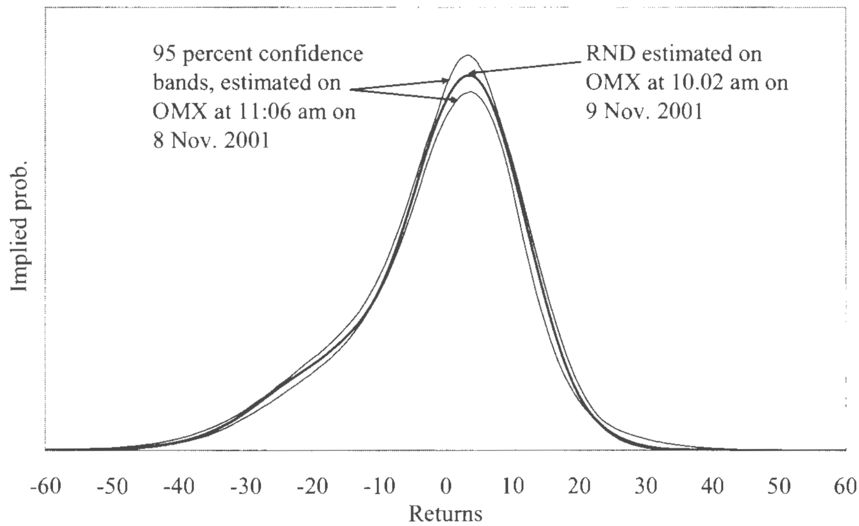


Figure 6. Total open interest for options with around 25 days to maturity and the sum of the 55 and 85 days contracts (monthly data November 1994 – October 2002)

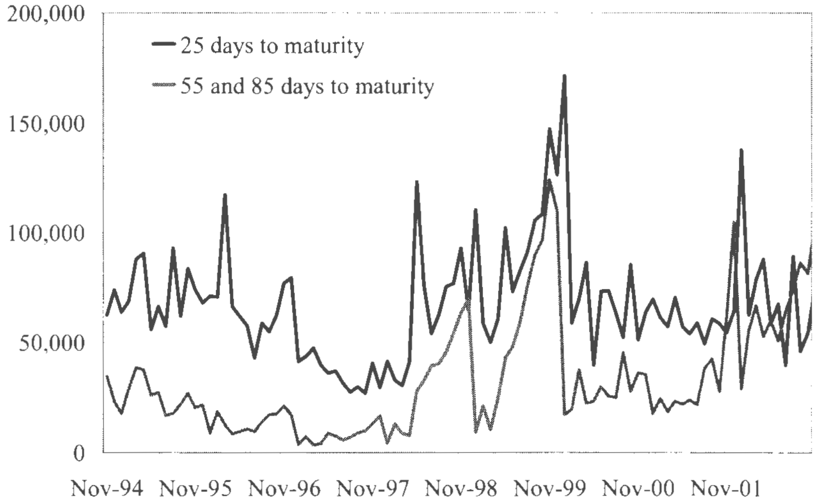


Figure 7. Total open interest for out-of-the money call and put options for options with 25 days to maturity (Monthly data November 1994 – Oct 2002)

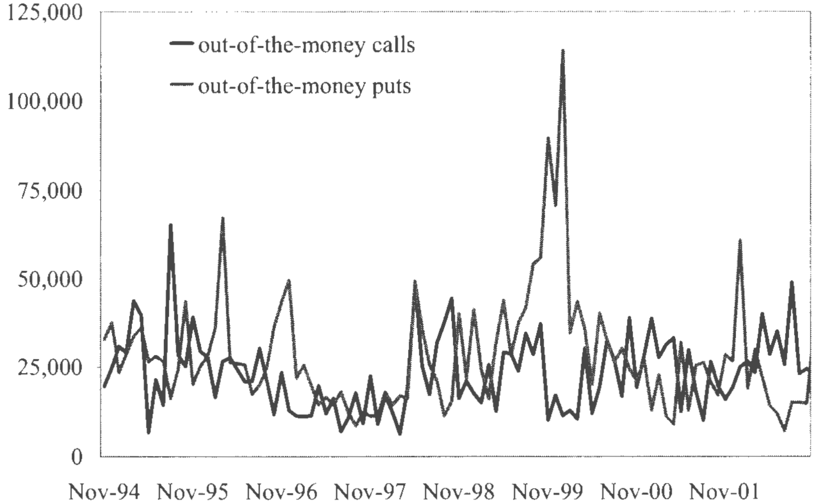


Figure 8. Total open interest for in-the money call and put options for options with 25 days to maturity (Monthly data November 1994 – Oct 2002)

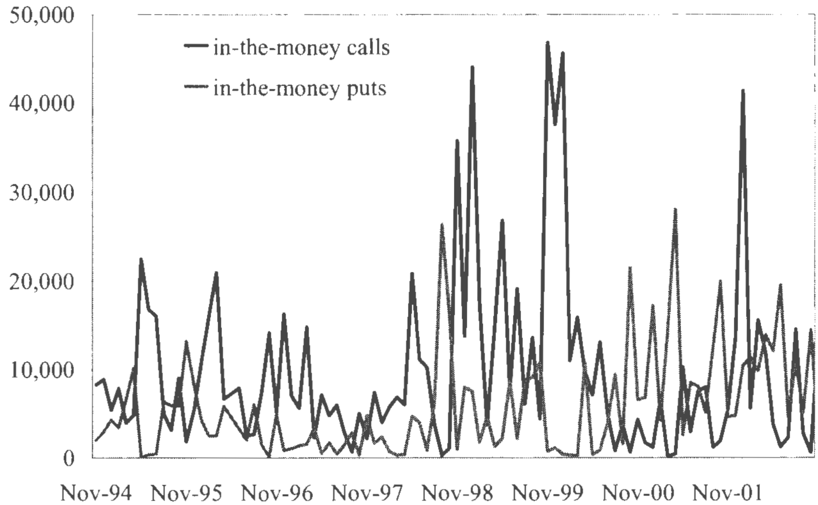


Table 1. Correlation between pricing errors of adjacent strikes: DLN method (panel A), **SPLINE method** (panel B)

	Correlation	P-value*	Number of obs.
Panel A			
Calls:			
In-the-money	0.122	0.154	73
Out-of-the-money	0.070	0.268	81
Deep-out-of-the-money	0.149	0.106	72
Puts:			
In-the-money	0.125	0.166	63
Out-of-the-money	0.173	0.069	75
Deep-out-of-the-money	0.109	0.181	71
Panel B			
Calls:			
In-the-money	0.065	0.255	105
Out-of-the-money	-0.002	0.492	100
Deep-out-of-the-money	0.113	0.138	96
Puts:			
In-the-money	0.008	0.468	95
Out-of-the-money	-0.133	0.093	99
Deep-out-of-the-money	-0.152	0.072	94

* Testing the null hypothesis of zero correlation against the two-sided alternative

Table 2. Evaluation of estimation methods

	Method	Average width of confidence bands*			Average number of spurious densities**
		RND	Skewness	Kurtosis	
Bootstrap 1	SPLINE	1	1	1	0
(Historical data)	DLN	4.6	4.5	27.6	206
Bootstrap 2	SPLINE	1	1	1	0
(Current data)	DLN	4.0	4.7	24.7	240

* The average width is in relative terms, i.e., the SPLINE is normalized to one.

** Densities that are not monotonically increasing to the left of the mode and/or not monotonically decreasing to the right of the mode.

Table 3. Evaluation of the impact of heteroscedasticity, DLN method

DLN method	Grouping	Average width of confidence bands*		
		RND	Skewness	Kurtosis
Bootstrap 1	Yes	1.00	1.00	1.00
(Historical data)	No	1.04	1.19	1.18
Bootstrap 2	Yes	1.00	1.00	1.00
(Current data)	No	1.11	1.00	1.04

* The average width is in relative terms, i.e., grouping is normalized to one.

Table 4. Summary statistics of the outstanding open interest (monthly data November 1994 – October 2002)

	in-the-money calls	out-of-the-money calls	in-the-money puts	out-of-the-money puts
mean	6,882	29,594	3,853	31,234
min	167	6,309	70	7,134
max	46,844	65,438	28,035	114,162

Why does the correlation between stock and bond returns vary over time?*'**

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Abstract

This article examines the impact of inflation and economic growth expectations and perceived stock market uncertainty on the time-varying correlation between stock and bond returns. The results indicate that stock and bond prices move in the same direction during periods of high inflation expectations, while epochs of negative stock–bond return correlation seem to coincide with subdued inflation expectations. Furthermore, consistent with the 'flight-to-quality' phenomenon, the results suggest that periods of elevated stock market uncertainty lead to a decoupling between stock and bond prices. Finally, it is found that the stock – bond return correlation is virtually unaffected by economic growth expectations.

Keywords: stock-bond return correlation, dynamic conditional correlation, macroeconomic expectations, implied volatility.

JEL classification: C10, E44

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** Forthcoming in "Applied Financial Economics"

1. Introduction

This article examines the impact of macroeconomic expectations and perceived stock market uncertainty on the time-varying correlation between stock and bond returns. Understanding the dynamics of the correlation between stock and bond markets is important for several reasons. The co-movements between stocks and bonds have, for instance, a direct impact on the formulation and implementation of investors' asset allocation and risk management strategies. In particular, investment strategies that assume a constant relationship between stock and bond returns may be improved by properly taking into account the observed time variation in the correlation between these two asset classes. Furthermore, a better understanding of the time-varying co-movements between stocks and bonds may also be useful for monetary policy purposes. Although central banks do not have specific price targets for financial assets such as bonds or stocks, monetary policy authorities are increasingly using the information contained in the prices of these assets to gauge, for instance, market participants' growth and inflation expectations. Hence, stock–bond return correlation estimates may offer policymakers useful complementary information to determine whether markets are changing their views on inflation or economic activity prospects.

The relationship between stock and bond returns has received considerable attention in literature. Shiller and Beltratti (1992) document a strong positive (negative) correlation between changes in stock prices and long-term bond prices (yields). They argue that this positive correlation is caused by the common discount rate effect.[13] Also Campbell and Ammer (1993) find a positive, albeit low, correlation between stock and bond returns. However, both Shiller and Beltratti (1992) and Campbell and Ammer (1993) implicitly assume that the relationship between stock and bond prices remains constant over time. More recently, several studies have shown that the correlation between

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[13] Stock prices should, in theory, equal the discounted sum of all expected future dividends. The discount rate consists of two components, a premium that investors demand for holding risky assets and the risk-free rate, the latter usually approximated by the yield on government bonds. Thus, if expected future dividends and the equity risk premium remain unchanged, higher risk-free rate will cause downward pressure on stock prices and thereby result in a positive correlation between bond and stock returns. Empirical evidence on the common discount rate effect is provided in Gulley and Sultan (2003).

stock and bond returns exhibits considerable time variation (Gulko, 2002; Cappiello et al., 2003; Ilmanen, 2003; Jones and Wilson, 2004; 70 Li, 2004; Connolly et al., 2005). Although stock and bond prices, in general, tend to move in the same direction, recent studies have also documented sustained periods of negative correlation.

Surprisingly little is known about the driving forces behind this time-varying correlation between stock and bond returns. One macroeconomic variable that, in theory, may affect the stock – bond return correlation is inflation. An increase in expected inflation tends to raise discount rates and hence, is inevitably bad news for the bond markets. However, the impact of increasing inflation on stock prices is ambiguous, as both the expected future cash flows and the discount rates are likely to be affected. Ilmanen (2003) uses US data to examine the impact of inflation on the correlation between stock and bond returns and finds that during periods of high inflation, changes in the discount rates dominate the changes in cash flow expectations, thereby inducing a positive stock – bond return correlation. Li (2004) examines the impact of uncertainty about expected long-term inflation on stock–bond return correlation and shows that greater concerns about future inflation tend to result in stronger co-movements between stocks and bonds.

Apart from the fundamental changes in the macroeconomic environment, financial market dynamics and changes in market participants' assessment about risk may also have an important impact on the relationship between stock and bond returns. For instance, in periods of financial market turbulence, the equity risk premium demanded by the investors to hold stock may increase relative to the term premium for bonds. This may cause the so-called 'flight-to-quality' portfolio shifts from the stock markets to the bond markets, leading to some divergence in the returns between these two asset classes. Gulko (2002) focuses on the stock – bond correlations around stock market crashes and shows that the periods of negative stock – bond correlation tend to coincide with stock market crashes. In a similar vein, Connolly et al. (2005) suggest that option-implied stock market volatility is a good indicator of financial market turmoil. They find that bond returns tend to be high (low) relative to stock returns during days when implied stock market volatility is high (low).

The purpose of this article is to examine how inflation and economic growth expectations and perceived stock market uncertainty affect the correlation between stock and bond returns. The main contribution of this article is the focus on the impact of expectations. The use of inflation and economic growth expectations, instead of the actual historical values, may be considered more appropriate, as stock and bond prices should reflect market participants' expectations of future values of these fundamentals. In addition, this article extends the literature by jointly examining the impacts of macroeconomic expectations and expected stock market uncertainty on the stock–bond return correlation. Following Connolly et al. (2005), volatility estimates extracted from option prices are used to assess stock market uncertainty. Finally, this article contributes to the literature by applying recent techniques proposed by Engle (2002) to measure the time-varying correlation between stock and bond returns.

The empirical findings reported in this article demonstrate that the correlation between stock and bond returns varies considerably over time. Using data from the US, the UK and Germany, we show that the stock – bond correlations in all the three countries are positive most of the time, although sustained periods of negative correlation are also observed. Our findings also demonstrate that the stock – bond correlation may change substantially and turn from positive to negative, in very short periods of time. Interestingly, the stock–bond correlations in the US, UK and Germany exhibit rather similar patterns over time, as for instance the periods of negative correlation seem to coincide.

Furthermore, our empirical findings indicate that expected inflation is positively related to the time-varying correlation between stock and bond returns. Stock and bond prices tend to move in the same direction during periods of high inflation expectations, while epochs of negative stock – bond correlation seem to coincide with the lowest levels of inflation expectations. The empirical findings also demonstrate that expected stock market uncertainty, as measured by implied volatility, is negatively related to the stock–bond correlation. In particular, the results strongly indicate that high stock market uncertainty leads to a decoupling between stock and bond prices. This finding is consistent with the 'flight-to-quality' phenomenon. Finally, we are unable to find any systematic relationship between economic growth expectations and stock–bond return correlations.

The remainder of this article is organized as follows. Section 2 describes the data used in the empirical analysis. The stock–bond return correlation measures used in this article are presented in Section 3. Section 4 discusses the behaviour of the stock – bond return correlations over time. The empirical findings on the impact of inflation and growth expectations and expected stock market uncertainty on the stock – bond return correlations are reported in Section 5. Finally, Section 6 provides concluding remarks.

2. Data

The empirical analysis in this article is performed using daily data on US, UK and German stock and bond returns. These three countries are generally considered the most important economies and the largest financial markets in the world.[14] The US stock returns are calculated from the S&P 500 index, the UK returns from the FTSE 100 index and the German returns from the DAX index. The stock index data used in the analysis are obtained from Reuters. The bond returns for the US, the UK and Germany are extracted from the benchmark 10-year government bond price indices.[15] These bond price indices are taken from Thomson Financial Datastream. The sample period spans from January 1991 to August 2006 for the US and from January 1992 to August 2006 for the UK and Germany.[16]

The impact of macroeconomic expectations on the stock–bond return correlation is examined using monthly data on inflation and economic growth expectations. We use expected growth rates of the US, UK and German consumer price indices (CPI) and real gross domestic products (GDP) over the next 12 months. The data on these macroeconomic expectations are obtained from Consensus Economics. Every month, Consensus Economics surveys about 600 economists for their forecasts regarding future macroeconomic developments. The average forecasts of this survey are used to measure inflation and economic growth expectations. The expectations data are published on the second Monday of each month and consist of year-on-year growth expectations for the current and the next year. In order to obtain a comparable and consistent time series of inflation and real GDP growth expectations, the expectations for the current year and the next year are weighted together to measure 12-month ahead expectations:

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[14] Due to data availability, we have excluded Japan from the analysis. However, although Japan is among the three largest stock markets in terms of market capitalization and trading activity, the bond markets in the US, UK and Germany are substantially larger in terms of the amounts of outstanding debt.

[15] The analysis was also conducted using 2-year government bond price indices. However, since the stock – bond return correlations are virtually similar regardless of the maturity of the bonds, we only report results based on 10-year bonds.

[16] The sample periods for the UK and Germany begin in January 1992 owing to data availability.

$$E_{12,t} = \frac{m}{12} E_{C,t} + \frac{12-m}{12} E_{N,t} \tag{1}$$

where $E_{12,t}$ denotes the 12-month ahead expectations of a certain macroeconomic variable at time t, $E_{C,t}$ and $E_{N,t}$ denotes the time t expectations of the macroeconomic variable for the current and the next year, respectively and m is the number of remaining months during the current year.

To examine the impact of expected stock market uncertainty on the stock – bond return correlation, we use implied volatilities extracted from the prices of stock index options. Option-implied volatility may be regarded as the market participants' forecast of the future volatility of the underlying asset over the remaining life of the option contract. Provided that market participants are rational, implied volatility should incorporate all the available information that is relevant for forming expectations about future volatility. Therefore, implied volatility is widely regarded as the best available estimate of market uncertainty.

To capture stock market uncertainty, we use the VIX and VDAX implied volatility indices, constructed by the Chicago Board Options Exchange (CBOE) and the Deutsche Börse, respectively. These implied volatility indices are obtained from Reuters. Furthermore, we use data on FTSE 100 index options to construct a corresponding implied volatility index for the UK. These index option data are obtained from the London International Financial Futures and Options Exchange (LIFFE). VIX is calculated from the S&P 500 index options as the average of eight near-term and close-to-money call and put options. The implied volatilities of these S&P 500 index options are weighed together to create a single implied volatility estimate, which represents the expected stock market volatility over the next 30 days.[17] Correspondingly, the VDAX is calculated from the DAX index options by weighing together implied volatilities of near-term and close-to-money call and put options. The VDAX has a constant maturity of 45 days, thereby representing the expected stock market uncertainty over the next 1½ months. The constructed implied volatility time series for the FTSE 100 index has a constant maturity of 3 months.

[17] For additional details on implied volatility indices, see e.g. Fleming et al. (1995), Blair et al. (2001) and Graham et al. (2003).

Figure 1 depicts the developments in the inflation and economic growth expectations and perceived stock market uncertainty. As can be noted from the figures, all three time series for all three countries appear rather smooth and persistent, although implied volatility is perceptibly the most volatile variable. Interestingly, the macroeconomic expectations and especially implied volatilities seem to exhibit very similar patterns in the US, UK and Germany. This suggests that these three economies are integrated to a large extent.

3. Measuring the correlation between stock and bond returns

We use two methods to measure the time-varying correlation between stock and bond returns: (i) a simple rolling window sample correlation and (ii) the dynamic conditional correlation (DCC) model.

The simplest method to capture the time-variation in the stock–bond return correlation is to compute sample correlation coefficients based on a rolling window of stock and bond returns. In this article, a monthly estimate of the correlation between stock and bond returns is computed for the 15th day of each month using the returns of the previous 22 trading days.[18] More formally, the 22-day rolling window correlation (RWC) is calculated by dividing the equally weighted covariance estimate over the last 22 trading days by the square root of the product of the two 22-day variance estimates:

$$\hat{\rho}_t = \frac{\sum_{i=1}^{22} r_{S,t-i} r_{B,t-i}}{\sqrt{\sum_{i=1}^{22} r_{S,t-i}^2 \sum_{i=1}^{22} r_{B,t-i}^2}} \qquad (2)$$

where $r_{S,t}$ and $r_{B,t}$ denote the stock and bond returns on day t, respectively. Although the RWC is simple to estimate, it captures, at least to some extent, the time variation and 'clustering' of the stock–bond return correlation. However, this correlation estimate also has some severe drawbacks, as the rolling estimates cannot adequately measure the dynamics of cross-return linkages. In particular, due to the equal weighting of the return observations in Equation 2, the correlation estimates adjust rather slowly to new information. Additionally, unusually small or large return observations will not gradually diminish over time, but instead lead to jumps in the correlation estimates when

[18] There are, on average, 22 trading days in a month.

these observations fall out of the estimation window. Furthermore, since correlation estimates depend on the market volatility, they may contain an upward bias over periods of market stress (Forbes and Rigobon, 2002).

An alternative method applied in this article to model the time-varying co-movements between stock and bond returns is the DCC model proposed by Engle (2002).[19] DCC is a simplified multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model. DCC has the flexibility of univariate GARCH models, but it still provides parsimonious correlation specifications without the computational difficulties of multivariate GARCH models

In this article, the time-varying covariance between stock and bond returns is assumed to be given by the following DCC(1,1) model:

$$
\begin{aligned}
r_{i,t} &= \gamma_i + \phi_i r_{i,t-1} + \varepsilon_{i,t} \\
\sigma_{i,t}^2 &= \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \\
\sigma_{ij,t} &= \overline{\sigma}_{ij} + \alpha\left(z_{i,t-1} z_{j,t-1} - \overline{\sigma}_{ij}\right) + \beta\left(\sigma_{ij,t-1} - \overline{\sigma}_{ij}\right)
\end{aligned}
\tag{3}
$$

where $r_{i,t}$ denotes the return on asset i at time t, $\sigma_{i,t}$ is the conditional volatility of asset i at time t, $\sigma_{ij,t}$ is the time t conditional covariance between assets i and j, $z_{i,t} = r_{i,t} / \sigma_{i,t}$, and $\overline{\sigma}_{ij}$ is the unconditional expectation of the cross product $z_{i,t}\, z_{j,t}$. The first equation performs the filtration of the original return series, and is specified in the form of an AR(1) process, where the constant is capturing a potential non-zero mean in the time-series and the lagged return is capturing the potential auto-correlation property of returns. The likelihood function of the DCC model can be separated into two parts, the volatility part and the correlation part, and therefore a two-step estimation procedure can be used. The second equation gives the univariate GARCH(1,1) model for the filtered returns and is estimated separately for bonds and stocks in the first step. In the second step, we estimate the third equation using the variance series obtained during the first step. A further description of the DCC model and the estimation procedure is provided in Appendix.

[19] DCC modelling has previously been used, e.g. by Bautista (2003), Cappiello et al. (2003), Lee (2006) and Manera et al.

(2006).

4. How does the correlation between stock and bond returns behave over time?

Descriptive statistics of the rolling window and conditional stock and bond return correlation estimates for the US, UK and Germany are reported in Table 2. On an average, the stock–bond correlations in all three countries are positive, with mean correlation estimates of about 0.12 in the US, about 0.11 in the UK and about 0.15 in Germany.[20] The conditional correlation ranges from -0.876 to 0.835 in the US, from -0.636 to 0.770 in the UK and from -0.439 to 0.739 in Germany. It can also be noted from Table 2 that in terms of means and medians, the rolling window and DCC estimates seem rather similar to each other.

Developments of the rolling window and dynamic conditional stock–bond return correlations in the US, UK and Germany are plotted in figures 2 and 3, respectively. Several interesting features emerge from these figures. Although the correlations in all three countries are positive on an average, it is apparent that the relation between stock and bond returns has been rather unstable over time and also sustained periods of negative correlation can be observed. Moreover, the figures indicate that the stock–bond correlations may change substantially in very short periods of time. For instance, in October 1997 the dynamic conditional stock–bond correlation estimate in the US was about 0.52, but already 1 month later in November the correlation had dropped to -0.18. These sudden changes in correlations may pose challenges for asset allocation and risk management procedures.[21]

Interestingly, figures 2 and 3 demonstrate that the stock–bond return correlations in the US, UK and Germany exhibit rather similar patterns over time, thereby suggesting that some common factors may determine the time-varying relation between the two main asset classes. For all countries, the correlations were constantly positive until November 1997 and then suddenly dropped to levels below zero for a short period during late 1997 and early 1998. The correlations again became positive in March 1998, but fell back to negative levels already in the summer of

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[20] Virtually similar correlation estimates were obtained when 2-year government bond indices were used instead of 10-year bonds.

[21] Investment strategies and asset allocation decisions that assume a constant relationship between stock and bond returns are obviously inappropriate and may lead to considerable losses during sudden changes in correlation structures. Moreover, commonly used risk monitoring techniques may result in spurious conclusions if the dynamics of stock – bond correlations are neglected.

1998. During the exceptionally optimistic growth period from spring 1999 until summer 2000, the stock–bond correlations were soundly positive. After the stock market correction started in March 2000, the correlations in the US, UK and Germany became less positive and started to wander at levels close to zero. The correlations for all three countries then turned negative in early 2001 and stayed below zero levels throughout 2002 and early 2003. During 2004, the stock–bond correlations gradually became less negative and started to hover in the positive territory in the spring of 2005. In general, the similarity of the stock–bond correlations in the US, UK and Germany indicates a high degree of market integration among these countries.

It can also be noted from figures 2 and 3 that the conditional and rolling window stock–bond return correlations exhibit a very similar pattern over time. However, as expected, the RWC estimates appear to be considerably more erratic than the conditional correlations produced by the DCC model. Also, DCC estimates should account for the changes in volatility and thereby be free from the potential upward bias during periods of financial turmoil.

5. Why does the correlation between stock and bond return vary over time?

The preceding analysis evidently demonstrates that the relation between bond and stock returns varies considerably over time. Against this background, it is of interest to examine what factors may cause this time variation in the correlation between stock and bond returns. A priori, the potential determinants of the time-varying stock and bond return correlation may be deduced from the asset pricing theory, which postulates that the price of an asset equals the present value of all future cash flows from the asset discounted at an appropriate discount rate. Hence, the price of a stock S at time t can be expressed as the discounted sum of all expected future dividends:

$$S_t = E_t\left[\sum_{t=1}^{\infty}\left(\frac{1+G_t}{1+Y_t+ERP_t}\right)^t D_t\right] \tag{4}$$

where D denotes dividends, Y is the government bond yield, G is the expected growth rate of the dividends and ERP is the equity risk premium demanded by investors. Correspondingly, the time t price of a government bond B can be written as the discounted sum of all future coupon payments and the face value of the bond:

$$B_t = E_t\left[\sum_{t=1}^{T}\frac{C_t}{(1+Y_t)^t}+\frac{FV}{(1+Y_T)^T}\right] \qquad (5)$$

where C denotes coupon payment and FV is the face value of the bond. The government bond yield Y, used as the discount rate, reflects expectations about future short-term rates and the required bond risk premium demanded by investors for holding longer-term bonds.

According to the Fisher decomposition, the nominal government bond yield Y may be decomposed into a real interest rate component and a compensation for the expected inflation over the remaining life of the bond. Moreover, Y may also include a term premium, which investors demand for holding longer (i.e. more risky) assets. Consequently, the nominal government bond yield Y can be expressed as:

$$Y_n = Y_n^r + \pi_n^e + \theta \qquad (6)$$

where Y_n denotes the n period nominal bond yield, Y^r_n is the n period real interest rate, π^e_n is the expected inflation rate over n periods and θ denotes the term premium. Since long-term real interest rates should, in theory, be closely linked to long-term real growth expectations, Equation 6 suggests that nominal government bond yields are decisively determined by growth and inflation expectations.[22] In particular, higher (lower) growth and/or inflation expectations should lead to higher (lower) bond yields. Consequently, given Equation 5, it is apparent that bond prices should be negatively related to growth and inflation expectations.

The impact of growth and inflation expectations on stock prices is rather ambiguous. Rising inflation or growth expectations may have no impact on stock prices, if the discount rates and expected growth rate of the dividends are equally affected by rising inflation and growth expectations. Nevertheless, in case of elevated inflation expectations, the discount rate effect may outweigh the changes in expected future dividends and hence, high inflation expectations tend to have a negative impact on stock prices (Ilmanen, 2003).

Also relative changes in the equity risk premium and the term premium of long-term bonds may significantly affect the time-varying relation between stocks and bond returns. The term and equity risk

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[22] The link between economic activity and the real interest rate dates back to Fisher (1907), who showed that the real interest rate is determined by the ratio of optimal future consumption to optimal current consumption. This ratio, including the discount factor adjustment, is the marginal rate of inter-temporal substitution reflecting agents' preferences and the presence of the discount factor ensures that the real rate of interest exceeds real consumption growth in the long run.

premiums ultimately depend on the asset's perceived risk characteristics and on investors' risk aversion. For instance, during periods of financial market turbulence investors tend to become more risk averse, thereby prompting shifts of funds out of the stock market into safer asset classes, such as long-term government bonds. These so-called 'flight-to-quality' episodes may be interpreted as an increase in the equity risk premium and a decrease in the bond term premium. Consequently, it may be expected that stock and bond prices move in the opposite direction during periods of market turmoil.

To examine how inflation and growth expectations and perceived stock market uncertainty affect the relationship between stock and bond returns, we calculate the average stock–bond return correlations in 12 different subsamples that are created based on the levels of CPI growth expectations, real GDP growth expectations and stock market volatility expectations. The average stock–bond return correlations in these 12 quantile subsamples are reported in Table 3. As can be seen from the table, expected inflation appears to be positively related to the correlation between stock and bond returns. Panel A of Table 3 shows that the average stock–bond return correlation in the United States is about 0.33 during periods in which the expected inflation is in the highest quartile. Similarly, Panels B and C show that also in the UK and Germany also, the correlations have been highly positive, about 0.55 and 0.47, during periods of high-expected inflation. On the contrary, during periods in which the expected inflation is in the lowest quartile, the correlations between stock and bond returns in all three countries are negative, being about -0.21 in the US, about -0.15 in the UK and -0.10 in Germany. The bootstrapped 95% confidence intervals for the mean correlation estimates (reported in parentheses) suggest that the observed differences in stock–bond return correlations between different quantile sub-samples are statistically significant.

Turning the focus onto the impact of growth expectations on stock–bond correlations, Table 3 shows no clear patterns. Regardless of the level of growth expectations, stock – bond correlations in the US and Germany are consistently positive, without any systematic differences between different subsamples. In the UK, the stock – bond correlation is most positive during periods in which the expected economic growth is in the highest quartile and negative in the 25th–50th quartile of growth expectations. However, the correlation in the US is most positive during periods of lowest growth expectations, while in Germany stock–bond correlation appears to be highest on medium levels of growth expectations. Consequently, no inferences about the impact of growth expectations on the time-varying correlation between stock and bond returns can be drawn from Table 3.

Finally, Table 3 clearly demonstrates that expected stock market uncertainty, as measured by implied volatility, is negatively related to the correlation between stock and bond returns. Panel A shows that the average stock–bond return correlation in the US is about -0.20 during periods of high stock market uncertainty and positive, 0.32, during periods in which implied volatility is in the lowest quartile. Correspondingly, Panels B and C show a similar pattern for the UK and German stock–bond correlations. During periods of stock market stress, stock–bond correlations are negative (-0.15 in the UK and -0.10 in Germany), while during periods of low market uncertainty the correlations are highly positive (0.26 and 0.35). The bootstrapped 95% confidence bounds suggest that these differences in stock–bond return correlations between different subsamples are statistically significant.

To further examine the impact of inflation and growth expectations and perceived stock market uncertainty on the correlation between stock and bond returns, we regress the stock–bond return correlation estimates on the expected growth rate of consumer prices, expected growth rate of real GDP and implied stock market volatility. A potential difficulty in regressing stock–bond return correlation estimates is that the correlation coefficient is, by definition, restricted to the range [-1, +1], whereas the right hand side of the regression is not restricted to produce values within this range. In order to make the dependent variable unrestricted, a generalized logit transformation is applied to transform the range of correlation estimates to [-∞, +∞]. Consequently, the following regression model is estimated:

$$\log\left(\frac{1+\rho_t}{1-\rho_t}\right) = \alpha + \beta_1 CPI_{t-1} + \beta_2 GDP_{t-1} + \beta_3 IV_{t-1} + \varepsilon_t \tag{7}$$

where ρ_t denotes the correlation between stock and bond returns at time t, *CPI* is the expected growth rate of consumer price index, *GDP* is the expected growth rate of real gross domestic product and *IV* is the implied stock market volatility. The Ljung–Box statistic indicates significant serial correlation in the residuals of the regressions and hence AR(1) terms are added to the regression specifications.

To ascertain whether the explanatory variables used in the regression are stationary, the augmented Dickey–Fuller(ADF) and Phillips–Perron(PP) unit root tests are performed. The lag length used in the tests is decided based on the Schwartz information criterion. The results of the unit root tests are reported in Table 4. As can be seen from the table, the unit root tests indicate that all explanatory variables are stationary, as the null hypothesis of a unit root can be soundly rejected for these time series. The regression results for the United States are reported in Panel A of Table 5. The estimation results suggest that expected inflation is positively related to the stock–bond return correlation. In both regression specifications, the estimated coefficient for CPI is positive. However, the coefficient is statistically significant only when the RWC is used as the dependent variable. The results in Panel A also demonstrate that expected stock market uncertainty has a negative impact on the correlation between stock and bond returns, as the estimated coefficient for implied volatility is negative and statistically significant at the 1% level in both regression specifications. Finally, it can be noted from Panel A that the estimated coefficients for expected economic growth are negative, but neither of the coefficient estimates appears statistically significant.

Panels B and C report the regression results for the UK and German stock–bond return correlations, respectively. The estimation results for the UK show that inflation expectations are positively related to stock–bond correlations, as the coefficients in both specifications are positive and statistically significant. Also for Germany, the estimated coefficient for CPI is positive and statistically highly significant when the RWC is used as the dependent variable. Furthermore, consistent with the results reported in Panel A, the estimated coefficients for implied volatility both in the UK and Germany are negative and statistically significant and thereby suggest that high stock market uncertainty tends to move stock and bond prices into opposite directions.

Finally, similarly to the US, there seems to be no systematic linkage between economic growth expectations and stock–bond correlations neither in the UK nor in Germany, as the coefficient estimates for GDP are statistically insignificant in all four regression specifications.[23]

Overall, the regression results for the US, UK and Germany are very similar. These results strongly indicate that expected inflation is positively related to the correlation between stock and bond returns. The estimated coefficients for expected growth rate of the CPI are positive

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[23] Given that the choice of the GDP variable may affect the results regarding the relationship between economic growth expectations and stock–bond correlations, we examined the robustness of our regression results by using the slope of the term structure as a proxy for economic growth expectations. For the US and UK, the choice of the economic growth variable does not make any difference, as the coefficient estimates for the slope of the term structure are statistically insignificant. For Germany, however, we find evidence for a positive relationship between stock – bond correlations and the slope of the term structure.

and statistically significant in four out of six regressions. Since bond prices should be negatively related to inflation expectations, our findings suggest that high inflation expectations have a larger impact on the discount rates than on the expected future dividends, thereby causing a negative relation between stock prices and inflation expectations and consequently a positive relation between inflation expectations and stock – bond return correlation. Furthermore, the estimated coefficients for implied volatility are negative and statistically significant in all six regression specifications. Hence, the estimation results strongly indicate that high stock market uncertainty tends to lead to a decoupling between stock and bond prices. This finding is consistent with the 'flight-to-quality' phenomenon. Finally, the results suggest that stock–bond return correlations are unaffected by economic growth expectations, as none of the six coefficient estimates for GDP appears statistically significant.

The results reported in this article evidently demonstrate that expected inflation and perceived stock market uncertainty can help to predict future co-movements between the two most important asset classes in the largest financial markets worldwide. These findings may be useful, for instance, for improving strategic asset allocation decisions.

6. Conclusions

This article examines the impact of macroeconomic expectations and perceived stock market uncertainty on the correlation between stock and bond returns. Our empirical findings demonstrate that the correlation between stock and bond returns varies considerably over time. Using data from the US, UK and Germany, we find that the stock–bond correlations in all three countries are positive most of the time, although sustained periods of negative correlation are also observed. Interestingly, the stock – bond correlations in the US, UK and Germany exhibit rather similar patterns over time, as for instance the periods of negative correlation seem to coincide. Furthermore, our findings demonstrate that the stock – bond correlation may change substantially and turn from positive to negative, in very short periods of time. These rapid changes in the relationship between stock and bond markets may pose challenges for asset allocation and risk management procedures.

Our empirical findings indicate that expected inflation is positively related to the time-varying correlation between stock and bond returns. Stock and bond prices tend to move in the same direction during periods of high inflation expectations, while epochs of negative stock–bond return correlation seem to coincide with the lowest levels of inflation expectations. The empirical findings also demonstrate that expected stock market uncertainty, as measured by implied volatility, is negatively related to the correlation between stock and bond returns. In particular, our results strongly indicate that high stock market uncertainty leads to a decoupling between stock and bond prices. This finding is consistent with the so-called 'flight-to-quality' phenomenon. Finally, we are unable to find any systematic relationship between economic growth expectations and stock–bond return correlations.

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Appendix

Let $r_t|F_{t-1} \propto N(0,H_t)$ denote an n-dimensional conditional multivariate normal process with zero expectations and a conditional covariance matrix $H_t = E_{t-1}(r_t r_t')$. To avoid unnecessary expansion, we get rid of the equation for mean in a GARCH process and assume that r_t are already detrended and demeaned residuals. Dynamic conditional correlation (DCC) model, being a generalisation of Bollerslev's (1990) constant conditional correlation model, shares the same conditional correlation estimator:

$$H_t = D_t R_t D_t .$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$ is a diagonal matrix of time-varying standard deviations of the residuals of the mean equation of univariate GARCH models:

$$h_{i,t} = E_{t-1}(r_{i,t}^2), r_{i,t} = \sqrt{h_{i,t}}\varepsilon_{i,t}$$

where $\varepsilon_{i,t} \propto WN(0,1)$ are standardised disturbances. In contrast to the constant conditional correlation model, the correlation matrix $R_t = E_{t-1}(\varepsilon_t \varepsilon_t')$ is now allowed to be time-dependent. Engle (2002) proposed to find the elements of D-matrix from the univariate GARCH models and to formulate the dynamic covariance structure as a following GARCH process:

$$q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij})$$

where $\bar{\rho}_{ij}$ is the unconditional correlation of $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ and $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$. Thus, the conditional correlations $\rho_{ij,t}$ depend on the common GARCH parameters, α and β, and on the unconditional correlations. Then, the time-varying correlation matrix is given by

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} .$$

If the sum of positive coefficients α and β is less than unity, the estimated model preserves mean-reversion of correlation. The covariance matrix $Q_t = (q_{ij,t})$ is a weighted average of a positive semi-definite and a positive-definite matrices, and thus it is positive-definite.

The log-likelihood estimator:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t)$$

can be decomposed into two parts that depend on volatility and on conditional correlation:

$$L = L_{vol} + L_{cor} ,$$

where

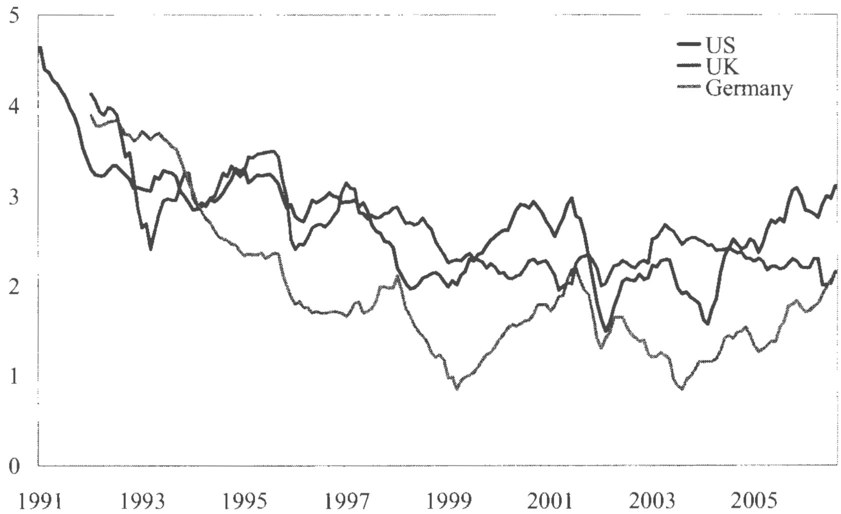
$$L_{vol} = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t) \text{ and:}$$
$$L_{cor} = -\frac{1}{2}\sum_{t=1}^{T}(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t)\ .$$

As suggested by Engle (2002), the log-likelihood may be estimated in a two-step procedure. Taking into account that D_t has a diagonal form, the volatility-dependent part of the likelihood function L_{vol} is the sum of separately estimated n likelihood functions for individual GARCH models, which are estimated in the first step. Given the maximising values of the variances obtained from the first step, the dynamic conditional correlations are then estimated in the second step.

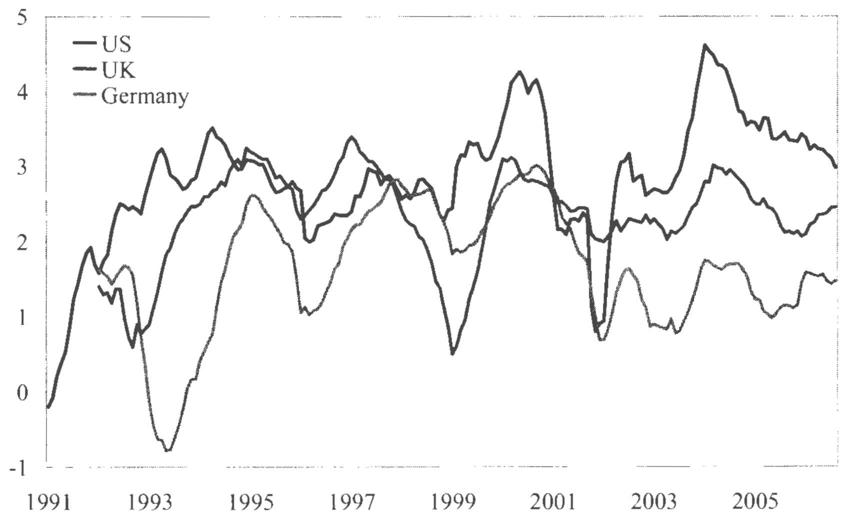
Figures and Tables

Figure 1. Macroeconomic expectations and perceived stock market uncertainty)

a) CPI (annual percentage changes)



b) GDP (annual percentage changes)



c) Implied volatility (percentages per annum)

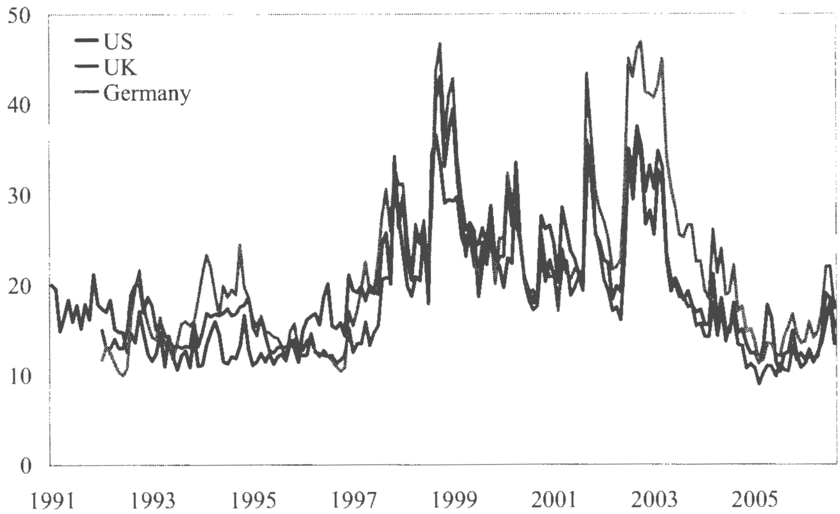


Figure 2. Rolling window stock–bond correlations

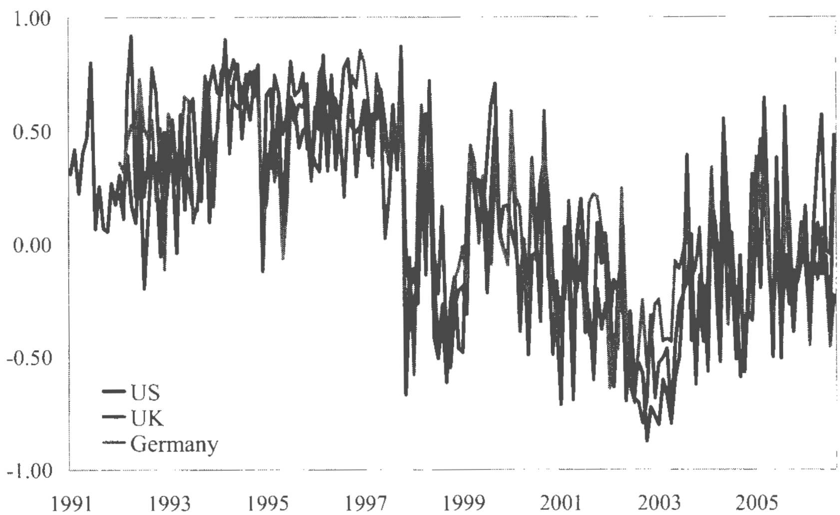


Figure 3. Dynamic conditional stock–bond correlations

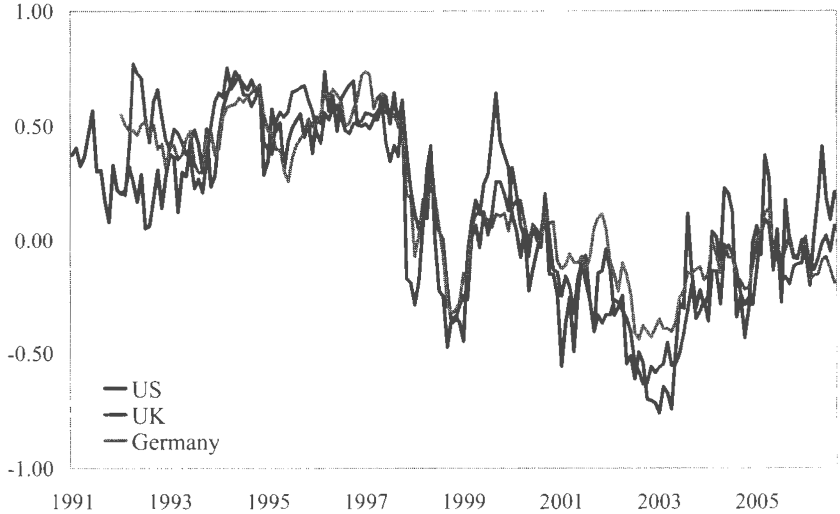


Table 1. Maximum likelihood estimates of the DCC(1,1) model

	US		UK		Germany	
	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
γ_S	0.000 **	2.349	0.000 *	1.761	0.000	1.564
γ_B	0.000	0.541	0.000	3.516	0.000	0.841
ϕ_S	-0.007	-0.473	0.011	1.163	-0.018	-1.214
ϕ_B	0.054 ***	3.700	0.040 ***	2.719	0.018	1.244
ω_S	0.005 ***	5.323	0.012 ***	5.228	0.041 ***	12.196
ω_B	0.003 ***	5.625	0.002 ***	6.919	0.001 ***	7.072
α_S	0.042 ***	14.105	0.077 ***	12.837	0.102 ***	23.694
α_B	0.034 ***	9.934	0.040 ***	15.694	0.046 ***	14.140
β_S	0.954 ***	286.804	0.910 ***	126.900	0.879 ***	135.741
β_B	0.951 ***	187.255	0.950 ***	337.422	0.944 ***	245.238
α	0.042 ***	12.234	0.025 ***	9.912	0.018 ***	12.708
β	0.950 ***	234.082	0.973 ***	333.259	0.980 ***	552.574

***significant at the 0.01 level
**significant at the 0.05 level
*significant at the 0.10 level

Note: The table reports the maximum likelihood estimates of the following DCC(1,1) model:

$$r_{i,t} = \gamma_i + \phi_i r_{i,t-1} + \varepsilon_{i,t}$$

$$\sigma^2_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1}$$

$$\sigma_{ij,t} = \bar{\sigma}_{ij} + \alpha\left(z_{i,t-1} z_{j,t-1} - \bar{\sigma}_{ij}\right) + \beta\left(\sigma_{ij,t-1} - \bar{\sigma}_{ij}\right)$$

where $r_{i,t}$ denotes the return on asset i at time t, $\sigma_{i,t}$ is the conditional volatility of asset i at time t, $\sigma_{ij,t}$ is the time t conditional covariance between assets i and j, $z_{i,t} = r_{i,t} / \sigma_{i,t}$, and $\bar{\sigma}_{ij}$ is the unconditional expectation of the cross product $z_{i,t}\, z_{j,t}$.

Table 2. Descriptive statistics of stock-bond return correlations

	US RWC	US DCC	UK RWC	UK DCC	German RWC	German DCC
Mean	0.121	0.123	0.098	0.121	0.147	0.158
Median	0.175	0.166	0.083	0.071	0.159	0.105
Minimum	-0.760	-0.876	-0.798	-0.636	-0.707	-0.439
Maximum	0.738	0.835	0.920	0.770	0.856	0.739
Standard Deviation	0.381	0.435	0.433	0.386	0.395	0.323
Skewness	-0.352	-0.345	-0.050	-0.073	-0.069	0.071
Kurtosis	2.204	2.150	1.945	1.787	1.897	1.769
No. of Observations	188	188	176	176	176	176

Note: The table reports descriptive statistics of the monthly rolling window correlation (RWC) and dynamic conditional correlation (DCC) estimates between stock and bond returns. The sample period extends from January 1991 to August 2006 for the US and from January 1992 to August 2006 for the UK and Germany.

Table 3. Stock–bond return correlations and economic expectations

Quantile	CPI	GDP	IV
Panel A: US			
75th-100th	0.332	0.023	-0.199
	(0.280 0.378)	(-0.056 0.107)	(-0.308 -0.095)
50th-75th	0.349	0.246	0.111
	(0.267 0.436)	(0.133 0.353)	(0.011 0.211)
25th-50th	0.004	0.027	0.251
	(-0.098 0.102)	(-0.108 0.150)	(0.167 0.344)
0-25th	-0.212	0.185	0.323
	(-0.304 -0.119)	(0.085 0.287)	(0.248 0.391)
Panel B: UK			
75th-100th	0.553	0.349	-0.151
	(0.507 0.594)	(0.2585 0.437)	(-0.232 -0.054)
50th-75th	0.153	0.131	0.031
	(0.041 0.265)	(0.018 0.234)	(-0.06 0.135)
25th-50th	-0.078	-0.126	0.349
	(-0.148 -0.00)	(-0.229 -0.01)	(0.247 0.440)
0-25th	-0.151	0.129	0.256
	(-0.221 -0.082)	(0.020 0.236)	(0.163 0.353)
Panel C: Germany			
75th-100th	0.469	0.156	-0.100
	(0.436 0.501)	(0.0860 0.230)	(-0.169 -0.021)
50th-75th	0.174	0.208	0.092
	(0.092 0.260)	(0.109 0.305)	(0.013 0.172)
25th-50th	0.077	0.109	0.284
	(-0.024 0.174)	(0.0125 0.210)	(0.193 0.369)
0-25th	-0.103	0.150	0.351
	(-0.155 -0.048)	(0.045 0.248)	(0.270 0.427)

Note: The table reports the average conditional correlations between stock and bond returns in month t for subsamples created by sorting inflation expectations (CPI), real GDP growth expectations and stock market volatility expectations (IV) in month t-1. The bootstrapped 95% confidence intervals for the correlation estimates are reported in parentheses.

Table 4. Unit root tests

	ADF	p-value	PP	p-value
US CPI	-2.740	0.069	-3.267	0.018
US GDP	-3.992	0.002	-3.957	0.002
US IV	-3.429	0.011	-4.624	0.000
UK CPI	-3.031	0.034	-3.001	0.037
UK GDP	-3.256	0.019	-2.683	0.079
UK IV	-3.276	0.018	-3.132	0.026
German CPI	-1.904	0.055	-1.975	0.047
German GDP	-3.059	0.032	-2.685	0.078

Note: The table reports Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests for the inflation expectations (CPI), real GDP growth expectations and stock market volatility expectations (IV). The lag length for the unit root tests is decided based on the Schwarz information criterion.

Table 5. The impact of economic expectations on stock–bond return correlations

	RWC Estimate		t-stat.	DCC Estimate		t-stat.
Panel A: US						
Constant	-0.060		-0.065	0.873		0.897
CPI	0.517	**	2.506	0.029		0.095
GDP	-0.039		-0.328	-0.131		-0.988
IV	-0.050	***	-3.205	-0.017	**	-2.268
AR(1)	0.428	***	5.521	0.879	***	20.962
Adjusted R2	0.435			0.806		
F-stat.	36.551	***		192.620	***	
No. of observations	188			188		
Panel B: UK						
Constant	-0.463		-0.995	-0.177		-1.084
CPI	0.364	**	2.183	0.149	**	2.253
GDP	-0.020		-0.225	-0.020		-0.614
IV	-2.069	**	-2.578	-0.703	**	-2.522
AR(1)	0.677	***	7.637	0.876	***	27.476
Adjusted R2	0.525			0.922		
F-stat.	46.765	***		512.893	***	
No. of observations	176			176		

Panel C: Germany						
Constant	-0.400		-0.741	0.380		0.774
CPI	0.514	***	3.359	-0.039		-0.259
GDP	0.088		0.583	0.052		0.620
IV	-0.018	**	-2.026	-0.013	***	-2.961
AR(1)	0.579	***	9.227	0.967	***	49.280
Adjusted R2	0.514			0.941		
F-stat.	46.765	***		688.069	***	
No. of observations	176			176		

Note: The reported results are based on the following regression specification:

$$\log\left(\frac{1+\rho_t}{1-\rho_t}\right) = \alpha + \beta_1 CPI_{t-1} + \beta_2 GDP_{t-1} + \beta_3 IV_{t-1} + \varepsilon_t$$

where ρt denotes the correlation between stock and bond returns at time t, CPI is the expected growth rate of consumer price index, GDP is the expected growth rate of real gross domestic product, and IV is the implied stock market volatility. RWC and DCC denote rolling window correlation and dynamic conditional correlation, respectively. Given that the Ljung-Box statistic indicates serial correlation in the residuals of the regressions, the residuals are modelled to follow an AR(1) process.

Which news moves the euro area bond market?*

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Abstract

This paper explores a long dataset (1999-2005) of intraday prices on German long-term bond futures and examines market responses to major macroeconomic announcements and ECB monetary policy releases. German bond markets tend to react more strongly to the surprise component in US macro releases compared to euro area and domestic releases, and the strength of those reactions to US releases has increased over the period considered. We also provide evidence that the outcome of German unemployment figures has been known to investors ahead of the pre-scheduled release.

Keywords: Monetary policy, intraday data, macroeconomic announcements

JEL classification: E43, E44, E58.

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1. Introduction

What causes financial market prices to undergo the sometimes strong swings observed during a trading day? The answer to this basic question is of outmost interest to anyone monitoring financial markets - from central banks using asset prices to gauge investors' macroeconomic expectations, to fund managers and traders exploring buying and selling opportunities from the prices fluctuating on their computer screens.

As financial assets are inherently forward-looking, only new news should cause revisions to what is currently built into asset prices, thereby immediately affecting prices. The availability of prices at very high frequencies allows for an in-depth analysis of the price discovery process. This in turn enables a "cleaner" analysis of market reactions surrounding major market-moving events compared with commonly used daily data, where other news during a trading day may blur instantaneous market reactions to events. In addition, the use of high-frequency data makes it possible to depict the dynamic market reactions to the constant flow of information.

The purpose of this paper is to examine the effects of macroeconomic data releases and of the ECB's monetary policy statements on the German long-term bond market. The sample period spans the period January 1999 through December 2005. We test the extent to which domestic and US macroeconomic announcements influence the German bond markets. In addition, given the strong real and financial market linkages in the euro area economy, aggregate euro area, Italian and French macro releases are also included.

The main findings are that German bond markets tend to react more strongly to the surprise component in US macro releases compared to aggregated and national euro area releases, and the strength of those reactions to releases has increased over the period considered. The level of bond returns appears to adjust quickly to new information whereas macro announcements have a stronger and more long-lasting impact on volatility. In addition, by splitting our sample into three different monetary policy regimes in the euro area, we find that the sensitivity of bond returns from US economic activity and employment news differs depending on the regime.

The paper contributes to the existing literature in a number of ways. First, the responses of the benchmark German long-term bond returns on macroeconomic and monetary policy announcements are examined, a topic which has received little attention in the empirical literature. Second, the combined use of German, French, Italian and aggregate euro area macroeconomic releases, in addition to the "traditional" US macroeconomic announcements, is novel. Third, we identify problems with macroeconomic releases that have been overlooked in previous announcement studies. In particular, evidence is provided that the outcome of the German employment reports is known to investors ahead of the pre-scheduled release. This finding solves the puzzle why our and previous high frequency studies find no significant impact on financial market prices around the time of the official release. Finally, we provide evidence that the sensitivity of bond returns to news is not constant but varies across monetary policy regimes.

The paper is structured as follows: Section 2 briefly reviews the literature within these fields, while Section 3 elaborates on the data used in the study. The econometric model and the results are reported in Section 4. Section 5 examines whether the price discovery process for the German bond markets differs depending on the monetary policy stance. Finally, Section 6 makes some concluding remarks.

2. Related literature

Overall, the literature about the macro announcements' impact on asset prices is large and spans across asset classes. Numerous studies have analysed financial markets in the US[24], while less attention has been paid to euro area, UK and Japanese markets.

As regards announcement studies applied on the euro area bond markets, the focus in these papers have concerned the impact stemming from US macro announcements. In general the findings support the notion that US data releases indeed not only affect US markets, but also exert a significant effect on the European bond markets, see Andersen et al. (2005) and Faust et al. (2003). The procedure by Ehrmann and Fratzscher (2002) is slightly different as it focuses on the impacts of monetary policy and macroeconomic announcements both in the euro area and in the United States on the money market rates in the two economies. They show a high and increasing interdependence between the euro area and the US with euro area money market rates reacting more strongly to US data releases in comparison with US interest rate reaction to euro area announcements.

The impact of monetary policy announcements on financial markets has received considerable attention, although the focus has primarily been

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[24] See for instance, Dwyer and Hafer (1989), Balduzzi et al. (2001) and Andersen et al. (2005).

on the impacts on the stock and foreign exchange markets.[25] The effect on bond markets has received less attention. Similarly to the macro announcement literature, the bulk of the studies have been applied to the United States.[26]

For the euro area, both Bernoth and von Hagen (2003) and Ehrmann and Fratzscher (2002) study the volatility reaction on money market rates following ECB Governing Council announcements. They both find that volatility generally tends to be higher on these days.

3. Data issues

The bond market data consists of five-minute intraday prices of long-term German government bond futures contracts from the beginning of 1999 until the end of December 2005. The dataset was purchased from TickData Inc. The eligible delivery bonds are usually a basket of both non-benchmark and benchmark German governments bonds with a remaining term of between 8.5 and 10.5 years. From the price data, bond returns are calculated as hundred times the logarithmic difference between consecutive prices.

Table 1 show all macro announcements and also highlights the distribution of the release days of the 43 macroeconomic announcements used in this study.

As seen in the table, most euro area macro data are released later than the US equivalents. The delayed release of the aggregate euro area statistics is linked to the time needed to compile the statistics from all EMU Member States. The delayed release of euro area macroeconomic statistics also implies that they potentially contain less new news as the national releases are already known to the investors at the time of publication. To account for this, the most important national German, French and Italian macro releases are also included in this study. German GDP is not included, as it is typically published before the German bond markets open, but overall, the dataset covers most of the macroeconomic information that is typically considered important for a fundamental analysis. In addition to the 43 macro announcements, the paper also examines the German bond market responses following actual monetary

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[25] See Bomfim (2000), Bentzen et al. (2004) or Wongswan (2005) for the impact on stock markets and Faust et al. (2002) or Andersen and Bollerslev (1997, 1998) for the impact on foreign exchange markets.

[26] See Fleming and Remolona (1997) and Fleming and Piazzesi (2005).

policy decisions by the ECB and the accompanying releases of the Introductory Statements.

When measuring financial market impact from news it is common to use the standardised surprise component of the news and also test for unbiased market expectations, see for instance Balduzzi et al. (2001). The surprise component is calculated as:

$$S_{i,t} = \frac{A_{i,t} - E_{i,t}}{\sigma_i} \qquad (1)$$

where $A_{i,t}$ and $E_{i,t}$ are the actual and the expected outcome of data release i at time t, respectively, and σ_i is the standard deviation of the forecast error of data release i.

The expected outcomes of the macroeconomic data releases are collected from Bloomberg and consist of median expectations of the survey panellists. The expectations regarding the outcome of the ECB decisions consist of the mean of analysts' survey-based expectations, collected one week before the Governing Council meetings and published by Reuters. The use of mean expectations thus differs with the use of median expectations for macroeconomic announcements. However, if median expectations would be employed for ECB monetary policy decisions would give rise to very few non-zero surprises compared with the mean expectations. The potential impact of the Fed's monetary policy decisions is not examined in this paper as they are released after the close of the trading day.

In order to test for unbiasedness in the expectations data, standard techniques used in the literature are employed, see Balduzzi et al. (2001). For the majority of the data releases, the null hypothesis of unbiased expectations cannot be rejected at the 10 percent level, which suggests that the survey expectations are of good quality.[27]

One issue which have been overlooked in earlier announcement studies is potential problems arising from leaks and early releases. Clearly, if the outcome of an announcement becomes available to investors ahead of the official release time it will have an impact on our analysis as the market reaction will then take place earlier. If the release of macroeconomic statistics prior to official release times only takes place infrequently, the overall effect on our results will typically be limited. However, if the macroeconomic numbers are released regularly prior to official release times, owing to early releases or systematic leaks to the

[27] The complete results of the bias test can be found in the working paper version of this study. See Andersson et al. (2006).

media ahead of official announcement times, our analysis will clearly be biased.

For the macroeconomic announcements used in this study there is no compelling evidence of the statistics being released early or of alleged leakages, with one notable exception, the German unemployment figures. This is an issue which has been described by news agencies[28], but has received little attention in the academic literature so far.

If these news reports about presumed leakages are true, it is reasonable to assume that bond markets should have incorporated the latest news in the German unemployment report already prior to the official release time, with little or no reaction taking place at the scheduled time. In fact, as shown in the econometric results in Section 4, the German unemployment statistics do not have a significant impact on German bond markets at the time of the official release. This non-significant response is in line with the previous literature. Goldberg and Leonard (2003), for example, find the releases of German employment statistics do not affect significantly German bond yields.

To gather information as to whether the German employment numbers are systematically available to investors ahead of the above-mentioned pre-scheduled announcement time, we collected news reports from Reuters and other market news agencies. The results suggest clear evidence that the numbers of German unemployed workers consistently have been known to investors prior to official releases, see Table 2. These apparent leaks took place prior to all releases in our sample with the exception of a few releases at the beginning of 1999. This finding solves the puzzle of why our and previous high frequency studies find no significant impact on financial returns around the time of the official releases.

There is by contrast no evidence that other German macroeconomic statistics are systematically leaked to the media: leaks only appear to affect the German unemployment figures from the Bundesanstalt für Arbeit. This is to some extent also supported in our later analysis, where some other German data releases are found to have a market impact at official release times.

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[28] See "German jobless leaks annoy analysts, investors - and officials" by Andreas Cremer, Bloomberg News, 9 April 2002.

4. Econometric analysis and results

In this section we investigate the influence macro announcements have on intraday returns in the German bond market by utilising a general econometric model, which simultaneously estimates both the level and volatility of intraday returns on German bonds. In order to capture the time-varying feature of intraday return variability, a semi-parametric model is employed.

The intraday statistical properties of the data suggest that three important features of the data should be taken into account in the econometric model. First, bond returns react sharply to macroeconomic announcements (announcement effect). This effect may be present in both the conditional mean and the conditional volatility of the series. Second, the intraday pattern with higher observed volatility in opening and closing sections of the trading days should, together with the inter-day and day-of-the-week effects, also be properly captured in the volatility equation (calendar effect). Third, the conditional heteroskedasticity of daily returns - commonly known to be present in financial time series at lower frequencies - should also be taken into account (ARCH effect).

The conditional mean of the five-minute German bond futures returns is specified as:

$$R_{t+1} = \alpha_0 + \sum_{i=1}^{P} \alpha_i R_{t-i+1} + \sum_{k=1}^{K} \sum_{j=0}^{R} \alpha_{kj}^{MA} MA_{t-j}^{k} + \sum_{j=0}^{Q} \alpha_j^{MS} MS_{t-j} + \varepsilon_t \tag{2}$$

where the 5-minute bond return R_{t+1}, which is the return from time t to time $t+1$, is modelled as a linear function of: i) $P=2$ values of lagged bond returns, ii) contemporaneous and $R=2$ lagged values of the standardised surprise of the $K=43$ announcements, and iii) contemporaneous and $Q=3$ lagged values of ECB's monetary surprises. Note that this model is able to separate the effects of concurrent announcements. The lag-lengths were suggested by the Akaike and Schwarz information criteria. Moreover, $T = 233{,}269$.

Regarding the conditional variance, we model the disturbance term in Eq. (2) to be heteroskedastic, and approximate its volatility by the following model:

$$|\varepsilon_t| = \beta_0 + \beta_1 \frac{\hat{\sigma}_{d(t)-1}}{\sqrt{N}} +$$
$$+\left\{\mu_1 \frac{n}{N_1} + \mu_2 \frac{n^2}{N_2} + \sum_{z=1}^{Z}\left[\phi_z \sin\left(\frac{2\pi zt}{N}\right) + \varphi_z \cos\left(\frac{2\pi zt}{N}\right)\right] + \sum_{i=1}^{D} \gamma_i WD^i_{wd(t)}\right\} +$$
$$+\sum_{k=1}^{K} \sum_{j=0,3,6} \lambda_{kj}^{MA} D_{t-j}^{MA} + \sum_{j=0,3,6} \lambda_j^{MP} D_{t-j}^{MP} + \sum_{j=0,3,6} \lambda_j^{IS} D_{t-j}^{IS} + u_t \tag{3}$$

where N denotes the number of 5-minute intervals on a trading day, n is the nth 5-minute interval on a trading day, and $N_1 = \sum_{i=1,N} i = N(N+1)/2$ and $N_2 = \sum_{i=1,N} i^2 = N(N+1)(2N+1)/6$ are normalising constants.

This general setup for the conditional mean and the volatility equations follow the procedure proposed by Andersen et al. (2003 and 2005) and Andersen and Bollerslev (1997 and 1998). For two of the terms in the equations however, we depart from their procedure. First, the second term in the volatility equation $\hat{\sigma}_{d(t)-1}$ represents the estimated daily conditional standard deviation. This term is usually approximated by a GARCH-type model. However, Sebestyén (2006) argues that realised volatility captures better the intraday return movements and consequently provides a better fit for the model than a parametric GARCH. Consequently the $\hat{\sigma}_{d(t)}$ is calculated as: $\hat{\sigma}_{d(t)} = \left[\sum_{m=1,M} R_m^2\right]^{1/2}$ where R_m is the *m*th 30-minute return. Notable is that a one day lag, *d(t)-1*, is used in the regression as all the observations needed to calculate realised volatility of day *d(t)* is not available in an intraday estimation framework. Evidently, the previous day's realised volatility may not reflect correctly the return variability on the current day, but, as the realised daily volatility is highly autocorrelated, the volatility on day *d(t)-1* is likely to be a good proxy for day *d(t)*'s volatility.

Second, in the conditional variance equation three dummy variables are used to capture decay in volatility, the first at the time of the announcement, the second from 5 to 15 minutes after the announcement, and the third between 20 to 30 minutes after the announcement. This differs from Andersen and Bollerslev (1998) who propose a polynomial decay structure of the volatility response pattern, and they estimate the degree to which an announcement loads into this pattern. In addition, they allow for an adjustment of one hour. This paper instead follows

Sebestyén (2006), whose findings suggest that generally 30 minutes are sufficient for the complete volatility adjustment.[29]

The terms in brackets in Eq. (3) serve to capture intraday, inter-day and inter-weekly patterns of the data. The second-order polynomial (i.e., n/N_I and n^2/N_I) approximates the intraday U-shape pattern of the volatility. The inter-day pattern is by standard trigonometric terms whereas the dummies $WD^i_{wd(t)}$, accounts for inter-weekly impacts.

Dummies accounting for the monetary policy communications are also included. (D^{MP}) and (D^{IS}) represent dummies for the monetary policy announcements and the Introductory Statement respectively. Note that initial experimentations have shown that the Introductory Statement dummy was insignificant in the conditional mean equation, hence it has been omitted from Eq. (2).

The model is estimated by two-step weighted least squares (WLS). In the first step Eq. (2) is estimated by ordinary least squares (OLS). Thereafter, Eq. (3) is estimated, and the fitted residuals $|\hat{\varepsilon}_t|$, are used to perform a WLS estimate of Eq. (2).

The econometric specification outlined above contains many variables and lags and therefore only the most interesting features is reported upon, see Table 3A and 3B. As regards the conditional mean equation, Table 3 presents estimates of $\alpha^{MA}{}_{k,j=0}$ and $\alpha^{MS}{}_{j=0}$. These correspond to the contemporaneous point estimates of the surprises in the most relevant /euro area/national macro announcements and the ECB's monetary policy decision, respectively, on the German bond market. In the same vein, Table 3 also reports on the λ^{MA}, λ^{MP}, and λ^{IS} which correspond to immediate and lagged volatility response from the macroeconomic surprises, the ECB monetary policy decisions and the volatility induced by the Introductory Statement read by the president at the press conference following the decisions.

Overall, the regression results reveal several interesting features. First, it turns out that many announcements (23 out of the 43) exert a significant impact on the level of German bond yields. In general, a higher than expected release should result in a negative sign of the surprise component coefficient apart for the US initial jobless claims and the unemployment data releases where a higher than expected number indicates that more people than anticipated are unemployed. As seen in the table, all of the significant estimates result in an expected sign. In this

[29] We also allowed for longer adjustment (up to one hour), but the results showed that 30 minutes were sufficient to capture the entire response pattern.

context it is also worth mentioning that the estimates of the lagged point estimates of the surprises in the /euro area/national macro announcements and the ECB's monetary policy decision, respectively, on the euro area bond markets are, with a few exceptions, not significant. This in turn suggests an immediate jump in the returns at the time of the announcements, and little reaction thereafter.[30]

Second, for the volatility impact, also here the bulk of the estimates at the time of the releases turn out significant. In stark contrast to the mean estimates though, the volatility stays elevated longer, and for some of the announcements volatility remains high up until 30 minutes after the actual release. Interestingly, both the monetary policy decision and the Introductory Statements induce higher than normal volatility up to half an hour after the announcements. This prolonged heightened volatility may arise as a consequence of differences in opinions among investors. Third, actual and forward looking measures of real economic activity and unemployment releases have a larger impact compared to price announcements. Fourth, US announcements influence the German bond returns more than euro area and national macro releases.

There are several reasons for the strong influence US data exerts on the German bond markets. First, the US can be perceived as the engine of global growth, which therefore explains its importance for the global financial markets, including Germany. Second, it may also be argued that business cycles have become more integrated and globalisation therefore has lead to a higher degree of interdependence between economies. Third, US macro data are typically released earlier than equivalent euro area and national data. Thus, market participants may therefore draw inferences about the euro area economy from the US data releases. In this respect, only euro area and national releases that cause investors to revise these inferences should lead to market reactions.

5. Do monetary regimes matter?

The constant estimates from the previous sections may not be completely representative as the impact of macro announcements and monetary policy decisions can change over time. There is no consensus in the literature on how to accurately gauge time-varying features of macro and monetary policy announcements. Ehrmann and Fratzscher (2002) use regression analysis in a rolling window, whereas Andersen et al. (2003) measure the impacts of macroeconomic variables in different business cycles. This paper takes a different approach and considers various

[30] See for instance Charts 9 and 10 in Andersson et al. (2006).

monetary policy regimes which is of particular interest for the German long-term bond markets given the introduction of the euro in January 1999.

Changes in news sensitivity may occur for several reasons, of which the following three are of most interest. First, policymakers can sometimes signal a preference for one or more macroeconomic indicators as input to their policy decisions for a given period, and thus may lead to increased responses in financial returns to those announcements. Second, a macroeconomic release may behave in an unusual manner at a certain point in the business cycle. Market participants may then perceive, at least temporarily, this variable as being particularly important. For example, employment data for the United States in late 2003 and early 2004 probably fell into both of these categories, given the growing concerns about a so-called jobless recovery. This in turn led to heightened attention being paid to the monthly non-farm payroll release and unemployment data releases.

Third, it is reasonable to assume different market reactions depending on the state of the business cycle. For instance, if a turning point of economic activity is expected, but the magnitude of the subsequent up- or downturn is unknown, some forward-looking variables may be monitored more closely by market participants.

In order to gauge if the reaction on the German bond markets to macroeconomic announcements and monetary policy decisions differs across monetary regimes, the sample is divided as follows: The first, a tightening regime, is assumed to start in May 1999 until October 2000 corresponding to the end of the month of the ECB's last decision to increase its key interest rate. The second, an accommodative regime is defined from November 2000 to June 2003, corresponding to the end of the month of the ECB's interest rate reduction in June 2003. Finally, the third, a neutral regime in which short rates have remained unchanged, start in July 2003, and lasting until September 2005, when the ECB, according to market participants, signalled a less accommodative monetary policy stance, by using the wording "strong vigilance" in the Introductory Statement of October, 2005. This was widely considered by market participants to be signalling increases in the main refinancing rate at the December meeting.

To gauge the price sensitivity across the three monetary policy regimes, the following econometric specification is employed:

$$R_t = \alpha_i + \beta_{1i} D_{1t} S_{i,t} + \beta_{2i} D_{2t} S_{i,t} + \beta_{3i} D_{3t} S_{i,t} + \varepsilon_t \tag{4}$$

where D_{1t}, D_{2t} and D_{3t} represents time dummies controlling for the three monetary regimes, respectively, i.e. they take on the value one in the corresponding monetary regime, and zero otherwise. $S_{i,t}$ represents the *i*th surprise variable.

The shortcoming of this approach is obviously that the length of the three regimes is relatively short (the first 18 months, the second 30 months and the third 27 months) and hence our estimates will suffer from small sample bias. Therefore, quarterly releases are dropped and only those for which there are observations available for almost each month of the corresponding regime are included. It is also noteworthy that expectations for most euro area announcements started in early 2001, which clearly also leads to some problems when comparing results across regimes.

Table 4 summarises the contemporaneous news response coefficients in the first, second and third monetary policy regimes. Several interesting features can be observed. First, US activity and employment announcements seem to increase in importance over time, in line with Bernanke et al. (2004). One may argue that this is due to the smaller sample size as it requires a larger t-value to reject the null hypothesis of zero response. However, the t-values for the US announcements during the ECB's tightening cycle are generally much smaller than in the other periods. Regarding the magnitude of the estimated significant coefficients, the most interesting characteristics concern the US employment data where the size (in absolute value) of both the non-farm payroll and the initial jobless claims estimates has increased over time. This higher asset return sensitivity to unemployment data in the United States can be related to the fact that the economic recovery since the 2001 recession has been accompanied by relatively large degree of slack in the labour market, raising concerns about a "jobless recovery". Again note that, in contrast to other variables, a positive sign is expected a priori for initial jobless claims and other unemployment variables.

Second, national announcements seem to have a larger impact on the German bond returns during the ECB's accommodative policy regime than in the neutral period observed between mid-2003 and mid-2005. This extra sensitivity can probably be linked to the state of the business cycle. Over this period, macro announcements may to a larger extent have signalled an increased likelihood of changes in the monetary and fiscal stance compared to the neutral period.

6. Concluding remarks

This paper finds that US and to some extent euro area and national macro releases exert a significant impact on the returns of long-term German government bonds. Overall, the announcements have a more long-lasting impact on volatility than on the level of bond returns.

US announcements seem to influence German bond returns more than euro area, German, French and Italian macro announcements. There are at least three probable explanations for these findings. First, the United States can be perceived as the engine of global growth, which therefore explains its importance for the global financial markets, including the euro area. Second, it may also be argued that biness cycles have become more integrated and globalisation therefore has lead to a higher degree of interdependence between economies. Third, US macro data are typically released earlier than equivalent euro area data. Thus, market participants may therefore draw inferences about the euro area economy from the US data releases. In this respect, only euro area releases that cause investors to revise these inferences should lead to market reactions.

By splitting our sample period into three sub-samples, reflecting three different monetary policy regimes (tightening, accommodative and neutral), we show that the impact of public information about economic activity and employment on German bond markets has increased over time. A possible explanation may be that in late 2003 and early 2004, US employment data were closely monitored by policymakers owing to growing concerns about the so-called 'jobless recovery'.

With regard to the ECB's monetary policy decisions and statements, the financial market tends to have predicted the outcomes of monetary policy decisions with a high degree of precision so far, possibly due to transparency around the intentions of the ECB. Nonetheless, heightened volatility is observed following both monetary policy decisions and the Introductory Statement read by the President at the Press Conference following the decisions.

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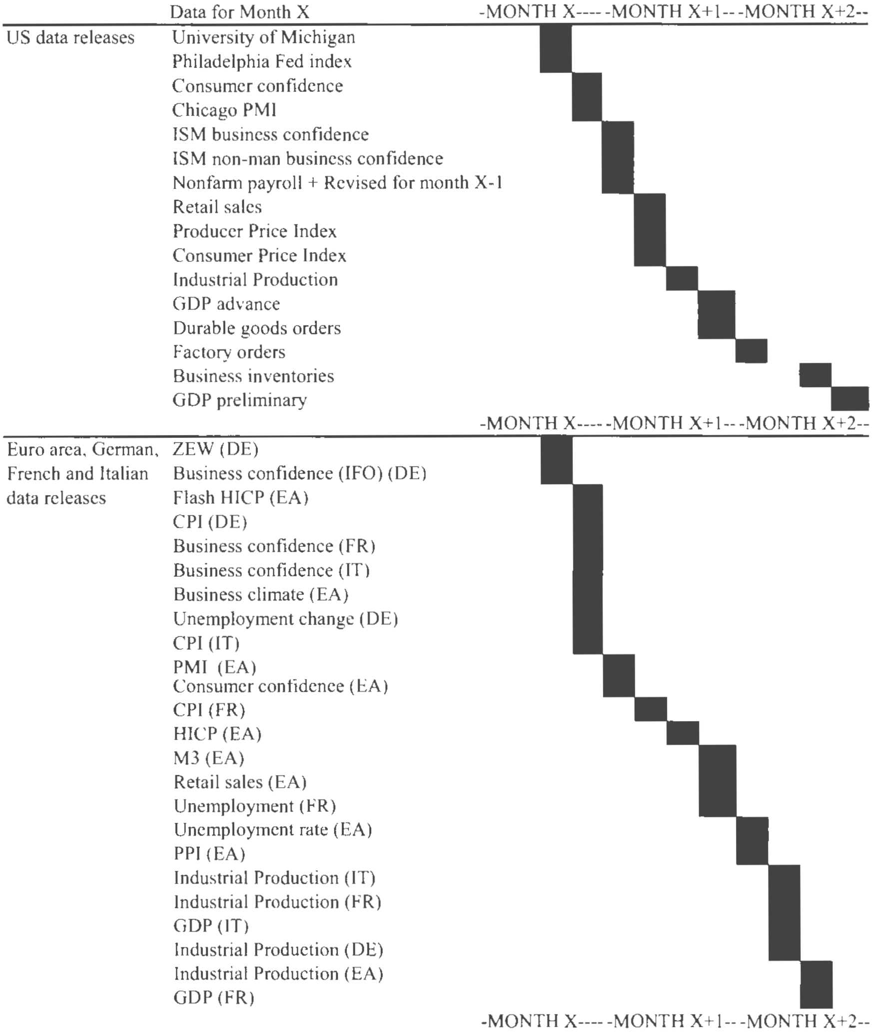
Tables

Table 1. Timing of macroeconomic announcements



Note: The figure shows the timing of macroeconomic news releases for month X. The earliest available release date for the macroeconomic releases has been chosen, which implies that some releases are only preliminary and subject to further revisions, such as University of Michigan and German CPI. Furthermore the release times are only indicative, as holidays and other events may move publication dates and represent the current typical publication times. US GDP Final is not included - this release is published in month X+3, just as initial jobless claims (US) is not included, as this data release comes weekly on Thursdays with data from Friday the week before.

Table 2. Selected media reports concerning German unemployment releases (Jan 2005 to March 2005)

Announcement date	Actual release	Early release / presumed leak	Quote
04 January 2005 09:14	17000	04 January 2005 08:33	The number of Germans out of work rose by a seasonally adjted 17,000 in December from November, Reuters said, citing unidentified people with knowledge of the figures from the Federal Labor Agency.
02 February 2005 09:07	227000	01 February 2005 18:06	Germany's adjusted jobless total increased by 227,000 in January from the previo month, a Federal Labour Office source told Reuters on Tuesday.
01 March 2005 09:55	161000	28 February 2005 20:00	The source said that unemployment rose by 161,000 in February versus the prior month on an adjusted basis, almost double the amount forecast by economists.
31 March 2005 08:55	92000	30 March 2005 13:29	Germany's seasonally-adjusted jobless total rose by a bigger-than-expected 92,000 in March, a Federal Labour Office source told Reuters on Wednesday.

Note: It has not been possible to identify the exact release times of all media reports. The presumed leaks may have occurred earlier, than the cited release times, as it may have been reported earlier in other news flashes or by other media. The media reports for the complete sample can be found in Andersson et al. (2006), Table 3.

Source: Factiva and Reuters.

Table 3A. Regression results United States

	Contemporaneous news response		Volatility responses		
			Minutes after the announcement (λ coefficients)		
Activity and employment	α coefficients	Std. dev. surprise	0	15	30
GDP advance	-0.093***	0.84	0.0600***	0.0110***	0.0064**
GDP preliminary	-0.015	0.23	0.0170***	0.0031	0.0003
GDP final	-0.018	0.24	0.0087	-0.0007	0.0017
Industrial production	-0.0239***	0.29	0.0169***	0.0060***	0.0047***
Nonfarm payroll	-0.0944***	100.61	0.1189***	0.0289***	0.0112***
Nonfarm payroll revisions	-0.0490*	0.00	n.a.	n.a.	n.a.
Initial jobless claims	0.0166***	19.01	0.0145***	0.0071***	0.0038***
Retail sales	-0.0494***	0.69	0.0371***	0.0078***	0.0042***
Factory orders	-0.0158***	0.58	0.0072*	0.0027	0.0029*
Durable Goods orders	-0.0472***	2.98	0.0216***	0.0071***	0.0036**
Business inventories	0.0041	0.23	0.0181***	0.0060***	0.0008
Forward-looking					
University of Michigan	-0.0192***	4.00	0.0136***	0.0083***	0.0020
ISM manufacturing confidence	-0.0395***	2.17	0.0580***	0.0120***	0.0056***
Chicago PMI	-0.0315***	4.36	0.0241***	0.0073***	0.0028
Consumer confidence	-0.0500***	5.01	0.0200***	0.0069***	0.0041**
Philadelphia Fed index	-0.0328***	8.88	0.0316***	0.0118***	0.0084***
ISM non-manufacturing confidence	-0.0489***	3.42	0.0151***	0.0062***	0.0032*

Prices					
Consumer price index	-0.0209*	0.13	0.0399***	0.0094***	0.0029*
Producer price index	-0.0158*	0.43	0.0197**	0.0081***	0.0035**

Note: Estimated contemporaneous news response coefficients and the standard deviation for the surprise components (second and third columns). The news response coefficient represents the average market return in the 5-minute interval following a macroeconomic release for a standardized surprise of one (see Eq. 1). Columns three, four and five represents the response in volatility immediately, 15 minutes and 30 minutes after release. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Sample period; January 1999 - December 2005.

Table 3B. Regression results for the euro area, Germany, France and Italy

	Contemporaneous news response		Volatility responses		
			Minutes after the announcement (λ coefficients)		
Activity and employment	α coefficients	Std. dev. surprise	0	15	30
EA Industrial production	-0.0078**	0.50	0.0044*	0.00030	0.0000
EA Retail sales	-0.0017	0.65	0.0032	0.0007	0.0007
EA Unemployment	0.0011	0.07	0.0005	0.0012	0.0003
Euro area forward-looking					
EA Business climate	-0.0004	0.17	0.0033	0.0059	0.0042
EA Consumer confidence	0.0038	1.16	-0.0025	-0.0018	-0.0033*
EA PMI	-0.0052	0.70	0.0033	0.0000	0.0009
Euro area prices					
EA Flash HICP	-0.0058	0.09	-0.0003	-0.0005	-0.0011
EA HICP	-0.0014	0.07	-0.0011	-0.0011	-0.0005
EA Producer price index	-0.0053	0.07	0.0033	0.0004	0.0000
EA M3	-0.0044	0.40	0.0021	0.0017	0.0016
National activity and employment					
GE Industrial production	-0.0059	1.42	0.0080***	0.0008	0.0016

Table 3B. Contd.

	α coefficients	Std. dev. surprise	0	15	30
GE Unemployment	-0.0042	28.04	-0.0007	0.0012	0.0029**
FR GDP	-0.0088	0.16	0.0008	0.0009	-0.0025
FR Industrial production	-0.0116***	0.70	0.0010	-0.0006	0.0004
FR Unemployment	0.0050	20.89	0.0022	0.0007	-0.0013
IT GDP	-0.0944	0.31	0.0011	0.0020	-0.0016
IT Industrial production	-0.0015	1.11	-0.0024	-0.0021	-0.0020
National forward-looking					
ZEW	-0.0394***	8.63	0.0147***	0.0079***	0.0036***
IFO	-0.0258***	1.13	0.0228***	0.0090***	0.0048***
FR Business confidence	-0.0136***	2.08	-0.0003	-0.0012	0.0011
IT Business confidence	-0.0076**	2.60	0.0007	0.0004	-0.0012
National prices					
GE Consumer price index	-0.0034	0.14	0.0010	-0.0001	-0.0005
FR Consumer price index	-0.0163***	0.14	0.0055*	0.0027	0.0000
IT Consumer price index	0.0044	0.33	-0.0008	0.0005	0.0008
ECB					
ECB monetary policy decision	0.0128**	n.a.	0.0190***	0.0125***	0.0058***
ECB Introductory Statements	n.a.	n.a.	0.0186***	0.0084***	0.0082***

Note: Estimated contemporaneous news response coefficients and the standard deviation for the surprise components (second and third columns). The news response coefficient represents the average market return in the 5-minute interval following a macroeconomic release for a standardized surprise of one (see Eq. 1). Columns three, four and five represents the response in volatility immediately, 15 minutes and 30 minutes after release. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Sample period; January 1999 - December 2005.

Table 4. Results under different monetary policy regimes

US Activity and Employment	First regime	Second regime	Third regime
US Industrial Production	-0.0515***	-0.0311***	-0.0189**
US Nonfarm payroll	-0.0622	-0.0406	-0.2073***
US Initial jobless claims	0.0112	0.0115*	0.0230***
US Retail sales	-0.1217*	-0.0464***	-0.0530**
US Factory orders	-0.0258*	-0.0157*	-0.0316***
US Durable goods orders	-0.0438***	-0.0439*	-0.0599*
US Forward-looking			
US University of Michigan consumer Sentiment Index	-0.0385***	-0.0044	-0.0260**
US ISM Manufacturing Confidence US	-0.1498***	-0.0220	-0.0265
US Chicago PMI	-0.0581***	-0.0427***	-0.0148
US Consumer confidence	-0.0250***	-0.0492***	-0.0582**
US Philadelphia Fed index	-0.0248*	-0.0388***	-0.0277*
US ISM Non-Manufacturing Confidence	-0.0033	-0.0660***	-0.0450***
National Activity and Employment			
DE Industrial Production	-0.0129	-0.0160**	0.0021
FR Industrial production	-0.0058	-0.0269**	-0.0107***

Table 4. Contd.

	First regime	Second regime	Third regime
National Forward-looking			
ZEW	n.a.	-0.0361***	-0.0375***
IFO	-0.0368	-0.0224***	-0.0081**
FR Business Confidence	n.a.	-0.0154***	-0.0068
IT Business Confidence	n.a.	-0.0128***	-0.0055
National Prices			
FR Consumer Price Index	0.0079	-0.0210***	-0.0070

Note: The news response coefficients represent β_{1i}, β_{2i} and β_{3i} in Eq. (4). Only the coefficients for the announcements which are significant in the full sample using the regression setup in Eq (2) and Eq. (3) are shown in the table. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Some announcements are not available for the entire first regime

Using intraday data to gauge financial market responses to Fed and ECB monetary policy decisions*,**

Magnus Andersson

Abstract

This paper examines bond and stock market volatility reactions in the euro area and the US following their respective economies' monetary policy decisions, over a uniform sample period (April 1999 to May 2006). For this purpose, intraday data on the US and euro area bond and stock markets are used. A strong upsurge in intraday volatility at the time of the release of the monetary policy decisions by the two central banks is found, which is more pronounced for the US financial markets following Fed monetary policy decisions. Part of the increase in intraday volatility in the two economies surrounding monetary policy decisions can be explained by both news of the level of monetary policy and revisions in the expected future monetary policy path. The observed strong discrepancy between asset price reactions in the US and in the euro area following monetary policy decisions still remains a puzzle, although some tentative explanations are provided in the paper.

Keywords: Monetary policy, intraday data

JEL classification: E52, E58, G14

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1. Introduction

How do financial markets react to the release of monetary policy decisions? The answer to this question is of fundamental interest to monetary policymakers, as it provides them with information as to first, how well decisions are anticipated by market participants, and second, how these agents adjust their views about future monetary policy, output growth and inflation in response to a given decision. Such information enables a central bank to judge the immediate "success" of any decision taken, i.e. whether market participants reacted in accordance with the policymakers' intentions.

The purpose of this paper is to assess bond and stock market reactions in the euro area and the US following monetary policy decisions by the European Central Bank (ECB) and the Federal Reserve over a uniform sample period (April 1999 to May 2006). Intraday data are used, and the asset price reaction is measured in terms of derived realised volatility measures over five-minute intervals. Two different angles are viewed. First, asset price volatility on monetary policy announcement days is compared to the volatility observed on non-announcement days. Second, the volatility pattern when the central bank changes policy rates as opposed to when the monetary policy rates are left unchanged is examined. Conditional on these two events, the extent to which monetary policy target and path surprises can explain the observed volatility is analysed.

The paper contributes to the existing literature in two main aspects. First, a direct comparison of the US and euro area bond and stock market intraday volatility patterns following monetary policy decisions is novel. Second, this paper is the first to examine the influence that monetary policy target and path surprises exert on intraday financial market volatility patterns, conditional on whether monetary policy rates have been altered or not.

The paper reaches three main findings. First, intraday US and euro area stock and bond market volatility strongly increases at the time of the release of monetary policy decisions, and is particularly pronounced for the US financial markets. Second, monetary policy target and path surprises by the ECB both significantly move the euro area financial markets, whereas path surprises by the Fed have on average a larger influence on US bond and stock market volatility compared with the target surprises. Third, the yield response sensitivity for the German bond markets following an ECB monetary policy target surprise is stronger on the occasions when the monetary policy rates have been altered compared with periods when the ECB decided to leave it unchanged.

Although some tentative explanations are given in the paper, the observed discrepancy between asset price reactions in the US and in the euro area following monetary policy decisions still remains a puzzle.

The remainder of this paper is organised as follows. Section 2 presents some background and related literature, while Section 3 discusses the data used. The bond and stock market volatility reactions in the euro area and the US following their respective economies' monetary policy decisions are elaborated upon in Section 4. Section 5 concludes.

2. Background and related literature

Volatility of prices of financial assets such as stocks and bonds surrounding monetary policy decisions can be used to gauge the extent to which they contain "new news" for market participants that would lead them to revise their expectations about the future monetary policy path and/or the macroeconomic outlook. If a monetary policy decision causes market participants to revise their expectations, this should then be reflected in higher volatility of financial market prices compared with a period free of such an event.

Several differences can be noted in both the frequency and magnitude of interest rate settings between the two central banks (see Table 1). First, the ECB conducts monetary policy decisions meetings more frequently compared with the Fed. Second, the Federal Reserve has, on average, changed the interest rate more often and by larger magnitudes than the ECB over recent years.

Both the degree of predictability of monetary policy decisions and the influence the decisions exert on financial asset prices have been discussed in the literature. As regards the former, many papers have shown that US monetary policy decisions in general have been well anticipated among market participants (see for example Bernanke and Kuttner (2004) and Flemming and Piazzesi (2005)). The same holds true for the euro area, where financial markets have also been able to foresee the ECB's monetary policy decisions (see for instance Wilhelmsen and Zaghini (2005)). In addition, monetary policy communication plays a key role in enhancing short-term predictability by allowing the public to understand monetary policy decisions, a fact which has been documented in a number of studies by Ehrmann and Fratscher (2005a, 2005b and 2005c).

A number of papers have also examined the impact monetary policy decisions exert on the level of financial asset prices. Applied to US data, Gürkaynak et al. (2005) and Wongswan (2006) find that the US stock and bond markets react significantly to news about the near-term level of monetary policy and to changes in expectations of the path of monetary policy. Similarly, for the euro area, Brand et al. (2006) suggest that revised ECB monetary policy expectations have a significant and sizeable impact on the level of medium to long-term interest rates in the euro area.

Fewer studies have been conducted on volatility reactions surrounding monetary policy communications. Applied to the United States, Andersen et al. (2005) find a significant rise in US long-term bond yield volatility surrounding monetary policy decisions by the Fed. Similarly, Ehrmann and Fratzscher (2002) show that the volatility on euro area money market rates tends to be higher following Governing Council statements by the ECB. This paper fills a gap in the existing literature by conducting a direct comparison between the US and euro area bond and stock market intraday volatility pattern following monetary policy decisions.

3. Description of data used

The data used to measure financial market reactions consist of intraday data on euro area and US bond and stock prices.

Asset	Exchange
German bond futures	EUREX
US bond futures	Chicago Board of Trade
EURO STOXX 50 futures	EUREX
S&P 500 index	Chicago Mercantile Exchange

The data have been provided by TickData Inc. The dates and times of when the Fed's monetary policy decisions have become available to the public are taken from the paper by Fleming and Piazzesi (2005).[31] The actual and expected outcome of the Fed's interest rate decisions are taken from the Bloomberg survey. The dates and times for the ECB's monetary policy decisions have been collected internally. With regards to market expectations for ECB monetary policy decisions, the expected outcome from the Reuters survey is used.

This paper derives a volatility measure V using regularly spaced five-minute intervals:

[31] With the exception of the 2005 and 2006 decisions, which are taken from Bloomberg.

$$V_t = abs\left(100 * \log\left(\frac{P_t}{P_{t-1}}\right)\right) \tag{1}$$

where P_t is the five-minute prices of the four assets.[32]

Table 2 summarises the descriptive statistics for the four return series used in the paper. The sample mean of the asset returns are all small and, given the sample standard deviations, not statistically different from zero. The returns are obviously not normally distributed given the large magnitudes of the skewness and kurtosis statistics.

Volatility is normally not constant throughout a trading day, but tends to be higher at opening and closing hours than during the middle of a trading day. This feature has to be taken into account when gauging whether policy decisions by central banks induce elevated price fluctuations. Figures 1 A–D show the average five-minute volatility during the trading days for the US and euro area bond and stock series.[33]

The German bond and euro area STOXX future contracts display a number of interesting intraday features (Figures 1B and 1B). First, volatility in general tends to be higher at the opening and closing hours of the trading day. At opening hours, prices normally have to adjust to new information, which may induce heightened price fluctuations. Higher volatility close to the end of the trading day is probably linked to some investors closing their trading books to avoid having open positions overnight. Second, the two spikes – occurring at 14:30 and 16:00 (Central European time) - correspond to the release of several important US macro announcements, such as the Non-farm payroll, Producer Price Index, Retail Sales, Consumer Price Index, ISM and Consumer Confidence. In addition, at 14:30 on the first Thursday of each month, the ECB holds a press conference at which information about the considerations concerning the monetary policy decision is conveyed. Third, the level of intraday volatility is higher for the euro area stock markets compared to

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[32] As an alternative the squared return could also be used as a measure of realised intraday volatility. This measure does not however change the interpretations

[33] Over the sample under consideration, the trading hours of the STOXX futures and the German Bund futures have not remained constant. The intraday volatility shown in Figures 1A and 1B is therefore calculated using only hours which have been traded over the entire sample.

the German bond future markets, which is something that is also observed for much lower frequencies such as daily data.

The US bond and stock markets show a broadly similar pattern to their European counterparts (Figures 1C and 1D). The spikes occurring at 07:30 and 9:00 mainly arise from releases of the above-reported US macro announcements. Overall, bond and stock markets on both sides of the Atlantic seem to display generally similar levels of volatility.

4. Asset price reactions following monetary policy decisions by the ECB and the Fed

The following three subsections examine financial market intraday volatility patterns surrounding monetary policy decisions by the ECB and the Fed. Target and path surprises implicitly embedded in the monetary policy decisions are computed. These surprises are used as explanatory variables to the observed intraday volatility pattern. In Section 4.1 the general volatility pattern is analysed. Section 4.2 provides some tentative explanations for the observed discrepancy between asset price reaction in the US and in the euro area following monetary policy decisions. Section 4.3 regresses the general intraday volatility pattern on monetary target and path surprises. Section 4.4 evaluates if the volatility pattern in financial markets differs depending on if monetary policy rates have been altered or not.

4.1. General intraday volatility pattern surrounding monetary policy decisions

Figures 2 and 3 display the ratio between five-minute bond and stock market volatility surrounding monetary policy decisions by the Fed and the ECB respectively, and the average five-minute volatility on the same weekdays and the same times but on non-announcement days, thereby controlling for both intraday and 'weekday' effects. A ratio above one can be interpreted as the monetary policy decisions inducing "higher than normal" volatility. As regards the timing, the Fed's interest rate decisions are usually released at 13:15, and the ECB's interest rate decisions at 13:45 (both local times).

It should be noted that the Fed's interest decisions, are also accompanied by a statement in which the outlook for the future monetary policy stance is conveyed.[34] This implies that, particularly for the Federal Reserve, there are two potential sources of new information arising from the interest rate decisions, a target surprise and a path surprise. The target surprise can be defined as the degree to which market participants have been able to anticipate the actual monetary policy decisions. The path surprise instead measures to what degree market participants have revised the future expected monetary policy path following the actual decision and/or monetary policy statements.

In contrast to the Fed, the ECB's interest decisions and statements are released to the public at separate times. Announcements of the actual outcome of monetary policy decisions are released at 13:45 local time. However, details about the economic and monetary analyses underlying each interest rate decision are instead conveyed in the Introductory Statement read by the ECB President 45 minutes later. As seen in the figures, the volatility pattern for the euro area bond and stock markets is therefore extended to include any financial market movements that take place surrounding the press conference as well.

Four interesting features can be inferred from the two figures. First, monetary policy decisions on both sides of the Atlantic tend to induce significantly "higher than normal" volatility on their respective economies' bond and stock markets. Second, this feature seems to be particularly pronounced for the US bond and stock markets following interest rate decisions by the Fed. Third, some volatility persistence can be observed, in particular for the US bond and stock markets, where "excess" volatility can be noted up to 40 minutes after the decisions have taken place. Fourth, in the euro area, the Introductory Statement read by the ECB President induces somewhat "higher than normal" volatility on the euro area bond market.

Potentially, any interpretations on the basis of Figures 2 and 3 could be spurious if important macro announcements were systematically released on the same days and at the same times as the monetary policy decisions of the Federal Reserve and the ECB. To examine this in detail, 43 US and euro area macro announcements were collected and tested to establish whether they were made within a 60-minute window of the monetary policy announcements by the two central banks.[35] The results of

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[34] The trading of the US 10-year Treasury future note closes at 14:00 Central Time, i.e. 45 minutes after the Fed's interest rate decisions. To enable a consistent comparison between the US bond and stock markets, the volatility window spans between 30 minutes before to 40 minutes after the decisions for these two markets.

[35] See Andersson et al. (2006), Table 1, where the 43 announcements are listed.

this examination suggested that none of the announcements under consideration occurred at the same time as the Federal Reserve decisions. The monetary policy decisions of the ECB coincided with the release of macro statistics on only two occasions, and both concerned the German CPI statistics released on 23 March 2001 and 26 April 2001. These two instances of concurrence should not, however, distort the interpretation, as previous announcement papers have found that the German CPI does not move the euro area financial markets in any significant way – see Andersson et al. (2006) and Ehrmann and Fratzscher (2003).

The small number of macro releases occurring at the time of the monetary policy decisions suggests that the observed upsurge in volatility is prompted by from the actual decisions and does not reflect market reactions to macro news. In stark contrast, the ECB press conference is usually held at times of important US macro announcements – in particular, the weekly initial jobless claims – making the volatility ratio difficult to interpret.[36] An analysis of the ECB press conference is, however, outside the scope of this paper, which purely concentrates on market reaction to the actual decisions.

The average reaction to asset prices shown in Figures 2 and 3 may not be static but rather changing over time. There are several reasons why price reaction can change over time. Andersson et al. (2006) suggest that policymakers can sometimes signal a preference for one or more macroeconomic indicators as input for their policy decisions. In addition, some macroeconomic releases may behave in an unusual manner at a certain point in the business cycle, which can in turn have an impact on monetary policy decisions. To check for potential time variation, yearly averages were computed.[37] The yearly averages are broadly similar across the years, suggesting that the pattern shown in Figures 2 and 3 can be deemed a general feature.

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[36] Over the sample April 1999 to May 2006, the Initial Jobless Claims was released at 106 times within a 60 minute window surrounding the 14.30 Press Conference. Similarly the release of the Philadelphia Fed Index occurred five times, Durable Goods two times, Business Inventories three times, Retail Sales at 4 times, CPI at 2 times, Advanced GDP at 3 times, GDP Preliminary at 2 times and GDP final at 2 times.

[37] See Appendix A in the Working Paper version (ECB WP no. 726) It shows the yearly volatility ratios for the five-minute periods immediately surrounding and 30 minutes ahead of the monetary policy decisions respectively.

4.2. Why intraday asset price movements are stronger in the US than in the euro area - some tentative explanations

The finding that there is a higher intraday asset price reaction in the US than in the euro area following their respective economies' monetary policy decisions is, interesting, but somewhat puzzling. The three best possible explanations for this discrepancy are as follows. First, potentially "more" information becomes available during the release of Fed interest rate decisions. In this respect, even though the actual decisions by the Fed have been anticipated by the markets, heightened volatility could still arise given an unexpected change in the tone of the accompanying statement. An interesting example of this took place in January 2004 when the Fed, as expected, held the policy rate unchanged (at 1 percent) but at the same time significantly changed its wording in the statement following the decision. As the Wall Street Journal wrote in its market commentary column the day after the decision; "*While investors had expected the Fed's decision to keep short-term interest rates on hold at 1%, the absence of the "considerable period" phrasing, used since August 2003 to describe how long the bank would keep rates low, caught market participants off guard [...] Prices plummeted in the immediate aftermath of the Fed's decision and the yield on the 10-year note shot up to 4.26%*".

Second, the announcement literature which examines the impact on financial prices surrounding important macro economic announcements, has in general found stronger asset price sensitivity to US news compared with euro area news, partly owing to the view that the US is currently perceived among investors as the main engine of global growth.[38]

Third, related liquidity and volume issues cannot be excluded as potentially important factors behind the apparent differences in observed asset price volatility across the Atlantic. This in turn can be divided into two subcategories, where the first concerns uncertainty regarding the timing of the decisions, and the second the fact that data on volumes may reveal presence of differences of beliefs among traders. As regards the first subcategory, Flemming and Piazzesi (2005) suggest that some uncertainty exists about the exact release of the US monetary policy announcements, which in turn have an impact on intraday market pricing in the US Treasury markets. In particular, liquidity tends to be low if an announcement is released minutes later than the expected 13:15. This in

[38] See for instance Andersson et. al. (2006), Ehrmann and Fratscher (2003) and Goldberg and Leonard (2003).

turn can trigger higher price sensitivity when the actual announcements are released. In contrast, timing uncertainty for the ECB's monetary policy decisions should not exist given the exact 13:45 release.

For the second subcategory, a sharp increase in volume may reveal higher levels of differences in opinions among traders which in turn can results in higher financial market volatility, everything else held equal, see Harris and Raviv (1993). Empirical studies have found that trading volume increases at the time of macroeconomic announcements and monetary policy decisions.[39] Recently, Gropp and Kadareja (2006) test the hypothesis as to whether differences in opinions among traders can induce heightened intraday volatility, applied on European banks stock data. The annual report is used as a measure of the precision of the information available about banks. The authors find, in line with theory, that intraday volatility of the banks' stocks following a monetary policy shock becomes larger the longer the lag is since the annual report was released.

The intraday data used in this study do not unfortunately contain volume information for the sample under consideration. However, the number of transactions within a specified time interval should closely track the volume in the markets, according to the data provider. For the series used in this paper, this data type is available for the German bond markets, the euro area stock markets and the US bond markets. Figures 4 - 6 replicate the volatility ratio calculations and display the ratio between the amount of transactions within five-minute intervals surrounding monetary policy decisions by the ECB and the Fed respectively, and the average five-minute transactions on the same weekdays and the same times but on non-announcement days.

The volume approximations for the German bond markets and the euro area stock markets reveal a similar picture and to some extent mimic the observed spikes in volatility shown in Figures 2 and 3. Overall the number of transactions in the two markets on average is more than double at the time of the ECB's monetary policy decisions compared with the number of transactions during Thursdays where there is no ECB monetary policy meeting.

A similar calculation was conducted for the US Treasury markets. The sample size is however shorter than for European assets above. The reason is that up until June 2003, only the number of so-called pit trades is available. From July 2003 and onwards the electronic trades were also

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[39] See for instance Balduzzi et. al. (2001) applied on economic news and Flemming and Piazzesi (2005) applied on Fed's monetary policy decisions.

included, making a comparison with the EUREX traded assets more accurate for this latter period. As seen in the figure, nearly ten times as many trades were conducted during the time of the Fed monetary policy decisions compared with the number of transactions during the same days but with no Fed monetary policy meeting.

Thus, it cannot be excluded that in the US markets, there are more investors with differences in opinions from the mean investor than in the euro area, which in turn may play a role in explaining the marked differences in intraday volatility.

4.3. Evaluating the impact monetary policy surprises have on intraday financial market volatility

All in all, it is reasonable to assume that the arrival of new information could induce heighten volatility surrounding monetary policy releases. To assess this in more detail, this and the next subsection will focus on the strong upturn observed at the time "0" in Figures 2 and 3, which corresponds to the realized asset price volatility immediately surrounding the monetary policy decisions by the Fed and the ECB respectively. The idea is to analyse to what extent the upswing in volatility can be explained by monetary policy surprises.

Monetary policy surprises are divided into two types: target surprises and path surprises. A target surprise is defined as the degree to which market participants have been able to anticipate the actual monetary policy decisions, whereas a path surprise measures the degree to which market participants have revised the future expected monetary policy path following the actual decision and/or monetary policy statements.

The target surprise can be derived from either available surveys or financial market prices. Both measures have their pros and cons. The main advantage of the former is that they in principle should contain the "true" mean expectations about upcoming future monetary policy decisions. On the other hand, financial market expectations benefit from the fact that they are available at a much higher frequency compared with survey-based measures. But, as shown by Piazzesi and Swanson (2004) and applied to US data, expectations derived from the financial markets could contain risk premia and market noise, which may blur the interpretation.

This paper will make uses a survey-based measure for the target surprise which represents the difference between the actual outcomes and the mean of analysts' expectations concerning the outcomes of the monetary policy decisions. This measure is chosen as the methodology used is identical for both the euro area and the US. As a cross-check, figure 7A and B show the target surprise used in this paper compared with market-based measures employed in some earlier studies. Overall the two measures exhibit very similar patterns which are also confirmed by the estimated correlation coefficients of 0.75 for the ECB target surprises, and 0.8 for the Fed target surprises. Thus, the survey-based measure should therefore be a good indicator of the target surprise as perceived among investors.

The path surprise component employed in this study is derived in line with Gürkaynak et. al. (2005):

$$\Delta f_{t-30,t} = \alpha + \beta * TS_t + PS_t \tag{2}$$

where $\Delta f_{t-30,t}$ represents the intraday changes in the expected three-month interest rate in six months' time surrounding the monetary policy decisions (Euribor and Eurodollar future contracts for the euro area and the US respectively). The *TS* represents the target surprise component as described above. The innovation from the regression in Equation (2) is defined as the path surprise (*PS*). Given that the purpose of this exercise is to examine the effects on financial markets surrounding the actual monetary policy decisions, potential information about future ECB monetary policy conveyed in the Introductory Statement at the ECB press conference is not included in the derived ECB path surprises.

To evaluate how the changes in the volatility ratios surrounding the monetary policy decisions by the Fed and the ECB as shown in Figures 2 and 3 can be explained by the target and/or path surprises, the following regression set-up is used:

$$\Delta Volratio_{t-30,t} = \alpha + \beta_1 * Abs(TS) + \beta_2 Abs(PS) + \varepsilon_t \tag{3}$$

The *Abs(TS)* and *Abs(PS)* variables in eq. (3) correspond to the absolute values of the target and the path surprises respectively. The $\Delta Volratio_{t-30,t}$ represents the difference between the observed volatility ratio in the period immediately surrounding the monetary policy decisions and the volatility ratio 30 minutes ahead of the decisions. The Appendix shows details of how the volatility ratio is calculated. The choice of the intraday impact relative to that of non-announcement days as a dependent variable is in line with the procedure by Ederington and Lee (1993). Table 3 outlines the results of the regression.

Three notable features can be inferred. First, a monetary policy target surprise induces significantly higher than normal volatility in the

German bond markets. Second, the ECB path surprises have a highly significant impact on the euro area stock markets. Third, in the US the results suggest that path surprises on average have a larger influence on the US bond and stock market volatility compared with target surprises.

One potential problem with the Equation (3) regression specification could be presence of multicollinearity between the explanatory variables. However, the classic symptoms of multicollinearity, such as i) high R2 and few significant t-ratios and ii) high pair-wise correlations between the regressors, cannot be detected. This suggests that it should be possible to isolate the individual impact that the target and the path surprises have on financial market prices.

4.4. Impact of monetary policy surprises on intraday financial market volatility, conditional on whether policy rates have been altered or not

One possible source for the different reaction patterns between the two economies could be that the markets react differently depending on whether monetary policy rates are changed or not. In this regard, monetary policy moves usually take place when market uncertainty can be expected to be higher than normal, such as risks of very low inflation or outright deflation[40], or when there is uncertainty regarding an expected future strengthening of economic activity.[41] Furthermore, some interest rate moves take place during extreme market conditions. One example was the joint interest rate reduction of 50 basis points by the ECB and the Fed in the aftermath of the September 11 terrorist attack. Using daily data, Wilhelmsen and Zaghini (2005) find less predictability – the latter

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[40] An example of this was the 25 basis point rate reduction by the Fed in June 2003. The accompanying statement justified the decision stating: "*The Committee perceives that the upside and downside risks to the attainment of sustainable growth for the next few quarters are roughly equal. In contrast, the probability, though minor, of an unwelcome substantial fall in inflation exceeds that of a pickup in inflation from its already low level.*"

[41] An example of this was the increase of 25 basis points by the ECB in December 2005. The accompanying introductory statement explained why: "*On the basis of our regular economic and monetary analyses, we have decided to increase the key ECB interest rates by 25 basis points, after two and a half years of maintaining rates at historically low levels. Looking ahead, on the external side, ongoing growth in global demand should support euro area exports, while on the domestic side, investment should benefit from continued favourable financing conditions and the robust growth of corporate earnings.*"

measured as the standard deviation in money market rates – when a modification in the official policy rate is decided on, compared with days when the monetary policy authority does not change the official rate. This pattern holds true for all 14 economies included in their study.

Figure 8 A-D decompose the volatility pattern between monetary policy events when policy rates are adjusted, and when they remained unchanged. As seen in Figures 8A and 8B, the elevated volatility, in euro area stock and bond markets during monetary policy announcements seems to be related to the periods when the ECB decided to change rates. In contrast, monetary policy decisions by the Fed induce elevated stock and bond market volatility independent of the outcome (see Figures 8D and 8D).

One possible explanation for the different pattern of behaviour across the two markets can be related to an asymmetry in the monetary policy surprises, i.e. that they are higher in magnitude when the ECB changes rates compared with no change events. Table 4 summarises the mean and the standard deviation of the surprises conditional on whether rates have been altered or not. Overall, the mean of the (absolute) surprises is somewhat higher in both economies (and for both categories of surprises) when rates were changed compared with those meetings when they remained unchanged. However, the difference is particularly pronounced for the computed target surprise of the ECB, which could partly explain why asset price volatility in the euro area is higher when policy rates are adjusted compared with periods when policy rates are left unchanged.

To examine the asymmetric issue further, a slight modification of the regression set-up in Equation (3) is used:

$$\Delta Volratio_{t-30,t+5} = \alpha_1 + \alpha_2 D + \beta_{1,t} X + \beta_{2,t} DX + \varepsilon_t \tag{4}$$

where D is a dummy variable which takes on a value of 1 when interest rates are changed, and a value of 0 if they are unchanged. The matrix X corresponds to the independent variables (i.e. the absolute values of the target and path surprises). Equation (4) has the following implications:

Mean volatility when $D = 0$ (i.e. monetary policy rates unchanged):

$$E(\Delta Volratio | D = 0, X) = \alpha_1 + \beta_1 X \tag{5}$$

Mean volatility when D = 1 (i.e. monetary policy rates altered):

$$E(\Delta Volratio|D=1,X)=(\alpha_1+\alpha_2)+(\beta_1+\beta_2)X \tag{6}$$

Four different possibilities can be tested using this set-up:

1) $\alpha_1 = \alpha_2$ and or $\beta_1 = \beta_2$; the two regressions are the same.

2) $\alpha_1 \neq \alpha_2$ and or $\beta_1 = \beta_2$; the two regressions differ in the intercept.

3) $\alpha_1 = \alpha_2$ and or $\beta_1 \neq \beta_2$; the two regressions have the same intercept but different slopes.

4) $\alpha_1 \neq \alpha_2$ and or $\beta_1 \neq \beta_2$; the two regressions have different intercepts and different slopes.

Thus, a significantly positive α_2 coefficient suggests that volatility on average is higher when monetary policy rates are altered compared with periods when rates are left unchanged. In the same vein, a significant positive coefficient of β_2 implies stronger asset price sensitivity when monetary policy rates are altered compared with periods when rates are left unchanged. Of particular interest is to test the significance of α_2 and/or β_2 for the German bond markets and the euro area stock markets. This could shed further light on the factors driving the elevated volatility following alterations of the ECB's monetary policy rates, as shown in Figure 8. Table 5 outlines the results of the regressions after dropping the non-significant variables from Equation (3).

The table reveals that asset price sensitivity is not linear for the German bond markets and the euro area stock markets. Instead, the volatility pattern is different depending on if policy rates have been altered or not. For the German bond market, the null-hypothesis of equal slope coefficient can be rejected at the five percent level. For the euro area stock markets the null-hypothesis of equal slope coefficient can be also be rejected, but only at the ten percent level. As regards the US, no differences in the asset price reaction following either scenario can be detected.

Figures 9 and 10 visualise the differences in asset price pattern for the German bond market volatility ratio by scatter-plotting the volatility ratios against the target surprises. The figures suggest that intraday volatility tend to be of larger magnitude (see Figure 10) when interest rates are changed than when they are not changed (see Figure 9), even when the surprise are of the same magnitudes. Comments from the financial press after the interest rate decisions highlighted in Figure 10 seem to suggest that the interest rate decisions took the markets by surprise during these occasions, see Table 6.

5. Concluding remarks

Monetary policy decisions and the expected path of future policy rates strongly influence asset prices. Among the worlds' leading central banks, monetary policy actions by the Federal Reserve and the ECB are particularly monitored among investors as they control short-term interest rates in the two major economies. This paper tries to shed some light on the link between monetary policy decisions and asset price reactions. Using long time series of intraday data, US and euro area bond and stock market intraday volatility patterns surrounding monetary policy decisions by the two central banks are derived. Overall both the ECB and the Fed decisions induce an upsurge in intraday volatility on their respective bond and stock markets. The reaction on US financial markets following the Fed's decisions are more pronounced compared with the reaction the ECB exerts on the German bond markets and the euro area stock markets. Although this paper provides some tentative explanations that partly explain this discrepancy between the two markets, their decoupling patterns still remain a puzzle.

As a next step, monetary policy target and path surprises are used as explanatory variables when explaining these upsurges in volatility. Monetary policy surprises are suitable candidates for this purpose, as only new news should in theory affect asset prices. The paper finds that monetary policy target surprises by the ECB significantly induce higher than normal volatility in the German bond markets. In addition, path surprises by the Fed have on average a larger influence on US bond and stock market volatility compared with target surprises.

When decomposing the asset price reaction based on whether monetary policy rates have been altered or not, the level of intraday volatility of the German bond markets and the euro area stock markets is found to be higher when interest rates are changed. This can probably be linked to two factors. First, monetary policy surprises are on average of a larger magnitude when the ECB decides to change rates compared with meetings which resulted in no change. Second, there is a non-linear asset volatility price sensitivity – which is particularly pronounced for the German bond markets - in that bond markets react significantly stronger to a given target surprise by the ECB when there has been a change in the official rate compared with periods when the policy rates have not been altered.

Building on this study, a key direction for future research would be to find further evidence of factors that could explain the pronounced asset price reaction in the US financial markets following interest rate decisions by the Federal Reserve, compared with the more muted feedback on euro area asset prices surrounding the ECB's monetary policy decisions.

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Appendix

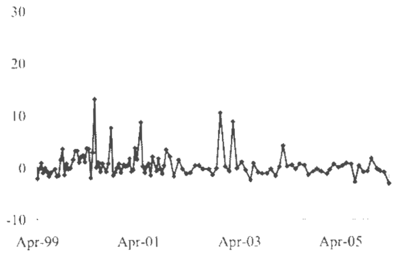
The volatility measure used as the dependent variable in regressions (3) and (4) is defined as the ratio between volatility on monetary policy days and volatility on the same weekdays and hours but when no monetary policy decision are taking place. More specifically, let $k = 1,2 \ldots K$ be the days of monetary policy decisions and $d = 1, 2 \ldots D$ be the same weekdays, but when no monetary policy decisions are taking place. The intraday change in the volatility ratio for asset i on a monetary policy decision day k is then calculated as:

$$\Delta Volratio^{i,k}_{t-30,t} = \left(\frac{abs(R^{i,k}_{t=0})}{\frac{1}{D}\sum_{d=1}^{D} abs(R^{i,d}_{t=0})} - \frac{abs(R^{i,k}_{t=-30})}{\frac{1}{D}\sum_{d=1}^{D} abs(R^{i,d}_{t=-30})} \right)$$

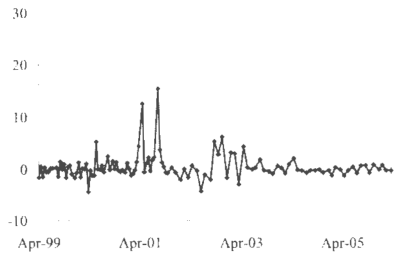
R represents the five-minute log-return.

Changes in volatility ratio

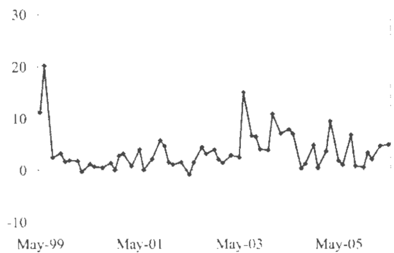
A. German bond markets



B. Euro area stock markets



C. US bond markets



D. US stock markets

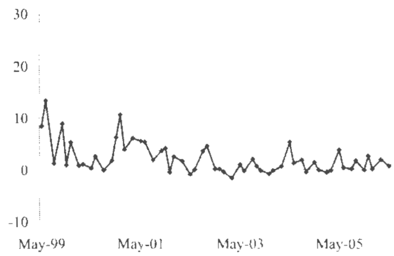
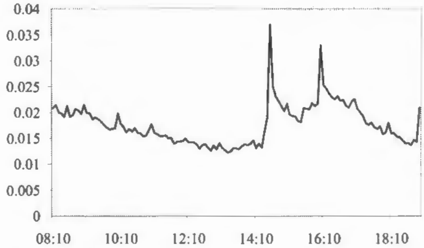
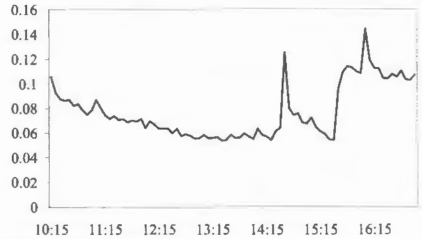


Figure 1. Intraday volatility in the euro area and US stock markets

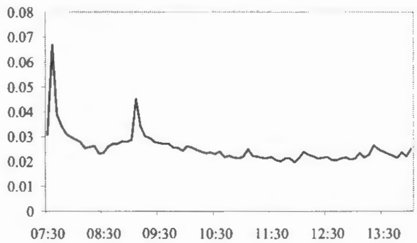
A. German intraday bond market volatility (April 1999 – May 2006, 8.00 – 19.00 Central European time zone)



B. Euro area intraday stock market volatility (April 1999 – May 2006, 10.15 – 17.00 Central European time zone)



C. US intraday bond market volatility (April 1999 – May 2006, 07.20 – 14.00 Central time zone)



D. US intraday stock market volatility (April 1999 – May 2006, 08.30 – 15.00 Central time zone)

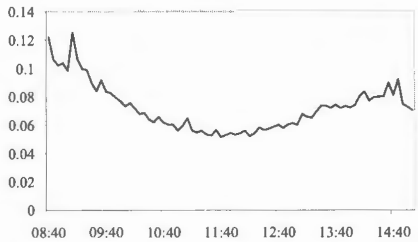
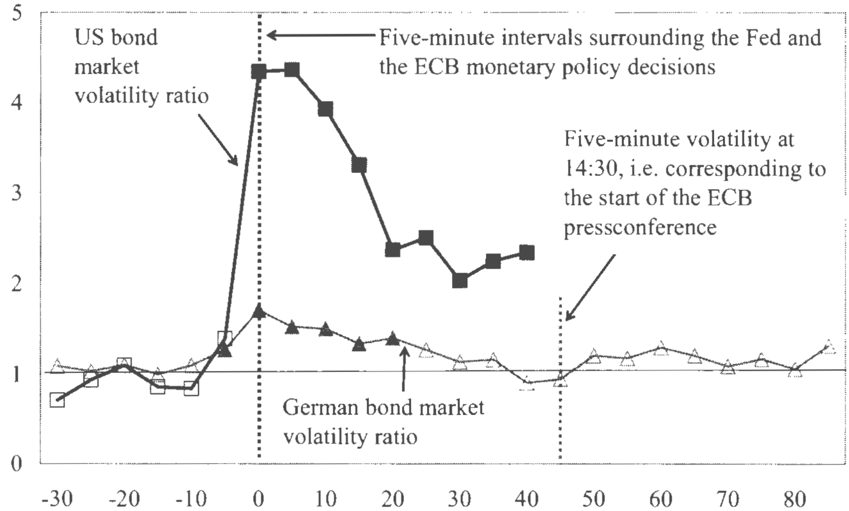
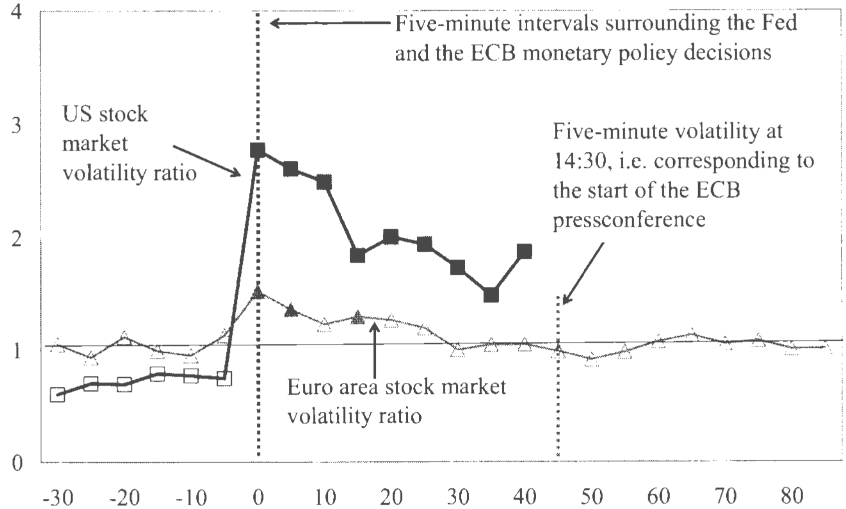


Figure 2. US and German bond market volatility ratio surrounding monetary policy decisions by the Fed and the ECB (April 1999 – May 2006)



Note: The volatility measures are calculated as the ratio between i) five-minute intraday volatility on the US and German long-term bond futures markets surrounding interest rate decisions by the Federal Reserve and the ECB, and ii) "normal volatility", the latter computed as the average absolute returns on the same week-days and same times but on non-announcement days. Using one-sided t-test, the filled dots implies that the ratio is significantly higher than 1 and empty dots that the ratio cannot be deemed as exceeding 1.

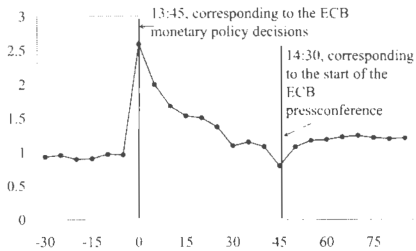
Figure 3. US and euro area stock market volatility ratio surrounding monetary policy decisions by the Fed and the ECB (April 1999 – May 2006)



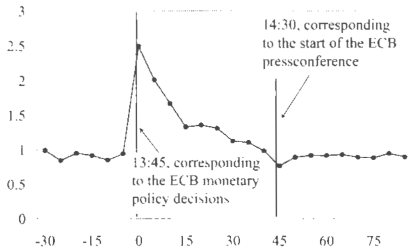
Note: The volatility measures are calculated as the ratio between i) five-minute intraday volatility on the US (S&P 500) and euro area (EURO STOXX) stock markets surrounding interest rate decisions by the Federal Reserve and the ECB and ii) "normal volatility", the latter computed as the average absolute returns on the same week-days and same times but on non-announcement days. Using one-sided t-test, the filled dots implies that the ratio is significantly higher than 1 and empty dots that the ratio cannot be deemed as exceeding 1.

Figure 4-6. Volume approximation surrounding monetary policy decisions

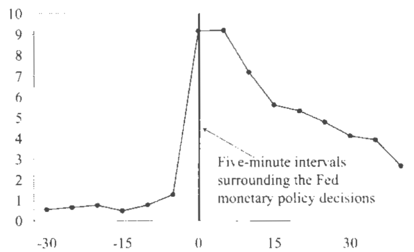
4. German bond markets surrounding monetary policy decisions by the ECB (April 1999 – May 2006).



5. German stock markets surrounding monetary policy decisions by the ECB (April 1999 – May 2006).



6. US bond markets surrounding monetary policy decisions by the Fed (July 2003 – May 2006).

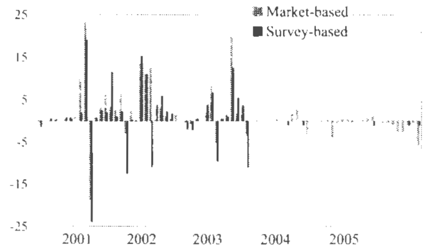


Note: For figures 4 and 5, the volume approximations are calculated as the ratio between i) the number of transactions in the five-minute intervals for the German long-term bond futures markets/euro area stock markets surrounding interest rate decisions by the ECB, and ii) the number of transactions on the same days and same times but on non-announcement days. The intervals span 30 minutes before to 85 minutes after the decisions for the ECB.

For figure 6, the volume approximations are calculated as the ratio between i) the number of transactions in the five-minute intervals for the US bond markets surrounding interest rate decisions by the Fed, and ii) the number of transactions on the same days and same times but on non-announcement days. The intervals span 30 minutes before to 40 minutes after the decisions for the Fed.

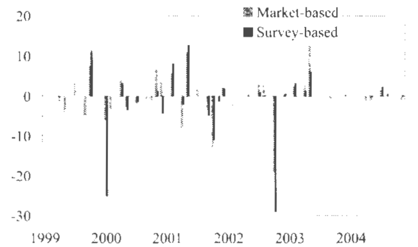
Figure 7. Market and survey-based target surprises

A. ECB (November 2000 – April 2006)



Note: The market-based measure comes from Brand, Buncic and Turunen (2006) and represents the 30-minute changes in the 30 day maturity euro area interest rates surrounding the ECB monetary policy decisions (interest rates are filtered using 64 instruments; deposit rates, EONIA and EURIBOR swap rates). The survey-based measure represents the difference between the actual outcome of the monetary policy decisions and analysts' mean expectations taken from the Reuters survey.

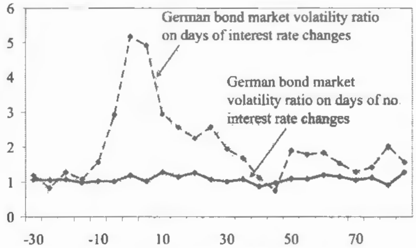
B. Federal Reserve (February 1999 – December 2004).



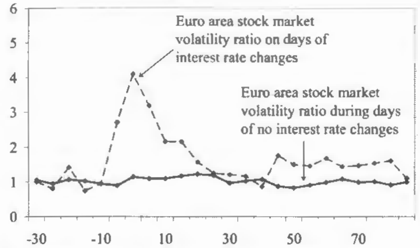
Note: The market-based measure comes from Flemming and Piazzesi (2005) and represents the one-hour changes in fed fund futures contracts surrounding the Fed monetary policy decisions. The survey-based measure represents the difference between the actual outcome of the monetary policy decisions and analysts' mean expectations taken from the Bloomberg survey.

Figure 8. Volatility ratios on days with and days without changes in monetary policy rates

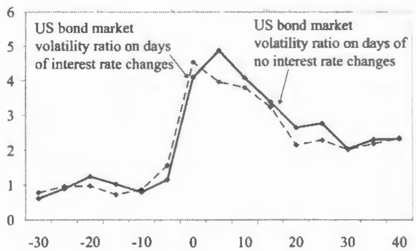
A. German bond markets (30 minutes before to 85 minutes after the decisions)



B. Euro area stock markets (30 minutes before to 85 minutes after the decisions)



C. US long-term bond markets (30 minutes before to 40 minutes after the decisions)



D. US stock markets (30 minutes before to 40 minutes after the decisions)

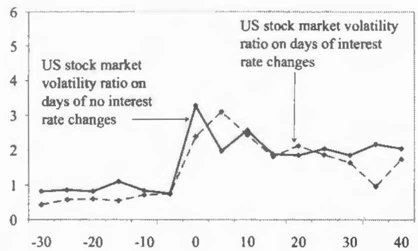


Figure 9. Changes in German bond volatility ratio (y-axis) **and the ECB monetary policy target surprise** (x-axis). **Sample includes only observations when the ECB left monetary policy rates unchanged** (April 1999 – May 2006)

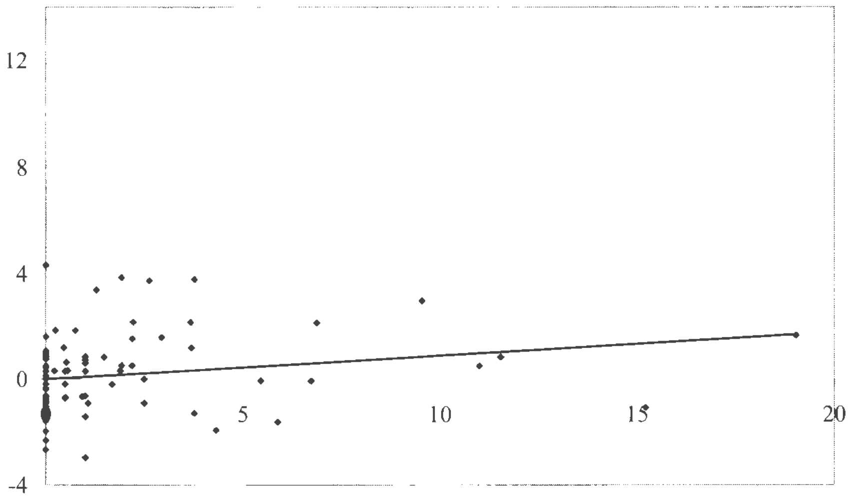


Figure 10. Changes in German bond volatility ratio (y-axis) **and the ECB monetary policy target surprise** (x-axis). **Sample includes only observations when the ECB altered monetary policy rates** (April 1999 – May 2006)

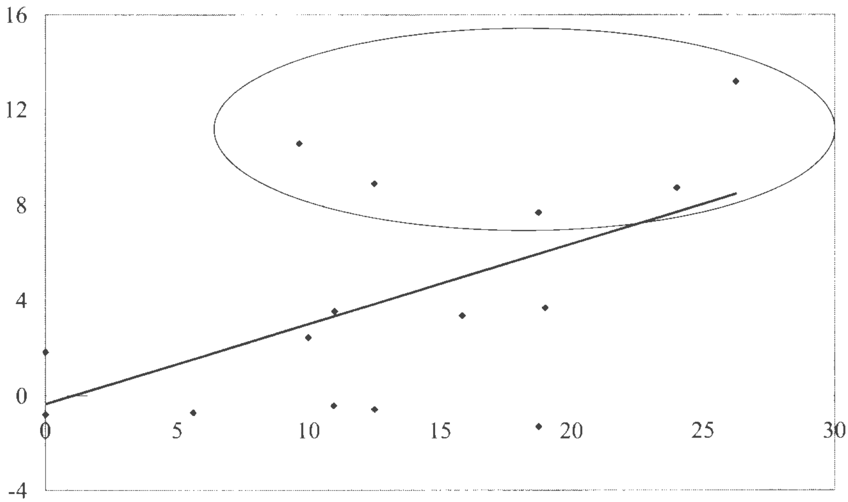


Table 1. Fed and ECB monetary policy decisions (April 1999 – May 2006)

	ECB	Fed
Total number of events	118	54
of which the monetary policy stance was changed	16	32
No of increases, 25 bp	7	21
No of increases, 50 bp	2	1
No of reductions, 25 bp	3	4
No of reductions, 50 bp	4	6

Note: In this study, for comparison, the data start in April 1999, as the ECB then began to release its monetary policy decisions at the regular time of 13:45 CET. All statistics exclude the 17 September 2001 observation. Unscheduled monetary policy meetings by the Federal Reserve are also excluded.

Table 2. Descriptive statistics, five-minute returns

	German bond futures	US bond futures	EURO STOXX 50 futures	S&P 500 index
Mean	0.0001	0.0001	-0.0001	-0.0003
Standard deviation	0.0258	0.0398	0.1252	0.1048
Skewness	-0.24	-0.30	-0.57	0.16
Kurtosis	17.73	55.07	37.82	12.43

Note: April 1999 to May 2006. The overnight returns are omitted when computing the descriptive statistics.

Table 3. Regression results

Dependent variable	Constant	Abs(TS)	Abs(PS)	R2	Corr(Abs(TS), Abs(PS))
ΔVolratiot-30,t					
German bond markets	-0.34*	0.22***	0.29	0.38	0.56
	(0.18)	(0.09)	(0.24)		
Euro area stock markets	-0.64***	0.06*	0.90***	0.38	0.56
	(0.13)	(0.04)	(0.12)		
US bond markets	1.25*	-0.10	0.77***	0.40	0.10
	(0.70)	(0.09)	(0.20)		
US stock markets	0.82	-0.05	0.43**	0.20	0.10
	(0.68)	(0.06)	(0.21)		

Note: The regression specifications are: $\Delta Volratio\text{-}30,\ t = \alpha_{1,t} + \beta_1 {*} Abs(TS) + \beta_2 {*} Abs(PS) + \varepsilon_t$ for the four asset classes respectively. *ΔVolratio* represents the changes in the volatility ratio (30 minutes before and five minutes after the monetary policy decisions) between observed volatility on monetary policy events and volatility on non-announcement days. *Abs(TS)* and *Abs(PS)* correspond to the absolute values of the target and the path surprises respectively. Newey-West heteroskedasticity-consistent standard errors are in parentheses. One, two and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 4. Summary statistics of the monetary policy surprises

	ECB		Fed	
	Target surprise	Path surprise	Target surprise	Path surprise
Mean of the absolute surprises				
Total sample	3.0	1.0	2.5	3.4
When rates were left unchanged	1.5	0.6	0.6	2.8
When rates were changed	13.0	1.4	4.0	4.0
Standard deviation of the absolute surprises				
Total sample	5.6	1.4	5.6	3.2
When rates were left unchanged	3.2	0.5	1.0	2.6
When rates were changed	7.7	1.9	7.1	3.5

Table 5. Regression results conditional on altered monetary policy rates

Dependent variable $\Delta Volratio_{t-30,t}$	Constant	Constant | D=1	Abs(TS)	Abs(TS) | D=1	Abs(PS)	Abs(PS) | D=1
German bond markets	0.00	-0.36	0.09*	0.25**		
	(0.15)	(1.58)	(0.05)	(0.11)		
Euro area stock markets	-0.39**	0.29	0.03	0.00	0.56***	0.43*
	(0.19)	(1.00)	(0.06)	(0.08)	(0.20)	(0.26)
US bond markets	1.83	-1.40			0.60***	0.24
	(1.14)	(1.35)			(0.22)	(0.34)
US stock markets	0.81	-0.40			0.59***	-0.20
	(0.88)	(0.99)			(0.19)	(0.19)

Note: The regression specification follows the one specified in Equation (4) to test whether price sensitivity differs during periods when the central banks change policy rates. Newey-West heteroskedasticity-consistent standard errors are in parentheses. One, two and three asterisks denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 6. Financial market comments to ECB monetary policy decisions

Date	Interest rate move	Target Surprise	Comment
8 June 2000	+ 50 bp	26.25	Financial Times 9 June 2000: "*The ECB rate rise demonstrated the bank is not afraid of making decisions that surprise the markets ... Most investors expected rates to go up by 25 basis points and did not price in a 50 basis points rise...German 10-year bund prices advanced despite the surprisingly aggressive rise in interest rates while the short-dated bonds sold off*".
10 May 2001	- 25 bp	-24	Financial Times 11 May 2001: "*Interest rates fall across Europe... Markets were stunned by the ECB's 0.25 percentage point reduction in its main interest rate to 4.5 per cent. It was the ECB's first cut for more than two years and caught investors unprepared*".
5 October 2000	+ 25 bp	18.75	Financial Times 6 October 2000: "*The biggest surprise in the government bond markets yesterday was the European Central Bank's decision to raise interest rates by 25 basis points to 4.75 per cent, with prices on government bonds falling in response... After the initial shock wore off, bond prices recovered*".
6 March 2003	- 25 bp	12.5	Financial Times 7 March 2003: "*Short-dated eurozone government bond prices recovered their early losses yesterday, despite the European Central Bank's decision to lower interest rates by a quarter rather than a half point. The ECB cut rates to 2.5 per cent, but comments by Wim Duisenberg, ECB president, suggested further easing was on the cards*".
5 Dec 2002	- 50 bp	-9.6	Financial Times 6 December 2002: "*European government bond trading was dominated yesterday by interest rate decisions, notably the European Central Bank's half-point cut to 2.75 per cent ... Eurozone bonds initially rose on the ECB's announcement of its first reduction in rates for more than a year*".

The Market Impact of Macroeconomic Announcements: A Learning Approach*

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Abstract

The information content in a given macroeconomic announcement is typically measured by its "surprise component", defined as the deviation between the actual outcome and a measure of market expectations. The main contribution of this paper is to derive, using a Bayesian learning model, a richer measure of the information content. This novel measure is the product of the standard surprise component and a term capturing the quality of the announcement as a signal of some underlying state variable of interest. We offer two empirical applications: one that analyses the process of expectations formation with respect to US manufacturing surveys, and another that provides new insights about German CPI releases.

Keywords: Macroeconomic announcements, learning

JEL classification: E54, G1

* The paper has benefited from comments and suggestions given during seminar participants at the ECB and the IFO institute. The paper is partly build on an internal ECB note which received helpful input from Francesco Drudi, Manfred Kremer, Philippe Moutot, Huw Pill and Thomas Westermann. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the ECB.

The market impact of macroeconomic announcements: a learning approach*

Magnus Andersson, Jacob W. Ejsing, Julian von Landesberger†

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The information content in a given macroeconomic announcement is typically measured by its "surprise component", defined as the deviation between the actual outcome and a measure of market expectations. The main contribution of this paper is to derive, using a Bayesian learning model, a richer measure of the information content. This novel measure is the product of the standard surprise component and a term capturing the quality of the announcement as a signal of some underlying state variable of interest. We offer two empirical applications: one that analyses the process of expectations formation with respect to US manufacturing surveys, and another that provides new insights about German CPI releases.

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1 Introduction

Macroeconomic announcements and the influence they exert on financial market prices are closely monitored by policymakers such as central banks. Asset price reactions can provide central banks with real-time measures of changes in the outlook for economic growth and inflation outlook as perceived by investors.

Recent advances in econometric techniques and the availability of intraday data have helped improve the understanding of market reactions to news, see e.g. Andersen, Bollerslev, Diebold, and Vega (2003) and Fleming and Remolona (1999). Important findings within this strand of the literature are that US announcements on average tend to have the largest impact on global financial markets, and that the price discovery processes are very quick. It is standard practice in these studies to measure the information content in a given announcement by its "surprise component", which is commonly defined as the deviation between the actual outcome of a release and market expectations implied by surveys of financial analysts.

The main contribution of this paper is to derive, using of a Bayesian learning model, a richer measure of the information content in macroeconomic announcements. This novel measure is the product of the standard surprise component and a term capturing the quality of the announcement as a signal of some underlying state of interest (essentially a "Kalman gain"). The signal quality of a given announcement will generally depend on both the amount of measurement noise as well as on the variability of the state variable. These two sources of time variation are not captured by the standard measure of information content typically used in the literature.

Our approach rests on the simple observation that macroeconomic announcements can be grouped into broad categories such as "business confidence" or "price developments" indicators. Within each such category, there is a host of different announcements, which can all be regarded as noisy measurements of the same underlying phenomenon. The proposed model is similar in spirit to the one used by Hautsch and Hess (2007), but it is better suited to study linkages between releases over time, as it specifies how different announcements are related to the state variable relevant for asset pricing. Another related paper is Rigobon and Sack (2006), in which the authors construct an estimator to correct for bias in price impact regressions induced by measurement errors in market expecations.

We offer two different empirical applications of the proposed framework. The first concerns surveys of the US manufacturing sector. It is studied how the release of an important regional survey, the Chicago PMI, leads investors' to update their expectations about the nationwide ISM survey, which is released a few days later. We illustrate how the signal quality of the Chicago PMI varies over time and show that this is reflected in the intra-day reactions of asset prices. Standard time-series models are used to construct time-varying measures measurement noise and state variability. The resulting model-based measure of information content is shown to dominate the standard measure in asset price impact regressions. Moreover, as a robustness check the time-series based measure is shown to co-move positively with an alternative gauge based on dispersion in survey responses.

The second application of the framework is to German CPI announcements. This analysis directly addresses the puzzling results from earlier studies. In particular, both Andersson, Hansen, and Sebestyén (2006) and Ehrmann and Fratzscher (2003) found that pan-German inflation releases have had a limited impact on euro area benchmark interest rates, which is surprising given their potential monetary policy implications. We show that the muted market impact is related to the fact that six German federal states (Bundesländer) publish their own estimates, before the aggregate German inflation data are released. In contrast to the previous findings, we uncover systematic asset price responses and show how the learning model handles the stochastic ordering of regional German CPI releases in a simple and consistent way. This suggests that German inflation data do indeed influence asset prices, but via the individual federal state releases, rather than the pan-German inflation release.

2 A Bayesian learning framework

This section outlines our model dynamically linking a set of macroeconomic announcements through Bayesian learning. Many macroeconomic announcements can be grouped into broad categories, within which they can all be regarded as noisy measurements of the same underlying phenomenon. The model specifies how similar announcements within such a group can be linked, and how their impact on asset prices can be related to the amount of new information they provide. In a related paper, Hautsch and Hess (2007) apply a simple learning model to the case of one important macroeconomic announcement, i.e. the US employment report. Their focus, though, is to examine the relevance of information precision for price discovery, while the methodology developed here aims at linking the market impact of different releases over time.

Our framework consists of two main building blocks.

Firstly, a time-series model for an $N \times 1$ vector of macroeconomic announcements $X_t = \{x_{1,t}, \ldots, x_{N,t}\}$, time subscripts t denote the reference period of the announcements, typically in time steps of one month. We assume that all announcements $x_{i,t} \in X_t$ are observed each period, but not necessarily simultaneously. We consider the following simple, autoregressive model for X_t

$$A(L)X_t = \Lambda Z_t + \Omega \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim N(0, I_N)$ and Z_t is a set of exogenous variables, e.g. commodity prices or taxes. $A(L)$ is a lag polynomium in X, and Λ and Ω are model parameters. Let $\Sigma = \Omega'\Omega$ denote the conditional covariance matrix. The model thus specifies the conditional mean and covariance of the macroeconomic announcements.

Secondly, asset prices are supposed to be linearly related to macroeconomic announcements through a function $f(X_t)$[1]. Therefore, asset prices respond as market participants update their estimate of $f(X_t)$ in light of new information. To facilitate a precise description of the market participants' information set, we introduce the additional real-time subscript τ, which is used to denote the precise (possibly intra-day) poins in time, e.g. the exact time of a release.

We assume that the log asset price at time τ, p_τ, is linearly related to the expectation of $f(X_t)$ as of time τ

$$p_\tau = \beta_0 + \beta_1 E_\tau f(X_t)$$

which implies that the return upon the release of new information is given by

$$\Delta p_\tau = \beta_1 \Delta E_\tau f(X_t) \tag{2}$$

where Δp_τ refers to log return over a short period surrounding the release. To isolate the information provided by the release from other news, it is common to compute the return over a very short window, such as the 10 minutes from 5 minutes before the release to 5 minutes after.

When some element x_i is released, market participants face an information extraction problem: how to update the estimate of $f(X_t)$ given the knowledge of previosuly released elements of X_t? To answer this question, we first partition X_t into two subsets. Let $X^\tau_{1,t}$ denote the set of yet unreleased announcements within the reference period t, as of time τ, i.e. $X^\tau_{1,t} = \{x_{i,t} | x_{i,t} \notin \Im_\tau\}$, where $\Im_\tau$ is the market participants information at time τ. Let $X_{2,t}$ contain those elements which have already been released, i.e $X^\tau_{2,t} = \{x_{i,t} | x_{i,t} \in \Im_\tau\}$. The actually released values of $X_{2,t}$ are denoted $A_{2,t}$.

Using this partition, and dropping time subscripts for notational simplicity, we can write the mean μ and covariance matrix Σ of X as

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

and

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12} & \Sigma_{22} \end{bmatrix}$$

[1] In our two empirical applications, f will simply be a weighted average of the $x_{i,t}$'s.

Standard results for the multivariate normal distribution now imply that the distribution of X_1 conditional on $X_2 = A_2$ is multivariate normal $(X_1|X_2 = A_2) \sim N(\bar{\mu}_{1|2}, \bar{\Sigma}_{1|2})$ where

$$\bar{\mu}_{1|2} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(A_2 - \mu_2) \tag{3}$$

and

$$\bar{\Sigma}_{11|2} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} \tag{4}$$

Equation (3) states how to optimally update the estimate of any unreleased elements in X_t, given an actual announcement 's deviation from its expectation. This deviation, $A_2 - \mu_2$, is commonly refered to as the 'surprise component' of the announcement. Using the updated expectations for X_t, the expectations of $f(X_t)$ can be updated accordingly. Note that the updating rule does not take into account any parameter uncertainty (or non-normality of innovations), and should as such be seen as a first-order approximation to the optimal update[2].

The updating rule in (3) makes intuitive sense. For example, in the case $N = 2$, Σ_{12} is simply the conditional covariance of the two announcements, and Σ_{22} is the conditional variance of the figure released first. So if the announcements are conditionally uncorrelated, i.e. $\Sigma_{12} = 0$, no updating takes as the first announcement is uninformative about the later one. Also, if the announcement released first is very noisy, i.e. Σ_{22} is large, little updating is performed reflecting that the measurement is not very reliable. On the contrary, the observation of a highly correlated and precise announcement, should lead to a large change in the expectation of $f(X_t)$.

Note that the model allows the ordering of the observations of the x_i's to vary from period to period, such that sometimes x_i will be released before x_j, sometimes vice versa. This will prove very useful in our second empirical application, where such stochastic ordering is a central issue.

An important benefit of this framework is that it allows us to theoretically link the market impact of different, but related macro economic announcements. Instead of investigating asset price responses to each release in isolation, the market impact of different releases can be compared using the same metric, namely the extent to which they lead to an update of the underlying quantity of interest, here captured by $\Delta E_\tau f(X_t)$.

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[2]Subramanyam (1996) show how uncertainty about the measurement precision lead to a non-linear price response as a function of the size of the surprise. This analysis has recently been applied to macroeconomic announcements by Hautsch, Hess, and Müller (2007). The non-linearity arises as K_t itself becomes a function of the surprise component, because an observed surprise in this set-up leads to an update of both the level of the process and the precision of its measurement.
We abstract from this potential non-linearity in this paper.

Below we empirically implement the three key equations (1), (2) and (3) in learnings model for two different sets of macroeconomic announcements, i.e. survey of the US manufacturing sector and state-level German CPI releases.

3 Empirical applications

3.1 Application 1: Manufacturing indices

Releases of business climate surveys covering the US manufacturing sector have historically had a sizeable impact on asset prices, see e.g. Andersen, Bollerslev, Diebold, and Vega (2003) for a thorough analysis on US data and Andersson, Hansen, and Sebestyén (2006) for the euro area. There exist a number of regional manufacturing indices in addition to the nation-wide and most closely watched ISM (Institute for Supply Management) index[3]. As can be seen from Fig. 1 (top panel), the ISM exhibits a clear cyclical pattern. The ISM index and the regional Chicago Purchasing Manager Index[4] (PMI) fit nicely into the framework developed in the previous section, as they have moved closely in tandem historically, see Fig. 1 (lower panel), supporting the intuition that they measure the same underlying quantity. These indicators are constructed as diffusions indices, which means that a reading above 50 indicates that the business climate is perceived to be improving; and below 50 indicates a worsening. For our purposes, it is important to note that the Chicago PMI is always published before the ISM release, typically preceding it by one or three business days[5].

Given that the responses of the manufacturing firms in the Chicago survey to some extent mirror the nation-wide ISM index, the Chicago release can be used by market participants to draw inferences about the outcome of the ISM. Thus, it is reasonable to assume that market participants would revise their ISM expectations to any news component in the Chicago PMI.

We now formalise the this updating process by specifying the dynamics of the ISM Manufacturing index as an AR(1) process

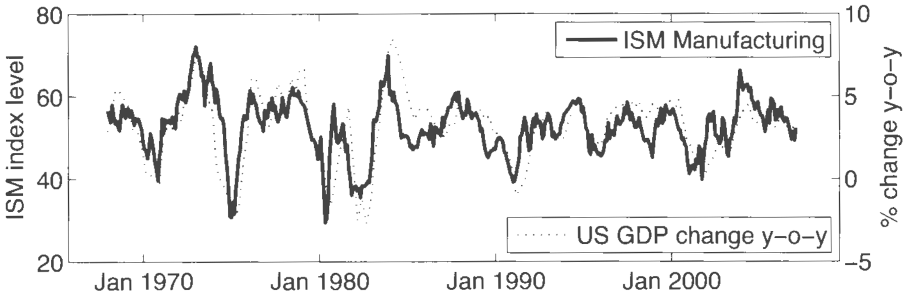
$$x_{1,t} = \alpha_0 + \alpha_1 x_{1,t-1} + \sigma_1 \varepsilon_{1,t} \tag{5}$$

and letting the Chicago PMI depend on the contemporaneous value of the ISM as well as its own lag to allow for some persistence in the deviation between the

[3] It is important to stress that the ISM survey is not an aggregation of the regional surveys, but an independent survey.

[4] The Chicago PMI is produced by the The National Association of Purchasing Management-Chicago and gauges factory health in the upper Midwest.

[5] For the 128 index releases referring to April 1997 through December 2007, in one case the ISM and Chicago PMI were published the same day, 64 times 1 day after, 45 times 2 or 3 days after, and 18 times 4 days or more.



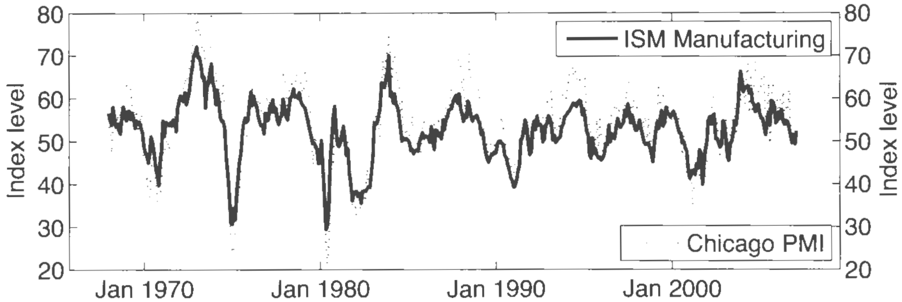


Figure 1: US Manufacturing indices. Top panel: ISM Manufacturing and change US GDP y-o-y in percent, quarterly GDP-data interpolated to monthly frequency. Lower panel: ISM Manufacturing and Chicago PMI. Monthly data. Jan. 1968 to Dec. 2006.

two series (see Fig. 1, lower panel)

$$x_{2,t} = \gamma_0 + \gamma_1 x_{1,t} + \gamma_2 x_{2,t-1} + \sigma_2 \varepsilon_{2,t} \tag{6}$$

Now, substitute equation (5) into (6) and notice that the system is a special case of the general framework introduced above (with $N = 2$ and $\Lambda = 0$), as we can write

$$\begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \gamma_0 + \gamma_1 \alpha_0 \end{bmatrix} + \begin{bmatrix} \alpha_1 & 0 \\ \gamma_1 \alpha_1 & \gamma_2 \end{bmatrix} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix} + \begin{bmatrix} \sigma_1 & 0 \\ \gamma_1 \sigma_1 & \sigma_2 \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

In this case, the conditional means are

$$\begin{aligned} \mu_1 &= \alpha_0 + \alpha_1 x_{1,t-1} \\ \mu_2 &= \gamma_0 + \gamma_1 \alpha_0 + \gamma_1 \alpha_1 x_{1,t-1} + \gamma_2 x_{2,t-1} \end{aligned}$$

and given that Chicago PMI is always released before the ISM, we immediately have the partitioning $X_{1,t}^{\tau} = x_{1,t}$ and $X_{2,t}^{\tau} = x_{2,t}$ upon the release of the Chicago PMI. This leads to the following covariance matrices

$$\begin{aligned} \Sigma_{11} &= \sigma_1^2 \\ \Sigma_{12} &= \gamma_1 \sigma_1^2 \\ \Sigma_{22} &= \gamma_1^2 \sigma_1^2 + \sigma_2^2 \end{aligned}$$

The updating rule in (3) then implies that

$$\begin{aligned} \bar{\mu}_{1|2} &= \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (a_2 - \mu_2) \\ &= \mu_1 + \frac{\gamma_1 \sigma_1^2}{\gamma_1^2 \sigma_1^2 + \sigma_2^2} (a_2 - \mu_2) \end{aligned}$$

Since the ISM is the nation-wide indicator, we will assume that it is the expectation of this figure which eventually matters for asset prices. We therefore take f to be[6]

$$f(X_t) = x_{1,t}$$

[6]This amounts to assuming that the level of bond yields is related to the level of the ISM index. This may be justified by the fact that monetary policy is oriented toward national, rather than regional data. Furthermore, it is common - especially among practioners - to construct so-called 'fair-value models', linking the level of long-term bond yields to e.g. the ISM index, core CPI inflation and the fed funds rate. A recent academic analysis along the same lines is Bandholz, Clostermann, and Seitz (2007). Alternatively, the relation could have arisen from a very stylized affine macro-factor term-structure model.

which implies that the update of the expectation of $f(X_t)$ upon observing the Chicago PMI release is given by[7]

$$\Delta_\tau E\left[f(X_t)\right] = \bar{\mu}_{1|2} - \mu_1 = \frac{\gamma_1 \sigma_1^2}{\gamma_1^2 \sigma_1^2 + \sigma_2^2}(a_2 - \mu_2) \tag{7}$$

This quantity can then be related to the impact on asset prices via equation (2). The empirical implementation of this model, to which we now turn, involves first recursively estimating the parameters σ_1, γ_1 and σ_2 and then quantifying the impact on expectations of $f(X_t)$ by (7).

3.1.1 Empirical implementation

To empirically implement the updating rule in equation (7), we need the parameter estimates $\hat{\gamma}_1^2$,$\hat{\sigma}_1^2$ and $\hat{\sigma}_2^2$. These were not known with certainty by market participants, and had to be estimated in real-time. Taking this into account, we estimate the time-series models in eqs. (5) and (6) based on variables which were part of market participants' real-time information set to produce the parameter estimates. The first step involves estimation of the univariate time-series model for ISM, reflecting the specification in (5). We fit an AR(1)-GARCH(1,1) model recursively to the ISM releases[8] and compute one-period ahead forecasts of the process's mean and conditional variance. This conditional variance is our estimate of $\sigma_{1,t}^2$.

The second step is to recursively estimate an ARMAX(1,0)-GARCH(1,1) to the Chicago PMI time-series with conditional mean as specified in equation (6). From this we construct one-period ahead forecasts of the mean and variance of the Chicago PMI using the one-period-ahead forecast of ISM in the conditional mean. The conditional variance from this model is the estimate $\hat{\sigma}_{2,t}^2$. From the equation for the conditional mean, we obtain the estimate $\hat{\gamma}_{1,t}$.

Now, we simply evaluate the updating equation (7) using these estimates which enables us to implement the asset price impact regression (2) which in this case reads

$$\Delta p_t = \beta_1 \hat{K}_t (x_{2,t} - \mu_{2,t}) \tag{8}$$

where

$$\hat{K}_t = \frac{\hat{\gamma}_{1,t} \hat{\sigma}_{1,t}^2}{\hat{\gamma}_{1,t}^2 \hat{\sigma}_{1,t}^2 + \hat{\sigma}_{2,t}^2} \tag{9}$$

[7]Clearly, upon the release of the ISM itself, the update in $E[f(X_t)]$ reduces to simply $E[f(X_t)] = a_1 - \mu_1$, reflecting the assumed perfect measurement of ISM.

[8]To have as long a sample as possible we use revised ISM data from January 1968 through March 1997, and unrevised data from April 1997 through December 2006. Since our price response regression start in 2000, we only use information available in real-time to form the parameter estimates.

measures how much market participants should update their estimate of the ISM given a surprise, $x_{2,t} - \mu_{2,t}$, in the Chicago PMI[9]. It is clear from (9) that a Chicago PMI surprise only leads to a noticeable update of the ISM expectation if the Chicago PMI is both related to the ISM, i.e. $\gamma_1 \neq 0$, and its associated measurement noise, σ_2^2 is reasonably low. Note that equation (8) can also be interpreted in the light of Rigobon and Sack (2006)'s discussion of the potential bias in the slope coefficient induced by an errors-in-variables problem.

Figure (2) shows the estimate $\hat{K}_t$ (top panel) over time as well as the absolute deviations between the ISM and the Chicago PMI. The estimated value of $\hat{K}_t$ exhibits considerable time-variation around its mean of 0.35, which means that, on average, a surprise in the Chicago PMI will induce an update of ISM expectations of about a third of the observed surprise. Interestingly, and in line with intuition, the value of $\hat{K}_t$ reach its lowest levels around the beginning of 2005, where the deviation between the ISM and Chicago was particularly high and volatile, see the lower panel of Figure 2. The model therefore suggests that in this period, the Chicago was an unreliable measure of nation-wide business confidence, implying that Chicago PMI surprises should be heavily discounted and thus have little market impact.

In addition, our learning model implies the following for asset price response to ISM itself, since $f(X_t) = x_{1,t}$

$$\Delta p_t = \beta_1 \Delta E_\tau f(X_t) = \beta_1 (x_{1,t} - \mu_{1,t}) \tag{10}$$

Therefore, the asset price impact of a surprise of in the Chicago PMI should be equal to $\hat{K}_t$ times the impact of a similar sized surprise in the ISM. After a brief description of the data, we present the results of the empirical counterparts to (8) and (10).

3.1.2 Data

For the manufacturing indices, we use monthly data provided by Bloomberg. Revised series, including revisions made after the first release, are available back to January 1968, while the time-series of actual releases, which is the series relevant for real-time price impact, only goes back to April 1997. Table 1 provides summary statistics. Nevertheless, the three decades worth of revised data are useful for the initial estimation of the time-series models, i.e. for the period before the out-of-sample exercise. The first out-of-sample mean and variance estimate for the ISM index refer to April 1987, based on data from Jan 1968 through March

[9]Note that this can also be interpreted as the optimal gain in a Kalman filter set-up, assuming no parameter uncertainty. The feature that we specify all variables to be observable, could be accomodated in a Kalman filter by adding a zero-noise measurement equation.

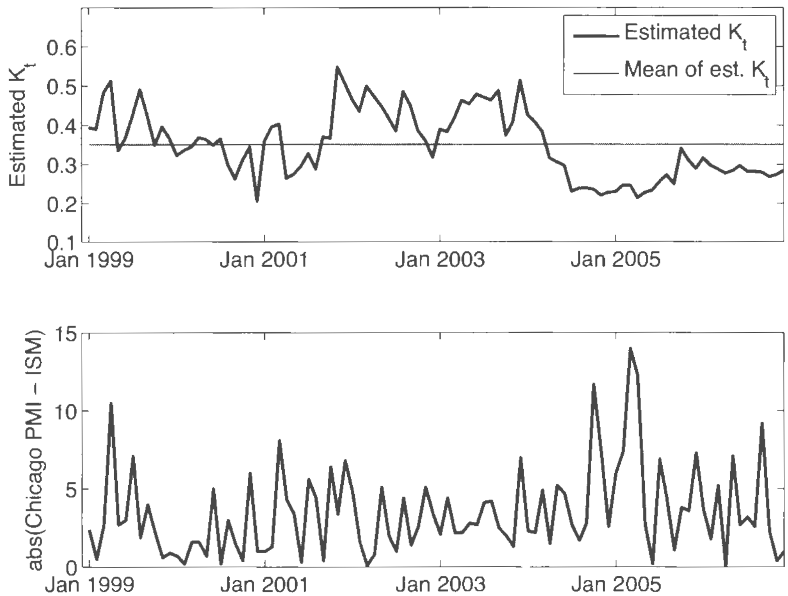


Figure 2: Top panel: $\hat{K_t}$ over time. Lower panel: Absolute difference between actual monthly releases of the ISM and the Chicago PMI. The sample is Jan. 1999 - Dec. 2006, N=96.

	N	Mean	St.dev.	Min	Max
Chicago PMI release revised	468.00	54.79	9.29	21.30	79.40
Chicago PMI release unrevised	117.00	55.04	7.03	35.00	69.20
Chicago PMI unrev. Jan. 1999-	96.00	54.69	7.47	35.00	69.20
10 min return around Chicago PMI	96.00	-0.00	0.16	-0.41	0.47
ISM release revised	468.00	52.67	6.76	29.40	72.10
ISM release unrevised	117.00	53.11	5.14	39.80	66.20
ISM unrev. Jan. 1999-	96.00	53.24	5.42	39.80	66.20
10 min return around ISM	96.00	-0.03	0.17	-0.66	0.51

Table 1: Descriptive statistics. Returns are 10 min. returns on US ten-year bond futures in percent

1987, a total of 231 observations. The first 120 monthly ISM forecasts are used for calibrating the time-series model for Chicago PMI, for which the first out-of-sample forecasts refer to January 1999. This amounts to a total of 96 monthly forecasts of Chicago PMI covering the period January 1999 through December 2006.

Intraday returns were calculated using data on ten-year bond futures data provided by TickData Inc. See Andersson, Hansen, and Sebestyén (2006) for more details about these data.

3.1.3 Results

Tables 2 and 3 show the parameter estimates for the time-series models used to generate the first out-of-sample forecasts, i.e. for January 1999 for the ISM and the Chicago PMI. Model selection according to AIC and BIC suggests that the AR(1)-GARCH(1,1) is well suited to ISM data, which display strong persistence in volatility. Likewise for the Chicago PMI, where the contemporaneous ISM release enters highly significantly into the model, while the evidence of time-variation in the conditional variance is somewhat less pronounced.

Table 4 reports the results of the regressions both including $\hat{K}_t$

$$\Delta p_t = \beta_0 + \beta_1 \hat{K}_t S_{i,\tau} + u_{i,\tau}$$

as well as the standard price impact regression typically employed in the literature

$$\Delta p_t = b_0 + b_1 S_{i,\tau} + v_{i,\tau}$$

The table shows that accounting for the time variation in the information content of the Chicago PMI with respect to the ISM, as captured by the estimated gain $\hat{K}_t$, more of the intra-day asset price response can be explained than by using

Parameter	Point est.	Std. error	t-statistic
α_0	3.43	0.83	4.14
α_1	0.93	0.02	59.85
ω_0	0.89	0.36	2.51
ω_1	0.66	0.08	7.82
ω_2	0.20	0.05	3.75

Table 2: Maximum likelihood estimates of the following GARCH(1,1) model for the conditional variance of ISM Manufacturing releases: $\sigma^2_{1,t} = \omega_0 + \omega_1 \sigma^2_{1,t-1} + \omega_2 \epsilon^2_{1,t}$. The parameters α_0 and α_1 are those specified in equation (5). The sample is Jan. 1968 - Dec. 1998, N=372.

Parameter	Point est.	Std. error	t-statistic
γ_0	-6.13	2.12	-2.89
γ_1	0.72	0.07	10.61
γ_2	0.44	0.05	8.63
ω_0	2.39	0.89	2.68
ω_1	0.34	0.15	2.21
ω_2	0.31	0.16	1.92

Table 3: Maximum likelihood estimates of the following GARCH(1,1) model for the conditional variance of Chicago PMI releases: $\sigma^2_{2,t} = \kappa_0 + \kappa_1 \sigma^2_{2,t-1} + \kappa_2 \epsilon^2_{2,t}$. The parameters γ_0, γ_1 and γ_2 are those specified in equation (6). The sample is Apr. 1987 - Dec. 1998, N=140.

	Point est.	t-value	R^2
S_τ from survey			
β_1 (regr. including $\hat{K}_t$)	-0.0822	-9.42	0.53
b_1(excluding $\hat{K}_t$)	-0.0270	-8.15	0.48
S_τ from AR-model			
β_1 (regr. including $\hat{K}_t$)	-0.0640	-7.65	0.40
b_1(excluding $\hat{K}_t$)	-0.0270	-7.84	0.38

Table 4: OLS estimates of the impact of surprises in Chicago PMI on bond futures prices. The results in the first line of the table refer to β_1 in the regression is $\Delta p_\tau = \beta_0 + \beta_1 \hat{K}_\tau S_\tau + u_\tau$. The results in the second line of the table refer to the standard price impact regression $\Delta p_\tau = \beta_0 + \beta_1 S_\tau + u_\tau$. Results are provided for both survey-based and model-based measured of the surprise component. Standard errors are Newey-West. Returns are calculated from the change in log prices of ten-year US bond futures from 5 min. before the release to 5 min. after. The sample is Jan. 1999 - Dec. 2006, N=96.

the standard set-up with the unadjusted surprise component. This holds whether survey-based or model-based measure of the surprise $S_{i,\tau}$ are used. Unsurpringly, the table also shows that when using the surprise component measure $S_{i,\tau}$ based on the purely autoregressive model, a smaller part of the variation in bond returns can be accounted for. This is to be expected as the model only uses historical values of the announcement series, and therefore do not reflect other sources of information which may be reflected in the survey expectation. The results illustrate the potential usefulness of including gain-measures in the price impact regression, while the inclusion of forward-looking information into the model-based expectation is left for future work[10].

Moreover, in a 'horse race regression' in the style of Fair and Shiller (2003), see Table 5, where returns are simultaneously regressed on both the standard surprise component and its gain-augmented counterpart, the standard surprise component is completely driven out.

We now turn to the implication that the raw coefficient of the ISM should not differ significantly from the coefficient of the Chicago PMI surprise adjusted by $\hat{K}_t$, i.e. β_1 reported in Table 4. As can be seen by comparing Table 4 and 6, the market impact of the Chicago appear to be slightly higher than expected given the estimated impact of the ISM releases. Note, however, that the respective 95% confidence intervals of the two parameter estimates overlap. This comparison illustrates how the learning framework allows for an assessment of the market

[10]This could be done e.g. by using the survey expectation of Chicago PMI as an additional measurement equation in a Kalman Filter set-up.

	Point est.	t-value
S_τ from survey		
β_1	-0.1026	-3.04
b_1	0.0073	0.71
S_τ from AR-model		
β_1	-0.0572	-1.73
b_1	-0.0026	-0.24

Table 5: OLS estimates of the impact of surprises in Chicago PMI on bond futures prices using a 'horse race regression'. The results refer to the regression is $\Delta p_\tau = \beta_0 + \beta_1 \tilde{K}_\tau S_\tau + b_1 S_\tau + u_\tau$. $R^2 = 0.53$. Results are provided for both survey-based and model-based measured of the surprise component. Standard errors are Newey-West. Returns are calculated from the change in log prices of ten-year US bond futures from 5 min. before the release to 5 min. after. The sample is Jan. 1999 - Dec. 2006. N=96.

	Point est.	t-value	R^2
$\beta_1(S_\tau$ from survey)	-0.0588	-7.27	0.46
$\beta_1(S_\tau$ from AR-model)	-0.0392	-6.10	0.28

Table 6: OLS estimates of the impact of surprises in ISM on bond futures prices. The β_1 refers to the regression is $\Delta p_\tau = \beta_0 + \beta_1 S_\tau + u_\tau$. Standard error are Newey-West. Returns are calculated from the change in prices of ten-year US bond futures from 5 min. before the release to 5 min. after. The sample is Jan. 1999 - Dec. 2006, N=96.

impact of different announcements by use of a common metric, i.e. the slope coefficient of the gain-adjusted regression. Future applications to wider set of business confidence indicators would a allow for a more rigorous assessment of the null hypothesis of parameter equality across releases.

3.1.4 Robustness checks

The learning model implies that investors should update their estimate of the ISM after having observed a surprise in the Chicago PMI. As shown, the magnitude of this update should in theory depend on the size of surprises, the covariance between the Chicago PMI and the ISM, and on the perceived precision of the Chicago PMI as a measure of the ISM.

Evidence, based on another data source, is now supplied that this updating indeed seems to take place in practice. News services, such as Bloomberg, collect individual analysts' forecasts concerning a large number of macro economic an-

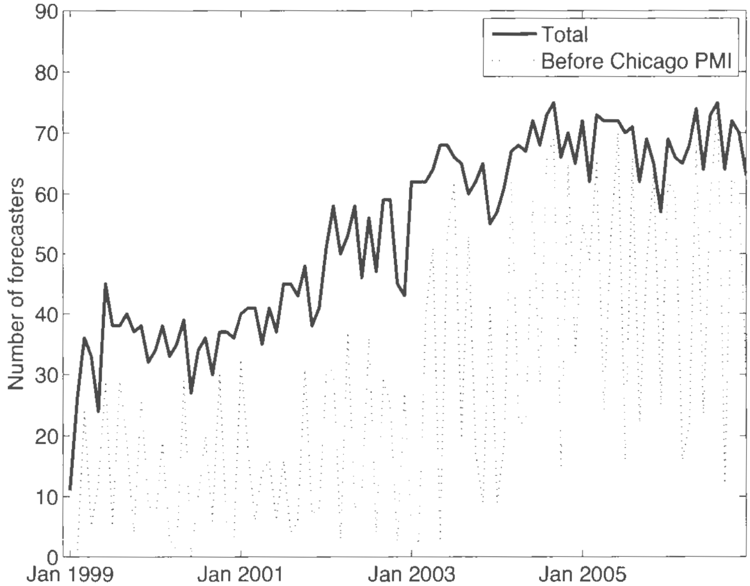


Figure 3: Total number of respondents in Bloomberg's ISM Manufacturing survey and the number of respondents submitting their estimate before the release of Chicago PMI.

nouncements, including the ISM and the Chicago PMI. By splitting the sample of ISM analysts' according to when they submitted their forecast to Bloomberg, proxies for market expectations of ISM before and after the release of Chicago PMI can be constructed.

Fig. 4 shows the change in the mean of these two samples plotted against the surprise component in the Chicago PMI (computed as the difference between actual outcome of the release and mean of individual analysts' forecasts). The figure shows that there is a positive relationship, suggesting that a higher (lower) than expected outcome of the Chicago PMI indeed causes market participants to revise up (down) their ISM expectations. However, the extent of the updating suggested by the surveys appear surprisingly small: on average, a one point higher than expected Chicago PMI outcome induces only a 0.1 percentage point upward revision in ISM survey expectations. Interestingly, this is much lower compared to the impact implied by the model, which is about 0.35 on average, see Figure 2. The size of the market reaction to Chicago PMI, as documented in Table 4 appears

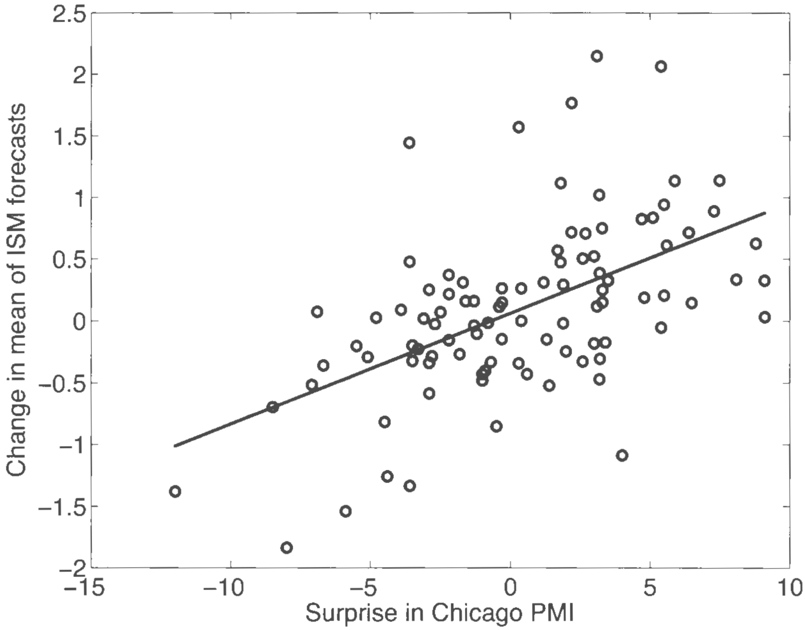


Figure 4: Surprise component of Chicago PMI and subsequent changes in ISM survey expectations. The slope of the regression line 0.089 (Newey-West t-value of 6.34. N=96).

to have been even stronger than the learning model would have suggested, which point an even higher value of K_t. So although surveys qualitatively gives the same picture, the limited amount of updating seen in surveys, may - in the light of the relatively strong market impact - indicate that the surveys in this cases have failed to fully capture the dynamic updating of investors' expectations.

As a cross-check of the time-series based measures of K_t used above, it is of interest to construct an alternative measure based on an independent source of information, namely surveys of financial market analysts. We use data from Bloomberg on individual forecasters' estimates and their dates of submission, covering the same 96 months as the regressions presented above. Fig. 3 shows the number of analysts who entered their ISM forecast before the Chicago PMI release, along with the total number of analysts that month. Forecasts submitted on the day of the Chicago PMI release are grouped as 'after', as it appears most likely that forecasters awaited this important piece of information, given that they choose to enter their estimate on this day. Although the total number of survey participants has grown steadily to reach a level of about 70, the size of the 'before' groups clearly oscillates from month to month.

From individual survey responses the 'disagreement' can be calculated, defined as the standard deviation of individual survey responses. The analysis in Gürkaynak and Wolfers (2006), where uncertainty is measured by implied densities derived form options on economic announcements, suggests that disagreement and uncertainty could be proportional[11]. Assuming proportionality and using the estimate $\hat{\gamma}_1$ from Table 3, we can construct an alternative measure for the gain as

$$\tilde{K}_t^{survey} = \frac{\hat{\gamma}_1 \tilde{\sigma}_{1,t}^2}{\hat{\gamma}_1 \tilde{\sigma}_{1,t}^2 + \tilde{\sigma}_{2,t}^2}$$

where $\tilde{\sigma}_{i,t}$ denotes disagreement about announcement i at time t. Figure (5) plots the two different measures of K over time. Even though they were obtained in two completely independent ways, they seem to capture the same underlying movements in the reliability of the Chicago PMi as a measure of ISM manufacturing. The much more erratic behaviour of the survey-based measure is partly attributable to large month-to-month variation in the number of available survey respondents, see figure 3.

Table 7 shows that this measure of the gain also improves the explanatory power of the price impact regression, strengthening the case for including gain-measures in the price impact regression. In a horse-race regression (not reported), both gain-augmented measures remain statistically significant, while the standard measure becomes insignificant.

Finally, a brief look at the forecasting performance of the estimated time-series models for ISM and Chicago PMI. The primary purpose of the models is to construct a rough gauge of the time variation in the conditional variances, rather than to provide precise forecasts the releases themselves. Nevertheless, as we would like model-implied forecasts to be reasonably accurate, it is of interest to compare the forecasts from these models with two obvious benchmarks, such as a naive (random walk/ 'no-change') forecast and consensus forecasts from surveys of analysts. Table 8 shows the root mean squared error (RMSE) of the alternative

[11]The disagreement (see e.g. Bomberger (1996) for a discussion) is typically much lower than uncertainty, i.e. the conditional standard deviation. This is because it measures the dispersion of the means of the individual respondents, which would e.g. be zero in the extreme situation were all analysts agree on the mean, while each respondent's distribution has a high variance - implying considerable uncertainty about the outcome. Wallis (2005) proposes a finite mixture distribution as a statistical model for combined density forecasts, in which case the combined density forecasts turn out to be the sum of the average individual variances and a measure of dispersion of the individual point forecasts. In this case, disagreement and uncertainty would not be proportional.

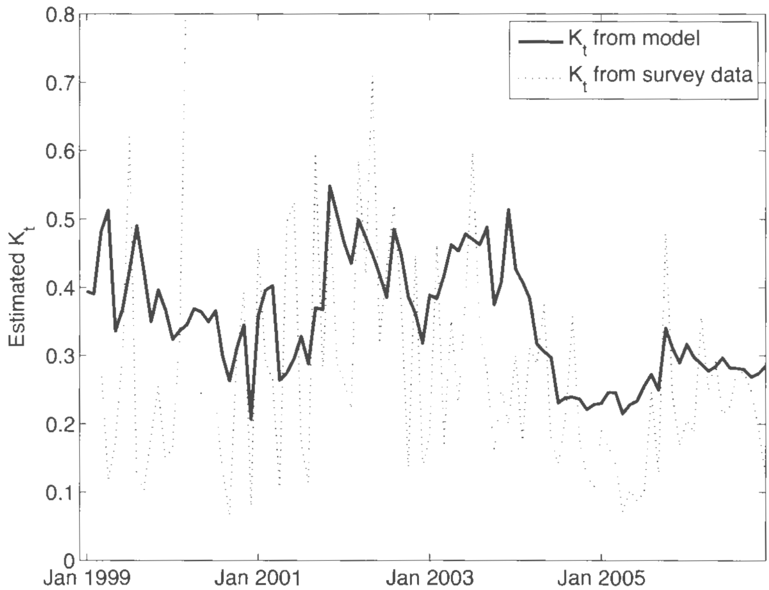


Figure 5: Model-based and survey-based $\hat{K}_t$ over time. The sample is Jan. 1999 - Dec. 2006, N=96, exluding two month where survey data where not available.

	Point est.	t-value	R^2
β_1 (regression including $\hat{K}_t^{survey}$)	-0.1478	-9.50	0.55
β_1 (regression including $\hat{K}_t$)	-0.0832	-9.49	0.54
b_1(standard surprise)	-0.0272	-8.10	0.48

Table 7: OLS estimates of the impact of surprises in Chicago PMI on bond futures prices using two different measures of K_t, one derived from surveys, the other from the time-series models. The S_τ's are constructed using surveys. The results in the first line of the table refer to β_1 in the regression is $\Delta p_\tau = \beta_0 + \beta_1 \hat{K}_\tau^{survey} S_\tau + u_\tau$. The second line refer to β_1 in the regression is $\Delta p_\tau = \beta_0 + \beta_1 \hat{K}_\tau S_\tau + u_\tau$. The third line refers to the standard price impact regression $\Delta p_\tau = \beta_0 + \beta_1 S_\tau + u_\tau$. Standard error are Newey-West. Returns are calculated from the change in prices of ten-year US bond futures from 5 min. before the release to 5 min. after. The sample is Jan. 1999 - Dec. 2006, N=94. In two instances there where no ISM survey data available prior to the Chicago release. These observations where deleted from all 3 regressions.

	RMSE	Normalised RMSE
ISM manufacturing		
Random walk	2.48	100.0
Survey	2.05	82.8
AR(1)-model	2.43	97.9
Chicago PMI		
Random walk	5.17	100.0
Survey	4.25	82.2
ARMAX(1,0)-model	4.63	89.7

Table 8: Root Mean Squared Errors for forecasts of ISM manufacturing and Chicago PMI. The sample is Jan. 1999 - Dec. 2006, N=96.

ISM and Chicago PMI predictions. The time-series models clearly outperform the naive alternative, while they - as should be expected given the reliance only on the past history of the series themselves - display inferior precision compared to surveys. Moreover, for the ISM we can compare survey forecasts made before and after the release of Chicago PMI, and the 'after' group appear to be slightly more precise, reflecting the superior information set.

3.2 Application 2: German CPI Inflation

We now turn to the application of the Bayesian learning framework to German CPI releases, which pose particular problems for the standard analysis of announcement effects. The reason is that consumer price data of six German federal states are released prior to the publication of the preliminary estimate by the Federal Statistical Office[12]. This often means that the surprise component in the aggregate release is rather small, which can explain to muted market reaction to this release found in previous studies. In principle, the standard methodology could overcome this problem by measuring the market impact of the state-level releases. There are, however, two institutional features which need to be taken into account before embarking on measuring the asset price sensitivity to the state-level releases. First, there are in general there no pre-announced publication calendar for the preliminary German CPI data, neither at the state nor at the federal level. However, market participants are informed that the data will mostly likely be published in an interval ranging between the 22nd and the 24th of the reference month. Second, the ordering of the individual state releases varies

[12]These are Baden-Wuerttemberg, Bavaria, Brandenburg, Hesse, North Rhine-Westphalia and Saxony. In a limited number of cases, Brandenburg published its data after the release of the pan-German estimate.

State	Weight. %
Baden-Wuerttemberg	24
North Rhine-Wesphalia	35
Bavaria	18
Hesse	10
Brandenbrug	8
Saxony	5

Table 9: Approximate weights of individual states in the preliminary pan-German CPI.

from month to month. The pan-German preliminary CPI release is not a purely mechanical aggregation of the six state CPI indices, but with the information from the six states available, an estimate within a ten basis points error band of the pan-German estimate can normally be computed. The weights for each state, reflecting the state consumption levels, differ quite substantially, see Table (9).

The strength of the market impact of a state release will generally depend on how many other states have already released their figures, the conditional covariance of regional releases as well on the weight of each state in the preliminary pan-German CPI. Standard price impact regression will fail to capture this time variation in the market impact.

It turns out that the learning framework presented above easily handles these complications. We model the regional inflation figures as in (1), allowing for exogenous variables and correlation between the error terms. Given a monetary policy framework oriented toward aggregate inflation it is reasonable to assume that asset prices are linked to aggregate inflation. In other words, we take f to be the weighted average

$$f(X_t) = \delta^T X_t \tag{11}$$

where δ are weights summing to one.

3.3 Estimates of market impact using the standard approach

As an analysis of the market impact of individual German states' CPI releases is new in itself, we begin by providing some suggestive results, which can be obtained with the standard event-study set-up. After that we turn to the additional insights offered by the learning framework.

To empirically assess the market impact within the standard framework, we need a measure of the surprise. Unfortunately, one cannot calculate the surprise component of the individual state releases in the standard way, as they are not

Parameter	Point est.	Std. error	t-statistic
β_{BW}	-0.0181	0.0168	-1.08
β_{NR}	-0.0239	0.0065	-3.68
β_{BV}	-0.0260	0.0139	-1.87
β_{HE}	-0.0151	0.0136	-1.11
β_{BR}	0.0095	0.0065	1.45
β_{SA}	0.0029	0.0066	0.45

Table 10: OLS estimates of 10 min. German bond futures returns regressed on surprises in CPI releases of individual German state. The regression is $\Delta p_\tau = \beta_0 + \beta_1 S_{i,\tau} + \theta controls_\tau + u_\tau$. Standard errors are Newey-West. Controls include concomitant euro area, US and UK releases. For the abbreviation used for German states, see the caption of Figure (6). Returns are calculated from the change in prices of ten-year German bond futures from 5 min. before the release to 5 min. after. The sample is Dec. 1999 - Dec. 2006, N=85.

covered in standard market surveys (such as Bloomberg's). In order quantify the incremental information embodied in the releases, a forecast for the individual state data was derived using autoregressive linear regression models (see the appendix for more details). It should be noted, however, that the forecasts can only be considered a very rough approximation of the market expectations.

Taking the forecasts at face value, surprises for German state CPI releases can be computed by subtracting the model based forecasts from the actual releases. German bond futures returns are regressed on these surprises using the standard event-study set-up

$$\Delta p_\tau = \beta_0 + \beta_1 S_{i,\tau} + \theta controls_t + u_\tau$$

where Δp_τ is the 10 min. return around the release, $S_{i,\tau}$ the surprise component and the controls include concomitant euro area, US and UK releases. Four findings can be inferred from Table (10). First, over the whole sample, the releases of the Bavaria and the North Rhine-Westphalia both exert a significant impact on the ten-year maturity spectrum and Bavaria also moves the two-year segment (not shown) - probably reflecting these states' relatively high weight. Second, although Baden-Wuerttemberg is the second most important state for the compilation of the pan-German estimate, surprisingly, the market seems not to react to the release. Third, in the case of Brandenburg and Saxony, the parameter estimates are insignificant, mirroring their low weight, see Table 9. Fourth, overall the coefficients are rather small.

To assess whether also the ordering of the releases matters for market reactions, Table 11 shows the results obtained when regressing bond futures returns

Parameter	Point est.	Std. error	t-statistic
β_1(first release)	-0.0335	0.0117	-2.87
β_2(second release)	0.0019	0.0059	0.31
β_2(third release)	-0.0059	0.0092	-0.64

Table 11: OLS estimates of 10 min. German bond futures returns regressed on surprises in CPI releases of individual German state grouped by order of release in each month. The regression is $\Delta p_\tau = \beta_0 + \beta_1 S_{i,\tau} + \theta controls_\tau + u_\tau$. Standard errors are Newey-West. Controls include concomitant euro area, US and UK releases. For the abbreviation used for German states, see the caption of Figure (6). Returns are calculated from the change in prices of ten-year German bond futures from 5 min. before the release to 5 min. after. The sample is Dec. 1999 - Dec. 2006, N=83, due to two missing observations.

on the surprise component of the first, second and third releases (independent of which state provided the estimate). Interestingly, the markets seem to react significantly to the first release of the monthly cycle. The second and third releases tend not to be particularly informative, as they are often insignificant. This finding suggests that the first release is considered as news for the market to trade on, while later releases are seen as less informative.

We now turn to consider these empirical patterns in the light of the learning framework.

3.3.1 Dynamic formation of CPI expectations

Using equations (2) and (3) together with (11), we can derive the theoretical update of the pan-German inflation estimate, $E_\tau f(X_t)$, associated with each release. This will, by virtue of the explicit learning framework, take into account the issues related to the weighting, ordering and correlation of releases and integrate the influence of these factors into one simple statistic, $\hat{K}_t$. Table 12 shows the result of a regression augmented the standard surprise component with $\hat{K}_t$, along with the standard regression. We see that while the standard surprise component is statistically insignificant, the augmented surprise measure enters very significantly.

The impact of a release x_i can be decomposed into two effects. The first effect is a direct effect equal to $\delta_i(x_{i,t} - E_\tau x_{i,t})$, which reflect the weight of the state in the pan-German CPI as well as the size of the surprise. The second effect is indirect and captures the fact that the whole vector $X_{1,t}$ is updated in response to each new release. Especially for the first few releases, the indirect effect may outweigh the direct effect. The intuition is that even a state with a small weight can have a large market impact if releases are highly correlated, as it conveys

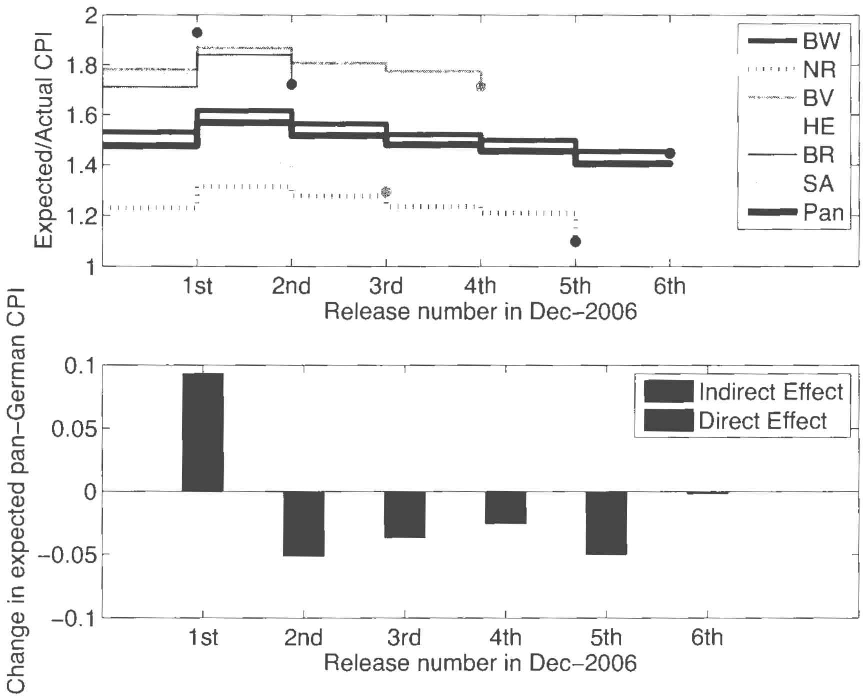


Figure 6: Dynamically learning about German CPI. The figure illustrates the six state-level CPI releases of one particular month, i.e. December 2006. The top panel shows how expectations of CPI change in response to the publication of each state-level release. The lines depict expectations, and the dots at the end of each line show the actually released value for the given state. The evolution of the expectation of the level of the pan-German is also shown (the thick black line). The lower panel shows the change in the expectation of the pan-German CPI in response to each state-level release, i.e. first differences of the thick, black line in the top panel (BW: Baden-Wuerttemberg, NR: North Rhine-Westphalia. BV: Bavaria. HE: Hesse. BR: Brandenburg, SA: Saxony and Pan: Pan-Germany).

	Point est.	t-value
β_1 (regression including $\hat{K}_t$)	-0.0022	-4.05
b_1(model excluding $\hat{K}_t$)	-0.1600	-0.36

Table 12: OLS estimates of the impact of surprises in individual German state CPI releases on bond futures prices. The results in the first line of the table refer to β_1 in the regression is $\Delta p_\tau = \beta_0 + \beta_1 \hat{K}_\tau S_\tau + u_\tau$. The results in the second line of the table refer to the standard price impact regression $\Delta p_\tau = \beta_0 + \beta_1 S_\tau + u_\tau$. Standard errors are Newey-West. Returns are calculated from the change in prices of ten-year German ten-year bond futures from 5 min. before the release to 5 min. after. The sample is Jan. 2004 - Dec. 2006, N=216 (36 months of 6 releases each).

information about more weighty states. The last release, on the other hand, can only carry information about this particular state, so the market impact will be confined to the direct effect. For the sake of illustrating this learning process, Figure 6 shows the model-implied updates in reponses to each state-level release in Dec. 2006. The first released figure this month was for Saxony, which showed a higher than expected CPI inflation. The expectations for each state CPI before this first release are the one-step ahead forecasts from the time-series model. As can be seen in the top panel of the figure, the expectation of all other states was adjusted upward in response to the Saxony release, giving this release a strong impact considering the Saxony's weight of just 5% in the pan-German figure. The lower panel of the figure shows the decomposition of the impact of the expectations of pan-German CPI into its direct and indirect components.

4 Conclusion

Each day, investors have to incorporate and filter the information content of a vast number of macroeconomic announcements, earning statements and monetary policy publications when they price financial assets. Previous studies in this strand of the literature have assumed that price reactions to data releases are directly and linearly related to the surprise component embedded in the data releases, the latter usually measured as the difference between actual and expected outcome of the releases. This procedure, however, misses out on one important feature, namely that asset price response also depends on the quality of the information embedded in the data releases.

Using a simple learning model, this paper proposes a general framework of how investors update their information set concerning a number of data releases that measure the same underlying phenomenon. Applied on monthly announcements, we use the learning setup to show that releases of early estimates induces revised expectations for those announcements that are released later on in the cycle. The magnitude of the revisions depends however not only on the surprise components but crucially also on the perceived reliability and variability of the early estimates.

The paper uses the learning model to examine the asset price impact on two, by the markets, closely monitored categories of data releases – business surveys covering the US manufacturing sector and regional German CPI releases. Intraday data on the US and German long-term bond futures are used to gauge the financial markets impacts from the US and German releases respectively.

For the US manufacturing releases, the resulting model-based measure of information content is shown to dominate the standard measure in asset price impact regressions. Moreover, as a robustness check the time-series based measure is shown to co-move positively with an alternative gauge based on dispersion in survey responses.

In the second case study, we show that the muted market impact on pan-German CPI releases is related to the fact that six German federal states (Bundesländer) publish their own estimates, before the aggregate German inflation data are released. In contrast to the previous findings, we uncover systematic asset price responses and show how the learning model handles the stochastic ordering of regional German CPI releases in a simple and consistent way. This suggests that German inflation data do indeed influence asset prices, but via the individual federal state releases, rather than the pan-German inflation release.

This paper has shown, in two case studies, that asset price sensitivity and expectations to data releases within the same category appear to be dynamically interrelated. Extensions to other announcements and economies are left for future research.

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A Appendix: Forecasting model for state-level German CPI

Since no surveys exist for the state-level German CPI releases, we construct a proxy for market expectation by use of forecasts from a dynamically reestimated time-series model, including relevant exogenous factors. The forecast for the individual states are constructed using autoregressive linear regression model estimated on a sample beginning in 1991:1 up to the respective forecast period, i.e. 1999:12 to 2006:12

$$\pi_t^i = \sum_{j=1}^{12} \alpha_j^i \pi_{t-j}^i + \beta f_t + \delta \Delta com_t + \phi tax_t + \varepsilon_t$$

where π_t^i is the annual percentage change in the CPI of a state (with i = BA, BR, BW, HE, NRW, SA) in period t, f_t is the Bloomberg expectation for the German CPI for the current month, Δcom_t is the annual percentage change in the HWWA (Hamburg Institute of International Economics) commodity price index and tax_t is the annual percentage change in a step dummy capturing the evolution of the mineral oil tax. For Saxony and Brandenburg, additional dummy variables are included for 1994:1 to capture price liberalisation in those two Länder. Up to and including January 2003, the forecast were computed on the basis of the original state CPIs (1995=100) as they were relevant. From February 2003 onwards, the CPI with weighting scheme from 2000 was used.

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