Discussion Paper No. 07-012

Stale Information, Shocks and Volatility

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Non-Technical Summary

Stock volatility can be the result of the arrival of public information, the presence of differences private information (or beliefs) among traders and the presence of irrational noise traders (mis-pricing). In this paper we use a new approach to estimate the effect of differences in private information on volatility. We examine the question in the context of high frequency stock returns for a set of large European banks. We use a well identified, unexpected shock (monetary policy surprises) and estimate the change in banks' stock return volatility. To measure volatility, we use "realised volatility", as recently proposed by Andersen et al. (2003). We relate the change in volatility to a proxy for the accuracy or "freshness" of public information available about banks, the annual report. Our hypothesis is that if the public information available is stale, we should observe a larger spike in volatility, if volatility is driven by traders with different private information or beliefs. We argue that higher quality, timelier public information results in a closer alignment of information sets of traders, leaving less room for private information or beliefs to drive volatility. We also hypothesise and test an inverse relation between the persistence of volatility and the quality of the publicly available information.

The paper can be viewed as a test of the theories on the effect of difference of opinions or differences in the interpretation of public information among traders on volatility. In our paper, we use the quality of the public information that traders receive as a proxy for the extent to which they will differ in their interpretation of this information. If the public signal is more precise this leaves less room for differences in interpretation and therefore the spike in volatility subsequent to a shock should be smaller and less persistent. In the paper, we use the vintage of the release of the annual report as a measure of the precision of the information available about banks and, hence, the degree to which traders may disagree as to the extent of the implications of the monetary policy shock. Specifically, we estimate the change in volatility due to the shock as a function of the number of months, since the bank published its last annual report. Hence, we examine whether the effect on volatility is smaller if the bank just published its annual report last month compared to the volatility response if the bank published its last annual report, say, 8 months ago. The argument is quite simple: The more recent the publication of the annual report, the smaller the disagreement of traders as to the implications of the shock for the future profitability of the bank. Equivalently, the more recent the publication of the annual report, the more aligned the information sets of traders and the less important private information. Of course, these arguments only apply, if annual reports of banks in fact convey any useful information to markets. In this sense, our approach is a joint test of the presence of private information and the value of bank annual reports to markets.

The paper is directly related to the question of the opacity of banks' assets (Morgan, 2002; Flannery et al., 2004) and whether publishing annual reports generally and whether improving the frequency and quality of these reports specifically, reduces this opacity and is valuable to the market. In this paper we relate opacity to the importance of private information in the market. If banks are indeed opaque, the volatility of banks' stocks can be expected to increase significantly upon the arrival of surprising and relevant news and evidence that this volatility spike is lower for banks for which fresher public information is available would suggest that the vintage and the quality of accounting information matters and reduces the degree of opacity. Our results suggest that (i) un-anticipated monetary policy shocks result in a significant short term increase in bank stock volatility; anticipated monetary policy shocks do not; (ii) the increase in volatility is significantly higher in the case of banks, for which publicly available information is stale; (iii) this difference is economically quite large; and (iv) the increase in volatility is significantly more persistent in the case of banks, for which the publicly available information is stale, although this effect is economically small.

The results have a bearing for the recent debate surrounding the idea to increase transparency of banks, reflected in Pillar III of the New Basel Accord. The New Accord will ask banks to significantly increase the information that they should report to markets. The results presented in this paper suggest that the implementation of these transparency requirements is important. The results of the paper would call for a relatively high frequency of information releases of banks, as the information tends to depreciate quickly in value. In the context of indirect market discipline of banks, namely the idea that supervisors use market prices (especially stock prices) to identify weak banks, this may aide supervisors (and potentially also market participants) to better identify such signals.

Stale Information, Shocks and Volatility

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Abstract
We propose a new approach to measuring the effect of unobservable private information or beliefs on volatility. Using high-frequency intraday data, we estimate the volatility effect of a well identified shock on the volatility of the stock returns of large European banks as a function of the quality of available public information about the banks. We hypothesise that, as the publicly available information becomes stale, volatility effects and its persistence should increase, as the private information (beliefs) of investors becomes more important. We find strong support for this idea in the data. We argue that the results have implications for debate surrounding the opacity of banks and the transparency requirements that may be imposed on banks under Pillar III of the New Basel Accord.

JEL codes: G21, G14

Key words: Realised volatility, public information, transparency

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Stale-- aged, not fresh, impaired in vigour or effectiveness
Merriam Webster's Collegiate Dictionary, 10th Edition

1 Introduction

Stock volatility can be the result of the arrival of public information, the presence of differences private information (or beliefs) among traders and the presence of irrational noise traders (mis-pricing). In this paper we use a new approach to estimate the effect of differences in private information on volatility. We examine the question in the context of high frequency stock returns for a set of large European banks. We use a well identified, unexpected shock (monetary policy surprises) and estimate the change in banks' stock return volatility. To measure volatility, we use "realised volatility", as recently proposed by Andersen et al. (2003). We relate the change in volatility to a proxy for the accuracy or "freshness" of public information available about banks, the annual report. Our hypothesis is that if the public information available is stale, we should observe a larger spike in volatility, if volatility is driven by traders with different private information or beliefs. We argue that higher quality, timelier public information results in a closer alignment of information sets of traders, leaving less room for private information or beliefs to drive volatility. We also hypothesise and test an inverse relation between the persistence of volatility and the quality of the publicly available information.

The paper can be viewed as a test of the theories proposed by Harris and Raviv (1993) and Shalen (1993). Harris and Raviv (1993) develop a model of trading in a speculative market based on the difference of opinion among traders. In the model traders share common prior beliefs and receive common information, but differ in the way in which they interpret this information. In our paper, we use the quality of the public information that traders receive as a proxy for the extent to which they will differ in their interpretation of this information. If the public signal is more precise this leaves less room for differences in interpretation and therefore the spike in volatility subsequent to a shock should be smaller and less persistent. Similarly, Shalen (1993) examines a noise rational expectations model and shows that the dispersion of beliefs (i.e. the degree to which traders disagree about the future) explains the volatility of returns. The higher this dispersion the higher volatility, which has a direct correspondence in our paper: the weaker the publicly available information, the greater the dispersion of trader's beliefs and the higher volatility.

Our work is closely related to the literature on the importance of informed traders to explain (excess) volatility in financial markets. French and Roll (1986), Barclay et al. (1990), Amihud and Mendelson (1991), Ito and Lin (1992), and Ito et al. (1998) compare volatility at the time when markets are open to volatility when they are closed to distinguish the role of private versus public information in explaining volatility. The seminal paper in this literature, French and Roll (1986) compare volatility when stock market are closed to when they are open, keeping the flow of public information constant. They find that return volatility decreases during these closures. They argue that since public information cannot be the reason and mis-pricing seems to be small, private information is the main source of high trading-time volatility at times when the exchanges are open. Along similar lines, Barclay et al. (1990) examine stock return volatility for the Tokyo Stock Exchange, exploiting the phase out of half-day trading on Saturdays. They show that weekend volatility fell after the phase-out.[3]

Amihud and Mendelson (1991), Ito and Lin (1992) and Ito et al. (1998) concentrate on the effect of lunch breaks on volatility. Amihud and Mendelson (1991) show that volatility during the lunch break is significantly lower than in the morning or the afternoon (U shape). Ito and Lin (1992) compare the lunch time volatility of the Tokyo Stock Exchange, which does break for lunch, with the one of the NYSE, which does not. They find that the dip in volatility at the NYSE is much smaller than in Tokyo and attribute that to the absence in Tokyo of trading based on private information. Ito et al. (1998) examine the effect of phasing out the lunch breaks at the Tokyo foreign exchange market. They find that volatility doubles with the introduction of trading over lunch and argue that this cannot be due to changes in the arrival of public information, as there was no change in public information flows associated with the change in opening hours of the exchange.

The paper is also related to the previous literature on the effect of macro announcements on asset levels and volatility (see e.g. Hautsch and Hess, 2002 (US T-Bond futures); Fleming and Remolona, 1999 (US Treasury market), Goodhart et al., 1993 (exchange rates); Almeida et al., 1998 (exchange rates); Ederington and Lee, 1993, 1995 (interest rates and exchange rates, forward rates)). Even though Hautsch and Hess (2002) examine the US Treasury bond futures market, their ideas are most similar to ours. They examine the effect of the release of the US employment report simultaneously on the mean and the variance of Treasury bond futures using an intraday ARCH model. The find that non-anticipated information leads to a sharp price reaction and even controlling for this, they find a strong and persistent increase in volatility. They interpret this finding as providing evidence for "considerable disagreement among traders about the precise implications of macroeconomic news, which are only slowly resolved." Hence, Hautsch and Hess (2002) share with this paper their concern for volatility arising from differences in views among traders (or differences in private information among traders) and the impact of the un-anticipated information itself. In Fleming and Remolona (1999), the authors also raise the issue of differences in private views driving volatility. They examine the effect of the arrival of public information on the level and

[3] It is possible that their result is driven by a decline in the arrival of public information, as Saturday announcements of public information and other market activities were also phased out.

volatility of prices in the U.S. Treasury Bill market. They find that the release of a major macroeconomic announcement induces a sharp and nearly instantaneous price change with a persistent effect on volatility. They argue that the persistence in the volatility stems from "residual disagreements among investors about what precisely the just-released information means for prices". However, they do not attempt to formally relate these differences in private views to differences in the underlying information sets.

We are not aware of any evidence on the effect of monetary policy on high frequency stock data.[4] Ehrmann and Fratzscher (2004), Thorbecke (1997), Bomfim (2003) and Lobo (2000) examine the effect of monetary policy on daily stock returns. Bomfim (2003), for example, similarly to our paper examines the effect of monetary policy surprises on stock price volatility. He finds, as we do, that monetary policy surprises increase volatility significantly in the short run; however, as in Fleming and Remolona (1999) he does not link the extent to which volatility increases to the information set of traders. As far as we are aware there is no evidence of the effect of monetary policy on bank stock prices, even though one could argue that banks' stocks should be a particularly interesting area for studying the effect of monetary policy.

Even so, our primary interest is not in the monetary policy shock *per se*. We chose un-anticipated monetary policy decisions, because their size and timing are easily identifiable. Similarly, bank stock prices are particularly interesting when examining the effect of differences in information sets of traders, as banks are generally considered to be particularly opaque (see e.g. Morgan, 2002) and analysing the value of publicly released information to market participants may be particularly interesting.[5]

In the paper, we use the vintage of the release of the annual report as a measure of the precision of the information available about banks and, hence, the degree to which traders may disagree as to the extent of the implications of the monetary policy shock. Specifically, we estimate the change in volatility due to the shock as a function of the number of months, since the bank published its last annual report. Hence, we examine whether the effect on volatility is smaller if the bank just published its annual report last month compared to the volatility response if the bank published its last annual report, say, 8 months ago. The argument is quite simple: The more recent the publication of the annual report, the smaller the disagreement of

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[4] Also related to is a paper by Andersen et al. (2005), who examine the effect of many different macroeconomic announcements on futures contracts. Among many other assets, they also consider the effect of US monetary policy decisions on futures contracts of the FTSE100 and the S&P 500. Their paper, however, focuses on conditional mean jumps, rather than volatility.

[5] For the opposing views that banks may not be particularly opaque (but rather "boring") see Flannery et al. (2004).

traders as to the implications of the shock for the future profitability of the bank. Equivalently, the more recent the publication of the annual report, the more aligned the information sets of traders and the less important private information. Of course, these arguments only apply, if annual reports of banks in fact convey any useful information to markets. In this sense, our approach is a joint test of the presence of private information and the value of bank annual reports to markets.

The paper is directly related to the question of the opacity of banks' assets (Morgan, 2002; Flannery et al., 2004) and whether publishing annual reports generally and whether improving the frequency and quality of these reports specifically, reduces this opacity and is valuable to the market. The only evidence we are aware of on this issue with regards to banks is provided in Baumann and Nier (2004). Baumann and Nier estimate a measure of annual volatility of banks' stocks as a function of a disclosure index based on the information available in Bankscope and some controls. Their results suggest that banks disclosing more items in Bankscope tend to show lower annual volatility. In this paper we relate opacity to the importance of private information in the market. If banks are indeed opaque, the volatility of banks' stocks can be expected to increase significantly upon the arrival of surprising and relevant news and evidence that this volatility spike is lower for banks for which fresher public information is available would suggest that the vintage and the quality of accounting information matters and reduces the degree of opacity.

Our results suggest that (i) un-anticipated monetary policy shocks result in a significant short term increase in bank stock volatility; anticipated monetary policy shocks do not; (ii) the increase in volatility is significantly higher in the case of banks, for which publicly available information is stale; (iii) this difference is economically quite large; and (iv) the increase in volatility is significantly more persistent in the case of banks, for which the publicly available information is stale, although this effect is economically small.

The paper is organised as follows: In the following section we describe the methodology employed in the paper to measure volatility. Section 3 presents the data and section 4 the empirical model. In section 5 we report the results, section 6 examines robustness and section 7 concludes.

2 Methodology: realised volatility

Until recently, common ways to model conditional second moments have been based either on the GARCH parameterization proposed by Engle (1982) and Bollerslev (1986) or the stochastic volatility methodology (see, for example, Hull and White, 1987, and Ghysels *et al.*, 1996, for a survey). In this paper, instead, we use the realised volatility approach of Andersen *et al*. (2003). This methodology has the advantage of being model-independent and simple. In addition, it offers the possibility of applying standard econometric techniques to the resulting time series of volatility.

The realised volatility is an *ex post* measure and is designed for high-frequency data. It is computed by cumulating squared compounded returns across a certain time window. The returns, in turn, are computed over tiny intervals of that time window as log differences of equity prices. As the interval becomes infinitely small, the realised volatility converges in probability to the quadratic variation process of the returns. Hence, the quadratic variation describes unexpected jumps of second moments of returns. Under suitable conditions, the quadratic variation it is shown to be an unbiased and highly efficient estimator for the conditional covariance matrix of returns.

Let $\mathbf{r}_{t+h,h}$ be the $n \times 1$ vector of compounded returns over the h window. Its conditional distribution can be demonstrated to read as follows (see Andersen *et al.* (2003)):

$$\mathbf{r}_{t+h,h} \left| \sigma\left\{ \boldsymbol{\mu}_{t+s}, \boldsymbol{\Sigma}_{t+s} \right\}_{s\in[0,h]} \sim N\left(\int_0^h \boldsymbol{\mu}_{t+s} ds, \int_0^h \boldsymbol{\Omega}_{t+s} ds \right) \right. . \tag{1}$$

$\sigma\{\cdot,\cdot\}_{s\in[0,h]}$ is the σ-field generated by $(\boldsymbol{\mu}_{t+s}, \boldsymbol{\Sigma}_{t+s})_{s\in[0,h]}$, where $\boldsymbol{\mu}_{t+s}$ is the conditional mean vector of returns and $\boldsymbol{\Sigma}_{t+s}$ is the associated covariance matrix.

In a discrete time, univariate context, the empirical counterpart to the *h*-time window quadratic return variation is given by the realised volatility, $RV_{t,h}$, which is computed as follows:

$$RV_{t,h} = \sum_{j=1,\ldots,h/\Delta} r^2_{t-h+j\Delta,\Delta} , \tag{2}$$

where $r_{t-h+j\Delta,\Delta}$ is the compounded return over the Δ interval and h is the time window.

We turn now to the choice of the Δ interval. In line with the recent microstructure literature (see, for instance, Andersen *et al.*, 2000b, and Bandi and Russell, 2005), this choice is subject to a trade-off. On the one hand, the smaller is the interval, the lower is the sampling variation of the realised volatility. On the other hand, the smaller is the interval, the larger is the contamination due to the microstructure noise. Bandi and Russell (2005) determine the optimal Δ interval minimising the mean-squared error of the contaminated variance estimator. Using IBM equity tick prices, they find that the optimal interval is approximately two minutes. We choose the same interval, since the frequency of our data is similar to that of IBM.

3 Data

3.1. Unanticipated monetary policy decisions

We use unanticipated monetary policy decisions in the euro area and the UK as our shock variable. We chose this particular macroeconomic shock because we have precise information on its exact timing (to the minute) and magnitude, which is crucial in the context of examining tick data, and it is straightforward to differentiate between an anticipated and an un-anticipated component of the shock. Our sample period, which is determined by the availability of tick data (see below), is from January 1999 until May 2004.

ECB monetary policy decisions during January 1999 to December 2001 were taken on every second Thursday. After December 2001, the ECB moved to taking decisions only on the first Thursday of each month. As for the Bank of England (BoE), monetary policy decisions are taken once a month, usually on Thursdays, but there are also decisions taken on Tuesdays and Wednesdays. The sample includes 101 and 66 ECB and BoE decision days, respectively. In order to differentiate between anticipated and unanticipated monetary policy decisions, we follow Ehrmann and Fratzscher (2003) and use expectation data based on a Reuters poll of 25-30 market participants. The polls are conducted on the Friday before the meetings of the ECB Governing Council and the BoE Monetary Policy Committee. We use the mean of this survey as our expectation variable. Surprises are defined as the difference between the actual change in the ECB's and BoE's policy rates minus the mean of the Reuters poll. Ehrmann and Fratzscher (2003) show that these expectations are unbiased and efficient.

Descriptive statistics on the monetary policy decisions are given in Table 1. As reported in Panel A, out of 101 ECB monetary policy decisions, 86 were to leave rates unchanged and on 15 days rates were either increased or decreased. Decreases and increases are about in balance, with seven changes up and eight changes down. In general, changes up were somewhat smaller on average (0.32%) compared to changes down (-0.44%). This is explained by the fact that the majority of increases were by 25 basis points and the majority of decreases was by 50 basis points. In total, there were 56 surprises: 35 represent surprises with monetary policy being tighter than expected and 21 represent surprises with looser than expected monetary policy. While market participants were more often wrong in the direction of looseness, their error was larger when they expected a tighter monetary policy. Given our definition of the monetary policy surprises, there is a surprise component on all days when rates were changed, although in many cases it is small. The statistics also suggest that there were 41 days when at least some market participants expected a change and the ECB decided to leave rates unchanged.

Panel B reports similar statistics for the Bank of England's monetary policy decisions. The Bank of England left rates unchanged 50 times out of 66 MPC meetings. A comparison between Panels A and B shows that the number of surprises relative to the BoE decisions is almost the same as that of ECB's, despite the higher number of ECB decision days. All decisions by the Bank of England to move rates were by 25 basis points. On the other hand, the magnitude of average surprises associated with the ECB decisions is larger than those of the Bank of England.[6]

3.2. Bank tick equity prices

In order to identify the effects of monetary policy shocks on volatility, we use tick equity transaction prices from three stock exchanges, the Deutsche Börse, Euronext (Amsterdam, Brussels and Paris), and the London Stock Exchange.[7] The adoption of high frequency data is essential for two reasons. First, it permits to calculate volatility series across intraday windows. These windows, in turn, can be chosen so that one of them will commence exactly when the monetary policy decision is announced. This would allow us to very precisely measure the effect on volatility due to monetary policy shocks. Second, the effects of monetary policy shocks should be largely uncontaminated by other pieces of news.

We constructed our sample of banks using sets of tick data covering the same period as our data on monetary policy shocks. In the case of Deutsche Börse and London Stock Exchange ("German sub-sample" and "UK sub-sample", respectively) we have data from 1 January 1999 to 31 May 2004; however for Euronext data are only available for 1 January 2002 to 31 May 2004 ("Euronext sub-sample"). The Euronext subsample is shorter because Euronext started making tick data available only in 2002. Within the three markets we limit ourselves to banks that are continuously traded throughout the sample period, which yields an initial number of six banks in the case of Euronext, six in the case of Deutsche Börse and five in the case of London Stock Exchange.

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[6] While there were a number of decisions taking place in the same week, which should not influence our results given our approach, same day decisions would be more problematic. There were two days with decisions of the Bank of England and the ECB on the same day during our sample period. The results reported below are robust to dropping those two days from the estimation.

[7] The two continental European stock exchanges for equity trading are order driven. The order types that may be submitted to the Central Order Book consist of market orders, limit orders, market-to-limit orders, stop orders and orders subject to special conditions. The London Stock Exchange also has market makers.

From a close examination of the bank trading frequency two distinct groups emerge. The first group includes Deutsche Bank, Commerzbank and Hypovereinsbank, for the German sub-sample, ING, ABN Amro, BNP Paribas and Société Générale, for the Euronext sub-sample, and HSBC, Abbey National Bank, Royal Bank of Scotland and Barclays, in the case of the London Stock Exchange. The second group contains IKB Deutsche Industriebank, DePfa, Bankgesellschaft Berlin, KBC, Natexis Banques Populaires and Standard Chartered. The equities of the banks belonging to the first group (German and UK) were traded on average about 1000 times per day, whereas the shares of the other group were traded on average between 100 and 400 times per day.

A preliminary analysis shows that, for the first group, the average volatility levels are quite similar across banks. Furthermore, volatilities exhibit the well-known U-shape across daily windows. Instead, volatility levels differ quite substantially within the second group and vis-à-vis the first group. In addition, volatilities behave quite erratically across daily windows. Therefore, we choose not to include the banks of the second group in our analysis, yielding a sample of eleven banks: Abbey National, ABN Amro, Barclays, Commerzbank, Deutsche Bank, HSBC, Hypovereinsbank, ING, BNP Paribas, Royal Bank of Scotland and Societe Generale. It turns out that these eleven banks represent, with one exception,[8] the largest publicly traded banks in Europe in terms of total assets.

We limit our sample to the day of the monetary policy decision of the ECB and the Bank of England, respectively, (usually a Thursday) and the days immediately before and after. Using only the two days immediately adjacent to the day of the monetary policy decision allows us to focus on the volatility effects of the surprises and, at the same time, to maintain a manageable sample size. For the Deutsche Börse sample this yields a sample size of 298 days for each of the three banks, for the shorter Euronext sample we obtain 86 days for each of the four banks.[9]

The computation of equity returns is problematic because observations are unequally spaced. In line with Andersen *et al.* (2003), we calculate two minute interval equity prices by linear interpolation of the two tick log prices immediately before and after the two minute time stamps. Slow trading activity before nine o'clock a.m. and after five o'clock p.m. justifies a choice of the trading day between 09:00:00 and 17:00:00. However, for the euro area sub-sample the trading day starts at 09:09:00

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[8] Dresdner Bank is the only bank among the largest in Europe not part of our sample, as it was acquired by Allianz in early 1999.

[9] During 1999 to 2004 there were 101 monetary policy decision days of the ECB (Table 1). As we use the day before and after the decision day, we generally have three days multiplied by 101 decision days, i.e. 303 days. However, there were 5 holidays in the sample for which no data are available. The sample for the Euronext banks was constructed equivalently, taking the shorter time period from 2002 to 2004 into account.

and ends at 16:49:00 CET for the following reason. We divide the day into ten equally spaced windows (each composed of 46 minutes), with the seventh one commencing exactly at 13:45:00, when the ECB monetary policy decision is announced. This yields a sample size of 298 days for three banks with nine intervals per day (we lose one interval as we use lagged realised volatilities as one of our dependent variables), in total 8046 observations for the Deutsche Börse sample. For the Euronext banks we equivalently obtain 86 days for four banks with nine intervals per day, i.e. 3096 observations.

As for the UK sub-sample, we also divide the trading day into ten equally spaced windows, 46 minutes each. The trading day starts at 08:56:00 and ends at 16:36:00 local time, with the fifth window beginning exactly at 12:00:00, when the Bank of England announces its monetary policy. The time difference between the two central banks' policy announcements, when they are made over the same day, is 45 minutes. With daily windows of 46 minutes there will be no overlapping between the windows immediately following the policy announcements. This yields a sample size of 198 days for four banks and nine intervals per day, i.e. 7128 observations. However, in case of the UK sample we had missing or incomplete data for some periods and also excluded some unreasonable small or large values for realised volatility (in excess of five standard deviations). These very high or low values were clustered within a few days and we excluded the entire day, if there was at least one outlier in a given day. In total the resulting sample contained 6678 observations on realised volatility for the four UK banks.[10] In total, therefore, the regressions below rely on 17820 observations for all banks combined.

Descriptive statistics for equity 46 minutes window returns, standardised equity returns[11], realised volatilities and log of realised volatilities are given in Appendix I. As shown by the Ljung-Box test (Q_{10}) with ten lags, realised and standardised returns exhibit no or low autocorrelation, while realised volatility and its log do. Return series on all banks and the related realised volatilities are not normal. Kurtosis is larger than three, indicating that the probability mass is concentrated more in the centre and tails relative to the normal. Data also show severely right skewed realised volatilities for all banks, whereas returns seem to be more symmetric, with the exception of Commerzbank. This is confirmed by the Jarque-Bera test for normality, and the theoretical quantile–quantile pictures (see Figure 1).

The standardised returns and the log of realised volatilities are close to normal, as seen from kurtosis, skewness, the Jarque-Bera statistics, and the theoretical

10 Excluded observations were for HSBC the days 05/04/2001, 06/04/2001, 10/05/2001,03/10/2001 and 10/01/2002; for Abbey National 06/06/2000 and 02/08/2000 (no data); for Royal Bank of Scotland 07/12/2000 and 08/05/2002; for Barclays 02/08/2000. Finally, the data set did not contain data for HSBC for the period 01/01/1999-31/06/1999.

11 Standardised equity returns are computed as the ratio of returns and their realised volatility.

quantile–quantile pictures (see Appendix I and Figure 1). Therefore, the distribution of standardised 46 minutes window returns and the relative log of realised volatilities can be assumed to be normal with $r_{it}\, RV_{it}^{-1/2} \sim N(0,1)$ and $ln(RV_{it}) \sim N(\mu, \sigma^2)$,

where r_{it} and RV_{it} are the return on asset *i* and the associated realised volatility, respectively. The assumption of normality allows us to use standard econometric methods when modelling the log of realised volatilities.

For all banks we plot the log of realised volatilities versus daily windows (see figures 2a-2k). The values associated with each window are equal to log volatility averages across days. Each picture contains two curves of volatility averages corresponding to days of no monetary policy decisions, and days when monetary policy comes as a surprise, respectively. All the graphs show that volatilities are U-shaped, i.e. the volatility is higher at the beginning and the end of the trading day. This pattern is well documented in the literature (see, for instance, Engle, 2000). The level of volatility is similar across banks. The timing of a monetary policy shock is depicted by a vertical line in the chart and we can see a noticeable spike in volatility if monetary policy was un-anticipated, which only slowly dissipates. In the remainder of the paper we will attempt to explain the magnitude of the change in volatility in response to the unanticipated monetary policy shock as a function of the quality of public information available about the bank, hoping to uncover differences in volatility due to unobservable differences in private information or beliefs.

4 The econometric specification

The objective of our model is to measure the effects of monetary policy surprises on volatility, taking into account information that investors possess at the time of the shock. We estimate the following basic model:

$$\begin{aligned} LNRV_t = \alpha_0 + \alpha_1 LNRV_{t-1} + \sum_{i=2}^{9} \beta_{i-1} d_t\_\text{int}_i + \sum_{i=1}^{5} \gamma_i d_t\_year_i + \sum_{i=1}^{6} \lambda_i d_t\_bank_i + \\ \varphi_1 d_t\_montue + \varphi_2 d_t\_thur + \varphi_3 d_t\_fri + \theta_1 mps_t + \theta_2 nomps_t + \rho d_t\_per \end{aligned}, \qquad (3)$$

where:

i) $LNRV_t$ is the log of realised volatility for the window *t*. We introduce an autoregressive term to capture the high persistence of the volatility as evidenced by the Ljung-Box test (see Table 2).[12]

[12] The construction of $LNRV_{t-1}$ is done in such a way so that the observations corresponding to the first window are excluded. This is done because our sample is not continuous across days.

ii) $d_t\_\mathrm{int}_i = \begin{cases} 1 & \textit{if the data correspond to ith daily window} \\ 0 & \textit{otherwise} \end{cases}.$

We introduce the time window dummies $d_t\_\mathrm{int}_i$ to accommodate the U-shape intra-daily volatility of asset returns. The fourth window is the omitted category.

iii) $d_t\_year_i = \begin{cases} 1 & \textit{if the data correspond to } year_i \\ 0 & \textit{otherwise} \end{cases}, year_i \in [1999, 2000, 2001, 2002, 2003]$. These time dummies take account of the possible changes in market volatility, for example related to the internet boom ending in 2001. 2004 is the omitted category.

iv) $d_t\_bank_i = \begin{cases} 1 & \textit{if the data correspond to } bank_i \\ 0 & \textit{otherwise} \end{cases},$

$bank_i \in [cb, hb, abn, ing, bnp, sg, hsbc, abbn, rbs, bar]$.[13] The bank dummies allow us to capture the differences in the level of realised volatility across banks. Deutsche Bank is the omitted category.[14]

v) $d_t\_montue = \begin{cases} 1 & \textit{if the trading day is a Monday or Tuesday} \\ 0 & \textit{otherwise} \end{cases}$

vi) $d_t\_thur = \begin{cases} 1 & \textit{if the trading day is Thursday} \\ 0 & \textit{otherwise} \end{cases}.$

vii) $d_t\_fri = \begin{cases} 1 & \textit{if the trading day is Friday} \\ 0 & \textit{otherwise} \end{cases}.$

Monday, Tuesday (which we combined as we had relatively few observations), Thursday and, above all, Friday effects are captured by the daily dummies d_t_montue, d_t_thur and d_t_fri. Wednesday is the omitted category.

viii) $mps_t = abs(\Delta i_t - reuters\ mean_t)$, where Δi_t is different from zero only over the fourth and sixth daily windows, corresponding to a BoE and ECB interest rate change, respectively, and $reuters\ mean_t$ is the average of the interest rate change expectations.

[13] We use the following abbreviations for the individual banks: *cb* stands for Commerzbank, *hb* for Hypovereinsbank, *abn* for ABN AMRO, *ing* for ING, *bnp* for BNP Paribas, *sg* for Société Générale, *hsbc* for HSBC Bank, *abbn* for Abbey National Bank, *rbs* for Royal Bank of Scotland and *bar* for Barclays.

[14] This approach is equivalent to running a fixed effects (for banks) panel regression. Results from a panel model are available from the authors upon request.

Expectations on monetary policy decisions are computed by Reuters with a poll of market participants.

ix) $$nomps_t = \begin{cases} 1 \;\; if \;\; mps_t = 0 \;\&\; \begin{cases} t = 6th \; window \; of \; the \; day \; when \; an \; ECB \; monetary \; policy \\ \quad decision \; is \; taken \\ t = 4th \; window \; of \; the \; day \; when \; a \; BoE \; monetary \; policy \\ \quad decision \; is \; taken \end{cases} \\ \\ 0 \;\; otherwise \end{cases}.$$

The dummy measures the effect of an anticipated monetary policy shock on volatility.

ix) $d_t\_per = d_{7-9;5-7,t}\_mps \cdot LNRV_{t-1}$, where

$$d_{7-5,t}\_mps = \begin{cases} 1 \;\; if \begin{cases} mps_t \neq 0 \;\&\; t = 7th,\, 8th \; or \; 9th \; window \; of \; the \; day \\ mps_t \neq 0 \;\&\; t = 5th,\, 6th \; or \; 7th \; window \; of \; the \; day. \end{cases} \\ 0 \;\; otherwise \end{cases}$$

This variable captures the volatility persistence over the three windows immediately after a monetary policy shock.

We want estimate the effect of unobservable differences in private information or beliefs on volatility. In order to do this we evaluate the volatility effect of an un-anticipated monetary policy shock in relation to the quality of public information available about the bank *ex ante*. Our measure of the quality of public information is the vintage of the last annual report released by the bank.[15] The vintage is given by the number of months since the bank published its last report.[16] We hypothesise that, as the report gets older, the information contained depreciates in value to traders. We argue that volatility is generated by a combination of the news effect of the monetary policy decision itself (public information) and by differences in the interpretation of the effect of this news on the banks (Harris and Raviv, 2003; Shalen, 2003). As the quality of the prior information about the bank increases (is more up to date and less stale), we would expect a smaller effect of the monetary policy shock on bank stock return volatility. This approach to testing for the presence of private information in the market has two important advantages. One, it does not suffer from reverse causality. Reverse causality could arise if banks react to

[15] We examine the effect of interim reports published by the bank below.

[16] We obtained the annual report release dates (and the dates of the release of interim reports, see below) from Reuters News service.

high volatility of their own stock price by releasing more information to the market (see e.g. Baumann and Nier, 2004). Second, by focusing on differences in volatility response to shocks within the same bank, we would argue that our results do not suffer from omitted variable bias, i.e. that the differences in volatility are driven not by differences in information but by differences in some omitted variable that is correlated with information. This problem frequently arises when the identification of the model largely relies on cross-sectional differences among banks. In our approach, we test whether the response in volatility of, say, Deutsche Bank is higher if the last annual report of Deutsche Bank was released 10 months ago compared to the response in volatility of Deutsche bank if the last annual report was released just 2 months ago.

Table 2 illustrates this point. It shows the number of months before a given monetary policy surprise (of the ECB or the Bank of England, respectively) the annual report of the bank was released. It shows that the sample is essentially uniformly distributed across the different time leads between publication and the monetary policy surprises in the sample. This is true both for the sample as a whole, as well as for each individual bank. Overall, this re-enforces our point that this time difference is indeed uncorrelated with the identity of the bank.

Therefore, we estimate a second specification which differs from the basic model in equation (2) by interacting monetary policy surprises with the number of months since the publication of the last annual report. The variables mps_t and d_t_per are replaced each by:

$$mps_t = \sum_{i=1}^{12} arep_{t,i} \text{ and } d_t\_per = \sum_{i=1}^{12} dp_{t,i} \; .$$

These variables are defined as follows: $arep_{t,i} = d_{ai,t} mps_t$, and $dp_{t,i} = d_{ai,t} d_t\_per$,

where $d_{ai,t} = \begin{cases} 1 \;\; if \;\; the\ annual\ report\ is\ released\ i\ months\ ago \\ 0 \;\; otherwise \end{cases}$ and i=1..12.

5 Empirical Results

In the first set of columns of Table 3 we report the estimation results of the basic model described by equation (3). Parameters are estimated by a pooled-OLS regression with cluster robust standard errors.[17] As expected, volatility is highly persistent: about 54% of a given shock is transmitted to the next time window. The bank dummies indicate the difference in volatility averages vis-à-vis Deutsche Bank. Commerzbank, Hypovereinsbank, ING, Abbey National, RBS and Barclays show

[17] The cluster option allows relaxing the assumption of observation independence within banks.

relatively higher volatility. The level of volatility of the other banks does not tend to be significantly different from that of Deutsche Bank. Time dummies indicate that volatility is more pronounced in the years before 2004, reaching higher levels in 2002 and 2003. This may be due to down market effects. The coefficients associated with the window dummies $d_t\_w_i$ broadly confirm the daily U-shape of the realised volatility (see figures 2a-2k) with the fourth window, commencing at 11:27 (11:16) and ending 46 minutes later for the euro area (UK), respectively. As regards to the day of the week dummies, we find no significant difference in volatility between Wednesdays (omitted category), Thursdays, Mondays and Tuesdays. However, volatility tends to be significantly higher on Fridays, which is consistent with the previous literature on intraday volatility in stock markets (see e.g. Andersen et al., 2000a).

When the monetary policy decision comes as a surprise, volatility significantly jumps up. A surprise, say, of 50 basis points generates, on average, an increase in volatility approximately equal to one percent.[18] On the other hand, volatility does not significantly change when the decision is fully anticipated by market participants ("nomps"). As seen from figures 2a-2k, the effect on volatility of a monetary policy surprise tends to be persistent. After the shock, the volatility measured in the days of surprises is, by and large, higher than the volatility computed over the other days. The coefficient associated with the three following time windows after the surprise, *d_per*, is significant at the one percent level, although quite small.

Next, let us consider the effect of the quality of public information on volatility, as proxied for by the vintage of the annual reports. Estimation results of the extended model are reported in the second set of columns of Table 3. In Figures 3 and 4 we plot, respectively, coefficient values corresponding to $arep_{t,1} - arep_{t,12}$ and $dp_1 - dp_{12}$ against the information lags. A simple regression line fitted to coefficient values is increasing, suggesting that, as information becomes outdated, the effect of surprises on volatility becomes higher and more persistent.[19] However, a number of the estimated coefficients are not significantly different from zero. Therefore, we combine the monthly variables into quarterly variables.[20] The coefficients for the resulting "Restricted Model" are reported in the third set of columns in Table 3.

[18] As the dependent variable is in logs, the reported coefficients are semi-elasticities.

[19] A second order polynomial fitted to the same data points is also monotonically increasing.

[20] We alternatively also used an F-test to aggregate variables. We first test the null hypothesis that the first two $arep_{t,i}$ coefficients are equal. If the null is not rejected, we test whether the third coefficient is equal to the first two. We continue until the null is rejected. When this occurs, we start again testing the null that the last coefficient is equal to the following one. The procedure ends when all coefficients are classified. The results are conditional on the choice of the starting null hypothesis. The choice is suggested by the shape of the second order polynomials. The results are consistent with the specification using quarterly variables.

They suggest that the effect of a monetary policy shock on volatility is about three times the size if the report is 10 to 12 months old compared to when the report is fresh, i.e. 1 to 3 months old. All coefficients are significant at least at the five percent level and the difference between annual reports being 1 to 3 months old to annual reports being 10 to 12 months is significant at the one percent level. Similarly, we find hardly any persistence in the shock when the annual report is fresh, whereas if the report is old, persistence increases by more than 1 percent. Again, the difference is significant at the one percent level. Economically, if the publicly available information about the banks is current, i.e. no more than 3 months old, a 50 basis point monetary policy surprise results in an increase in volatility of about 0.6 percent. If the information is stale (i.e. 10 to 12 months old), this increases to more than 2 percent.

However, we also find that the increase in volatility is not monotonic. Both for the volatility spike itself and for its persistence we estimate a noticeable dip if the annual report is 7 to 9 months old. We hypothesised that this may have to do with the publication of interim and, in particular, semi-annual reports. These reports could also contribute to aligning trader's information sets. Since banks typically publish a semi-annual report about six months after publishing their annual report, the dip in the volatility effect may be due to the information contained in those reports. However, many of the banks in the sample also publish quarterly reports and they, even though they contain significantly less information compared to annual reports, may also be useful to traders.

As a consequence we performed two additional estimations. One, we estimate whether the simple fact that the bank published an interim report (whether quarterly or semi-annual) had information value to traders. We do this by interacting the "arep" variables with a dummy equal to one, if an interim report was published during the period. If interim reports contain important information, we would expect to find that even if the annual report was published quite some time ago, the volatility effect of a monetary policy surprise remains small if an interim report was published recently. The results for this exercise are reported in Table 4 and suggest that in general this does not seem to be the case and interim reports provide no additional information to traders.

Second, we started from which information traders would find useful in estimating the impact of an unanticipated interest rate shock on banks and what is contained in the "most extensive" reports in our sample. We identified eight items:

1. Information interest rate risk and how the bank deals with it
2. Breakdown of the loan portfolio into variable rate and fixed rate loans
3. Breakdown of loan commitments into variable rate and fixed rate

4. Data on the use of interest rate derivatives
5. Detailed value-at-risk information for interest rate risk
6. Fair value reporting of the loan portfolio
7. Remaining term to maturity breakdown for loans and deposits
8. Detailed explanations of interest income and expenses

We then checked to which extent this type of information is available in annual or interim reports and classified reports as informative if at least 6 of the eight items were available and uninformative otherwise. It turns out that this approach results in the classification of all annual reports as informative. In addition, all interim reports are classified as uninformative with the following exceptions:[21]

Deutsche Bank: Interim report Q2 1999

Barclays: all semi-annual reports from 1998-2004

HSBC: all semi-annual reports from 2001-2004

Abbey National: Semi-annual report 2003

BNP Paribas: Interim reports Q2 from 2002-2004[22]

Societe Generale: Interim report Q2 2003

Based on this information we re-coded the "arep" variables to reflect the latest informative report, whether annual or interim and re-estimated the model. The results are reported in Table 4 ("Interim report model II"). It appears that traders value informative reports, as defined here. The dip in the effect on volatility for 7 to 9 months information is now much smaller than in previous specifications (a coefficient of 3.24 relative to 1.86); however, overall the results suggest that information does not depreciate linearly in value to traders. There is a steep increase in volatility if informative reports are older than 3 months (the impact of a monetary policy surprise doubles) but little additional depreciation as an informative report becomes even older.

Overall, we interpret these results as consistent with the presence of private information in markets. As investors have more accurate information about the bank (because the annual report is recent and informative), they disagree less about the effect of the shock on the earnings potential of the bank. Therefore, the impact volatility of the monetary policy surprise is lower and less persistent. This effect is economically quite significant. The results also suggest that the information given in

[21] Appendix III gives more details on interim reports.

[22] BNP Paribas publishes an "extensive" interim report for the second quarter of each year and a short version for Q1 and Q3.

annual reports (and some interim reports) by banks is valuable to market participants and conveys useful information about banks, at least in the context of aiding markets to interpret the impact of unanticipated monetary policy on banks. Annual reports appear to reduce the opacity of banks. Finally, we show that the value of information contained in banks' annual reports depreciates relatively quickly over time.

6 Robustness

We conduct two exercises to check whether the above result is robust to changes in the definition of monetary policy shocks. First, instead of interacting the vintage of the annual report with the size of the monetary policy surprise, we interact the vintage of the annual report with a dummy variable indicating whether or not there was a surprise. Hence, we abstract from the size of the monetary policy shock (Table 5, robustness I). The results are economically and econometrically extremely similar to those reported in Table 3, although the depreciation over time seems to be smoother compared to the earlier specifications.

Second, we examined the euro area and the UK separately, as there may important differences in the way monetary policy is conducted and the communication policy of the respective central banks. The results are reported in Table 5 and show that the impact of monetary policy shocks is larger if the annual report is older in both economic areas, even though there is a level effect (no matter the vintage of the annual report), since the overall magnitude of the coefficients is higher in the UK compared to the euro area.[23] The magnitude of the effect of the vintage of the annual report is significant in both cases: If the annual report is 10 to 12 months old, the effect of monetary policy surprises on stock price volatility is five times (two times) compared to the effect when the annual report was just published in the euro area (the UK).[24]

Finally, we also have some banks which are cross-listed in the US New York Stock exchange and some banks that are not. Listing at the NYSE implies that banks have to fulfil certain additional transparency requirements in line with US GAAP, including for example reporting fair values on its loan portfolio in the notes to the

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[23] This suggests that the impact of monetary policy shocks on bank stock volatility is overall higher in the UK. One interpretation of this finding would be that market participants find the effect of monetary policy surprises on bank profitability more difficult to estimate in case of UK banks. This may have a myriad of reasons, including a more complex balance sheet structure, greater exposure to more complex assets or other issues.

[24] The dip after six months is also present in both economic areas when estimating the model separately, as we did not use the information contained in "informative" interim reports in this section.

annual report.[25] If this additional information is valuable, banks that are cross-listed should exhibit a smaller increase in volatility (and less persistence). We find strong evidence for this idea: A dummy indicating whether or not the bank was cross-listed in the US interacted with the monetary policy surprise was highly significant and negative, suggesting that impact of monetary policy surprises for those banks is smaller. While we think that these results overall provide further support to our ideas, they are a little difficult to interpret, as the dummy on cross-listing is endogenous and may reflect other differences in releasing information or business policy about the bank. A complete set of these results are available upon request.

7 Conclusions

The objective of this paper is to analyse the effects of monetary policy surprises on the volatility of equity returns for the largest European banks, taking into account the quality of public information available at the time of the surprise. We use this as a new approach to testing for the importance of differences in opinions among traders in explaining volatility. We provide evidence that stale public information (older annual and interim reports) significantly increase volatility upon an un-anticipated monetary policy shock. We find a similar information effect on persistence of volatility. Finally, our results suggest that accounting information may depreciate quite quickly over time, i.e. within three months, suggesting a relatively high frequency of information releases by banks.

The results in this paper are in our view strong evidence in support of Harris and Raviv (2003) and Shalen (2003), in the sense that they suggest that if investors information set is poorly aligned to due stale publicly available information, the impact on volatility of an unanticipated shock (in this case a monetary policy shock) is larger than if the publicly available information is fresh. Disagreements among traders based on differences in interpretation of the publicly available information become more important in case public information is stale. This adds to the body of literature showing that private information in markets matters for explaining volatility (e.g. Amihud and Mendelson (1991), Ito and Lin (1992) and Ito et al. (1998) Hautsch and Hess, 2002 and Fleming and Remolona, 1999). The methodology used in the paper and most importantly the approach used to identify the effect of private information differs sharply, however, from the previous literature.

The findings can also be interpreted as providing a new perspective on the question of bank opacity (Morgan, 2002; Flannery et al, 2004). While we do not provide direct evidence on whether banks are more or less opaque than non-financial firms,

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[25] For a summary of the debate surrounding the introduction of fair value accounting for banks in Europe in connection with IAS 39, see Enria et al. (2004) and Michael (2004).

we show that bank transparency, detail in annual reports and, especially, the issuance of frequent reports, reduces opacity and is valuable to investors. This is also interesting in light of the recent debate surrounding the idea to increase transparency of banks, reflected in Pillar III of the New Basel Accord. The New Accord will ask banks to significantly increase the information that they should report to markets. The results presented in this paper suggest that the implementation of these transparency requirements is important. The results of the paper would call for a relatively high frequency of information releases of banks, as the information tends to depreciate quickly in value. In the context of indirect market discipline of banks, namely the idea that supervisors use market prices (especially stock prices) to identify weak banks, this may aide supervisors (and potentially also market participants) to better identify such signals (see e.g. Borio et al., 2004 for an overview).

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Table 1: Descriptive statistics of monetary policy decisions

Panel A : ECB Monetary policy decisions (January 1999 - May 2004)

Monetary policy decision days		Size of monetary policy decisions		Unexpected monetary policy decisions	
Total	101	Average rate increase	0.32	Days with surprises	56
without rate changes	86	Average rate decrease	-0.44	Days with positive surprises *	35
with rate changes	15	Number of days with 0.25 increase	5	Days with negative surprises **	21
no. of rate increases	7	Number of days with 0.5 increase	2	Days without surprises	45
no. of rate decreases	8	Number of days with 0.25 decrease	2	Average positive surprise *	0.09
		Number of days with 0.5 decrease	6	Average negative surprise **	-0.22

* Tighter than expected monetary policy
** Looser than expected monetary policy

Panel B : BoE Monetary policy decisions (January 1999 - May 2004)

Monetary policy decision days		Size of monetary policy decisions		Unexpected monetary policy decisions	
Total	66	Average rate increase	0.25	Days with surprises	51
without rate changes	50	Average rate decrease	-0.25	Days with positive surprises *	29
with rate changes	16	Number of days with 0.25 increase	7	Days with negative surprises **	22
no. of rate increases	7	Number of days with 0.5 increase	0	Days without surprises	15
no. of rate decreases	9	Number of days with 0.25 decrease	9	Average positive surprise *	0.036
		Number of days with 0.5 decrease	0	Average negative surprise **	-0.054

* Tighter than expected monetary policy
** Looser than expected monetary policy

Table 2: Monetary policy surprises and annual reports: descriptive statistics

Number of months before a monetary policy surprise that the annual report was released. Monetary policy surprises are defined as the difference in the Reuter's poll and the change in the respective policy rate.

	1	2	3	4	5	6	7	8	9	10	11	≥12	Total
Euro area													
Deutsche Bank	6	6	4	6	3	5	3	6	6	4	3	4	56
Hypovereinsbank	5	6	4	5	5	7	2	3	8	4	2	5	56
Commerzbank	5	6	5	6	5	3	5	4	7	3	2	5	56
ABN Amro	2	1	1	2	1	1	0	2	1	1	0	2	14
ING Bank	2	1	1	2	1	1	1	1	1	1	1	1	14
BNP Paribas	2	1	0	2	2	1	1	1	1	1	1	1	14
Société Générale	2	1	1	2	1	1	1	1	1	1	1	1	14
UK													
HSBC	4	3	3	4	4	1	2	4	4	4	4	5	42
Abbey National	4	5	5	5	4	1	1	5	4	4	5	7	50
Royal Bank of Scotland	5	5	5	5	3	2	3	5	4	4	5	5	51
Barclays	6	5	4	6	4	1	1	5	3	4	3	8	50
Total	43	40	33	45	33	24	20	37	40	31	27	44	417

Table 3: Estimation results

Estimated using equation (2) in the text using OLS with robust standard errors (clustering for banks). Omitted categories: Deutsche Bank, 2004, interval 4, Wednesdays. The unrestricted and the restricted model contain the same non-monetary policy control variables as the basic model. ** and * suggest significance at 1%, and 5 % level, respectively. LNRV denotes the natural log of realised volatility, HSBC stands for HSBC, ABBN for Abbey National Bank, RBS for Royal Bank of Scotland, BAR for Barclays, ABN for ABN Amro, ING for ING Bank, BNP for BNP Paribas, SG for Société Générale, DB for Deutsche Bank, HB for Hypovereinsbank, and CB for Commerzbank. The dependent variable is the natural log of realised volatility (as described in the text) in window t for bank i.

Basic Model			**Unrestricted Model**			**Restricted Model**		
Variable	Coef.	t-stat.	Variable	Coef.	t-stat.	Variable	Coef.	t-stat.
$LNRV_{t-1}$	0.54**	14.42	arep1	2.52*	2.67	arep1_3	1.21**	2.57
d_cb	0.11**	11.94	arep2	0.97*	2.66	arep4_6	3.40***	4.60
d_hb	0.10**	12.30	arep3	0.97	1.45	arep7_9	1.86***	3.17
d_abn	-0.02	-1.13	arep4	3.61**	4.08	arep10-12	4.50***	4.25
d_ing	0.05*	2.33	arep5	3.88**	6.09	dp1_3	-0.00	-0.63
d_bnp	-0.00	-0.02	arep6	0.83	0.47	dp4_6	0.017***	3.65
d_sg	0.03	1.48	arep7	2.19	1.98	dp7_9	0.005	1.39
d_hsbc	-0.01	-2.03	arep8	1.17	1.75	dp10_12	0.012***	3.54
d_abbn	0.16**	13.00	arep9	3.10*	2.84			
d_rbs	0.14**	16.35	arep10	6.10**	5.47			
d_bar	0.12**	15.04	arep11	4.64	1.62			
d_1999	0.16**	4.19	arep12	3.85*	2.21			
d_2000	0.19**	5.14	dp1	-0.00	-0.11			
d_2001	0.19**	6.16	dp2	-0.00	-0.69			
d_2002	0.26**	14.44	dp3	-0.01	-0.81			
d_2003	0.20**	21.06	dp4	0.02**	3.41			
d_int1	0.02	1.50	dp5	0.02**	4.11			
d_int2	0.04**	5.66	dp6	0.00	0.20			
d_int3	0.02*	3.00	dp7	0.02*	2.41			
d_int5	0.03**	3.19	dp8	-0.01	-1.31			
d_int6	0.09**	5.13	dp9	0.01	1.90			
d_int7	0.16**	17.53	dp10	0.01	0.89			
d_int8	0.20**	8.91	dp11	0.01	0.97			
d_int9	0.37**	4.38	dp12	0.02**	5.41			
d_montue	0.02	1.27						
d_thur	0.01	1.51						
d_fri	0.03**	5.25						
nomps	0.07	2.20						
mps	2.05**	4.23						
d_per	0.01**	3.51						
constant	-2.71**	-12.01						
N	17820			17820			17820	
R^2	0.41			0.43			0.43	

Table 4: Information content of interim reports

Estimated with OLS using robust standard errors. In interim model I arep4_6int is equal to the size of the monetary policy surprise if the annual report was published 4 to 6 months ago and an interim report was published during the period. Equivalently arep4_6nint is equal to the size of the monetary policy shock if the annual report was published 4 to 6 months ago and no interim report was published during the period. In interim model II all "arep" variables were recoded measuring the number of months since an informative report (whether annual or interim) was published. "Informative" defined in the text. Both models include all variables of the previous specification. Only coefficients of interest reported for brevity.

	Interim Report Model I		**Interim Report model II**		
Variable	Coeff.	t-stat	Variable	Coeff.	t-stat
arep1_3	1.19**	2.55	arep1_3	1.64	1.87
arep4_6int	3.54***	15.94	arep4_6	4.51**	2.81
arep4_6nint	3.07	1.47	arep7_9	3.24**	2.92
arep7_9int	1.85*	2.12	arep10_12	4.96***	5.09
arep7_9nint	1.40***	7.91			
arep10_12int	4.98***	5.22			
arep10_12nint	4.65***	2.76			
N	17820			17820	
R^2	0.43			0.44	

Table 5: Robustness checks

Estimated using OLS using robust standard errors. Robustness I reflects a model in which the monetary policy surprises are measured with a dummy variable, i.e. the size of the surprise does not enter. All models include all variables of the previous specifications. Only coefficients of interest reported for brevity.

	Robustness I			**Euro area banks only**		**UK banks only**	
Variable	Coeff.	t-stat.	Variable	Coeff.	t-stat	Coeff.	t-stat
dumsup1_3	0.13***	3.19	arep1_3	0.51***	4.22	3.62*	2.86
dumsup4_6	0.19***	4.41	arep4_6	2.68**	3.52	6.91**	4.53
dumsup7_9	0.32***	5.25	arep7_9	1.32*	2.42	3.03	2.17
dumsup10_12	0.47***	5.86	arep10_12	2.73**	3.33	7.63*	3.05
N	17820			11142		6678	
R^2	0.43			0.53		0.52	

Appendix I: Descriptive statistics of equity returns, standardised equity returns, realised volatilities and log of realised volatilities

	RT_HSBC	STRT_HSBC	RV_HSBC	LNRV_HSBC
Mean	0.00009	0.00408	0.00640	-5.27404
Median	0.00000	0.00000	0.00478	-5.34376
Maximum	0.02388	4.79583	0.12424	-2.08552
Minimum	-0.02293	-2.67198	0.00030	-8.10619
Std. Dev.	0.00417	0.69636	0.00663	0.60708
Skewness	0.24660	0.19919	7.87243	0.72634
Kurtosis	6.78	4.77	103.43	4.68
Jarque-Bera	1024.6	231.9	727673.6	346.3
Probability	0.00000	0.00000	0.00000	0.00000
Q(10)	10.17	8.36	**181.04**	**1128.00**
Observations	1690	1690	1690	1690
	RT_ABBN	**STRT_ABBN**	**RV_ABBN**	**LNRV_ABBN**
Mean	0.00005	0.03038	0.00942	-4.87976
Median	-0.00001	-0.00228	0.00736	-4.91173
Maximum	0.08441	4.79583	0.09371	-2.36759
Minimum	-0.05402	-3.19664	0.00121	-6.71609
Std. Dev.	0.00762	0.80058	0.00768	0.63178
Skewness	0.28898	0.67459	3.82857	0.27901
Kurtosis	15.53549	6.64651	27.88452	3.45253
Jarque-Bera	12401.0	1190.5	53382.3	40.6
Probability	0.00000	0.00000	0.00000	0.00000
Q(10)	11.86	**27.33**	**393.77**	**1127.90**
Observations	1890	1890	1890	1890
	RT_RBS	**STRT_RBS**	**RV_RBS**	**LNRV_RBS**
Mean	0.00002	0.00927	0.00859	-4.97074
Median	0.00000	0.00000	0.00652	-5.03309
Maximum	0.06851	4.14226	0.07386	-2.60559
Minimum	-0.05431	-4.79583	0.00131	-6.63635
Std. Dev.	0.00704	0.78757	0.00714	0.61412
Skewness	0.40899	-0.27529	3.52423	0.59460
Kurtosis	14.04592	6.15693	22.21690	3.42949
Jarque-Bera	9661.2	808.7	32993.9	125.9
Probability	0.00000	0.00000	0.00000	0.00000
Q(10)	**25.70**	14.36	**617.33**	**1103.30**
Observations	1890	1890	1890	1890
	RT_BAR	**STRT_BAR**	**RV_BAR**	**LNRV_BAR**
Mean	-0.00018	-0.01719	0.00848	-4.99245
Median	-0.00008	-0.01229	0.00655	-5.02860
Maximum	0.03562	4.79583	0.07901	-2.53824
Minimum	-0.03522	-4.79583	0.00128	-6.66281
Std. Dev.	0.00653	0.79561	0.00726	0.63030
Skewness	-0.01037	-0.24625	3.73863	0.50216
Kurtosis	7.01948	6.52590	24.56051	3.47069
Jarque-Bera	1252.1	982.3	40359.3	95.3
Probability	0.00000	0.00000	0.00000	0.00000
Q(10)	11.33	15.60	**388.40**	**1184.70**
Observations	1860	1860	1860	1860

Appendix I – Cont'd

	RT_ABN	STRT_ABN	RV_ABN	LNRV_ABN
Mean	-0.00015	-0.02533	0.00662	-5.18191
Median	0.00000	0.00000	0.00533	-5.23517
Maximum	0.03942	2.36589	0.02872	-3.55013
Minimum	-0.02908	-3.09757	0.00158	-6.45095
Std. Dev.	0.00656	0.82940	0.00412	0.56227
Skewness	0.01531	-0.13809	1.59031	0.28705
Kurtosis	7.04426	3.08834	5.92887	2.51144
Jarque-Bera	586.1	3.01267	669.9	20.36339
Probability	0.00000	0.22172	0.00000	0.00004
Q(10)	11.70	8.61	**3220.60**	**3511.60**
Observations	860	860	860	860
	RT_ING	**STRT_ING**	**RV_ING**	**LNRV_ING**
Mean	-0.00034	-0.02326	0.00771	-5.02258
Median	-0.00049	-0.07191	0.00623	-5.07770
Maximum	0.04948	2.58890	0.03541	-3.34064
Minimum	-0.04329	-2.53604	0.00174	-6.35512
Std. Dev.	0.00823	0.89216	0.00474	0.54963
Skewness	-0.05213	0.06679	1.75587	0.28097
Kurtosis	7.62067	2.60450	7.19859	2.62759
Jarque-Bera	765.5	6.24466	1073.6	16.28465
Probability	0.00000	0.04405	0.00000	0.00029
Q(10)	**19.22**	**19.52**	**2828.70**	**3354.20**
Observations	860	860	860	860
	RT_BNP	**STRT_BNP**	**RV_BNP**	**LNRV_BNP**
Mean	-0.00004	-0.00242	0.00659	-5.13648
Median	0.00000	0.00000	0.00579	-5.15100
Maximum	0.03824	2.47729	0.03044	-3.49195
Minimum	-0.03114	-2.64988	0.00179	-6.32304
Std. Dev.	0.00647	0.85248	0.00347	0.46896
Skewness	0.02326	0.00579	1.84142	0.31058
Kurtosis	6.46575	2.74881	8.46773	2.80742
Jarque-Bera	430.5	2.26574	1557.3	15.15468
Probability	0.00000	0.32211	0.00000	0.00051
Q(10)	11.72	6.82	**1693.10**	**1774.00**
Observations	860	860	860	860
	RT_SG	**STRT_SG**	**RV_SG**	**LNRV_SG**
Mean	-0.00013	0.00721	0.00711	-5.07650
Median	0.00003	0.00787	0.00618	-5.08696
Maximum	0.04909	2.49453	0.02743	-3.59621
Minimum	-0.03181	-2.10022	0.00124	-6.69607
Std. Dev.	0.00713	0.81710	0.00390	0.50335
Skewness	0.21757	0.05793	1.53935	0.21594
Kurtosis	8.29535	2.54741	5.98942	2.65952
Jarque-Bera	1011.6	7.82122	659.9	10.83757
Probability	0.00000	0.02003	0.00000	0.00443
Q(10)	14.26	5.84	**2266.00**	**2361.20**
Observations	860	860	860	860

Appendix I – Cont'd.

	RT_DB	STRT_DB	RV_DB	LNRV_DB
Mean	0.00020	0.03619	0.00654	-5.13929
Median	0.00021	0.03937	0.00576	-5.15712
Maximum	0.05052	2.63303	0.03673	-3.30418
Minimum	-0.04452	-2.36576	0.00157	-6.45493
Std. Dev.	0.00634	0.81330	0.00336	0.45982
Skewness	0.20751	0.05163	1.94191	0.22775
Kurtosis	8.31199	2.80247	9.51167	3.12052
Jarque-Bera	3525.0	6.16832	7137.8	27.56603
Probability	0.00000	0.04577	0.00000	0.00000
Q(10)	12.62	9.49	**6323.30**	**6249.60**
Observations	2980	2980	2980	2980
	RT_HB	**STRT_HB**	**RV_HB**	**LNRV_HB**
Mean	0.00007	0.01273	0.00857	-4.88640
Median	0.00017	0.02667	0.00745	-4.89958
Maximum	0.08342	2.66851	0.05749	-2.85620
Minimum	-0.07068	-2.65283	0.00091	-6.99887
Std. Dev.	0.00827	0.78716	0.00479	0.49526
Skewness	0.19120	-0.02375	2.38755	0.16990
Kurtosis	13.29451	3.04163	14.98986	3.14043
Jarque-Bera	13177.0	0.49537	20681.0	16.78465
Probability	0.00000	0.78061	0.00000	0.00023
Q(10)	13.22	13.65	**5729.90**	**6012.20**
Observations	2980	2980	2980	2980
	RT_CB	**STRT_CB**	**RV_CB**	**LNRV_CB**
Mean	0.00003	-0.00511	0.00816	-4.92025
Median	-0.00008	-0.01368	0.00698	-4.96502
Maximum	0.10784	2.79882	0.05705	-2.86389
Minimum	-0.05053	-2.68253	0.00097	-6.93674
Std. Dev.	0.00741	0.71869	0.00436	0.45992
Skewness	1.60941	0.10068	2.27839	0.33847
Kurtosis	27.15508	3.37760	12.94284	3.43269
Jarque-Bera	73733.7	22.73835	14853.4	80.14704
Probability	0.00000	0.00001	0.00000	0.00000
Q(10)	**25.40**	15.44	**8317.10**	**7758.80**
Observations	2980	2980	2980	2980

RT stands for realised returns, STRT for standardised realised returns, RV for realised volatility, and LNRV for log of realised volatility.

HSBC stands for HSBC, ABBN for Abbey National Bank, RBS for Royal Bank of Scotland, BAR for Barclays, ABN for ABN Amro, ING for ING Bank, BNP for BNP Paribas, SG for Société Générale, DB for Deutsche Bank, HB for Hypovereinsbank, and CB for Commerzbank.

The realised returns are the sum of the two minute returns within a 46 minute window. Values are reported in fractions. The realised volatility is the square root of the sum of squared two minute returns within a 46 minute window. Standardised returns are the ratio of realised returns and their corresponding realised volatilities.

Appendix II: Descriptive statistics of variables used in the regressions

LNRV represents the log of realised volatility. HSBC stands for HSBC, ABBN for Abbey National Bank, RBS for Royal Bank of Scotland, BAR for Barclays, ABN for ABN Amro, ING for ING Bank, BNP for BNP Paribas, SG for Société Générale, DB for Deutsche Bank, HVB for Hypovereinsbank, and CB for Commerzbank. d99 to d04 represent year dummies. d_1 to d_9 represent the time windows during the day and d_montue, d_wed, d_thur and d_fri are dummies representing the days of the week, respectively. mps is the monetary policy surprise as defined by the absolute value of the difference between the mean of the Reuter's poll and the change in the policy rate. nomps represent days on which there was a monetary policy decision but no surprise.

Variable	N	Mean	Standard deviation	Minimum	Maximum
lnrv	17820	-5.04	0.55	-8.11	-1.90
lnrv1	17820	-5.05	0.54	-8.11	-1.90
d_cb	17820	0.15	0.36	0	1
d_db	17820	0.15	0.36	0	1
d_hvb	17820	0.15	0.36	0	1
d_abn	17820	0.04	0.20	0	1
d_ing	17820	0.04	0.20	0	1
d_bnp	17820	0.04	0.20	0	1
d_sg	17820	0.04	0.20	0	1
d_hsbc	17820	0.09	0.28	0	1
d_abbn	17820	0.10	0.29	0	1
d_rbs	17820	0.10	0.30	0	1
d_bar	17820	0.10	0.30	0	1
d99	17820	0.17	0.37	0	1
d00	17820	0.18	0.38	0	1
d01	17820	0.18	0.38	0	1
d02	17820	0.19	0.39	0	1
d03	17820	0.20	0.40	0	1
d04	17820	0.08	0.27	0	1
d_int1	17820	0.11	0.31	0	1
d_int2	17820	0.11	0.31	0	1
d_int3	17820	0.11	0.31	0	1
d_int4	17820	0.11	0.31	0	1
d_int5	17820	0.11	0.31	0	1
d_int6	17820	0.11	0.31	0	1
d_int7	17820	0.11	0.31	0	1
d_int8	17820	0.11	0.31	0	1
d_int9	17820	0.11	0.31	0	1
d_montue	17820	0.03	0.17	0	1
d_wed	17820	0.33	0.47	0	1
d_thur	17820	0.33	0.47	0	1
d_fri	17820	0.31	0.46	0	1
mps	17820	0.00	0.01	0	0.5
nomps	17820	0.01	0.12	0	1
d_per	17820	-0.35	1.28	-6.61	0

Figure 1: theoretical quantile–quantile pictures

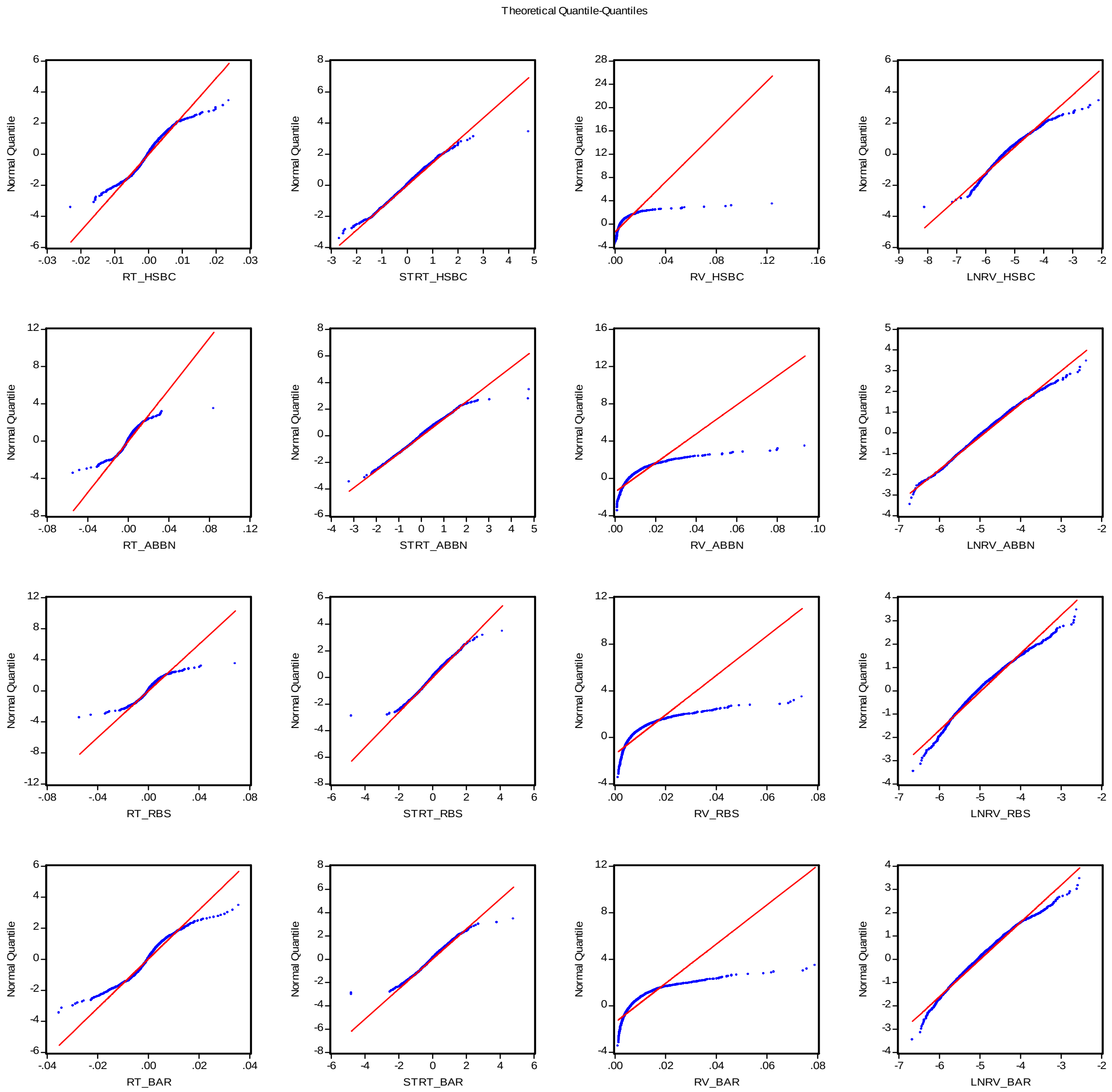
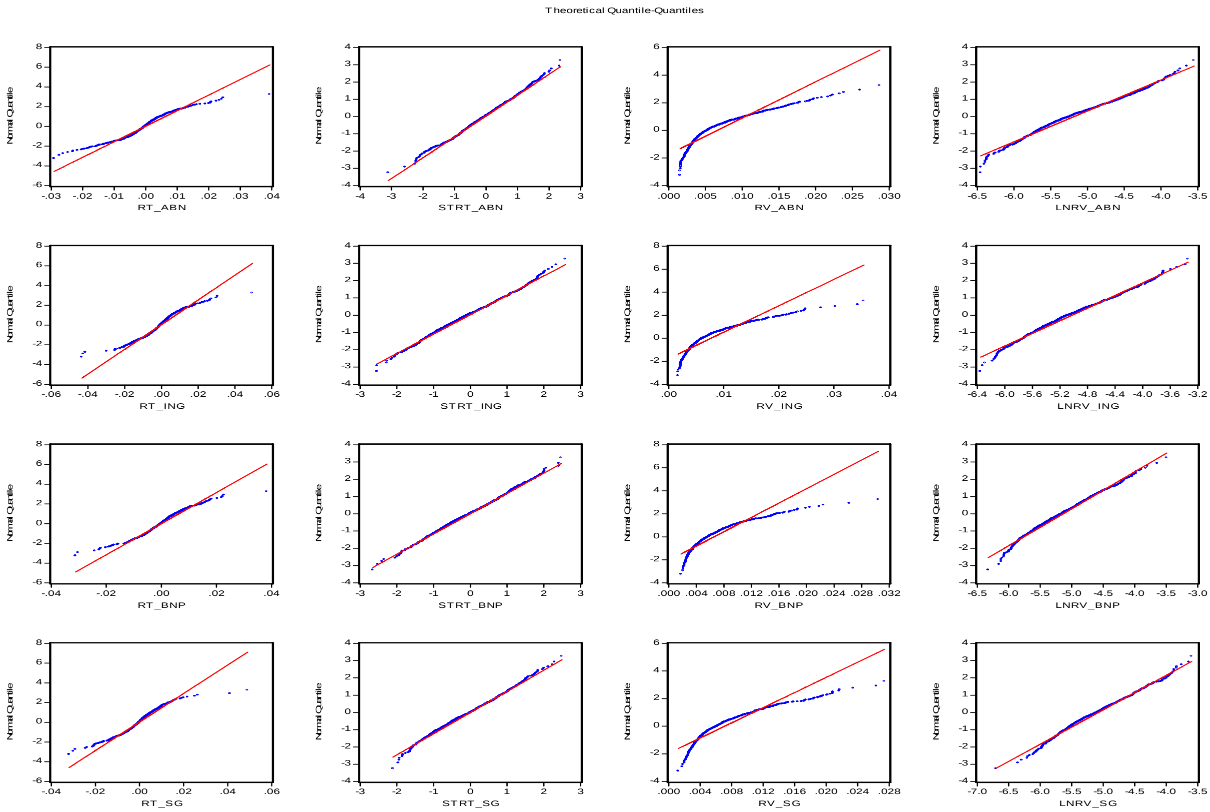
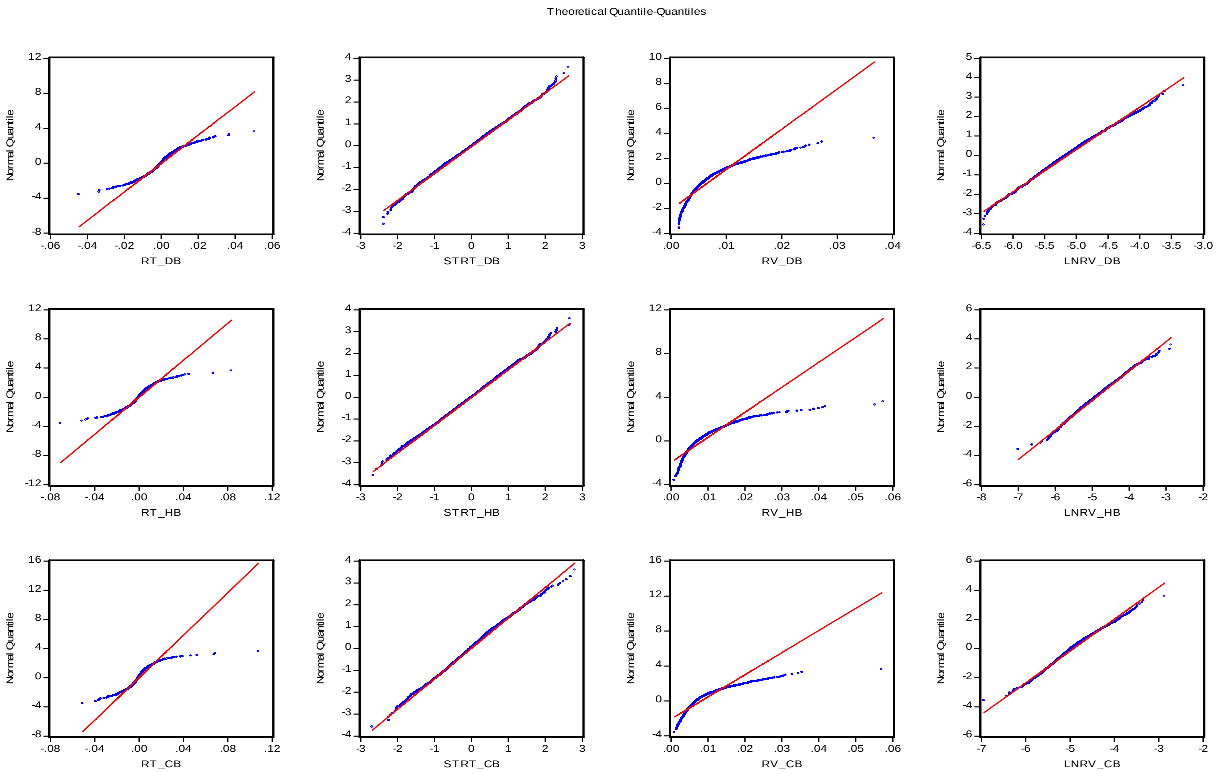
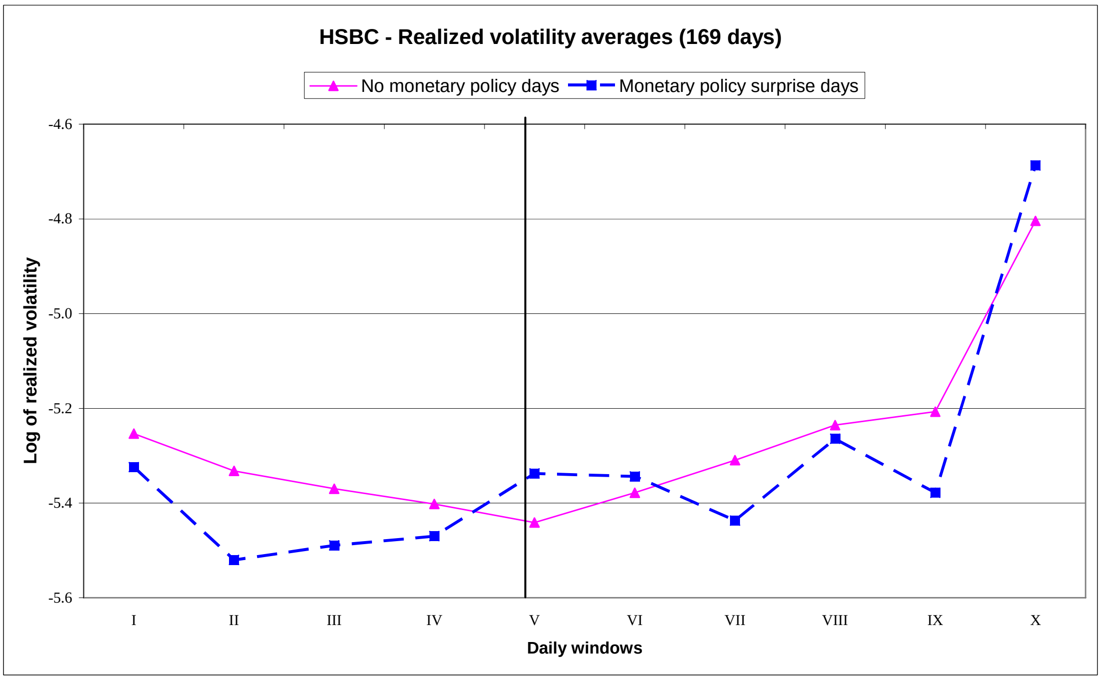


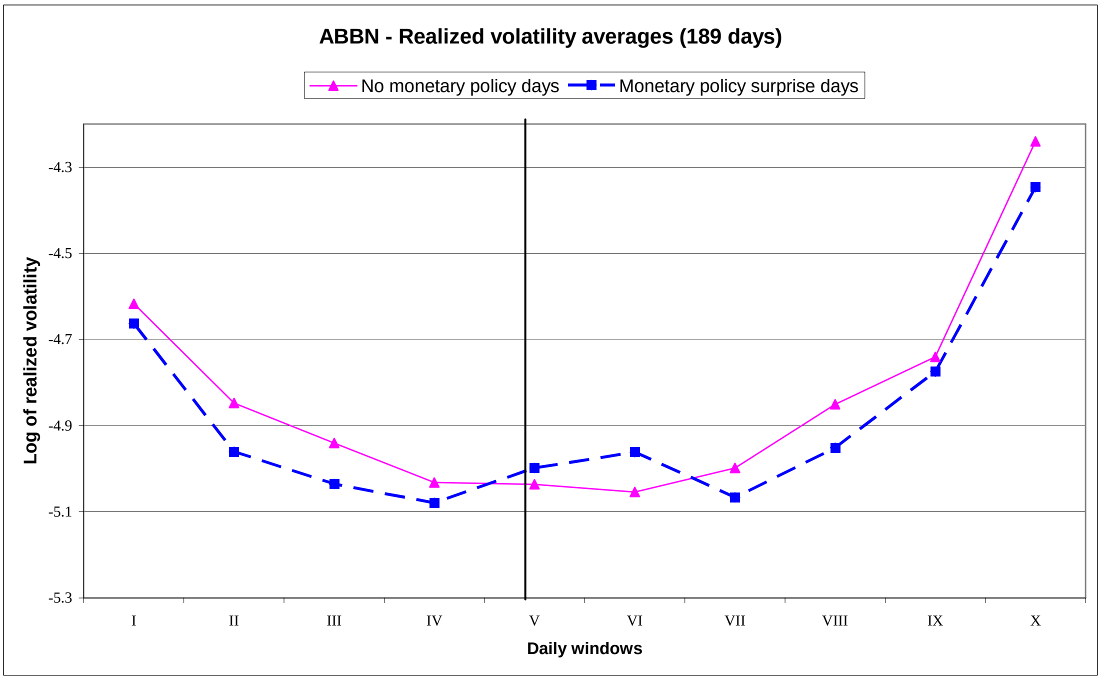
Figure 1 - Continued





Figures 2a-2k





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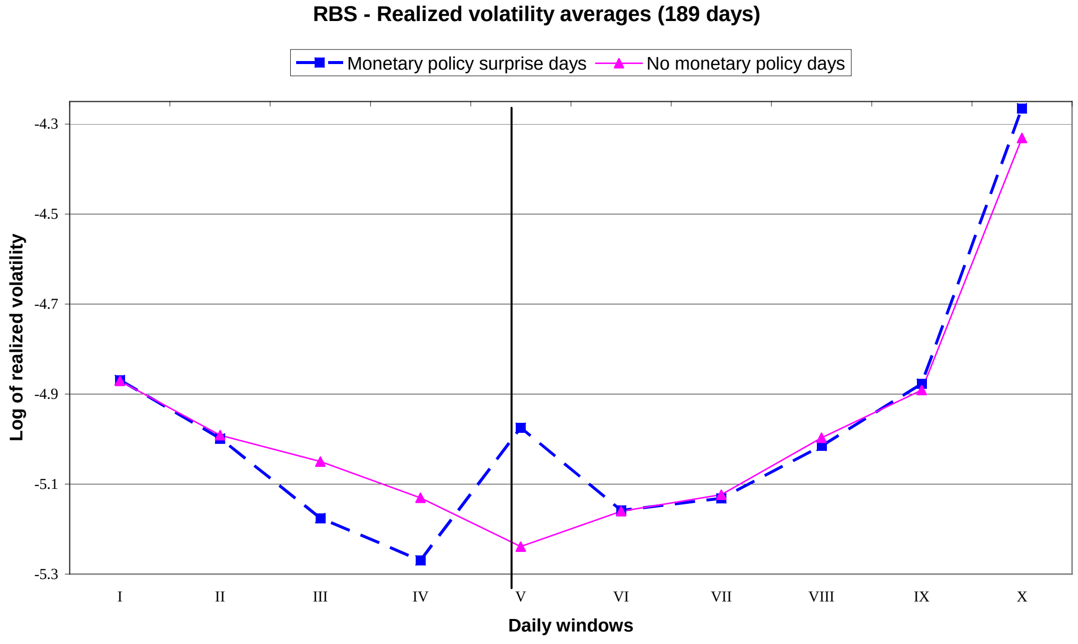
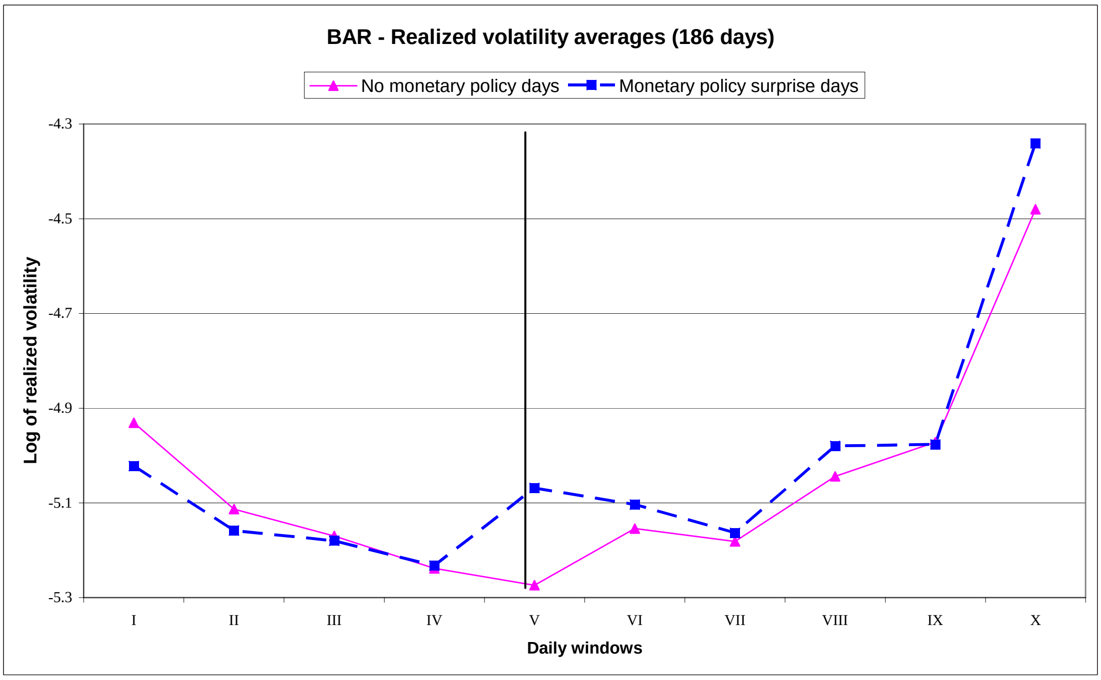
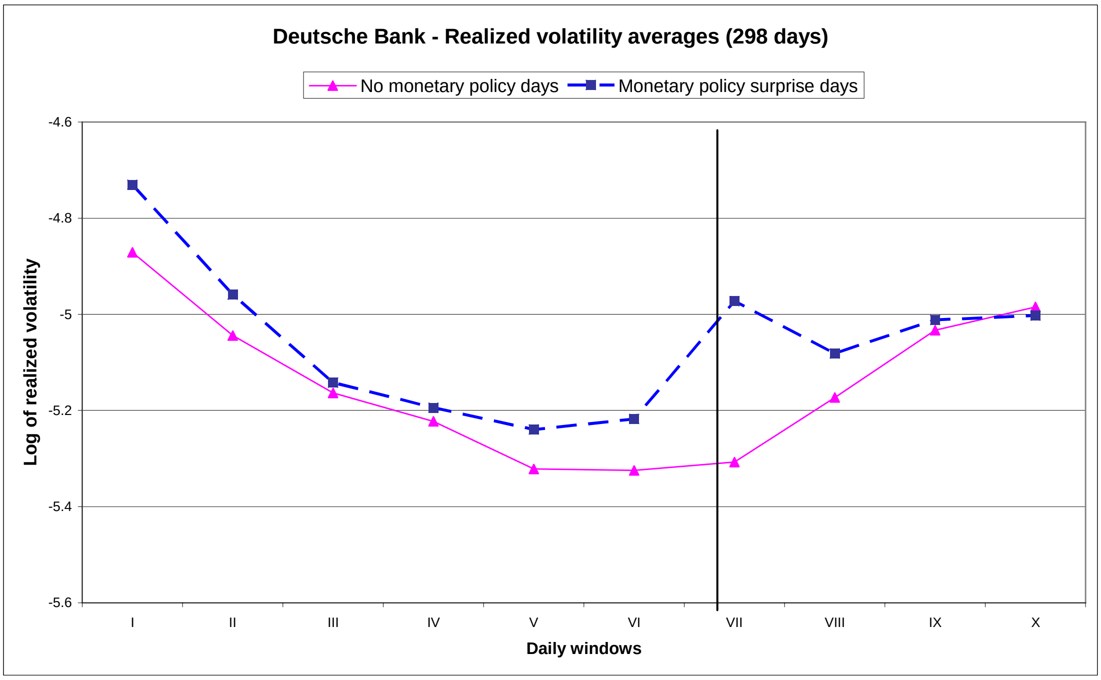
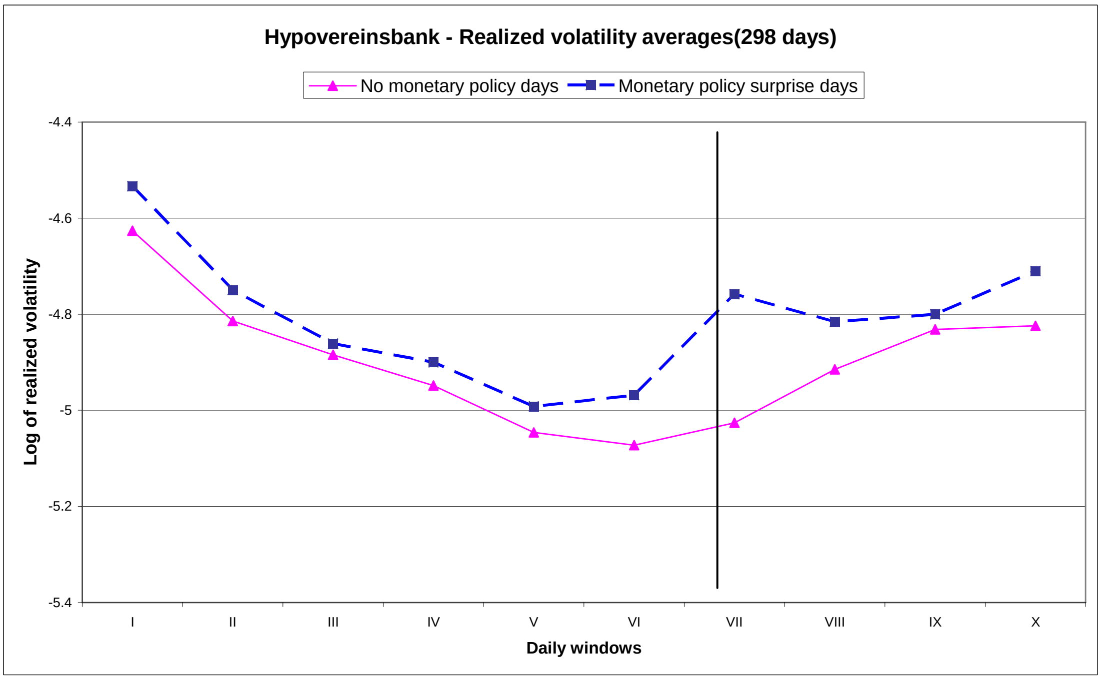




Figures 2 – continued





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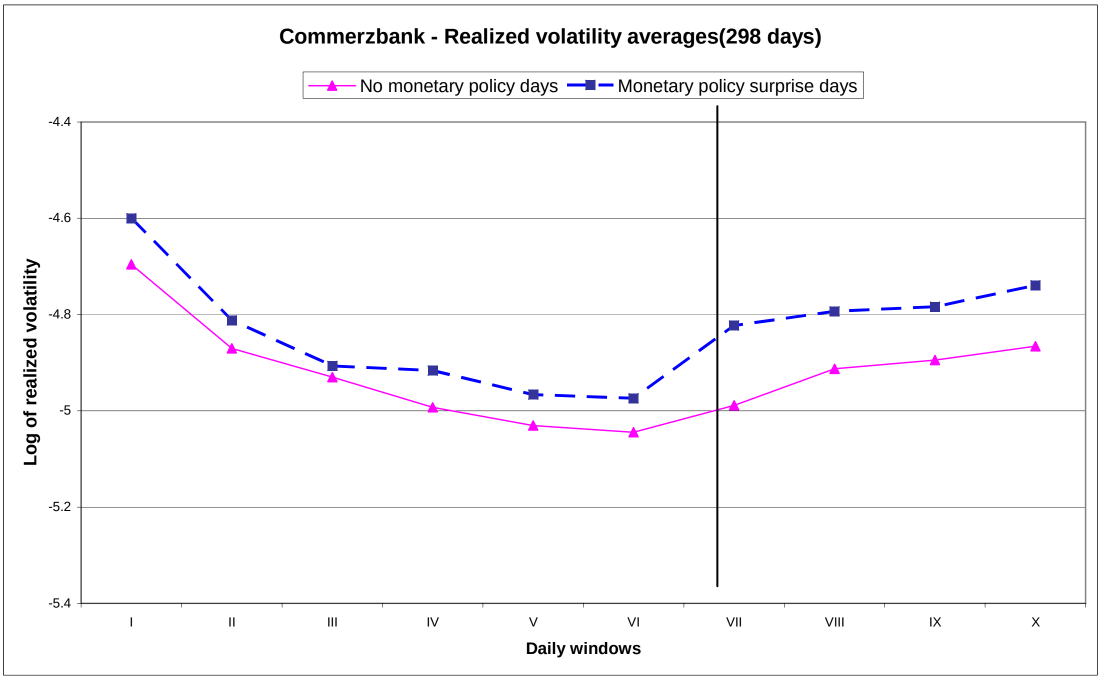

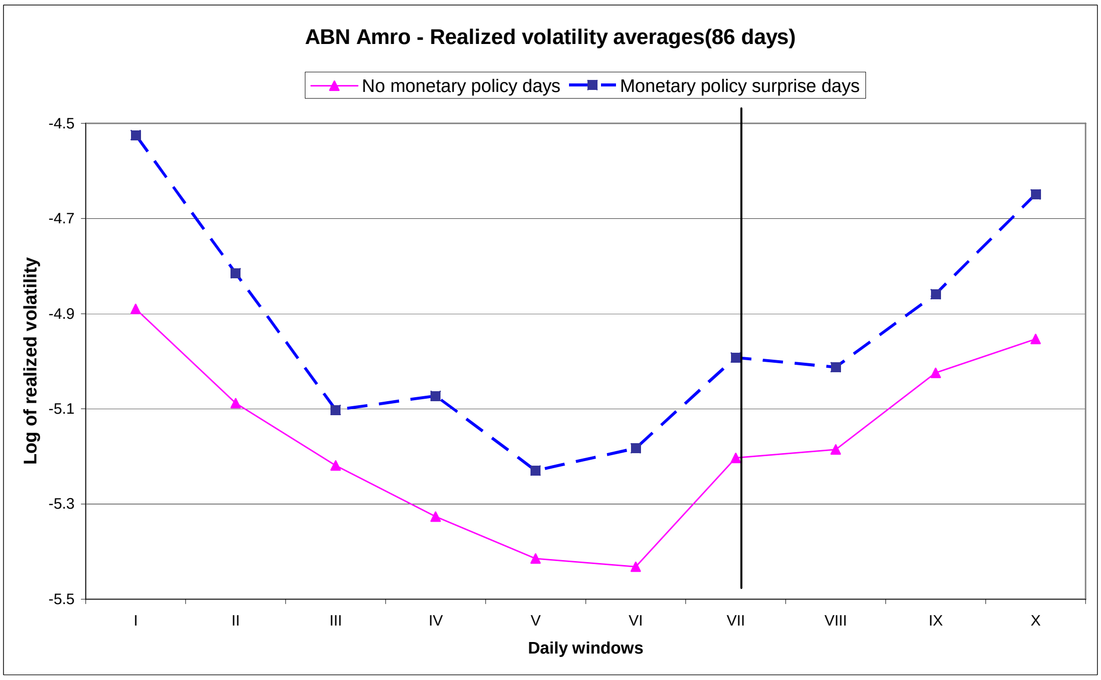

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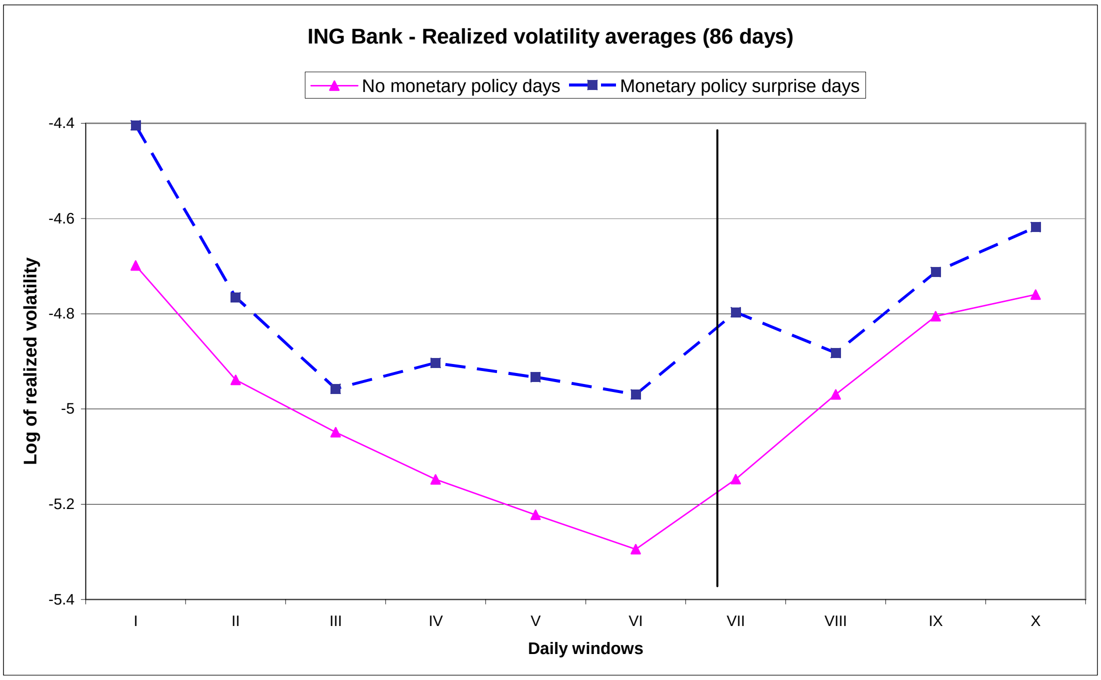

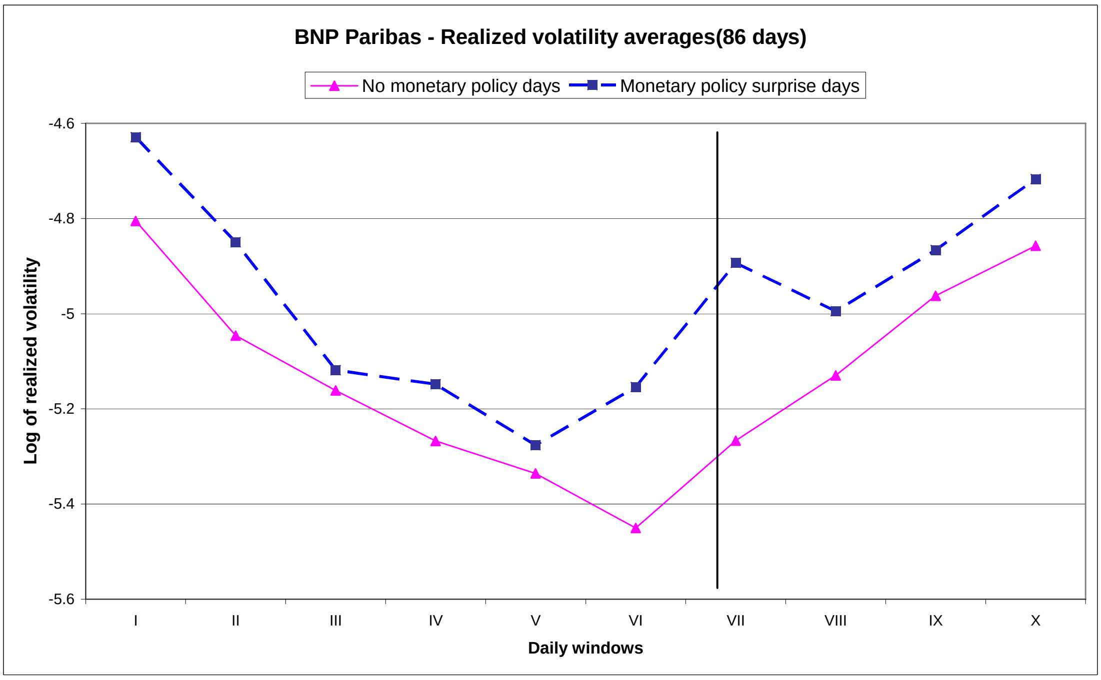

Figures 2 – continued