Banco de México

Documentos de Investigación

Banco de México

Working Papers

N° 2009-15

Macroeconomic News, Announcements, and Stock Market Jump Intensity Dynamics

José Gonzalo Rangel
Banco de México

December, 2009

Documento de Investigación 2009-15

Working Paper 2009-15

Macroeconomic News, Announcements, and Stock Market Jump Intensity Dynamics*

José Gonzalo Rangel†
Banco de México

Abstract
This paper examines the effect of macroeconomic releases on stock market volatility through a Poisson-Gaussian-GARCH process with time varying jump intensity, which is allowed to respond to such information. It is found that the day of the announcement, per se, has little impact on jump intensities. Employment releases are an exception. However, when macroeconomic surprises are considered, inflation shocks show persistent effects while monetary policy and employment shocks show only short-lived effects. Also, the jump intensity responds asymmetrically to macroeconomic shocks. Evidence that macroeconomic variables are relevant to explain jump dynamics and improve volatility forecasts on event days is provided.
Keywords: Conditional jump intensity, conditional volatility, macroeconomic announcements.
JEL Classification: C22, G14.

Resumen
Este artículo examina el efecto de los anuncios macroeconómicos en la volatilidad del mercado de valores utilizando un proceso Poisson-GARCH Gaussiano con intensidad de saltos que varía en el tiempo, a la cual se le permite reaccionar a dicha información macroeconómica. Se encuentra que el día del anuncio, per-se, tiene un impacto pequeño en la intensidad de los saltos. Los anuncios de empleo son una excepción. Sin embargo, cuando se consideran sorpresas macroeconómicas, los choques inflacionarios muestran un efecto persistente, mientras que los choques de política monetaria y empleo muestran únicamente efectos de corto plazo. También, la intensidad de los saltos responde de manera asimétrica a las sorpresas macroeconómicas. Se proporciona evidencia de que las variables macroeconómicas son relevantes para explicar la dinámica de los saltos y para mejorar los pronósticos de volatilidad en días de eventos.
Palabras Clave: Intensidad de saltos condicional, volatilidad condicional, anuncios macroeconómicos.

*I am grateful to Jim Hamilton and Rob Engle for helpful discussions throughout this project. I also thank Carlos Capistrán, Bruce Lehmann, Allan Timmermann, Camilo Tovar, Christopher Woodruff and Carla Ysusi for their helpful comments. Financial support provided by CONACYT and UCMEXUS is gratefully acknowledged. I also thank Informa Global Markets for kindly providing a sample of the MMS survey data. The opinions expressed in this article are those of the author and do not necessarily reflect the point of view of Banco de México.

† Dirección General de Investigación Económica. Email: jgrangel@banxico.org.mx.

1 Introduction

The responses of asset prices and market volatility to information releases concerning fundamental variables are of key interest for relevant financial and economic decisions, such as risk management, asset pricing, and portfolio allocation. Since changes in prices and volatility primarily occur through trades motivated for reasons of information, then the form of those responses can be related to the nature of the process of information arrival, as suggested in Clark (1973) and Ane and Geman (2000).[1] Discontinuities in information flow drive jumps in the price process, which are generally associated with periods of intense market activity.[2] The empirical evidence has rejected continuous models, and has favored those with discontinuities (e.g., Chernov, Gallant, Ghysels, and Tauchen (2003), Eraker, Johannes, and Polson (2003), Eraker (2004), and Maheu and McCurdy (2004)). In addition, recent literature also confirms the importance of jumps, not only in characterizing a feature of the information process driving returns at high frequencies, but also in describing the transmission mechanism of policy decisions. For instance, Das (2002) and Johannes (2004) analyze interest rates and find that jumps are a primary conduit through which macroeconomic information enters the term structure.

All the above mentioned studies agree with the close connection among jumps in

[1] In these studies, the cumulated arrival of relevant information is a reasonable measure of time changes at high frequencies.

[2] The simplest version of models incorporating jumps is the popular "jump-diffusion", which is obtained when the cumulated arrival of information has a finite number of discontinuities in a finite horizon. Geman, Madan, and Yor (2000) motivate more general purely discontinuous processes relating time changes to measures of economic activity at high frequencies.

the returns process, large changes in market volatility, and the arrival of events (such as macroeconomic releases) that might take the market by surprise. However, less is known about the specific form of this connection, or about whether the impacts on volatility dynamics are heterogeneous with respect to the type of news event. This paper addresses these two concerns by focusing on events associated with the disclosure of public information regarding fundamental macroeconomic variables. In particular, I consider a set of releases that are disclosed in regularly scheduled announcements and convey information about monetary policy, inflation, and growth (employment). In this context, I explore the effects of announcements and news events on the conditional volatility of returns through a non-linear channel associated with jumps in the return process. Specifically, I focus on the conditional jump intensity of stock market returns. In addition, I examine the extent to which heterogeneity among scheduled announcements explains differences in the dynamic behavior of such jump component, shedding more light on the sources of persistence in the conditional second moment of market returns, and providing a criterion to distinguish between permanent and transitory effects of particular types of shocks.

A number of studies have analyzed the effect of macroeconomic announcements on the volatility of asset returns using daily and intradaily data (e.g., Jones, Lamont, and Lumsdaine (1998), Andersen and Bollerslev (1998), and Flannery and Protopapadakis (2002)). The common parametric approach has used a multiplicative filter to model a structural volatility change on event days. However, this strategy does not allow

direct interactions between surprises and jump dynamics. Non-parametric approaches have exploited recent developments in measuring the quadratic variation of an stochastic process using intradaily data. For instance, Huang (2007) separates financial market responses into continuous volatility effects and jumps on news days. He finds evidence that there are more days with large jumps on announcement days than on non-announcement days for several types of macroeconomic announcements. Moreover, he finds larger proportions of news days in jump days than in the whole sample. This evidence suggests that the jump intensity may be affected by macroeconomic news and the present study proposes a parametric strategy to model such impacts in a dynamic setup that allows macroeconomic releases to have direct effects (with different types of persistence) on the conditional jump intensity of market returns.

The framework of this paper follows the approach of Maheu and McCurdy (2004) in terms of modeling the returns process through a mixture of a GARCH model with a compound Poisson jump process in a discrete time setting at a daily frequency.[3] I follow such a model by allowing the jump intensity to be time varying with serial correlation; although, on the one hand, I model differentiated impacts of heterogeneous news linking parametrically the jump arrival intensity with announcement and news variables and, on the other hand, I allow for asymmetric effects of shocks on the jump volatility component, which introduces an additional source of good/bad news effects on the conditional volatility of returns.

[3] Oomen (2002) motivates the use of the compound Poisson process as a flexible model to characterize dynamic properties of returns at high frequencies.

Using daily returns on the S&P500 and measures of real time U.S macroeconomic news, the results suggest that incorporating fundamental news variables into the specification of the jump intensity is relevant to characterize the effect of such news on conditional volatilities and to improve measures of jump occurrence. Indeed, heterogeneous news effects are found. Inflation surprises show asymmetric effects on the jump intensity and on the conditional mean of market returns. In addition, while Producer Price Index (PPI) inflation shocks have a persistent effect on jump intensities, and therefore on conditional volatilities, monetary policy and employment shocks show only short-lived effects. The results of this paper suggest that introducing macroeconomic surprises is relevant for explaining and predicting the dynamic behavior of jump probabilities on monetary policy and employment announcement days. To address the issue of in-sample overfitting, common in heavily parameterized non-linear models, this paper also performs out-of-sample forecast comparisons.[4] In this regard, I provide evidence that the in-sample results are not an artifact of overfitting and that using jump intensity specifications with news variables leads to out-of-sample improvements in forecasting volatility on event days.

The paper is organized as follows: Section 2 presents a review of the literature regarding the effect of macroeconomic news on market volatility. Section 3 introduces the model characterizing the conditional return distribution. Section 4 provides a description of the data used in the empirical analysis, and defines the measures of surprises

[4] Clark (2004) shows that out-of-sample forecast comparisons are effective to avoid data mining-induced overfitting.

used in this paper. Section 5 reports estimation results for different jump model specifications. Finally, a comparison with competing GARCH models is presented in section 6, and section 7 concludes.

2 News Effects on Financial Volatility

The relation between stock market volatility and uncertainty about fundamentals has been the focus of an active research agenda oriented to understand and test the economic factors that cause stock market volatility. At low frequencies, Schwert (1989) finds weak evidence that macroeconomic volatility can explain stock return volatility. Instead, he suggests that it is more likely that stock market volatility causes macroeconomic volatility. He also finds that the average level of volatility is considerably higher during recessions. From a theoretical standpoint, David and Veronesi (2008) develop an equilibrium asset pricing model in which positive inflation and/or negative earnings surprises induce additional uncertainty of switching to high inflation and/or low earnings regimes, which are associated with a raise in the overall stock return volatility. Engle and Rangel (2008) find a strong relationship between the low frequency component of market volatility and macroeconomic variables such as inflation, growth, and macroeconomic volatility. These papers only examine a long-term relation between returns volatility and fundamentals.

From a short-run prospective, other studies have addressed the market volatility reaction to fundamental news released on announcement days. Most of this research

has focused on the dynamics of conditional volatility based on the ARCH/GARCH framework introduced by Engle (1982) and Bollerslev (1986). For example, Li and Engle (1998) examine the degree of persistence heterogeneity associated with scheduled macroeconomic announcement days and non-announcement days in the Treasury futures market. They introduce a filtered GARCH model that takes care of cyclical patterns of time-of-the-week effects and announcement effects by decomposing returns volatility into a transitory and a non-transitory component. They find heterogeneous patterns in persistence when comparing announced versus non-announced macroeconomic releases. Specifically, announced releases are associated with less volatility persistence. They also reject risk premia on announcement days.

Jones, Lamont, and Lumsdaine (1998) present a similar analysis for the Treasury bond market. They find evidence of existence of "U" shaped day-of-the week effects and "calm before the storm" effects for bond returns volatility. In contrast to Li and Engle (1998), they find that announcement day shocks do not persist at all; they are purely transitory. This fact supports the Mixture of Distribution Hypothesis of Clark (1973), which implies that volatility persistence is due only to serial correlation in the information process. In addition, they suggest risk premia on announcement days, which favors a GARCH-M specification.

Andersen and Bollerslev (1998) study potentially different effects on volatility of scheduled versus unscheduled announcements using intradaily foreign exchange returns data (five-minute returns). Their results suggest that macroeconomic announcements

have a large impact on five-minute returns when they hit the market, although the induced effects on volatility are short-lived. At a daily level, the significance of these announcements for volatility is tenuous.

In terms of stock returns, Flannery and Protopapadakis (2002) use a GARCH model to detect the effect of macro announcements on different stock market indices. They consider as a potential "risk factor" any macro announcement that either affects returns or increases conditional volatility. Their results suggest that inflation measures (CPI and PPI) affect only the level of stock returns, and three real factor candidates (Balance of Trade, Employment/Unemployment, and Housing Starts) affect only the return's conditional volatility.

Bomfim (2003) examines the effect of monetary policy announcements on the volatility of stock returns. His work is based on the framework by Jones et al. (1998), and his results suggest that unexpected monetary policy decisions tend to boost significantly the stock market volatility in the short run. As expected, positive sign surprises tend to have a larger effect on volatility than negative sign surprises.

The basic setup considered by all of these studies is based on a multiplicative filter with announcement dummies. This suggests that, on announcement days, there is a deterministic shift in the standard diffusion component describing the news process. In other words, announcement effects are basically modelled as seasonal effects. Recent research has pointed out that it is not the occurrence of an announcement that matters

per se, but the surprise content of the release.[5] Naturally, the surprise component is unexpected, and it is typically associated with a jump in the return process. With the recent availability of high-frequency data, new econometric developments around the realized volatility framework of Andersen, Bollerslev, Diebold, and Labys (2003) have been suggested to filter the contribution of jumps to the realized variance measure (see Andersen, Bollerslev, and Diebold (2007) and Barndorff-Nielsen and Shephard (2004)). In this context, Huang (2007) finds a larger proportion of days with jumps within macroeconomic announcement days and, among the group of days with jumps, the largest proportion corresponds to days in which macroeconomic surprises were observed. Following this intuition, I present an alternative approach to characterize the volatility effect of surprises on announcement days by modeling such impact using a jump component in the return process and characterizing the response of the jump intensity to macroeconomic events.

3 Description of the Model

First, I consider a stock return process in discrete time that is affected by heterogeneous information shocks. Following the framework of Maheu and McCurdy (2004), the return process innovations are driven by a latent news process that has two separate components distinguished by their news impact: a) ε_{1t} represents "normal" news events, which are assumed to drive smooth price changes; b) ε_{2t} denotes "surprising"

[5] See Johannes (2004) for further discussion.

news events, which cause relatively infrequent large price changes.[6] Thus, under the information set Ω_{t-1} conveying the information of past returns (and possibly exogenous variables known before time t), the returns process can be specified as follows:

$$r_t = \mu_t + \varepsilon_{1t} + \varepsilon_{2t} \tag{1}$$

where,

$$\varepsilon_{1t} = \sigma_t z_t, \qquad z_t \sim iidN(0,1) \text{ for any } t,$$

$$\varepsilon_{2t} = \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim iidN(0,\delta^2) \text{ for } j = 1,2,...,N_t,$$

$$N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t),$$

λ_t =time varying arrival intensity= $E(N_t \mid \Omega_{t-1})$,

$\mu_t = \mu(X_t)$ =time varying conditional mean (X_t denotes a vector of explanatory variables).[7]

Note that $\varepsilon_{1t}|\Omega_{t-1} \sim N(0,\sigma_t^2)$ provided $\sigma_t \in \Omega_{t-1}$. Under this assumption, the dynamics of σ_t can be described by a GARCH process, and therefore the return process follows a mixed GARCH-Jump model. Otherwise, when $\sigma_t|\Omega_{t-1}$ is random, we have a stochastic volatility model with jumps, and $\varepsilon_{1t}|\Omega_{t-1}$ is not Gaussian.[8]

[6] This framework is also introduced in Chan and Maheu (2002).

[7] The jump intensity is assumed to be measurable with respect to Ω_{t-1}, and the innovations z_t and c_{jt} are assumed to be independent. However, the conditional autoregressive jump intensity dynamics considered later does not depend on this condition (see Chan and Maheu (2002))

[8] In this case $\varepsilon_{1t}|\Omega_{t-1}$ is a subordinated stochastic process, which can be seen as a Gaussian process with random variance. See Clark (1973) and Andersen (1996) for details.

Why jump models with time varying intensities? Models that account for large market movements or fat tails have been of academic interest for several years. In this regard, stochastic volatility (SV) models and jump models with stochastic jumps have been widely explored. From an empirical point of view, Eraker (2004) argues that none of these models have proved to be entirely successful. SV models have problems in explaining market crashes since they would require an implausible high volatility level both prior and after the crash. On the other hand, standard jump models assume that the jump intensity is constant. This assumption makes it difficult to explain the tendency of large movements to cluster over time. The framework taken in the present study combines these two approaches in a discrete time framework, and relaxes the assumption of a constant jump intensity.[9] The result is a model with high flexibility in describing the dynamics of the return process. Indeed, time varying arrival intensities makes also higher order moments time varying, which easily captures changes in the shape of the tails of the conditional distribution associated with periods of financial distress.

A number of plausible specifications for the jump intensity have been proposed in the literature. For instance, Jorion (1988) considers a constant jump intensity; Das (2002) proposes a model with different regimes for both the jump intensity and the unconditional volatility; Eraker (2004) models the jump intensity as an affine function of a stochastic volatility component; Maheu and McCurdy (2004) specify the jump

[9] GARCH(1,1) models can be seen as discrete approximations of diffusions used in continuous SV models (see Nelson (1990)).

intensity as a mean reverting autoregressive process. This approach is appealing because it gives high flexibility to capture dynamic features of the jump intensity, such as persistence and sensitivity to the arrival of new information. For this reason, I follow Maheu and McCurdy's specification for λ_t augmented with other explanatory variables associated with macroeconomic announcements and surprises. Notice also that the specification of the jump intensity has direct implications for the conditional volatility. In fact, if the model is correctly specified, the conditional variance takes the following form:

$$var(r_t|\Omega_{t-1}) = \sigma_t^2 + \lambda_t \delta^2 \tag{2}$$

Hence, surprises can influence conditional volatility either through their effect on the jump arrival intensity or through the GARCH process describing σ_t^2. Moreover, under this specification, the impact of news on market volatility might be driven by the effect of previous surprises on the conditional probability of observing a jump arrival in the price process. This dynamic behavior is able to describe the excess of volatility associated with a "peso problem situation". Equation (2) is key for the interpretation of my empirical results since any effect on λ_t will also govern the conditional volatility provided δ is significantly different from zero.

The following proposition characterizes the conditional density of a return process described by (1), as well as a filter that describes the conditional expected number of jumps in the process.[10]

[10]Equations (3) and (4) are referred as equations (23) and (24) in Maheu and McCurdy (2004).

Proposition 1 *If returns follow a process described in expression (1) with* $0 < \sigma_t < \infty$ *and* $0 < \lambda_t < \infty$, $\forall t$. *Then the conditional density of returns given a relevant set of parameters* Θ *takes the form:*

$$f(r_t|\Omega_{t-1},\Theta) = \sum_{j=0}^{\infty} \frac{\exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi(\sigma_t^2 + j\delta^2)}} \exp\left(-\frac{(r_t-\mu_t)^2}{2(\sigma_t^2 + j\delta^2)}\right) \tag{3}$$

Moreover, the conditional density of the number of jumps observed at time t, given the updated information, can be expressed as:

$$p(N_t = j|\Omega_t) = \left(\frac{\frac{\exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi(\sigma_t^2+j\delta^2)}} \exp\left(-\frac{(r_t-\mu_t)^2}{2(\sigma_t^2+j\delta^2)}\right)}{f(r_t|\Omega_{t-1},\Theta)}\right) \tag{4}$$

The proof is given in Appendix A1.

Note that these densities involve an infinite sum that makes infeasible their analysis for estimation purposes. However, finite order approximations based on Taylor's expansions can be taken in practical applications. This is a common practice for the analogous continuous time jump-diffusion models.[11] In fact, the first order approximation of Equation (3), which seem to work well when λ_t is "small", is given by[12]:

$$f^1(r_t|\Omega_{t-1},\Theta) = \frac{(1-\lambda_t)}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{(r_t-\mu_t)^2}{2\sigma_t^2}\right) + \frac{\lambda_t}{\sqrt{2\pi(\sigma_t^2+\delta^2)}} \exp\left(-\frac{(r_t-\mu_t)^2}{2(\sigma_t^2+\delta^2)}\right) \tag{5}$$

[11] See Ait-Sahalia (2004) and Yu (2007) for conditions for existence and uniqueness of the approximate densities in continuous time jump-diffusion models and maximum likelihood estimation.

[12] Previous studies have found values for λ_t varying between 0.01 and 0.30. See for example Johannes (2004), and Maheu and McCurdy (2004). Therefore, this assumption does not seem to be very restrictive and simplifies the likelihood in a convenient way.

Equation (5) takes a quite convenient form given by a mixture of Gaussian densities driven by the time varying arrival intensity. The expression can also be associated with a process with jumps governed by a Bernoulli random variable with time varying parameter, which corresponds to the conditional probability of observing a jump at time t given the past information. Instead, Maheu and McCurdy (2004) use a truncated sum as an approximation of Equation (3). I follow this approach in the empirical part of this paper[13].

A full characterization of the likelihood requires parameterizations for λ_t and σ_t. In the present study, I consider two main specifications for the jump intensity that extend the model of Maheu and McCurdy (2004) by incorporating the effects of exogenous explanatory variables in two different ways: one is persistent, and the other is short-lived. I characterize these specifications as:

a) Jump Intensity with Persistent Effects:

$$\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1} + \Lambda(a'x_t) \tag{6}$$

b) Jump Intensity with Transient Effects:

$$\lambda_t = c + \rho(\lambda_{t-1} - \Lambda(a'x_{t-1})) + \gamma\zeta_{t-1} + \Lambda(a'x_t), \tag{7}$$

[13] An earlier version of this study considered the first order approximation of the likelihood in Equation (5), as well as a second order approximation. It is found that the empirical results associated with announcement and news effects are not affected by this choice.

where $\Lambda(\cdot) = 2 * \left[\frac{\exp(\cdot)}{1+\exp(\cdot)} - \frac{1}{2}\right]$, x_t is a vector of exogenous explanatory variables, known before time t, $|\rho| < 1$, and ζ_t is a revision or jump intensity residual term defined as follows[14]:

$$\zeta_{t-1} = E(N_{t-1}|\Omega_{t-1}) - E(N_{t-1}|\Omega_{t-2}). \tag{8}$$

The logistic functional form of Λ retains the attractive intuition of a logit model where the probability of observing a jump is partially explained by exogenous regressors, which will be defined in the next section. It is important to note that the information set has been extended to include not only past returns but also exogenous news variables that are known before the realization of r_t.[15] In addition, this specification turns out to be convenient for estimation since it smooths the effects of extreme values of such regressors. Regarding the revision term, note that $E(N_{t-1}|\Omega_{t-2}) = \lambda_{t-1}$, and $E(N_{t-1}|\Omega_{t-1})$ gives the expected number of jumps given the current information. Indeed, this last term is obtained by updating the conditional expectation using Bayes rule and a finite order approximation of the density in (4). For instance, considering a truncated version of the likelihood, this conditional expectation can be approximated as follows:

$$E^{(k)}(N_t|\Omega_t) = \frac{\sum_{j=1}^{k} \frac{\exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi(\sigma_t^2+j\delta^2)}} \exp\left(-\frac{(r_t-\mu_t)^2}{2(\sigma_t^2+j\delta^2)}\right)}{f^{(k)}(r_t|\Omega_{t-1},\Theta)} \tag{9}$$

[14] This revision term forms a martingale difference sequence.

[15] Even though such variables are labeled as contemporaneous, the empirical exercise considers variables that are known before the closing of the market. For instance, CPI, PPI, and employment announcements are released early in the morning (before the market opens), and monetary policy announcements occur in general a few hours before the market closes.

and,

$$\zeta_t = E^{(k)}(N_t|\Omega_t) - \lambda_t \tag{10}$$

Additionally, I parameterize the diffusive volatility component as a standard GARCH(1,1):

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2, \tag{11}$$

where $\sigma_t^2 = E\left(\varepsilon_{1t}^2|\Omega_{t-1}\right)$, $\varepsilon_t = \varepsilon_{1t} + \varepsilon_{2t}$, and the parameters satisfy standard stationarity assumptions $(g, b \geq 0,\ g + b < 1)$.[16]

4 Description of the Data and Measures of Surprises

In this study, I use daily data of the S&P500 index, which was obtained from the CRSP database. The sample period goes from January 2, 1992 to August 29, 2008. The data is divided into in-sample and out-of-sample portions. The first portion is used in the specification search and includes data from January 2, 1992 to December 31, 2003. The out-of-sample part is used for forecast comparisons and includes data from January 2,

[16] In terms of higher moments, the assumptions described in (1) imply zero conditional skewness and time varying conditional kurtosis, which is given by:

$$K_{t+1} = \frac{E(r_{t+1}^4|\Omega_t)}{\left(E(r_{t+1}^2|\Omega_t)\right)^2} = 3\left(1 + \frac{\lambda_{t+1}\delta^4}{\left(\sigma_{t+1}^2 + \lambda_{t+1}\delta^2\right)^2}\right) \tag{12}$$

2004 to August 29, 2008.[17] Relevant macroeconomic variables include the Consumer Price Index (CPI), the Producer Price Index (PPI), the Federal Funds Rate (FFR), Nonfarm Payroll Employment (NFP) and the Unemployment Rate (Ump).[18] With the exception of the short-term interest rate, data on the other macroeconomic releases are obtained from the Bureau of Labor Statistics.[19] Macroeconomic forecasts are obtained from the Money Market Services (MMS) survey for the in-sample period 1992-2003. They include data from telephone surveys conducted normally one week or less before any macroeconomic news release.[20] Based on this information and following Balduzzi, Elton, and Green (2001), a standardized surprise for release k on day t is calculated as follows:

$$S_{kt} = \frac{Y_{kt} - \widehat{Y}_{kt}}{\widehat{\sigma}_k} \tag{13}$$

where Y_{kt} is the realization of variable k, $\widehat{Y}_{kt}$ is the corresponding median consensus forecast, and $\widehat{\sigma}_k$ is the standard deviation of the forecast error. Surprises are computed in this way for announcements where the consensus forecast is obtained explicitly from the surveys mentioned above.

[17] Clark (2004) and Ashley, Granger, and Schmalensee (1980) have favored the approach of splitting the sample in two non-overlapping in-sample and out-of-sample portions to evaluate the predictive power of models and prevent overfitting.

[18] Previous studies including shocks of several macroeconomic variables have concluded that only few of them are significant for equity returns. In particular indicators of inflation and output seem to be the most important. See Andersen, Bollerslev, Diebold, and Vega (2003) for exchange rates; Li and Engle (1998), and Gurkaynak, Sack, and Swanson (2005) for interest rates; and Schwert (1981) for stock market returns.

[19] These releases are usually made at 8:30 am on regularly scheduled announcement days by the Department of Labor

[20] This data was kindly provided by Informa Global Markets/MMS. Balduzzi, Elton, and Green (2001) concluded that the MMS survey data is an accurate representation of the consensus expectation in the market. Pearce and Roley (1985) find MMS forecasts unbiased and efficient.

Regarding monetary policy shocks, recent literature has pointed out that the federal funds futures dominate all other instruments for predicting near-term changes in the federal funds rate (FFR). Therefore, these instruments can be used to compute monetary policy surprises surrounding Federal Open Market Committee (FOMC) announcements as follows:

$$S_{it} \equiv i_t - E_{t-1} i_t = \left(\frac{D}{D-d} \Delta f f_t \right) \tag{14}$$

where i_t denotes the federal funds rate, $\Delta f f_t$ is the change in the rate of the current month's futures contract, D represents the number of days in the month, and d indicates the day of the month in which the FOMC meeting occurs.[21]

Figure 1 shows dynamic patterns of S&P500 returns and volatility over the in-sample period. This volatility measure is based on the high-low range volatility introduced by Parkinson (1980). Both panels illustrate the presence of several extreme events that tend to cluster in some periods. Table 1 illustrates the distribution of announcements by day-of-the-week. This distribution suggests that day-of-the-week effects might be present in this sample. For instance, almost all of the employment releases occur on Fridays, most of the FOMC meetings are concentrated on Tuesdays and Wednesdays, and very few releases occur on Mondays. However, using the high-low range volatility measure, Table 2 shows that the day-of-the-week effects are not significant during this sample period.

[21] See Kuttner (2001) and Gürkaynak, Sack and Swanson (2002, 2003) for further details.

Table 3 describes the distribution of this volatility proxy by kind of announcement. From this description, we can observe that volatility seems to increase on announcement days, particularly on those associated with monetary policy (FFR) and employment (NFP and Ump) releases. A t-test for equality of means suggests that these effects are significant. In addition, the average volatility exhibits a level below the average on the days before announcements of FFR and NFP/Ump information. This phenomenon is known as the "calm before the storm". However, the t-tests indicate the effect is not significant.[22] Overall, this description confirms the importance of disentangling heterogeneous effects associated with different kinds of news events.

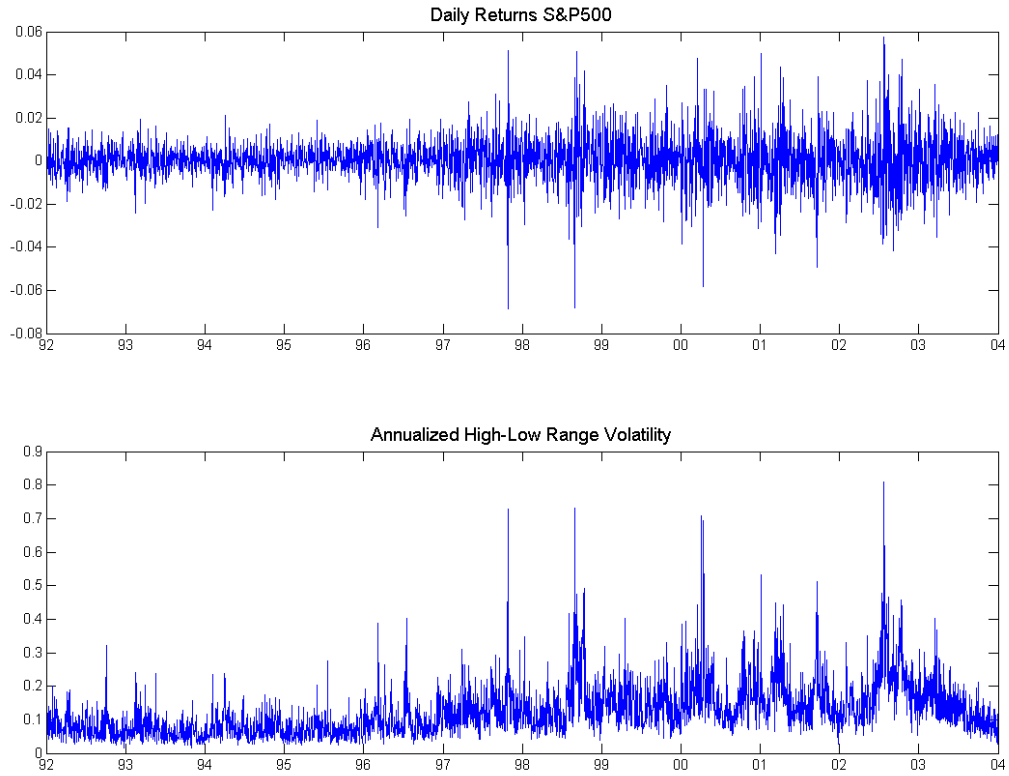
5 Estimation and Results

This section discusses estimation results for the jump model described in section 3. The estimation is based on the truncated approximation of the likelihood given in (3) (up to the 10th term of the sum), the specification of the diffusive volatility given in (11), and a number of models for the jump intensity. First, I consider a model without announcement/news effects using the jump intensity specification of Maheu and McCurdy (2004). Later, I estimate equations (6) and (7), where the announcement and news variables defined in the previous section are included as explanatory variables.[23]

[22] For a shorter sample period, Bomfim (2003) finds significant "calm before the storm" effects for monetary policy announcements.

[23] An earlier version of this study considered the first order approximation in Equation (5). Overall, the empirical results presented in this section are not sensitive to this change.

Figure 1: S&P Returns and High-Low Range Volatility



5.1 Results for a baseline model without explanatory variables

In the baseline model, the jump intensity is defined as $\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1}$, where ζ_{t-1} is defined in (8).[24] In this case, the set of parameters is $\{\mu, \delta, c, \rho, \gamma, w, g, b\}$.[25] This model is estimated using the in-sample portion of the data (from January 2, 1992 to December 31, 2003). Table 4 shows the estimation results, which suggest that all the coefficients are highly significant. The estimate of ρ indicates a highly persistent jump intensity, which is consistent with the findings of Maheu and McCurdy (2004) about jump clustering in returns for market indices.[26] The impact of a revision in the expected number of jumps, described by γ, implies an adjustment of about 47% of its magnitude on the jump intensity. This confirms the flexibility of the model to adjust quickly to large price changes that affect the conditional probability of jumps. The parameter δ, associated with the variance of the jump size, is also highly significant, which supports the relevance of the jump term in the conditional volatility of returns. Similarly, the GARCH parameters of the diffusive volatility component are significant and, as it is usual, the GARCH term is very persistent, and the ARCH effect is small. This indicates that including jumps does not affect the significance of the terms characterizing the dynamics of the smoother volatility term. Panel A of Figure 2 illustrates the conditional variance and Panel B shows the contribution of its two components (the GARCH term

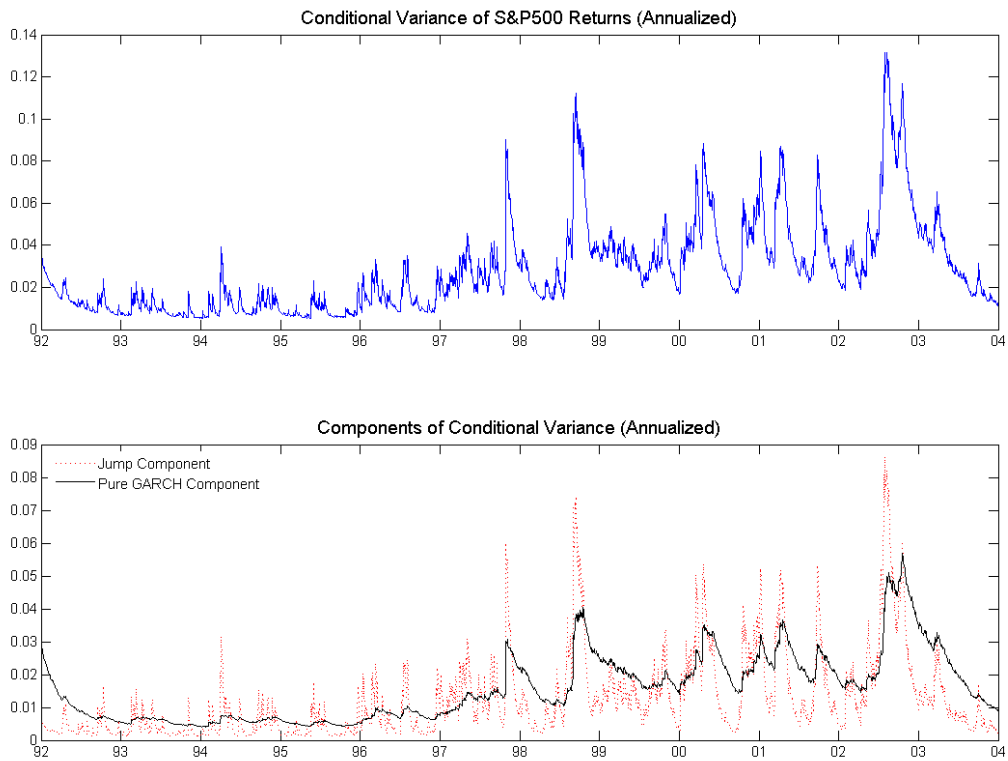
[24] This is a simplified version of the model of Maheu and McCurdy (2004) since in this case the GARCH variance component does not include asymmetric effects.

[25] The baseline model assumes a constant conditional mean μ.

[26] In Maheu and McCurdy (2004) the estimates for ρ are 0.948, 0.831, and 0.979 for the Dow Jones Industrial Average (DJIA), Nasdaq 100, and the CBOT Technology Index (TXX), respectively. Their results suggest larger persistency for indices than for individual firms.

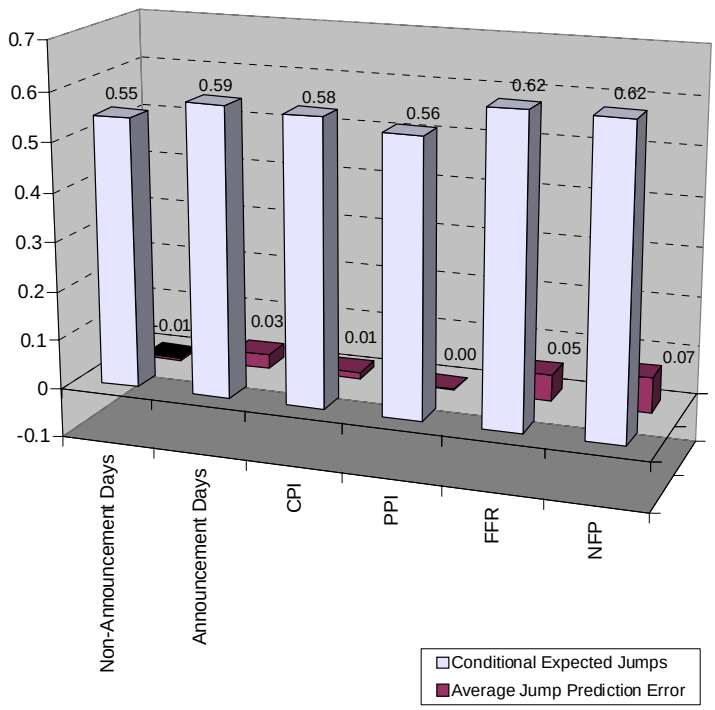
and the jump variance).

Figure 2: Conditional Variance Components



Using this baseline specification that does not include any news/announcement variables, we can explore some patterns of conditional jump probabilities on event days and non-event days. This is useful to evaluate whether the pure autoregressive structure is able to capture on average the dynamics of the jump component. Figure 3 shows the average of the ex-post conditional expected number of jumps across different types of event days. These conditional expectations are estimated from Equation (9). The

Figure 3: Jump Components



results suggest that the expected number of jumps is higher on announcement days, especially on those associated with monetary policy and employment releases, where the average number of expected jumps is about 11% higher than on non-announcement days. Figure 3 also presents the average jump prediction error defined in (8).The results confirm that the baseline model tends to underestimate the expected number of jumps on event days since the prediction error shows a positive bias, especially on monetary policy and employment announcement days.

5.2 Jump models with announcement and news effects

The previous results suggest that jump intensities show different patterns on macroeconomic announcement days. To explain such empirical findings, I incorporate the effect of macroeconomic announcement and news variables on jump intensities. Based on equations (6) and (7), a number of specifications are examined. First, I incorporate pure announcement effects by replacing $\Lambda(a'x_t)$ by $\eta_1 I^A_{t,K}$ in these two equations. $I^A_{t,K}$ is an indicator of a type-K announcement. The model where the announcement effects are persistent (see Equation 6), due to the autoregressive form of the baseline jump intensity, is labeled as Model A-1. On the other hand, the model that has transient announcement effect (see Equation 7) is labeled as Model A-2. In addition, I allow the conditional mean in Equation (1) to incorporate directly news effects in order to control for changes in the conditional mean on event days. This term is specified as:

$$\mu_t = \mu + b_1|S_{t,K}| + b_2 I^-_{t,K}|S_{t,K}|, \tag{15}$$

where $S_{t,K}$ is a type-K news variable, as defined in Equation (13), and $I^-_{t,K}$ is an indicator of a negative news event ($S_{t,K} < 0$). The specification is empirically appealing because it separates not only jumps in conditional mean but also asymmetric effects associated with bad news.

Models A-1 and A-2 are estimated for each type of macroeconomic release (CPI, PPI, FFR, and UMP/NFP). Table 5 presents the estimation results. The set of parameters is $\{(\mu, \delta, c, \rho, \gamma, w, g, b), (b_1, b_2, \eta_1)\}$. The first group includes the baseline parameters

which estimates are very similar to those described in Subsection 5.1. Hence, I will focus on the second group. Regarding news effects on conditional mean, only the CPI inflation releases show statistical significance and their effects are economically sensible. Indeed, higher than expected inflation affects returns negatively and lower than expected inflation affects returns positively, but its impact is smaller. This result is consistent with Flannery and Protopapadakis (2002) who find important effects of CPI surprises for the conditional first moment of stock returns, but not for the conditional volatility. Regarding pure announcement effects, the results suggest that the jump intensity is significantly higher only on employment announcement days. This is found for both the persistent and the non-persistent specifications of the jump intensity; however, the effect is bigger in the non-persistent case, and in-sample fit measures, such as the likelihood and the Schwarz criterion (SC), favor a jump intensity with non-persistent employment announcement effects.

A second exercise examines the effect of news variables on jump intensities. Following the intuition that it is the surprise component of a release what matters for conditional volatility, I use news variables that account for the size of announcement surprises rather than the fact of the announcement *per se*. I also examine specifications that account for asymmetric effects of news variables on jump intensities. Specifically, the term $a'x_t$ in equations (6) and (7) is replaced by $a_1|S_{t,K}|+a_2I^-_{t,K}|S_{t,K}|$. As explained earlier, $S_{t,K}$ is a type-K news variable (see Equation (13)) and $I^-_{t,K}$ is an indicator of negative news. In the first specification (Model S-1) the shocks persist through the jump

persistence parameter, ρ. In contrast, the second specification (Model S-2) restricts the shocks to be non-persistent. Each of these models is estimated using one type of macroeconomic shock at a time. Table 6 presents the estimation results for Model S-1. The results suggest that PPI inflation shocks significantly impact the jump intensity and their effects are persistent. Moreover, they show asymmetric impacts that are consistent with the evidence of Jones et al. (1998) and Li and Engle (1998). Specifically, positive inflation surprises (inflation higher than expected) raise the jump probability and therefore, the conditional volatility of returns. For example, an inflation shock of size one (i.e., of size equal to one standard deviation based on the in-sample distribution of PPI shocks) increases the jump intensity by 0.48, if the shock is positive.[27] In contrast, when inflation is lower than expected, the effect on the jump intensity is completely offset. These results are also consistent with David and Veronesi (2008) in the sense that positive inflation shocks might introduce additional uncertainty of switching to a high inflation regime. Moreover, it is found that the persistent model fits well the data when PPI inflation shocks are considered. Indeed, the likelihood and the Schwarz criterion favor such a model suggesting that surprises about inflation can be associated with persistent and asymmetric effects on jump intensities. In other words, positive inflation shocks are likely to increase stock market volatility with significant persistent effects.

Regarding non-persistent news effects on jump intensities, Table 7 shows the results

[27] In the logistic function Λ the coefficient for positive news is a_1 and the coefficient for negative news is $a_1 + a_2$.

for Model S-2, which is estimated for each type of macroeconomic news at a time. As in the models discussed above, only CPI news effects are significant for the conditional mean of stock market returns. The models with CPI and PPI inflation shocks do not show significant impacts of news variables on jump intensities. In contrast, monetary policy and employment shocks have highly significant non-persistent effects on jump intensities. Specifically, surprises about FFR releases increase the jump intensity. For example, either a positive or a negative FFR surprise of size one (i.e., of size equal to one standard deviation based on the in-sample distribution of monetary policy shocks) is associated with an increase in the conditional jump intensity of 0.86 (i.e., 0.86 more jumps are expected). The coefficient of asymmetry is not significant in this case. Notice that these results support the connection between events such as surprising Federal Reserve target changes and jump arrivals, as pointed out by Johannes (2004) in the term structure case. Comparing these results with those of specification S-1, we can conclude that the effect of monetary policy shocks on market volatility is unlikely to be persistent. Moreover, in terms of model selection, the likelihood and the Schwarz criterion favor the non-persistent model and confirm that short-lived effects seem to characterize better the impact of monetary policy surprises on jump intensity and stock market volatility dynamics.

With respect to employment shocks, the estimation results show significant impacts on jump intensities of both unemployment and NFP employment surprises. These results are consistent with Huang (2007) and Flannery and Protopapadakis (2002).

The first study finds that among different macroeconomic announcements, employment event days are associated with the highest frequency of jumps. The second paper finds significant employment announcement effects on the stock market volatility. My results indicate that a NFP surprise of size one (in terms of the standard deviation of NFP surprises) is associated with an increase of 0.95 in the jump intensity. Thus, such event can be associated with one additional expected jump conditional on the information before the opening of the trading session. The effect of unemployment surprises is asymmetric and only negative surprises increase the jump intensity. Indeed, a negative unemployment surprise of size one is associated with an increase of 0.92 in the conditional expected number of jumps. A positive surprise reduces the conditional expected number of jumps by 0.17. Economically, negative unemployment surprises along with positive surprises in NFP employment typically signal an upward revision of growth expectations and possible future increases in interest rates. This is consistent with the findings of Boyd et al. (2005) in the sense that good news for employment can be bad news for stocks due to the dominant effect of the interest rate component of stock prices. However, my results also suggest that bad news for NFP employment can lead to increases in jump intensities and market volatility. Comparing these results with those of the persistent specification (Model S-1), it is more likely that employment surprises on conditional volatility are short-lived. This is also suggested by the model fit measures where the likelihood and the Schwarz criterion considerably favor the non-persistent models A-2 and S-2 for employment events (see tables 5, 6, and 7).

Figure 4: Average Estimated Jump Intensity Residuals on Announcement Days for Models with and without News Effects

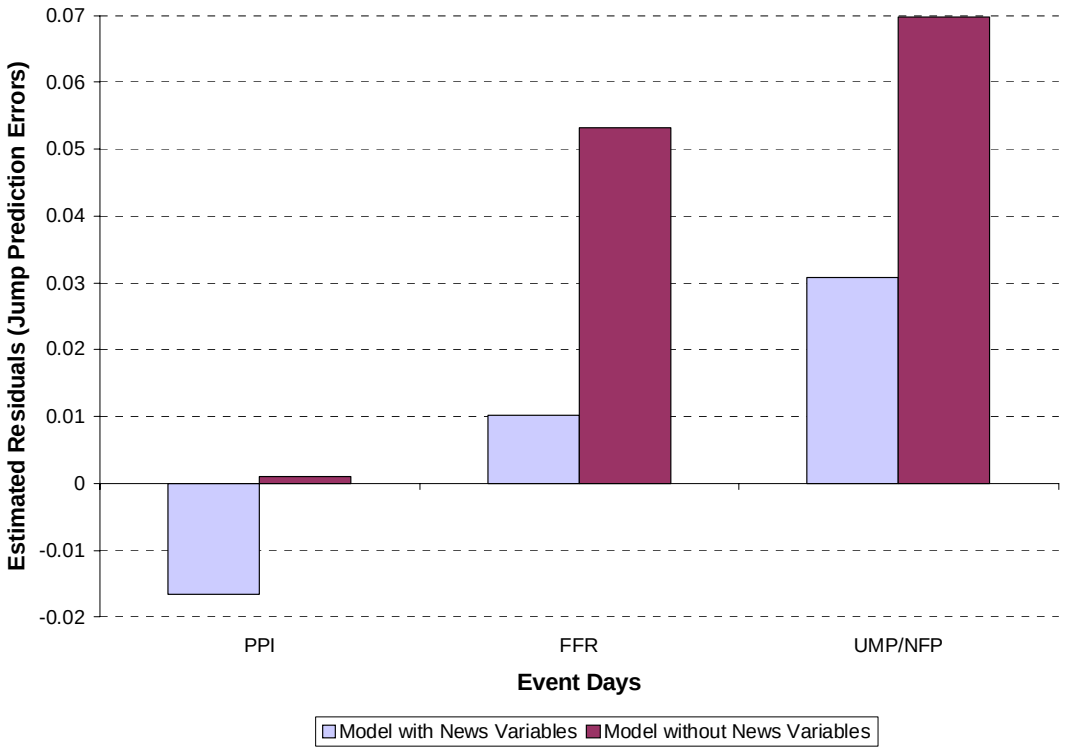


Figure 5: Notes: Models with news effects correspond to Model S-1 for PPI, and Model S-2 for FFR and NFP/UMP (see estimated coefficients in Tables 4, 5 and 6, respectively).

To further illustrate the importance of introducing news variables into the specification of jump intensities, Figure 4 presents averages of the estimated jump intensity prediction errors from the preferred models for each type of macroeconomic release, and compares such values with the averages obtained from the baseline specification estimated in subsection 5.1 (see Figure 3). These averages are taken over the subsamples of PPI, FFR and NFP/Ump announcement days using Equation (10) for each jump intensity specification (the baseline model, specification S-1 for PPI event days, and specification S-2 for FFR and NFP/UMP event days). Figure 4 confirms that for monetary policy and employment releases, when the surprise component of an announcement is incorporated into the jump probabilities, the discrepancy between the ex post assessment of the probability of a jump occurrence, $P(N_t > 0|\Omega_t)$, and its ex ante estimator, λ_t, is substantially reduced. For inflation shocks the positive bias is more than offset and a negative bias is introduced. Hence, macroeconomic surprises can be seen not only as important determinants of conditional volatilities but also as relevant predictors of ex post (or realized) jump probabilities.[28] Nonetheless, these results are in-sample and need to be complemented by out-of-sample forecasting tests that allow us to rule out potential problems of overfitting.

[28] The average jump intensity residual for non announcement days is -0.0078 for the specification without news variables. For the preferred specifications with PPI, FFR and NFP/Ump surprises, the average is -0.0093, -0.0071 and -0.0063, respectively. This suggests that introducing news variables does not worsen the errors in predicting jumps on non announcement days.

6 Jump Intensity Forecasts

The results in the previous section indicate that the effects of different types of news events are heterogenous not only in terms of their impact on conditional mean but also in terms of their effect on jump and volatility dynamics. In this section I perform an out-of-sample forecasting exercise that compares the baseline model and the preferred models for each type of announcement. Using the estimated coefficients presented in Tables 4-7 and data from January 2, 2004 to August 29, 2008, jump intensities and volatility forecasts are computed during this out-of-sample period. These forecasts are one-day ahead recursive forecasts that are constructed by sequentially updating the returns information up to the day preceding a specific announcement.

The models are compared in terms of their volatility prediction using the high-low range volatility, as the realization measure, and volatility forecasts constructed from Equation (2), the GARCH volatility in (11), and the models for the jump intensity considered in Figure 4. These include the baseline model, Model S-1 for PPI event days, and Model S-2 for monetary policy and employment announcement days. The models are compared in terms of their accuracy in forecasting volatility using a mean squared error (MSE) loss function. The squared root of such statistic (RMSE) is shown in Table 8 for the baseline specification and the models with news effects. Under the most realistic scenario it is natural to assume that surprises cannot be forecasted (no foresight). In such a case, Table 8 shows that the models that were estimated incorporating news variables are associated with a smaller RMSE statistic than the

baseline model, for all of the announcement types. In addition, I present results of an unrealistic case in which the econometrician is able to forecast a monetary policy shock on the day before the FOMC announcement (perfect foresight). In such a case, the last row of Table 8 indicates that the model with FFR news effects would show a further decline in its RMSE statistic.[29]

7 Conclusions

In this paper, I present an alternative approach to analyze the effect of public regularly-scheduled announcements related to fundamental variables, on the conditional jump intensity and volatility of stock market returns. Based on a mixture of a GARCH model with a Poisson jump process, I model the response of conditional volatility to announcements and surprises through the response of the jump arrival intensity, which can capture non-linear features of returns associated with fat tails and non-normalities. Following a fully parametric approach, the conditional volatility of returns is composed of two factors: one related to a standard diffusive component parametrized as a GARCH process, and the other related to a pure jump component parametrized as a compound Poisson process with time varying arrival intensity. The contribution of this paper to the existing literature consists on the examination of a different non-linear channel through which announcements and surprises might affect the dynamics of volatility. In addition, this study successfully disentangles the role of heterogeneous news events in

[29] The case of perfect foresight was considered only for FFR announcements because, for the other announcements, recent MMS survey forecasts are not available.

jump intensity dynamics.

The fundamental variables considered in the paper include measures of inflation (CPI, PPI), employment (NFP Employment and an Index of Unemployment), and short-term interest rates (Federal Funds Rate). The results suggest that the day of the announcement, *per se*, has little impact on conditional volatility for most of the announcements (only announcements about unemployment tend to boost volatility). In contrast, when the surprise component of the announcements is incorporated into the model, the impacts of fundamentals' news become more important. In line with other results in the literature, the effects of shocks seem to have a short duration for most of the variables considered here. Indeed, while employment and monetary policy surprises show significant short-lived effects on the conditional jump intensity and volatility of market returns, the evidence of persistent effects is only significant for PPI inflation shocks. Moreover, the direction of the effects is consistent with previous theoretical and empirical evidence. Higher than expected inflation, short-term interest rates, and NFP employment induce an increase in the conditional jump intensity and volatility. Similarly, lower than expected NFP employment and short-term interest rates also raise the volatility component associated with jumps. The results also suggest significant asymmetric effects of inflation shocks. Negative shocks offset the overall effect of positive shocks for the PPI.

Overall, these empirical findings point out the relevance of incorporating heterogeneous news events to explain different volatility patterns and suggest that jumps play

an important role in explaining the effects on market volatility of macroeconomic events that take market participants by surprise. Moreover, this paper shows evidence that the information of macroeconomic surprises has predictive power for jump probabilities that leads to volatility forecast improvements on event days.

References

Ait-Sahalia, Y. (2004): "Disentangling Diffusion from Jumps," *Journal of Financial Economics*, 74, 487–528.

Andersen, T. G. (1996): "Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility," *Journal of Finance*, 51, 169–204.

Andersen, T. G., and T. Bollerslev (1998): "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies," *Journal of Finance*, 53, 219–265.

Andersen, T. G., T. Bollerslev, and F. X. Diebold (2007): "Roughing It Up: Including Jump Components in Measuring, Modeling and Forecasting Asset Return Volatility," *Review of Economics and Statistics*, 89, 701–720.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003): "Modeling and Forecasting Realized Volatility," *Econometrica*, 71, 579–625.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003): "Micro Effects of Macro Announcements: Real Time Price Discovery in Foreign Exchange," *American Economic Review*, 93, 38–62.

Ane, T., and H. Geman (2000): "Order Flow, Transaction Costs and Normality of Asset Returns," *Journal of Finance*, 55, 2259–2284.

Ashley, R., C. Granger, and R. Schmalensee (1980): "Advertising and Aggregate Consumption: An Analysis of Causality," *Econometrica*, 48, 1149–1167.

Balduzzi, P., E. J. Elton, and T. C. Green (2001): "Economic News and Bond Prices: Evidence from the US Treasury Market," *Journal of Financial and Quantitative Analysis*, 36, 523–543.

Barndorff-Nielsen, O., and N. Shephard (2004): "Power and Bipower Variation with Stochastic Volatility and Jumps," *Journal of Financial Econometrics*, 2, 1–37.

Bollerslev, T. (1986): "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31, 307–327.

Bomfim, A. N. (2003): "Pre-announcement Effects, News Effects, and Volatility: Monetary Policy and the Stock Market," *Journal of Banking and Finance*, 27, 133–151.

Chan, W. H., and J. M. Maheu (2002): "Conditional Jump Dynamics in Stock Market Returns," *Journal of Business and Economic Statistics*, 20, 377–389.

Chernov, M., R. Gallant, E. Ghysels, and G. Tauchen (2003): "Alternative Models for Stock Price Dynamics," *Journal of Econometrics*, 116, 225–257.

Clark, P. (1973): "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices," *Econometrica*, 41, 135–155.

Clark, T. (2004): "Can out-of-sample forecast comparisons help prevent overfitting?," *Journal of Forecasting*, 23, 115–139.

Das, S. R. (2002): "The Surprise Element: Jumps in Interest Rates," *Journal of Econometrics*, 106, 27–65.

David, A., and P. Veronesi (2008): "Inflation and Earnings Uncertainty and Volatility Forecasts: A Structural Form Approach," *Working Paper, University of Chicago GSB*.

Engle, R. (1982): "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance on the U.K. Inflation," *Econometrica*, 50, 987–1008.

Engle, R., and J. Rangel (2008): "The Spline-GARCH Model for Low Frequency Volatility and Its Global Macroeconomic Causes," *Review of Financial Studies*, 21, 1187–1222.

Eraker, B. (2004): "Do Stock Market and Volatility Jump? Reconciling Evidence from Spot and Option Prices," *Journal of Finance*, 59, 1367–1403.

Eraker, B., M. Johannes, and N. Polson (2003): "The Impact of Jumps in Volatility and Returns," *Journal of Finance*, 58, 1269–1300.

Flannery, M., and A. Protopapadakis (2002): "Macroeconomic Factors Do Influence Aggregate Stock Returns," *Review of Financial Studies*, 15, 751–782.

Geman, H., D. Madan, and M. Yor (2000): "Asset Prices are Brownian Motion: Only in Business Time," *Chapter of the Book: Quantitative Analysis in Financial Markets*, World Scientific Publishing Company.

Gurkaynak, R., B. Sack, and E. Swanson (2005): "The Sensitivity of Long-Term Interest Rates to Economic News:Evidence and Implications for Macroeconomic Models," *American Economic Review*, 95, 425–436.

HUANG, X. (2007): "Macroeconomic News Announcements, Financial Market Volatility and Jumps," *Working Paper, Duke University.*

JOHANNES, M. (2004): "The Statistical and Economical Role of Jumps in Continuous-Time Interest Rate Models," *Journal of Finance*, 59, 227–260.

JONES, C., O. LAMONT, AND R. LUMSDAINE (1998): "Macroeconomic News and Bond Market Volatility," *Journal of Financial Economics*, 47, 315–337.

JORION, P. (1988): "On Jump Processes in the Foreign Exchange and Stock Markets," *Review of Financial Studies*, 1, 427–445.

KUTTNER, K. (2001): "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47, 523–544.

LI, L., AND R. ENGLE (1998): "Macroeconomic Announcements and Volatility of Treasure Futures," *Discussion Paper, University of California, San Diego.*

MAHEU, J. M., AND T. H. MCCURDY (2004): "News Arrival, Jump Dynamics and Volatility Components for Individual Stock Returns," *Journal of Finance*, 59, 755–793.

NELSON, D. (1990): "ARCH Models as Diffusion Approximations," *Journal of Econometrics*, 45, 7–38.

OOMEN, R. (2002): "Statistical Models for High Frequency Security Prices," *Manuscript, Warwick Business School.*

PARKINSON, M. (1980): "The Extreme Value Method for Estimating the Variance of the Rate of Return," *Journal of Business*, 53, 61–65.

Pearce, D., and V. Roley (1985): "Stock Prices and Economic News," *Journal of Business*, 58, 49–67.

Schwert, G. (1981): "The adjustment of Stock Prices to Information about Inflation," *Journal of Finance*, 36, 15–29.

——— (1989): "Why Does Stock Market Volatility Change Over Time?," *Journal of Finance*, 44, 1115–1153.

Yu, J. (2007): "Closed-Form Likelihood Estimation of Jump-Diffusions with an Application to the Realignment Risk of the Chinese Yuan," *Journal of Econometrics*, 141, 1245–1280.

TABLES

Table 1

Macroeconomic Announcements by Day of the Week

		Announcements (1992-2003)			
Dayweek	total	CPI	PPI	FFR	NFP/Unemployment
M	575	0	0	3	1
T	621	41	16	55	0
W	619	38	17	36	0
Th	608	26	44	5	5
Fr	603	39	70	3	135
Total	3026	144	147	102	141

Table 2

Volatility Proxy: High-Low Range Volatility S&P500 (%)

Dayof the week	Mean	Std. Dev.	t-stat[a]	min	max
M	0.1231	0.0850	-0.51	0.0258	0.7301
T	0.1262	0.0839	0.51	0.0242	0.7275
W	0.1240	0.0787	-0.25	0.0252	0.8084
Th	0.1249	0.0755	0.06	0.0169	0.4920
Fr	0.1253	0.0771	0.20	0.0169	0.6938
Total	0.1247	0.0800		0.0169	0.8084

a) t-test on the equality of means with respect to the other week days. Ho:$\mu_1=\mu_2$, Ha: $\mu_1\neq\mu_2$

Table 3

S&P500 High-Low Range Volatility by Day-of-Announcement (%)

		Release day			Day before			Day after		
Release	Obs	Mean	Std. Dev.	t-stat[a]	Mean	Std. Dev.	t-stat[a]	Mean	Std. Dev.	t-stat[a]
CPI	137	0.1335	0.0886	1.46	0.1269	0.0851	0.64	0.1276	0.0899	0.69
PPI	144	0.1263	0.0771	0.62	0.1231	0.0761	0.13	0.1280	0.0859	0.78
FFR	101	0.1415	0.0965	**1.99**	0.1203	0.0742	-0.25	0.1286	0.0803	0.78
NFP/UMP	141	0.1470	0.0794	**3.61**	0.1160	0.0660	-1.03	0.1187	0.0781	-0.49
Non-ann	2503	0.1222	0.0788							
Total	3026	0.1247	0.0800							

a) t-test on the equality of means with respect to the sample of non-announcement days. Ho:$\mu_1=\mu_2$, Ha: $\mu_1\neq\mu_2$
Significant values at 5% are highlighted.

Table 4

Estimation Results from the Baseline Model[a]

	Parameters							
	μ	δ	c	ρ	γ	w	g	b
Estimates	0.0677	0.8907	0.0134	0.9756	0.4671	0.0015	0.0091	0.9806
T-Statistics	4.91	3.91	2.43	82.79	4.04	2.20	2.54	182.43

a) The baseline model is defined as follows:

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{j,t}, \;\; c_{j,t} \sim iidN(0, \delta^2), \;\; \forall j, \;\; N_t \sim Poisson(\lambda_t)$$

$$\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1}$$

$$\zeta_{t-1} = E(N_{t-1} \mid \Omega_{t-1}) - E(N_{t-1} \mid \Omega_{t-2})$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2$$

Table 5

Estimation Results for Models with Persistent and Non-Persistent Announcement Effects

	Event Days and Estimated Models[a]							
	CPI		PPI		FFR		UMP/NFP[b]	
Parameters	**Model A1**	**Model A2**	**Model A1**	**Model A2**	**Model A1**	**Model A2**	**Model A1**	**Model A2**
μ	0.069	0.069	0.069	0.069	0.064	0.064	0.067	0.066
	(0.014)*	(0.014)*	(0.014)*	(0.014)*	(0.013)*	(0.015)*	(0.013)*	(0.013)*
δ^2	0.923	0.875	0.913	0.906	0.886	0.858	0.939	0.873
	(0.259)*	(0.243)*	(0.272)*	(0.251)*	(0.208)*	(0.228)*	(0.33)*	(0.205)*
c	0.016	0.014	0.015	0.013	0.010	0.014	0.009	0.015
	(0.006)*	(0.003)*	(0.007)*	(0.006)*	(0.007)	(0.004)*	(0.007)	(0.005)*
ρ	0.973	0.975	0.974	0.975	0.976	0.976	0.970	0.973
	(0.01)*	(0.013)*	(0.014)*	(0.012)*	(0.014)*	(0.014)*	(0.021)*	(0.009)*
γ	0.480	0.489	0.471	0.461	0.465	0.456	0.504	0.502
	(0.115)*	(0.113)*	(0.14)*	(0.117)*	(0.129)*	(0.116)*	(0.155)*	(0.093)*
w	0.0014	0.0015	0.0015	0.0015	0.0016	0.0015	0.0015	0.0014
	(0.0008)**	(0.0006)*	(0.0007)*	(0.0007)*	(0.0008)**	(0.0007)*	(0.0007)*	(0.0006)*
g	0.010	0.009	0.009	0.009	0.009	0.009	0.010	0.008
	(0.004)*	(0.004)*	(0.004)*	(0.004)*	(0.004)*	(0.004)*	(0.005)*	(0.003)*
b	0.980	0.981	0.980	0.980	0.980	0.980	0.980	0.982
	(0.006)*	(0.006)*	(0.005)*	(0.005)*	(0.006)*	(0.005)*	(0.007)*	(0.004)*
η_1	-0.042	0.104	-0.023	-0.046	0.093	0.153	0.128	0.487
	(0.071)	(0.155)	(0.06)	(0.07)	(0.084)	(0.116)	(0.064)*	(0.174)*
b_1	-0.260	-0.253	-0.217	-0.227	0.094	0.103	0.008	0.037
	(0.109)*	(0.111)*	(0.15)	(0.148)	(0.178)	(0.183)	(0.128)	(0.129)
b_2	0.302	0.320	0.258	0.267	0.126	0.131	0.122	0.102
	(0.125)*	(0.136)*	(0.174)	(0.167)	(0.21)	(0.207)	(0.154)	(0.149)
$b_{1(NFP)}$							-0.044	-0.045
							(0.123)	(0.129)
$b_{2(NFP)}$							0.082	0.090
							(0.15)	(0.164)
-Log-likelihood	3981.1	3981.00	3983.1	3983.06	3981.1	3981.10	3981.6	3976.50
SC	8050.4	8050.30	8054.4	8056.40	8050.4	8050.30	8051.3	8041.10

a) Following the returns process in Equation 1, models A-1 and A-2 are defined as follows:

$$Model\ A-1: \lambda_t = c + \eta_1 I_t^A + \rho\lambda_{t-1} + \gamma\zeta_{t-1}$$

$$Model\ A-2: \lambda_t = c + \eta_1 (I_t^A - \rho I_{t-1}^A) + \rho\lambda_{t-1} + \gamma\zeta_{t-1}$$

$$where,\ \ \zeta_{t-1} = E(N_{t-1} \mid \Omega_{t-1}) - E(N_{t-1} \mid \Omega_{t-2}),\ \ I_t^A = Announcement\ Indicator$$

Ω_{t-1} includes past returns and news variables known before the close of trading day *t*.

$$GARCH\ Variance:\ \sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2.\ \ Conditional\ Mean:\ \mu_t = \mu + b_1 \mid S_{t,K} \mid + b_2 I_{t-1,K}^- \mid S_{t,K} \mid$$

Standard errors are reported in parentheses. Asterisks denote: *significance at the 5% level, **significance at the 10% level.

b) On employment event days, the coefficients b_1 and b_2 correspond to the conditional mean effects of unemployment news, and $b_{1(NFP)}$ and $b_{2(NFP)}$ correspond to the conditional mean effects of NFP news.

Table 6

Estimation Results for Model with Persistent News Effects[a]

	Event Days				
Parameters	CPI	PPI	FFR	UMP	NFP
μ	0.0625	0.0611	0.0590	0.0580	0.0618
	(0.013)*	(0.013)*	(0.013)*	(0.013)*	(0.013)*
δ^2	0.5149	0.4993	0.7078	0.6838	0.7388
	(0.074)*	(0.074)*	(0.163)*	(0.158)*	(0.164)*
c	0.4589	0.3971	2.2672	1.8771	2.0528
	(0.278)**	(0.291)	(0.618)*	(0.746)*	(0.84)*
ρ	0.9956	0.9932	0.9682	0.9737	0.9604
	(0.002)*	(0.002)*	(0.014)*	(0.011)*	(0.017)*
γ	0.2548	0.2845	0.5768	0.5290	0.6619
	(0.074)*	(0.059)*	(0.115)*	(0.135)*	(0.161)*
w	0.0226	0.0230	0.0017	0.0017	0.0018
	(0.009)*	(0.01)*	(0.001)*	(0.001)*	(0.001)*
g	0.0416	0.0342	0.0091	0.0083	0.0102
	(0.012)*	(0.011)*	(0.004)*	(0.004)*	(0.004)*
b	0.8508	0.8535	0.9797	0.9803	0.9786
	(0.039)*	(0.044)*	(0.006)*	(0.007)*	(0.007)*
a_1	-0.0475	0.9866	0.1205	0.3628	0.5297
	(0.169)	(0.528)**	(0.307)	(0.257)	(0.347)
a_2	0.1564	-0.9823	-0.0134	-0.3397	-0.2401
	(0.217)	(0.506)**	(0.367)	(0.263)	(0.401)
b_1	-0.2933	-0.1756	0.0871	-0.0445	-0.0734
	(0.112)*	(0.15)	(0.182)	(0.097)	(0.131)
b_2	0.3602	0.2269	0.1416	0.1743	0.0995
	(0.134)*	(0.173)	(0.202)	(0.118)	(0.158)
Log-likelihood	3983.10	3981.70	3988.30	3987.80	3987.80
SC	8062.30	8058.60	8072.80	8071.90	8071.80

a) Following the returns process in Equation (1), Model S-1 is defined as follows:

$$\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1} + \Lambda(a'x_t)$$

$$where,\ \ \zeta_{t-1} = E(N_{t-1}\,|\,\Omega_{t-1}) - E(N_{t-1}\,|\,\Omega_{t-2}),\ \ \Lambda(\cdot) = 2*\left[\frac{\exp(\cdot)}{1+\exp(\cdot)} - \frac{1}{2}\right]$$

$$a'x_t = a_1 I^A_{t,k}\,|\,S_{t,K}\,| + a_2 I^-_{t,K}\,|\,S_{t,K}\,|,\ \ I^A_{t,K} = 1(announcement\ of\ type\ K),\ \ I^-_{t,K} = 1(S_{t,K} < 0)$$

Ω_{t-1} includes past returns and news variables known before the close of trading day t.

$$GARCH\ Variance:\ \ \sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2$$

$$Conditional\ Mean:\ \ \mu_t = \mu + b_1\,|\,S_{t,K}\,| + b_2 I^-_{t-1,K}\,|\,S_{t,K}\,|$$

Standard errors are reported in parentheses. Asterisks denote: *significance at the 5% level, **significance at the 10% level.

Table 7

Estimation Results for Model with Non-Persistent News Effects[a]

	Event Days				
Parameters	CPI	PPI	FFR	UMP	NFP
μ	0.0616	0.0591	0.0580	0.0580	0.0609
	(0.014)*	(0.014)*	(0.014)*	(0.014)*	(0.014)*
δ^2	0.5091	0.4823	0.5186	0.5060	0.5139
	(0.085)*	(0.07)*	(0.062)*	(0.068)*	(0.086)*
c	0.5280	0.4031	0.4306	0.5416	0.4625
	(0.279)**	(0.275)	(0.237)**	(0.26)*	(0.239)**
ρ	0.9958	0.9968	0.9963	0.9957	0.9958
	(0.002)*	(0.002)*	(0.002)*	(0.002)*	(0.002)*
γ	0.2507	0.2043	0.2386	0.2663	0.2392
	(0.072)*	(0.071)*	(0.069)*	(0.071)*	(0.066)*
w	0.0223	0.0166	0.0220	0.0217	0.0173
	(0.008)*	(0.007)*	(0.007)*	(0.007)*	(0.005)*
g	0.0416	0.0419	0.0404	0.0381	0.0407
	(0.012)*	(0.012)*	(0.011)*	(0.011)*	(0.01)*
b	0.8508	0.8649	0.8553	0.8561	0.8732
	(0.037)*	(0.027)*	(0.035)*	(0.036)*	(0.026)*
a_1	0.9155	0.8217	2.5604	-0.3367	3.5711
	(0.769)	(0.976)	(1.045)*	(0.109)*	(2.074)**
a_2	-0.6360	-1.4175	-1.6316	3.6408	-0.3596
	(0.805)	(0.965)	(1.226)	(0.834)*	(2.149)
b_1	-0.2821	-0.1491	-0.0472	-0.0460	-0.0474
	(0.138)*	(0.165)	(0.227)	(0.087)	(0.115)
b_2	0.3683	0.2002	0.3216	0.1727	0.1330
	(0.16)*	(0.182)	(0.256)	(0.118)	(0.166)
Log-likelihood	3982.60	3983.20	3979.80	3980.10	3975.20
SC	8061.40	8062.60	8055.80	8056.30	8046.50

a) Following the returns process in Equation (1), Model S-2 is defined as follows:

$$\lambda_t = c + \rho(\lambda_{t-1} - \Lambda(a' x_{t-1})) + \gamma\zeta_{t-1} + \Lambda(a' x_t),$$

$$\textit{where,}\ \ \zeta_{t-1} = E(N_{t-1} \mid \Omega_{t-1}) - E(N_{t-1} \mid \Omega_{t-2}),\ \ \Lambda(\cdot) = 2 * \left[\frac{\exp(\cdot)}{1+\exp(\cdot)} - \frac{1}{2}\right]$$

$$a' x_t = a_1 I^A_{t,k} \mid S_{t,K} \mid + a_2 I^-_{t,K} \mid S_{t,K} \mid,\ \ I^A_{t,K} = 1(\textit{announcement of type } K),\ \ I^-_{t,K} = 1(S_{t,K} < 0)$$

Ω_{t-1} includes past returns and news variables known before the close of trading day t.

$$\textit{GARCH Variance}:\ \ \sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2$$

$$\textit{Conditional Mean}:\ \ \mu_t = \mu + b_1 \mid S_{t,K} \mid + b_2 I^-_{t-1,K} \mid S_{t,K} \mid$$

Standard errors are reported in parentheses. Asterisks denote: *significance at the 5% level, **significance at the 10% level.

Table 8

Root Mean Squared Error of Out-of-Sample Volatility Forecasts on Macroeconomic Announcement Days

	RMSE ON EVENT DAYS		
	PPI	*FFR*	*UMP/NFP*
Baseline Model	2.0693	2.5579	1.6580
News Model (No Foresight)	**1.9887**	**2.5239**	**1.5903**
News Model (Perfect Foresight)		*2.2676*	

The RMSE is computed considering realizations of the high-low range volatility and one-step-ahead recursive forecasts, which are constructed by fixing the estimates obtained in the estimation period (01/02/92-12/31/2003), and updating the volatility process using returns data up to the day preceding an announcement, during the forecasting period (01/02/2004-08/29/2008). Under "No Foresight" the news variables are equal to zero. Under "Perfect Foresight" they are equal to their realization.

Appendix A1

Proof of Proposition 1. From Equation (1), we have:

$\varepsilon_{1t} = \sigma_t z_t, \qquad z_t \sim N(0,1), \qquad \{z_t\}_{t=1}^{\infty}\ iid$

$\varepsilon_{2t} = \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim N(0,\delta^2), \qquad iid \text{ for } j = 1,2,...,N_t$

where,

$P(N_t = j|\Omega_{t-1},\Theta) = \frac{\lambda_t^j \exp(-\lambda_t)}{j!}$

and Θ denotes a set of relevant parameters

Now, conditioning upon the event $N_t = n$

we can define $\widetilde{\varepsilon}_{2t} \equiv \sum_{j=1}^{N_t} c_{jt} \mid N_t = n \sim N(0, n\delta^2)$

Given that ε_{1t} and $\widetilde{\varepsilon}_{2t}$ are independent, the density of the sum is obtained through the convolution of the individual densities:

$$\begin{aligned} f_{\varepsilon_{1t}+\widetilde{\varepsilon}_{2t}}(\omega) &= \int_{-\infty}^{\infty} f_{\varepsilon_{1t}}(\omega - z) f_{\widetilde{\varepsilon}_{2t}}(z)dz \\ &= \int_{-\infty}^{\infty} \left\{ \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{(\omega-z)^2}{2\sigma_t^2}\right)\right\} \left\{ \frac{1}{\sqrt{2\pi n\delta^2}} \exp\left(-\frac{z^2}{2n\delta^2}\right)\right\} dz \\ &= \int_{-\infty}^{\infty} \left\{ \frac{1}{2\pi\sqrt{n\sigma_t^2\delta^2}} \exp\left(-\frac{1}{2}\left(\frac{(\omega-z)^2}{\sigma_t^2} + \frac{z^2}{n\delta^2}\right)\right)\right\} dz \end{aligned}$$

Using the following relation,

$$\left(\frac{(\omega-z)^2}{\sigma_t^2} + \frac{z^2}{n\delta^2}\right) = \left(\frac{z\sqrt{\sigma_t^2+n\delta^2}}{\sqrt{n\sigma_t^2\delta^2}} - \frac{n\omega\delta^2}{\sqrt{\sigma_t^2+n\delta^2}\sqrt{n\sigma_t^2\delta^2}}\right)^2 + \frac{\omega^2}{\sqrt{\sigma_t^2+n\delta^2}}$$

and integrating the term involving z, we have

$$f_{\varepsilon_{1t}+\widetilde{\varepsilon}_{2t}}(\omega) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_t^2+n\delta^2}} \exp\left(-\frac{\omega^2}{2\left(\sigma_t^2+n\delta^2\right)}\right) = f(r_t|N_t = n, \Omega_{t-1}, \Theta)$$

Then, integrating the number of jumps out using the Poisson density, Equation (3) follows:

$$f(r_t|\Omega_{t-1},\Theta) = \sum_{n=1}^{\infty} \frac{\exp(-\lambda_t)\lambda_t^n}{n!} \frac{1}{\sqrt{2\pi(\sigma_t+n\delta^2)}} \exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t+n\delta^2)}\right)$$

Now, from Bayes rule, we obtain

$$P(N_t = j \mid r_t, \Omega_{t-1}, \Theta) = \frac{f(r_t|N_t=n,\Omega_{t-1},\Theta)P(N_t=j|\Omega_{t-1},\Theta)}{f(r_t|\Omega_{t-1},\Theta)}$$

and by simple substitution, Equation (4) follows. ■