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Stock market volatility and price discovery : three essays on the effect of macroeconomic information

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Stock Market Volatility and Price Discovery: Three Essays on the Effect of Macroeconomic Information

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics

by

Jose Gonzalo Rangel

Committee in charge:

Professor James D. Hamilton, Chair
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2006

The dissertation of Jose Gonzalo Rangel is approved, and it is acceptable in quality and form for publication on microfilm:

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Chair

University of California, San Diego

2006

To my parents Gonzalo and Luz,

and my sister Leyla.

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ABSTRACT

Stock Market Volatility and Price Discovery: Three Essays on the Effect of Macroeconomic Information

by

Jose Gonzalo Rangel
Doctor of Philosophy in Economics

University of California San Diego, 2006

Professor James D. Hamilton, Chair

This dissertation investigates the response of the stock market to macroeconomic fundamental information by studying its effects on short and long term patterns of market volatility, and the mechanism through which this information enters stock prices (price discovery process).

The first chapter examines the effects of announcement and news on the high frequency dynamics of stock market volatility. The return distribution is parametrized using two orthogonal stochastic processes. One is described by a jump Poisson-Gaussian model with time varying jump intensity. The other follows a standard GARCH(1,1) model. Information surprises and announcements affect conditional volatility through a non-linear channel described by the jump intensity. The day of the announcement, per se, has little impact on jump intensities. In contrast, when the surprise component of the announcement is incorporated into the model, inflation shocks show persistent effects and monetary policy shocks show short-lived effects.

The second chapter proposes modeling equity volatilities as a combination of macroeconomic effects and time series dynamics. High frequency return volatility is specified to be the product of a slow moving deterministic component, represented by an exponential spline, and a unit GARCH. This deterministic component is the low frequency volatility, which is then estimated for nearly 50 countries over various sample periods of

daily data. Recognizing that the macroeconomy is slowly evolving, macroeconomic determinants of low frequency volatility are investigated. The model allows long horizon forecasts of volatility to depend on macroeconomic developments.

The third chapter investigates heterogeneity in the market assessment of public macroeconomic announcements by modeling the price discovery process. Using a structural microstructure framework, the proposed model describes jointly two main venues through which macroeconomic news might enter stock prices: Instantaneous fundamental news impacts consistent with the asset pricing view of symmetric information, and permanent order flow effects consistent with a microstructure view of asymmetric information related to heterogeneous interpretation of public news. Significant instantaneous news impacts are detected for news related to real activity, investment, inflation, and monetary policy; however, significant order flow effects are also observed on employment announcement days.

Chapter 1

News, Announcements, and Stock Market Volatility Dynamics

1.1 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 (in general) for reasons of information, then the form of those responses can be related to the nature of the process of information arrival.

Studies regarding the link between price changes and the process of information arrival have used different classes of stochastic processes describing asset prices, among which are the subordinated processes of Clark (1973) and the more general stochastic time changes described in Ane and Geman (2000). In this context, the cumulated arrival of relevant information is a reasonable measure of time changes at high frequencies. Moreover, when this process of information arrival is “continuous”, the returns process is also continuous. In contrast, when there are discontinuities in the arrival of information, the price process also observes certain "jumps".[1] 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. In this setting, the jumps are associated with periods of intense market activity, such as financial crashes.

The empirical evidence has rejected continuous models, and has favored those with discontinuities. For instance, Chernov, Gallant, Ghysels, and Tauchen (2003), Eraker, Johannes, and Polson (2003), Eraker (2004), and Maheu and McCurdy (2004) point out the inability of continuous time Gaussian-models to generate fat tails and, in turn, present different models for stock returns that incorporate jumps and variations of volatility processes. Moreover, 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) studied the economic and statistical role of jumps in continuous time models of the short term interest rate, and concluded 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 the returns process, large changes in market volatility, and the arrival of events that take the market by surprise (risk events). However, little 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. The present paper addresses these two concerns by focusing on events associated with the disclosure of public information regarding fundamental variables. In particular, since it is difficult to keep track of all the relevant information that causes reactions on the stock market, I consider a set of news released in regularly scheduled announcements. These are news releases regarding monetary policy, inflation, employment, and earnings on the stock market index. In this context, I explore announcement and news effects on the conditional volatility of returns through a non-linear channel associated with jumps in the return process. In addition,

[1] Geman, Madan, and Yor (2000) motivate more general purely discontinuous processes relating time changes to measures of economic activity at high frequencies.

I examine the extent to which heterogeneity among scheduled announcements explains differences in volatility persistence, shedding more light on the sources of persistence in asset returns volatility, and providing a criterion to distinguish between permanent and transitory effects of particular types of shocks.

The framework of this paper follows 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.[2] 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 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.

The results suggest that incorporating fundamental news variables in 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. In addition, while PPI shocks have a persistent effect on jump intensities, and therefore on conditional volatilities, monetary policy and employment shocks show only short lived effects. Models with jumps are compared with GARCH competitors with news effects, but without jumps. Based on the Schwarz information criterion, mixed GARCH models with jumps outperform GARCH models without jumps. Moreover, the results of this paper suggest that introducing macroeconomic surprises improve the prediction of ex post assessments of jump ocurrences.

The paper is organized as follows: Section 1.2 presents a review of the literature regarding the effect of macroeconomic news on equity prices and market volatility. Section 1.3 introduces the model characterizing the conditional return distribution. Section 1.4 provides a description of the data used in the empirical analysis, and defines the measures of "surprises" used in this paper. Section 1.5 reports estimation results for

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

different jump model specifications. Finally, a comparison with competing GARCH models is presented in section 1.6, and section 1.7 concludes.

1.2 Literature Review

This section presents a review of the literature on the effects of announcements and news regarding fundamental variables on asset prices. Given that each type of information release involves particular institutional features, most of the empirical literature has focused on specific types of news and distributional features. Thus, this section classifies the literature based on implications for conditional mean and conditional volatility of returns. Although the present paper focuses on conditional volatility, it is useful to review effects of news on conditional expected returns in order to explore possible return-volatility tradeoffs.

1.2.1 News Effects on Conditional Mean

Regarding monetary policy effects on expected returns, several papers have addressed the issue of endogeneity of the policy instrument. To overcome this problem, Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), and Poole and Rasche (2000) assume that shocks on event (announcement) days are completely due to monetary policy surprises. Therefore, they estimate the equity returns response to these shocks using only a sample of event days. Their results suggest positive responses of yields and negative responses of stock returns. Rigobon and Sack (2004) and Craine and Martin (2003) relax the previous assumption, and identify the effects of monetary policy surprises based on the heteroskedasticity associated with announcement days. They found larger negative impacts on stock returns. There are other approaches that analyze the response of stock prices to monetary policy shocks. For example, Goto and Valkanov (2002) use a structural VAR approach to estimate the impulse response of stock returns to policy shocks. Their analysis uses data at lower frequency (monthly), and their results suggest that the covariance between inflation induced by policy shocks and equity prices may be one reason for the response of stock markets to monetary policy.[3]

[3] Under the VAR approach, however, some identification issues arise due to the endogeneity of the policy instrument mentioned before.

Boyd, Jagannathan, and Hu (2005) examined how stocks respond to unemployment news. They argue that the unemployment rate is viewed as news worthy by the stock market, since it may convey information about three primitive factors of stock prices: growth rate expectations, interest rates, and risk premia. Using event windows including announcement days and/or days prior to the announcement, they estimated the effect of unemployment surprises on the S&P500 and bonds returns. They found asymmetric effects in expansions and contractions. In particular, unemployment surprises appeared to affect returns positively during expansions and negatively during contractions. Surprisingly, unemployment news events were not significant for bonds in contractions. Based on this fact, they concluded that unemployment news must be conveying information about growth rate expectations and risk premia. Indeed, they found a significant negative impact of unemployment surprises on growth rate expectations (this effect is stronger during contractions).

Other recent studies have examined the effects of macroeconomic news on prices of different kinds of financial assets, like T-Bills, stocks, or exchange rates, based on the characterization of the price discovery process. Naturally, market microstructure models have provided a dominant framework that relies on the use of high-frequency data. Some examples are: Balduzzi, Elton, and Green (2001), and Fleming and Remolona (1999) for the bond market, Andersen, Bollerslev, Diebold, and Vega (2003) for exchange rates, and Andersen, Bollerslev, Diebold, and Vega (2005) for multiple financial markets. These studies find important effects of news regarding price level (CPI and PPI), employment, and monetary policy variables on the price formation process of financial assets.

1.2.2 News Effects on Conditional Volatility

The relation between stock market volatility and uncertainty about fundamentals has been an important research topic to understand and test the factors that cause stock market volatility. From an empirical standpoint, 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 (2004) 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. These mentioned papers examine a long-term relation between returns volatility and fundamentals.

From a short-run prospective, other studies have addressed the market reaction to fundamental news released on announcement days in terms of volatility. Such research has focused on conditional volatility implied by ARCH/GARCH models introduced by Engle (1982) and Bollerslev (1986). For example, Li and Engle (1998) examine the degree of persistence heterogeneity associated with scheduled macroeconomic announcement dates and non-announcement dates in the Treasury futures market. They present a filtered GARCH model that takes care of cyclical patterns of time-of-the-week effects and announcement effects by decomposing returns volatility into transitory and non-transitory parts. They find heterogeneous effects 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 found 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, 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 (1998b) 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 can be described as follows:

$$r_t = \mu(X_t) + \sigma_t(X_t)F_t(X_t)z_t \tag{1.1}$$

where z_t is an $iid(0,1)$ random variable, X_t is a vector of state variables, and σ_t follows a GARCH process. The main difference relies in the specification of the "latent" volatility σ_t, and the filter F_t, which is the component that captures structural breaks induced by day-of-the-week effects and announcement effects. For example, Li and Engle proposed the following filter to account for structural changes on announcement, pre-announcement, and post-announcement days:[4]

$$F_t^2 = (1 + \eta_1 I_t^A)(1 + \eta_2 I_t^{A-})(1 + \eta_3 I_t^{A+}) \tag{1.2}$$

It is important to note that these models imply 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 seen 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

[4] I_t^A, I_t^{A-}, and I_t^{A+} are indicators of announcement, pre-announcement, and post-announcement days, respectively

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

unexpected, and it is typically associated with a jump in the return process. Following this intuition, the next section describes an alternative approach to modeling surprises on announcement days introducing a jump component in the return process.

1.3 Description of the Model

First, consider a stock return process in discrete time that is affected by heterogeneous information shocks. Following Maheu and McCurdy (2004), I argue that 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" news events, which cause relatively infrequent large price changes.[6] Thus, under the information set Ω_t conveying all the information known at time t, the returns process can be specified as follows:

$$r_t = \mu + \varepsilon_{1t} + \varepsilon_{2t} \tag{1.3}$$

where,

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

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

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

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

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.[7]

Why jump models with time varying intensities?

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

[7] 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 datails.

Models that account for large market movements or fat tails have been of academic interest for several years. In this context, two major approaches have been taken in the literature: a) Stochastic volatility models, in which returns innovations are Gaussian with a variance that changes randomly; and b) Models that introduce stochastic discontinuous jumps. Eraker (2004) argued that none of these models have proved to be entirely empirically successful. Stochastic volatility 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 discrete time, and relaxes the assumption of constant jump intensity.[8] The result is a model with high flexibility in describing 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 stress.

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 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 intensity as a mean reverting autoregressive process. The present study follows Maheu and McCurdy's specification for λ_t augmented with other explanatory variables associated with announcements and "surprises". This approach is motivated by the flexibility given to the jump arrival intensity to capture persistence and jump clustering. Notice 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:

$$var(r_t|\Omega_{t-1}) = \sigma_t^2 + \lambda_t \delta^2 \tag{1.4}$$

Thus, "surprises" can influence conditional volatility either through their effect on the jump arrival intensity or through the GARCH process describing σ_t^2. Moreover,

[8]GARCH models can be seen as discrete approximations of diffusions used in continuous SV models.

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 (1.4) 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 than zero.

The following proposition characterizes the conditional density of a return process described by (1.3), as well as a filter that describes the conditional expected number of jumps in the process.[9]

Proposition 1.1. If returns follow a process described in expression (1.3) 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

$$f(r_t|\Omega_{t-1}, \Theta) = \sum_{j=1}^{\infty} \frac{\exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi(\sigma_t^2 + j\delta^2)}} \exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2 + j\delta^2)}\right) \tag{1.5}$$

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

$$p(N_t = j|\Omega_t) = \left(\frac{\frac{\exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi(\sigma_t^2+j\delta^2)}} \exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+j\delta^2)}\right)}{f(r_t|\Omega_{t-1}, \Theta)} \right) \tag{1.6}$$

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.[10] In fact, the first order approximation of Equa-

[9]Equations (1.5) and (1.6) are referred as equations (23) and (24) in Maheu and McCurdy (2004).

[10]See Ait-Sahalia (2004) and Yu (2003) for conditions for existence and uniqueness of the approximate densities in continuous time jump-diffusion models, and maximum likelihood estimation.

tion (1.5), which seem to work well when λ_t is "small", is given by[11]:

$$f^1(r_t|\Omega_{t-1},\Theta) = \frac{(1-\lambda_t)}{\sqrt{2\pi\sigma_t^2}}\exp\left(-\frac{(r_t-\mu)^2}{2\sigma_t^2}\right) + \frac{\lambda_t}{\sqrt{2\pi(\sigma_t^2+\delta^2)}}\exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+\delta^2)}\right) \tag{1.7}$$

Note that Equation (1.7) 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. A second order approximation of Equation (1.5) is given by:

$$\begin{aligned} f^{(2)}(r_t|\Omega_{t-1},\Theta) &= \frac{(1-\lambda_t+\frac{\lambda_t^2}{2})}{\sqrt{2\pi\sigma_t^2}}\exp\left(-\frac{(r_t-\mu)^2}{2\sigma_t^2}\right) + \\ &\quad \frac{\lambda_t-\lambda_t^2}{\sqrt{2\pi(\sigma_t^2+\delta^2)}}\exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+\delta^2)}\right) + \\ &\quad \frac{\lambda_t^2}{2\sqrt{2\pi(\sigma_t^2+2\delta^2)}}\exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+2\delta^2)}\right) \end{aligned} \tag{1.8}$$

A full characterization of the likelihood requires parametrizations 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. These specifications are defined as,

Persistent Effects:

$$\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1} + \Lambda(a'x_t) \tag{1.9}$$

Transient Effects:

$$\lambda_t = c + \rho(\lambda_{t-1} - \Lambda(a'x_{t-1})) + \gamma\zeta_{t-1} + \Lambda(a'x_t) \tag{1.10}$$

[11] 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.

where $\Lambda(z) = 2 * \left[\frac{\exp(z)}{1+\exp(z)} - \frac{1}{2}\right]$, 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[12]:

$$\zeta_{t-1} = E(N_{t-1}|\Omega_{t-1}) - E(N_{t-1}|\Omega_{t-2}). \tag{1.11}$$

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. Also, 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 (1.6). For instance, considering the second order approximation of the likelihood described in (1.8), this conditional expectation can be approximated as follows:

$$E^{(2)}(N_t|\Omega_t) = \frac{\frac{\lambda_t-\lambda_t^2}{\sqrt{2\pi\left(\sigma_t^2+\delta^2\right)}}\exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+\delta^2)}\right) + \frac{\lambda_t^2}{\sqrt{2\pi\left(\sigma_t^2+2\delta^2\right)}}\exp\left(-\frac{(r_t-\mu)^2}{2(\sigma_t^2+2\delta^2)}\right)}{f^{(2)}(r_t|\Omega_{t-1},\Theta)} \tag{1.12}$$

and,

$$\zeta_t = E^{(2)}(N_t|\Omega_t) - \lambda_t \tag{1.13}$$

In addition, I parametrize the diffusive volatility component as a standard GARCH(1,1):

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2, \tag{1.14}$$

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 $(g, b \geq 0, g + b < 1)$.

In terms of higher moments, the assumptions described in (1.3) imply zero condi-

[12]This revision term forms a martingale difference sequence. Note that the information set is extended, i.e., Ω_{t-1} includes the history of returns and exogenous variables know before time t.

tional skewness and time varying conditional kurtosis, which is given by:

$$K_{t+1} = \frac{E(r^4_{t+1}|\Omega_t)}{\left(E(r^2_{t+1}|\Omega_t)\right)^2} = 3\left(1 + \frac{\lambda_{t+1}\delta^4}{\left(\sigma^2_{t+1} + \lambda_{t+1}\delta^2\right)^2}\right) \tag{1.15}$$

1.4 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. Relevant macroeconomic variables include the Consumer Price Index (CPI), the Producer Price Index (PPI), Nonfarm Payroll Employment (NFP) and the Unemployment Rate (Ump).[13] Data on the corresponding macroeconomic releases are obtained from the Bureau of Labor Statistics.[14] Macroeconomic forecasts are obtained from the Money Market Services (MMS) survey, which includes data from telephone surveys conducted normally one week or less before any macroeconomic news release.[15] Information regarding releases and forecasts of earnings on the S&P500 are obtained from the Institutional Brokers Estimates System (IBES) dataset, which provides consensus analysts' forecasts on earnings. Based on this information a surprise for release k on day t is calculated as follows:

$$S_{kt} = \frac{Y_{kt} - \widehat{Y}_{kt}}{\sigma_k} \tag{1.16}$$

where Y_{kt} is the realization of variable k, $\widehat{Y}_{kt}$ is the corresponding median forecast, and σ_k is the standard deviation of the forecast error. Surprises are computed in this way for announcements where the concensus forecast is obtained explicitly from the surveys mentioned above. These announcements include: CPI, PPI, NFP employment, and the Unemployment index.

[13]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.

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

[15]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 FOMC announcements as follows:

$$S_{it} \equiv i_t - E_{t-1} i_t = \left(\frac{D}{D-d} \Delta f f_t \right) \tag{1.17}$$

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.[16]

The sample used in this study is from January 1992 to December 2003. Figure 1.1 shows the patterns of S&P500 returns and absolute returns over the sample period. Both panels illustrate the presence of several extreme events that tend to cluster in some periods. Table 1.1 illustrates the distribution of announcements by day-of-the-week. The data suggest that day-of-the-week effects might be present in the 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, based on distributional features of absolute returns, which serve as a volatility proxy, Table 1.2 suggests that day-of-the-week effects are statistically insignificant for average volatility.[17]

Table 1.3 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 this effect is significant only for employment releases.[18] Note also that average volatility exhibits a decrease the day before the announcement for FFR and NFP/Ump. This phenomenon is known as the "calm before the storm". However, the effect is not significant.[19]

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

[17] The conclusion is the same when we consider square returns as an alternative volatility proxy.

[18] This conclusion is confirmed from regressions of squared returns on announcement days controlling for days-of-the-week effects.

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

Overall, this description confirms the importance of disentangling heterogeneous effects associated with different kinds of news events.

1.5 Estimation and Results

This section discusses estimation results for the jump model described in section 1.3. The estimation is based on the second order approximation of the likelihood given in Equation (1.8), where the diffusive volatility is given in Equation (1.14), and the jump intensity follows different specifications based on Equations (1.9) and (1.10), in which the announcement and news variables defined in the previous section are included as explanatory variables.[20] Recall that these specifications capture differences in persistence associated with announcements and surprises. Also, this approach models the effects of these variables on the conditional volatility of returns through the jump volatility component described by the second term of Equation (1.4), which provides a volatility decomposition used to illustrate the main results of this paper.

To clarify the interpretation of the estimation results, I discuss separately the baseline volatility parameters of the conditional volatility, which include those of the GARCH (1,1) component and those of the jump term, excluding announcement and news variables. Specifically, this set of parameters contains $\{\mu, \delta, c, \rho, \gamma, w, g, b\}$. Now, considering the estimates presented in Table 1.4, which correspond to the PPI, it is clear that those baseline parameters are highly significant for all the specifications of the jump intensity. Moreover, the estimate of ρ suggests high persistence in the jump intensity. For all the cases, this estimate fluctuates between 0.95 and 0.98 providing evidence of jump clustering in the returns process. These large values are consistent with the results of Maheu and McCurdy (2004) for market indices.[21] The impact of a revision in the expected number of jumps, described by γ, implies an adjustment of about 45% 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

[20] An earlier version of this study considered the first order approximation in Equation (1.7). Overall, the empirical results presented in this section are not sensitive to this change.

[21] 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.

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 positive and significant. The GARCH term is very persistent, and the ARCH effects are small. This indicates that including jumps does not affect the significance of the terms characterizing smooth volatility dynamics. Panel A of Figure 1.2 illustrates the conditional variance, and Panel B shows the contribution of its two components, the GARCH term and the jump component. Similar results are obtained for the other announcements relative to these baseline parameters (see Tables 1.5-1.9). Since the purpose of this study is analyzing announcement and news effects on conditional volatility, in what follows, I will exclusively focus on these effects.

Starting with inflation releases, Table 1.4 presents estimation results for the PPI. Models A-1 and A-2 consider specifications in which pure announcement effects are captured by a type-K announcement dummy, $I^A_{t,K}$. Specifically, the term $\Lambda(a'x_t)$ in Equations (1.9) and (1.10) is replaced by $\eta_1 I^A_{t,K}$. In model A-1, the announcement effects are persistent due to the autoregressive form of the baseline jump intensity. On the other hand, Model A-2 describes a situation in which the announcement effects are transient. The results suggest that pure PPI announcement effects are not significant in Model A-2 and only weakly significant, with negative sign, in Model A-1.

Using the size of the announcement surprise rather than the fact of the announcement alone motivates different specifications for the jump intensity. I propose specifications that account for asymmetric effects of news variables. Specifically, the term $a'x_t$ in Equations (1.9) and (1.10) is replaced by $a_1|S_{t,K}| + a_2 I^-_{t,K}|S_{t,K}|$, where $S_{t,K}$ is a type-K news variable, as defined in Equation (1.16), and $I^-_{t,K}$ is an indicator of negative news. In model S-1 the shocks persist through the jump persistence parameter, ρ. On the contrary, model S-2 restricts the shocks to be non-persistent.[22] The results suggest that inflation shocks are significant only for specification S-1. In this case, the effect is asymmetric, which is consistent with 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. By contrast, when infla-

[22]Appendix A2 presents a more general version of a model that nests S-1 and S-2.

tion is lower than expected, the effect becomes negative, dropping conditional volatility, but less than proportional with respect to the positive effect of positive news. For example, an inflation shock of size one increases the jump intensity by 0.30, if the shock is positive, and decreases the jump intensity by 0.17 if the shock is negative[23] These results are also consistent with David and Veronesi (2004), in the sense that positive inflation shocks might introduce additional uncertainty of switching to a high inflation regime. Among all the specifications, model S-1 seems to fit the data the best. In fact, the Schwarz criterion favors the model persistent asymmetric shocks. Thus, these results suggest that positive inflation shocks are likely to increase stock market volatility with significant persistent effects.

Table 1.5 gives the estimation results for the federal funds rate. As before, the first two columns display estimates for specifications that account for pure announcement effects. In models A-1 and A-2, the announcement dummy is not significant, suggesting that scheduled FOMC meeting days are not, *per se*, the events that drive the jump component of conditional volatility. This result contrasts with Bomfim (2003), who finds significant positive effects of FOMC meetings on conditional volatility.

On the other hand, when monetary policy surprises are included in the specification of the jump probability, the impact of these shocks becomes significant. Specifically, the estimated coefficients associated with shocks in specification S-2 indicate that monetary policy shocks have a non-persistent effect on conditional volatility by increasing the jump component of volatility. Here positive and negative shocks increase the jump intensity. The coefficient of asymmetry is not significant in this case. Notice that these results support the connection between events such as surprise Federal Reserve target changes and jump arrivals, as pointed out by Johannes (2004) in the term structure case. The results for specification S-1 indicate that the coefficients of surprises are no longer significant when the effects are persistent. This suggests that the effect of monetary policy shocks on market volatility is unlikely to be persistent. Moreover, in terms of model selection, the Schwarz criterion favors the specification in model S-2. Therefore, short-lived effects seem to characterize better the short run impact of monetary policy

[23] In the logistic function Λ the coefficient for positive news is α_1 and the coefficient for negative news is $\alpha_1 + \alpha_2$.

surprises on the stock market volatility.

Table 1.6 gives results for employment releases. These announcements convey important information on whether the economy is expanding or contracting. Notice that, in this case, pure announcement effects (which are captured in specifications A-1 and A-2) are highly significant, especially when the effects are non persistent (as in model A-2). In this regard, there are differing empirical findings. For instance, Li and Engle (1998) do not find significant effects of unemployment announcements on the volatility of treasury futures. Similarly, Boyd et al (2005) do not find a significant impact of unemployment news on the equity risk premium, which is measured by the volatility of stock returns. On the other hand, in line with the present study, Flannery and Protopapadakis (2002) find significant employment announcement effects on the stock market volatility.

In relation to surprising effects, NFP employment shocks show non persistent impacts on the jump intensity. In fact, the estimates of model S-2 indicate that the effect of NFP surprises is statistically significant and increases the jump intensity. The coefficient of asymmetry is negative, but it is not significant. Regarding unemployment surprises, specification S-2 also shows a weakly significant impact of negative unemployment surprises, which, along with positive surprises in NFP employment, typically signal an upward revision of growth expectations and changes in interest rates. In contrast, the persistent specification in model S-1 show no significant effects of employment shocks on jump intensities suggesting that the effect of employment surprises on conditional volatility seems to be short-lived. This is confirmed by the model selection results where the Schwarz criterion considerably favors the non persistent models, specifically model S-2 with NFP news effects and model A-2.

The other announcements considered in this paper correspond to the CPI and earnings on the S&P500. Table 1.7 presents results for CPI releases. In this case, pure announcement effects show no significant impacts on jump intensities. On the other hand, news effects are significant only for the non persistent specification in model S-2, where positive shocks increase the jump intensity. This effect is mostly offset when the shocks are negative. These results, along with those for the PPI, suggests asymmetric effects of inflation shocks on the jump component of volatility. Nevertheless, although CPI surprises show statistical significance in model S-2, the Schwarz criterion favors the specifications without news effects. 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. With respect to earnings releases, neither pure announcement effects nor news effects are significant under any of the specifications considered in this study. A possible explanation might be that most of the effects of earnings surprises are already discounted based on the results at the firm level. In addition, since earnings releases occur at a quarterly basis, my sample of announcements is quite small, which makes the estimation of models with many parameters difficult. Naturally, the Schwarz criterion favors a model without earnings effects. Results for earning announcements are presented in Table 1.8.

To further illustrate the importance of introducing news variables in the specification of jump intensities, Figure 1.3 shows patterns of average estimated (jump intensity) residuals associated with the preferred models discussed above and a specification without news variables, considering subsamples of PPI, FFR, and NFP/Ump announcement days. Specifically, the model without news effects has a pure autoregressive conditional jump intensity as in Maheu and McCurdy (2004), i.e., $\lambda_t = c + \rho\lambda_{t-1} + \gamma\zeta_{t-1}$. The jump intensity residual, ζ_t, is computed from Equation (1.13). Its average value over the subsamples of PPI, FFR and NFP/Ump announcement days is compared with the average value of jump intensity residuals obtained from specification S-1, for the PPI subsample, and from specification S-2, for the FFR and NFP/Ump subsamples. Figure 1.3 confirms that when the surprise component of an announcement is incorporated in 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. Thus, 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.[24]

Another question addressed in this paper refers to whether announcement days present

[24]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.

different volatility persistence or are more like "regular" days. This concerns the possibility of structural changes in ρ, the parameter characterizing the persistence of the intensity. Results in Table 1.9 suggest that structural changes in the arrival intensity's persistence are not significant for any type of announcement, which indicates that the persistence of jumps on announcement days is not different than that on non-announcement days. Therefore, the structural source of volatility persistence associated with the non-linear jump component does not seem to be different on announcement days. This parallels the result of Jones et al. (1998), who find no significant structural changes in the GARCH component of conditional volatility.

1.6 Model Evaluation

This section presents an in-sample evaluation of the jump models estimated above. Based on a model selection criterion, I will compare them with different competing GARCH specifications that have been used in the literature. First, I consider a modified GARCH(1,1) model that includes the same announcement and news variables used in the previous section. This model can be expressed as follows:

$$\begin{aligned} r_t &= \mu + \varepsilon_t \\ \varepsilon_t|\Omega_{t-1} &\sim N(0, \sigma_t^2) \\ \sigma_t^2 &= w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_1 I_t^A + a_1|S_{t,K}| + \\ & \quad a_2 I_{t,K}^-|S_{t,K}| + a_3|S_{t-1,K}| + a_2 I_{t-1,K}^-|S_{t-1,K}| \end{aligned} \tag{1.18}$$

Recall that I_t^A is the dummy variable for announcement days, I_t^- is the dummy variable for negative surprises, and $S_{t,K}$ denotes surprises in variable k, as defined by Equations (1.16) and (1.17).

Another plausible model specification can be derived from the GARCH models with filters introduced earlier in section 1.2.[25] In this setting, conditional volatility might respond to announcements in two different ways. One is transitory in the sense that

[25] See equations (1.1) and (1.2). These models were introduced by Jones et al. (1998) and Li and Engle (1998).

the response does not carry over to the next day. This effect is captured by a filter that describes the volatility seasonality on announcement days. The other is persistent, and it is captured by the GARCH volatility specification. This model can be described as follows:

$$\begin{aligned} r_t &= \mu + \sqrt{s_t}\varepsilon_t \\ \varepsilon_t|\Omega_{t-1} &\sim N(0, \sigma_t^2) \\ F_t &= 1 + \eta_1 I_t^A \end{aligned} \tag{1.19}$$

Based on the Schwarz criterion applied to nested versions of Equations (1.18) and (1.19), and statistical significance of the relevant explanatory variables, I chose to use specific GARCH models that are "best" in their class for each type of announcement (see Appendix A2).[26] The selected models are compared with the "best" candidate of the jump models estimated above. Focusing on the PPI, Table 1.10 gives estimation results for these competing models (recall from Table 1.4 that model S-1 can be selected as a preferred jump specification). For all models, the effects of inflation shocks are asymmetric and go in the same direction. This supports the findings described in section 1.5. Also the GARCH and ARCH effects are highly significant. Moreover, in both GARCH specifications, the GARCH effect is reduced, and the ARCH effect becomes larger, relative to the GARCH/ARCH terms in the jump model. This suggests that introducing jumps reduces the variance of the conditional volatility associated with the diffusive term, σ_t^2, and also increases its persistence.[27] The Schwarz model selection criterion clearly favors the jump model S-1 for the PPI.

Table 1.11 compares estimation results for the FFR. For the first two GARCH models, monetary policy shocks have a significant positive impact on conditional volatility; however, consistent with the jump specifications, the asymmetric effects are not significant. As in the previous section, models with non persistent effects of monetary policy shocks are preferred over those with persistent effects (see Appendix A2, Tables 1.15 and 1.16). Overall, the Schwarz criterion favors the specification with jumps.

[26]Based on the results in section 1.5, I restrict the analysis in this part to announcements on the PPI, the short term interest rate, and the unemployment index.

[27]This result is also observed for the other announcements considered in this section.

Table 1.12 compares models for employment releases. The selected GARCH specifications derived from Equations (1.18) and (1.19) are nested models that include exclusively pure announcement effects (see Appendix A2, Tables 1.17 and 1.18). All the models corroborate that the effect of employment announcements is likely to be short-lived, although the specification with jumps is favored by the Schwarz criterion.

Through an in-sample comparison with different plausible competing specifications, I find evidence that the mixed GARCH models with jumps, compared with models without jumps, perform quite well in capturing the effect on conditional volatility of macroeconomic events associated with fundamentals that might take the market by surprise.

1.7 Concluding Remarks

In this paper, I present an alternative approach to analyze the effect of public regularly-scheduled announcements related to fundamental variables, on the conditional volatility of the 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 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.

The fundamental variables considered in the paper include measures of inflation (CPI, PPI), employment (NFP Employment and Index of Unemployment), short term interest rates (Federal Funds Rate), and earnings (Earnings on the S&P500). 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 addition, there is no evidence of a structural change in the persistence of the jump component of volatility on announcement days. 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. Only shocks in the PPI show significant persistent effects on volatility. Moreover, the direction of the effects is consistent with theoretical and empirical evidence. Higher than expected inflation, short term interest rates, and NFP employment induce an increase in the jump intensity and conditional 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 CPI and change the direction of the effect for the PPI. Earnings announcements on the S&P500 do not show significant impacts on volatility, suggesting that earning surprises at the firm level might be needed in the analysis. Overall, these empirical findings point out the relevance of incorporating heterogeneous news events to explain different volatility patterns.

Comparing different jump model specifications, based on the Schwarz criterion, provides conclusive model selection results for the PPI, short term interest rate, and employment news. I compare the selected specifications with competing GARCH models without jumps that account for announcement and news effects, finding evidence suggesting that mixed GARCH models with jumps outperforms models without jumps. This confirms that jumps play an important role in explaining the effects on returns volatility of macroeconomic events that take market participants by surprise. Moreover, this paper shows that macroeconomic surprises are relevant predictors of ex post assessments of a jump occurrence.

What is left in the paper for future research concerns a further evaluation of the jump models in terms of forecasting. In addition, given that responses of stocks to news releases might vary according to the industry and the size of the firms considered, it would be interesting to perform this analysis disentangling industry and size effects. Furthermore, analyzing these effects for different countries might provide valuable insights in explaining differences in volatility dynamics across countries.

1.8 Figures

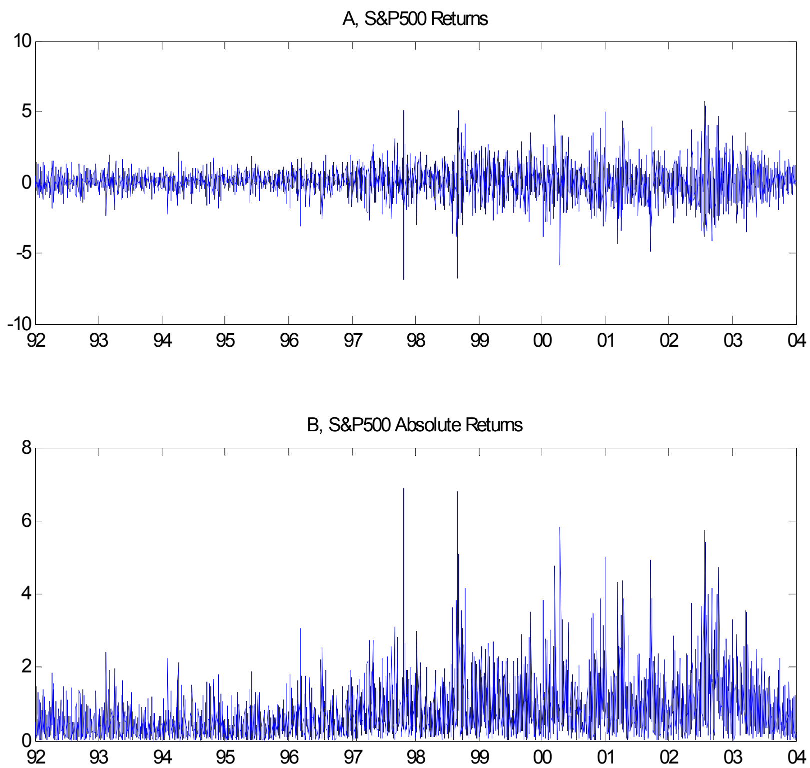

Figure 1.1: Returns and Absolute Returns

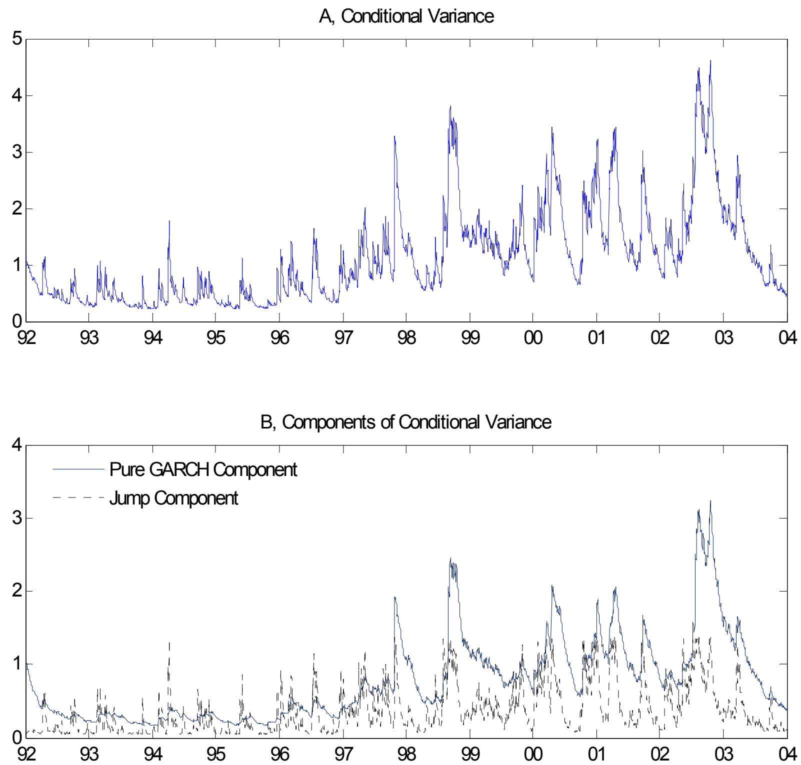

Figure 1.2: Conditional Variance Components

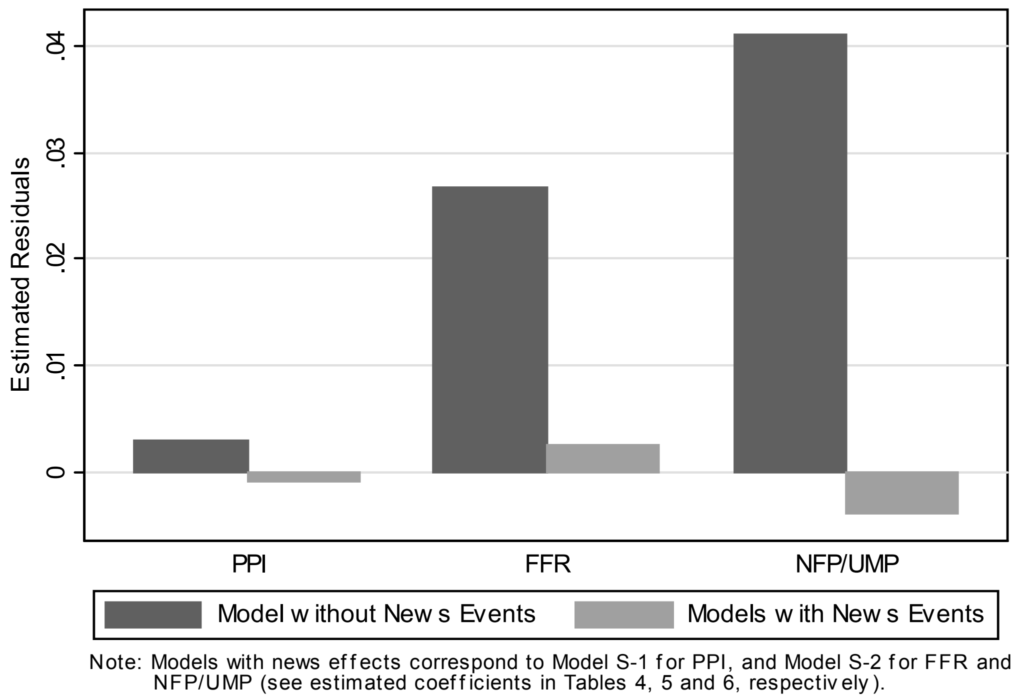

Figure 1.3: Average Estimated Jump Intensity Residuals on Announcement Days for Specifications with and without News Effects

1.9 Tables

Table 1.1: Announcement Days in the Sample 1992-2003

		Announcements (1992-2003)				
Dayweek	total	CPI	PPI	Earnings	FFR	NFP/Unemp
M	575	0	0	3	3	1
T	621	41	14	9	55	0
W	619	38	17	8	36	0
Th	608	26	42	10	5	5
Fr	603	39	70	15	3	135
Total	3,026	144	143	45	102	141

Table 1.2: Descriptive Statistics for Absolute Returns

Volatility Proxy: Absolute Returns S&P500 (%)					
Dayweek	mean	Sd	t-stat[a]	min	max
M	0.7745	0.8234	0.5240	0.0013	6.8667
T	0.7795	0.7788	0.7566	0	5.1164
W	0.7094	0.7120	-1.9014	0.0009	5.7315
Th	0.7665	0.7224	0.2969	0	4.7639
Fr	0.7646	0.7295	0.2228	0.0011	5.8278
Total	0.7586	0.7535		0	6.8667

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 1.3: 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	144	0.8089	0.8058	0.98	0.8201	0.8835	1.05	0.8255	0.8151	1.21
PPI	143	0.7598	0.8232	0.26	0.7600	0.7455	0.29	0.8041	0.8610	0.85
Ear	45	0.7027	0.7896	-0.33	0.7736	0.8997	0.24	0.9302	1.0282	1.23
FFR	102	0.8843	0.9476	1.51	0.7302	0.7277	-0.15	0.8627	0.8244	1.46
NFP/Ump	141	0.9631	0.8060	**3.19**	0.6766	0.6519	-1.14	0.7039	0.7431	-0.58
Non-Ann Days	2469	0.7413	0.7336							

a)t-test on the equality of means with respect to the sample of non-announcement days. Significant values at 1% are highlighted.

Table 1.4: Announcement and News Effects of the PPI

	Model A-1		Model A-2		Model S-1		Model S-2	
Param	coeff	stde	coeff	Stde	coeff	stde	coeff	stde
μ	0.0680	0.017	0.0664	0.014	0.0659	0.015	0.0669	0.015
δ^2	1.4693	0.250	1.3852	0.305	1.3439	0.174	1.4167	0.270
c	0.0127	0.005	0.0092	0.003	0.0078	0.003	0.0092	0.004
ρ	0.9764	0.015	0.9754	0.013	0.9784	0.012	0.9716	0.017
γ	0.4919	0.125	0.4406	0.087	0.3960	0.087	0.4539	0.095
w	0.0019	0.001	0.0021	0.001	0.0017	0.001	0.0021	0.001
g	0.0178	0.005	0.0180	0.006	0.0159	0.004	0.0180	0.005
b	0.9716	0.007	0.9704	0.009	0.9735	0.006	0.9705	0.008
η_1	-0.1162	0.063	-0.0332	0.042				
a_1					0.6361	0.278	0.0510	0.311
a_2					-0.9846	0.261	-0.1577	0.282
-lnL	3985.4		3985.2		3980.1		3985.4	
SC	8042.93		8042.53		**8040.35**		8050.95	

Specification for returns* :

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim iidN(0, \delta^2), \qquad N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t)$$

Model A-1:

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

Model A-2:

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

Model S-1

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

Model S-2

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

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

$$a' x_t = a_1 I_t^A \mid S_{t,K} \mid + a_2 I_{t,K}^- \mid S_{t,K} \mid$$

$$I_{t,K}^A = 1(announcement\ of\ type\ K)$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K}$$

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

(*) The information set is extended and includes past returns and exogenous variables.
(b) SC=Schwarz Criterion

Table 1.5: Announcement and News Effects of the FFR

	Model A-1		Model A-2		Model S-1		Model S-2	
Param	coeff	stde	coeff	stde	coeff	stde	coeff	Stde
μ	0.0655	0.014	0.0660	0.015	0.0663	0.014	0.0635	0.012
δ^2	1.3944	0.262	1.3982	0.252	1.4427	0.230	1.5447	0.280
c	0.0066	0.003	0.0090	0.003	0.0090	0.005	0.0063	0.004
ρ	0.9757	0.016	0.9742	0.012	0.9733	0.024	0.9808	0.020
γ	0.4406	0.088	0.4383	0.114	0.4999	0.142	0.4435	0.085
w	0.0020	0.001	0.0020	0.001	0.0020	0.001	0.0019	0.001
g	0.0177	0.005	0.0179	0.005	0.0180	0.006	0.0160	0.006
b	0.9711	0.007	0.9708	0.008	0.9711	0.008	0.9742	0.007
η_1	0.0600	0.051	0.0365	0.067				
a_1					-0.1812	0.195	0.5410	0.161
a_2					0.2772	0.229	0.1063	0.105
-lnL	3985.4		3985.3		3982.7		3979.0	
SC[b]	8042.93		8042.73		8045.55		**8030.13**	

Specification for returns[*] :

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim iidN(0,\delta^2), \qquad N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t)$$

Model A-1:

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

Model A-2:

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

Model S-1

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

Model S-2

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

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

$a'x_t = a_1 I_t^A \mid S_{t,K} \mid + a_2 I_{t,K}^- \mid S_{t,K} \mid$

$I_{t,K}^A = 1(\text{announcement of type } K)$

$I_{t,K}^- = 1(S_{t,K} < 0)$

$S_{t,K} = \text{shock in variable K}$

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

(*) The information set is extended and includes past returns and exogenous variables.
(b) SC=Schwarz Criterion

Table 1.6: Announcement and News Effects of the NFP Employment and the Unemployment Index

	Model A-1		Model A-2		Model S-1				Model S-2			
					NFP		Unemp		NFP		Unemp	
Param	coeff	stde	coeff	Stde	coeff	Stde	Coeff	Stde	coeff	Stde	Coeff	Stde
μ	0.065	0.014	0.066	0.016	0.066	0.014	0.066	0.014	0.066	0.014	0.065	0.014
δ^2	1.535	0.343	1.509	0.28	1.538	0.244	1.482	0.191	1.367	0.234	1.427	0.173
c	0.007	0.005	0.008	0.005	0.009	0.005	0.009	0.004	0.008	0.002	0.01	0.004
ρ	0.959	0.032	0.967	0.026	0.962	0.035	0.97	0.017	0.977	0.011	0.968	0.013
γ	0.545	0.211	0.433	0.124	0.715	0.15	0.468	0.172	0.447	0.09	0.438	0.102
w	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001
g	0.019	0.006	0.019	0.006	0.021	0.006	0.018	0.005	0.018	0.005	0.019	0.005
b	0.969	0.007	0.97	0.009	0.968	0.008	0.971	0.007	0.971	0.008	0.969	0.008
η_1	0.103	0.056	0.293	0.105								
a_1					0.344	0.249	0.046	0.152	1.289	0.504	-0.032	0.053
a_2					-0.156	0.261	-0.004	0.165	-0.442	0.563	0.399	0.23
-lnL	3984		3978.6		3982.6		3985.6		3974.8		3983.5	
SC[b]	8039.5		**8029.3**		8045.3		8051.3		**8029.7**		8047.1	

Specification for returns[*] :

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim iidN(0,\delta^2), \qquad N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t)$$

Model A−1:

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

Model A−2:

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

Model S−1

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

Model S−2

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

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

$$a'x_t = a_1 I_t^A \mid S_{t,K} \mid + a_2 I_{t,K}^- \mid S_{t,K} \mid$$

$$I_{t,K}^A = 1(\textit{announcement of type } K)$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K}$$

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

(*) The information set is extended and includes past returns and exogenous variables.

(b) SC=Schwarz Criterion

Table 1.7: Announcement and News Effects of the CPI

	Model A-1		Model A-2		Model S-1		Model S-2	
Param	coeff	stde	coeff	stde	coeff	stde	coeff	Stde
μ	0.0658	0.015	0.0663	0.015	0.0679	0.012	0.0685	0.015
δ^2	1.4719	0.204	1.4155	0.324	1.3587	0.200	1.4112	0.289
c	0.0110	0.005	0.0089	0.004	0.0058	0.004	0.0114	0.004
ρ	0.9705	0.019	0.9743	0.016	0.9767	0.016	0.9692	0.014
γ	0.4677	0.134	0.4362	0.106	0.4038	0.081	0.5772	0.135
w	0.0020	0.001	0.0019	0.001	0.0021	0.001	0.0023	0.001
g	0.0180	0.005	0.0174	0.005	0.0178	0.006	0.0204	0.006
b	0.9710	0.007	0.9715	0.007	0.9702	0.009	0.9676	0.008
η_1	-0.0339	0.040	0.0764	0.109				
a_1					0.0767	0.138	0.7088	0.355
a_2					0.1113	0.196	-0.6248	0.306
-lnL	3985.9		3985.1		3984.0		3984.0	
SC[b]	8043.93		**8042.33**		8048.15		8048.15	

Specification for returns[*] :

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \quad c_{jt} \sim iidN(0,\delta^2), \quad N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t)$$

Model A-1:

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

Model A-2:

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

Model S-1

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

Model S-2

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

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

$a' x_t = a_1 I_t^A \mid S_{t,K} \mid + a_2 I_{t,K}^- \mid S_{t,K} \mid$

$I_{t,K}^A = 1(announcement\ of\ type\ K)$

$I_{t,K}^- = 1(S_{t,K} < 0)$

$S_{t,K}$ = shock in variable K

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

(*) The information set is extended and includes past returns and exogenous variables.
(b) SC=Schwarz Criterion

Table 1.8: Announcement and News Effects of Earnings on the SP500

	Model A-1		Model A-2		Model S-1		Model S-2	
Param	coeff	stde	coeff	stde	coeff	Stde	coeff	Stde
μ	0.0661	0.016	0.0662	0.015	0.0614	0.015	0.0593	0.011
δ^2	1.4577	0.279	1.4298	0.263	1.0943	0.201	1.1534	0.206
c	0.0097	0.004	0.0088	0.004	0.0080	0.005	0.0088	0.004
ρ	0.9710	0.014	0.9747	0.016	0.9855	0.015	0.9793	0.013
γ	0.4624	0.107	0.4428	0.111	0.3839	0.085	0.3918	0.080
w	0.0020	0.001	0.0021	0.001	0.0030	0.001	0.0035	0.001
g	0.0174	0.006	0.0178	0.005	0.0226	0.006	0.0246	0.006
b	0.9717	0.008	0.9709	0.008	0.9619	0.008	0.9592	0.010
η_1	-0.0266	0.068	-0.0254	0.064				
a_1					-0.1757	0.615	-0.1494	0.477
a_2					0.6051	0.698	-0.2323	0.519
-lnL	3986.1		3985.5		3989.6		3989.7	
SC[b]	8044.33		**8043.13**		8059.35		8059.55	

$Specification\ \ for\ returns^{*}:$

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim iidN(0,\delta^2), \qquad N_t \mid \Omega_{t-1} \sim Poisson(\lambda_t)$$

$Model\ \ A-1:$

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

$Model\ \ A-2:$

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

$Model\ \ S-1$

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

$Model\ \ S-2$

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

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

$a' x_t = a_1 I_t^A \mid S_{t,K} \mid + a_2 I_{t,K}^{-} \mid S_{t,K} \mid$

$I_{t,K}^A = 1(announcement\ \ of\ \ type\ \ K)$

$I_{t,K}^{-} = 1(S_{t,K} < 0)$

$S_{t,K} = \text{shock in variable K}$

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

(*) The information set is extended and includes past returns and exogenous variables.
(b) SC=Schwarz Criterion

Table 1.9: Change in ro's Persistence on Announcement Days

	CPI		PPI		Earnings		FFR		NFP/Unemp	
Param	coeff	stde	coeff	stde	Coeff	stde	coeff	stde	Coeff	Stde
M	0.065	0.013	0.066	0.016	0.065	0.014	0.065	0.014	0.067	0.014
δ^2	1.827	0.413	1.522	0.535	1.486	0.501	1.807	0.491	1.132	0.207
c	0.007	0.003	0.005	0.004	0.005	0.004	0.008	0.003	0.002	0.001
ρ	0.969	0.023	0.990	0.033	0.980	0.027	0.940	0.035	0.975	0.016
γ	0.365	0.134	0.288	0.151	0.284	0.153	0.404	0.135	0.141	0.093
w	0.002	0.001	0.003	0.001	0.003	0.001	0.003	0.001	0.006	0.002
g	0.023	0.007	0.025	0.008	0.026	0.008	0.024	0.007	0.041	0.009
b	0.965	0.008	0.962	0.010	0.960	0.011	0.964	0.009	0.933	0.014
η_1	-0.130	0.343	-0.284	0.284	-0.129	0.337	0.620	0.693	0.508	0.432
-lnL	3988.4		3988.0		3988.2		3987.9		3986.2	
SC[b]	8048.9		8048.1		8048.5		8047.9		8044.5	

Model:

$$r_t = \mu + \sigma_t z_t + \sum_{j=1}^{N_t} c_{jt}, \quad c_{jt} \sim N(0,\delta^2), \quad N_t \sim Poisson(\lambda_t)$$

$$\lambda_t = c + \rho(1+\eta_1 I_{t,K}^A)\lambda_{t-1} + \gamma\zeta_{t-1}$$

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

$$I_{t,K}^A = 1(announcement\ of\ type\ K)$$

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

(*) The information set is extended and includes past returns and exogenous variables.
(b) SC=Schwarz Criterion

Table 1.10: Comparison of Modified GARCH, Filtered GARCH and GARCH-Jump Models for the PPI

	Model G1-8		Model G2-8		Model S-1	
Param	coeff	Stde	coeff	stde	coeff	stde
μ	0.0593	0.014	0.0588	0.014	0.0659	0.015
δ^2					1.3439	0.174
c					0.0078	0.003
ρ					0.9784	0.012
γ					0.3960	0.087
w	0.0058	0.003	0.0049	0.002	0.0017	0.001
g	0.0660	0.011	0.0646	0.009	0.0159	0.004
b	0.9278	0.010	0.9295	0.010	0.9735	0.006
η_1			-0.0474	0.111		
a_1	0.2897	0.119	0.3059	0.105	0.6361	0.278
a_2	-0.3150	0.121	-0.3223	0.102	-0.9846	0.261
-lnL	4026.2		4026.8		3980.1	
SC	8100.4		8109.7		**8040.3**	

$Model-G1-10:$

$r_t = \mu + \varepsilon_t$

$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$

$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^{-} \mid S_{t-1,K} \mid$

$Model-G2-10$

$r_t = \mu + F_t \varepsilon_t$

$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$

$F_t = (1 + \eta_1 I_{t,K}^{A})$

$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^{-} \mid S_{t-1,K} \mid$

$Model \quad S-1:$

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

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

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

$where,\ I_{t,K}^{A} = 1(announcement\ of\ type\ K)$

$I_{t,K}^{-} = 1(S_{t,K} < 0)$

$S_{t,K}$ = shock in variable K at time t

$a' x_t = a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^{-} \mid S_{t-1,K} \mid$

Table 1.11: Comparison of Modified GARCH, Filtered GARCH and GARCH-Jump Models for the FFR

	Model G1-9		Model G2-9		Model S-2	
Param	coeff	Stde	coeff	stde	coeff	stde
μ	0.0590	0.014	0.0582	0.015	0.0635	0.012
δ^2					1.5447	0.280
c					0.0063	0.004
ρ					0.9808	0.020
γ					0.4435	0.085
w	0.0051	0.002	0.0046	0.035	0.0019	0.001
g	0.0624	0.009	0.0641	0.028	0.0160	0.006
b	0.9345	0.009	0.9328	0.058	0.9742	0.007
η_1			0.0661	0.293		
a_1	0.6251	0.350	0.5638	0.278	0.5410	0.161
a_2	-0.1050	0.413	0.0010	0.553	0.1063	0.105
-lnL	4023.8		4024		3979.0	
SC	8095.6		8104.1		**8030.13**	

$Model-G1-11:$

$r_t = \mu + \varepsilon_t$

$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$

$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b(\sigma_{t-1}^2 - a_1 \mid S_{t-2,K} \mid - a_2 I_{t-2,K}^- \mid S_{t-2,K} \mid) + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid$

$Model-G2-9$

$r_t = \mu + F_t \varepsilon_t$

$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$

$F_t = (1 + \eta_1 I_{t,K}^A)$

$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b(\sigma_{t-1}^2 - a_1 \mid S_{t-2,K} \mid - a_2 I_{t-2,K}^- \mid S_{t-2,K} \mid) + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid$

$Model\ S-2:$

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

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

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

$where,\ I_{t,K}^A = 1(announcement\ of\ type\ K)$

$I_{t,K}^- = 1(S_{t,K} < 0)$

$S_{t,K}$ = shock in variable K at time t

$a' x_t = a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid$

Table 1.12: Comparison of Modified GARCH, Filtered GARCH and GARCH-Jump Models for the Unemployment Index

	Model G1-10		Model G2-10		Model A-2	
Param	coeff	Stde	coeff	stde	coeff	stde
μ	0.0599	0.014	0.0583	0.015	0.0647	0.014
δ^2					1.4683	0.272
c					0.0083	0.004
ρ					0.9750	0.019
γ					0.4593	0.077
w	0.0050	0.002	0.0040	0.002	0.0022	0.001
g	0.0717	0.010	0.0717	0.010	0.0178	0.005
b	0.9243	0.010	0.9258	0.010	0.9709	0.008
η_1	0.5259	0.147	0.7207	0.217	0.2656	0.091
η_2			0.0330	0.038		
a_1						
a_2						
-lnL	-4018.9		-4020		3979.5	
SC	8077.9		8088.2		**8031.1**	

$Model-G1-12:$

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b(\sigma_{t-1}^2 - \eta_1 I_{t-1,K}^A) + \eta_1 I_{t,K}^A$$

$Model-G2-12$

$$r_t = \mu + F_t \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$F_t = (1 + \eta_1 I_{t,K}^A)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_2 I_{t,K}^A$$

$Model\ A-2:$

$$\lambda_t = c + \eta_1 I_{t,K}^A + \rho(\lambda_{t-1} - \eta_1 I_{t-1,K}^A) + \gamma\zeta_{t-1}$$

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

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

$where,\ I_{t,K}^A = 1(announcement\ of\ type\ K)$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$S_{t,K}$ = shock in variable K at time t

1.10 Appendix A1

Proof of Proposition 1. From Equation (1.3), we have:

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

$\varepsilon_{2t} = \sum_{j=1}^{N_t} c_{jt}, \qquad c_{jt} \sim N(0,\delta^2), \qquad iid$ 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 (1.5) 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 (1.6) follows. $\square$

1.11 Appendix A2

Table 1.13: Modified GARCH (1,1) Model with Persistent Announcement Effects for PPI

			Coefficient Mean Equation[1]		
μ	0.0597**	0.0593**	0.0594**	0.0587**	0.0411
	0.0142	**0.0142**	**0.0142**	**0.0141**	**0.0449**
		Coefficients Variance Equation			
w	0.0065*	0.0058*	0.0074*	0.0053*	1.0126**
	0.0030	**0.0025**	**0.0030**	**0.0024**	**0.3316**
g	0.0705**	0.0660**	0.0653**	0.0640**	0.1219**
	0.0114	**0.0108**	**0.0107**	**0.0105**	**0.0368**
b	0.9259**	0.9278**	0.9281**	0.9302**	0.5603**
	0.0104	**0.0102**	**0.0102**	**0.0100**	**0.1414**
η_1	-0.0016		-0.0525		-0.3469[a]
	0.0490		**0.0727**		**0.1975**
a_1		0.2897*	0.3340*	0.3666	-0.1624
		0.1193	**0.1394**	**0.2926**	**0.4087**
a_2		-0.3150**	-0.3347**	-0.3816	-0.2259
		0.1210	**0.1225**	**0.3187**	**0.4075**
a_3				-0.0836	-0.1278
				0.2945	**0.4631**
a_4				0.0696	-0.1570
				0.3200	**0.4639**
lnL	-4033.20	-4026.15	-4025.36	-4025.13	-4815.61
SC	8106.48	8100.39	8106.83	8117.05	9706.56

Maximum likelihood estimates of the model:

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_1 I_{t,K}^A + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid + a_3 \mid S_{t-2,K} \mid + a_4 I_{t-2,K}^- \mid S_{t-2,K} \mid$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Table 1.14: Modified GARCH (1,1) Model with Non Persistent Announcement Effects for PPI

	Coefficient Mean Equation[1]		
μ	0.0591**	0.0588**	0.0589**
	0.0148	**0.0142**	**0.0139**
	Coefficients Variance Equation		
w	0.0049[a]	0.0049*	0.0049**
	0.0025	**0.0024**	**0.0017**
g	0.0693**	0.0646**	0.0639**
	0.0099	**0.0094**	**0.0084**
b	0.9275**	0.9295**	0.9304**
	0.0102	**0.0100**	**0.0086**
η_1	-0.0254	-0.0474	-0.1067
	0.0967	**0.1107**	**0.1259**
η_2	0.0209		
	0.0387		
a_1		0.3059**	0.5428
		0.1050	**0.4570**
a_2		-0.3223**	-0.5431
		0.1024	**0.4498**
a_3			-0.2452
			0.4418
a_4			0.2228
			0.4334
lnL	-4034.2	-4026.8	-4026.6
SC	8116.6	8109.7	8125.3

Maximum likelihood estimates of the model:

$$r_t = \mu + F_t \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$F_t = (1 + \eta_1 I_{t,K}^A)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_2 I_{t,K}^A + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid + a_3 \mid S_{t-2,K} \mid + a_4 I_{t-2,K}^- \mid S_{t-2,K} \mid$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Table 1.15: Modified GARCH (1,1) Model with Non Persistent Announcement Effects for FFR

			Coefficient Mean Equation[1]		
μ	0.0593**	0.0604**	0.0600**	0.0588**	0.0585**
	0.0143	**0.0142**	**0.0143**	**0.0140**	**0.0141**
		Coefficients Variance Equation			
w	0.0049[a]	0.0058**	0.0049[a]	0.0053**	0.0046[a]
	0.0029	**0.0022**	**0.0029**	**0.0019**	**0.0026**
g	0.0712**	0.0721**	0.0716**	0.0621**	0.0620**
	0.0114	**0.0115**	**0.0114**	**0.0100**	**0.0100**
b	0.9249**	0.9246**	0.9249**	0.9346**	0.9345**
	0.0105	**0.0105**	**0.0105**	**0.0093**	**0.0092**
η_1	0.0530		0.0349		0.0303
	0.0749		**0.0681**		**0.0672**
a_1		0.0955	0.0747	0.6151	0.5953
		0.1530	**0.1504**	**0.5392**	**0.5498**
a_2		-0.0919	-0.0853	0.0361	0.0391
		0.1598	**0.1563**	**0.7249**	**0.7324**
a_3				-0.6232	-0.6165
				0.5069	**0.5137**
a_4				-0.0110	-0.0116
				0.6812	**0.6881**
lnL	-4032.31	-4031.76	-4031.50	-4021.58	-4021.38
SC	8104.70	8111.60	8119.11	8109.95	8117.57

Maximum likelihood estimates of the model:

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_1 I_{t,K}^A + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid + a_3 \mid S_{t-2,K} \mid + a_4 I_{t-2,K}^- \mid S_{t-2,K} \mid$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Table 1.16: Modified GARCH (1,1) Model with Non Persistent Announcement Effects for FFR

	Coefficient Mean Equation[1]		
μ	0.0564**	0.0571**	0.0586**
	0.0139	**0.0139**	**0.0139**
	Coefficients Variance Equation		
w	0.0043	0.0050	0.0050
	0.0278	**0.0275**	**0.0272**
g	0.0690**	0.0694**	0.0632*
	0.0265	**0.0266**	**0.0262**
b	0.9281**	0.9280**	0.9337**
	0.0595	**0.0590**	**0.0592**
η_1	0.4820	0.4794*	0.0458
	0.5244	**0.2350**	**0.1510**
η_2	0.0329		
	0.2518		
a_1		0.0580	0.5752
		0.6787	**0.5919**
a_2		-0.0635	0.0128
		0.6710	**0.6972**
a_3			-0.5766**
			0.0949
a_4			0.0058
			0.1786
lnL	-4028.6	-4028.3	-4023.6
SC	8105.3	8112.8	8119.3

Maximum likelihood estimates of the model:

$$r_t = \mu + F_t \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$F_t = (1 + \eta_1 I_{t,K}^A)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_2 I_{t,K}^A + a_1 |S_{t-1,K}| + a_2 I_{t-1,K}^- |S_{t-1,K}| + a_3 |S_{t-2,K}| + a_4 I_{t-2,K}^- |S_{t-2,K}|$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Table 1.17: Modified GARCH (1,1) Model with Non Persistent Announcement Effects and Persistent Shocks for Unemployment

		Coefficient Mean Equation[1]	
μ	0.0599**	0.0605**	0.0606**
	0.0141	**0.0138**	**0.0138**
		Coefficients Variance Equation	
w	0.0050**	0.0050	0.0050
	0.0018	**0.0257**	**0.0257**
g	0.0717**	0.0693**	0.0694**
	0.0101	**0.0263**	**0.0264**
b	0.9243**	0.9266**	0.9268**
	0.0102	**0.0594**	**0.0591**
η_1	0.5259**	0.5128*	0.2627*
	0.1467	**0.1020**	**0.1112**
a_1		0.0518	0.3011
		0.4802	**0.3902**
a_2		-0.0765	-0.0897
		0.5188	**0.4201**
a_3			-0.2446*
			0.1056
a_4			0.0230
			0.1386
lnL	-4018.90	-4017.90	-4017.30
SC	8077.90	8091.90	8106.60

Maximum likelihood estimates of the model:

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b(\sigma_{t-1}^2 - \eta_1 I_{t-1,K}^A) + \eta_1 I_{t,K}^A + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid + a_3 \mid S_{t-2,K} \mid + a_4 I_{t-2,K}^- \mid S_{t-2,K} \mid$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Table 1.18: Filtered GARCH (1,1) Model with Non Persistent Announcement Effects for Unemployment

	Coefficient Mean Equation[1]		
μ	0.0583**	0.0599**	0.0600**
	0.0150	**0.0138**	**0.0138**
	Coefficients Variance Equation		
w	0.0040[a]	0.0038	0.0046
	0.0023	**0.0256**	**0.0254**
g	0.0717**	0.0684**	0.0696**
	0.0096	**0.0266**	**0.0265**
b	0.9258**	0.9292**	0.9279**
	0.0095	**0.0594**	**0.0596**
η_1	0.7207**	0.6773*	0.3889
	0.2166	**0.3398**	**0.2993**
η_2	0.0330		
	0.0380		
a_1		0.1026	0.2462
		0.3497	**0.3528**
a_2		-0.0999	-0.0720
		0.3465	**0.3256**
a_3			-0.1862*
			0.0808
a_4			0.0053
			0.1379
lnL	-4020	-4017.8	-4015.8
SC	8088.2	8091.8	8103.7

Maximum likelihood estimates of the model:

$$r_t = \mu + F_t \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$F_t = (1 + \eta_1 I_{t,K}^A)$$

$$\sigma_t^2 = w + g\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \eta_2 I_{t,K}^A + a_1 \mid S_{t-1,K} \mid + a_2 I_{t-1,K}^- \mid S_{t-1,K} \mid + a_3 \mid S_{t-2,K} \mid + a_4 I_{t-2,K}^- \mid S_{t-2,K} \mid$$

$$where,\ I_{t,K}^A = 1(\text{announcement of type k at day t})$$

$$I_{t,K}^- = 1(S_{t,K} < 0)$$

$$S_{t,K} = \text{shock in variable K at time t}$$

Note[1]: Standard errors are highlighted
(**) Significant at 1%
(*) Significant at 5%
(a) Significant at 10%

Chapter 2

The Spline GARCH Model for Low Frequency Volatility and its Global Macroeconomic Causes

2.1 Introduction

After more than 25 years of research on volatility, the central unsolved problem is the relation between the state of the economy and aggregate financial volatility. The number of models that have been developed to predict volatility based on time series information is astronomical, but the models that incorporate economic variables are hard to find. Using various methodologies, links are found but they are generally much weaker than seems reasonable. For example, it is widely recognized that volatility is higher during recessions and following announcements but these effects turn out to be a small part of measured volatility.

Officer (1973) tried to explain the high volatility during the 30's based on leverage and the volatility of industrial production. Schwert (1989) sought linkages between financial volatility and macro volatility but concluded that "The puzzle highlighted by the results in this paper is that stock volatility is not more closely related to other measures of economic volatility."

An alternative approach examines the effects of news or announcements on returns.

With simple or elaborate regression models, contemporaneous news events are included in return regressions. Roll (1988), and Cutler, Poterba, and Summers (1990) for example developed such models which are found to explain only a fraction of volatility ex post, and more recent versions such as Andersen and Bollerslev (1998b), Fleming and Remolona (1999), Balduzzi, Elton, and Green (2001), or Andersen, Bollerslev, Diebold, and Vega (2005) use intraday data but with more or less similar results.

This paper will introduce a simple model of the relation between macroeconomics and volatility and then apply this to the problem of explaining the financial volatility of 50 markets over time. Along the way a new volatility model, the SPLINE GARCH, will be introduced to allow the high frequency financial data to be linked with the low frequency macro data. As a result it will be possible to forecast the effect of potential macroeconomic events on equity volatility and to forecast the volatility that could be expected in a new market. Moreover, the assumption that volatility is mean reverting to a constant level, which underlies almost all GARCH and SV models estimated over the last 25 years, will be relaxed by the Spline-GARCH model.

This paper is organized as follows. In Section 2.2, we describe a model of financial volatility in a macroeconomic environment. In Section 2.3, we introduce the Spline-GARCH model for low frequency volatility. In Section 2.4, we show estimation results for the Spline-GARCH model using time series of returns in a global context. Section 2.5 presents a description of the country specific data followed by a discussion on the definition and construction of the variables involved in the cross-sectional analysis. In this section, we motivate the econometric approach for the cross-sectional analysis and discuss the estimation results of the determinants of long run volatilities. In Section 2.6, we analyze the effects of country heterogeneity in our results. Section 2.7 presents a further robustness analysis with estimation of alternative models using other proxies for long term volatilities. Section 2.8 provides concluding remarks.

2.2 A Model of Financial Volatility in a Macroeconomic Environment

The now highly familiar log linearization of Campbell (1991) and Campbell and Shiller (1988) delivers an easy expression for the surprise in the return to a financial asset. Let r_t be the log return and d_t be the log dividend paid during period t. Then

$$r_t - E_{t-1}(r_t) = \sum_{j=0}^{\infty} \rho^j \left(E_t - E_{t-1}\right)\left(\Delta d_{t+j}\right) - \sum_{j=1}^{\infty} \rho^j \left(E_t - E_{t-1}\right)\left(r_{t+j}\right), \qquad (2.1)$$

which can be written as

$$r_t - E_{t-1}(r_t) = \eta_t^d - \eta_t^r. \qquad (2.2)$$

Unexpected returns can be described as innovations to future cash flows or expected returns. Shocks to dividends have a positive effect on returns while shocks to interest rates or risk premiums have a negative effect. Different news events may have very different impacts on returns depending on whether they have only a short horizon effect or a long horizon effect. As macroeconomic events in the future will influence dividends and profitability of required returns, the relevant macroeconomic variables are the innovations to predictions of the future. The variance of these innovations will be changing over time and can be forecast using current information.

In order to explain the size effects of these shocks, much research has decomposed unexpected returns into its news components. Equation (2.2) can be written as

$$r_t - E_{t-1}(r_t) = \sum_{i=1}^{K} \beta_i e_{t,i}, \qquad (2.3)$$

where there are K news sources. The magnitude of the news event is indicated by e which could be the difference between prior expected values and the announced value. It is clear that announcements cannot be the only source of news since the gradual accumulation of evidence prior to the actual announcement must also affect prices. This model is only useable if all news is observable. If it is not, then Equation (2.3) can be written with one innovation that represents all the remaining news. When no news announcements are identified this remains the only shock.

The innovation to stock returns will have a variance that changes over time. Two effects can be identified. This variance can be a result of constant news intensity with an impact on returns that varies over time. It is natural to think of this impact multiplier as dependent on the macroeconomic environment, which is characterized by a vector of state variables $\overrightarrow{z}_t$. For example, news about a firm may be more influential in a recession than in a fast growth period. Thus, the innovation to returns can be written as:

$$r_t - E_{t-1}(r_t) = \sqrt{\tau_1\left(\overrightarrow{z}_t\right)} u_t. \tag{2.4}$$

In addition, the magnitude and the intensity of the news may be varying in response to the macroeconomy and other unobserved variables. Then

$$u_t = \sqrt{\tau_2\left(\overrightarrow{z}_t\right) g_t} \varepsilon_t, \tag{2.5}$$

where g_t is a non-negative time series such as a GARCH with unconditional mean of one. In this expression, ε has constant variance of one. Hence,

$$r_t - E_{t-1}(r_t) = \sqrt{\tau\left(\overrightarrow{z}_t\right) g_t} \varepsilon_t. \tag{2.6}$$

where $\tau\left(\overrightarrow{z}_t\right) = \tau_1\left(\overrightarrow{z}_t\right) \tau_2\left(\overrightarrow{z}_t\right)$. Without more information, these components cannot be separately identified.

In this paper we will estimate (2.6) directly by specifying a relationship for $\tau\left(\overrightarrow{z}_t\right)$, the low frequency variance component. A second approach is to calculate the realized variance over a time period and then model the relation between this value and the macro variables. The realized variance is given by its expected value plus a mean zero error term with unspecified properties. This gives:

$$\widehat{\sigma}_T^2 = \sum_{t=1}^{T} \left(r_t - E_{t-1}(r_t)\right)^2 = \sum_{t=1}^{T} \tau\left(\overrightarrow{z}_t\right) + w_t \tag{2.7}$$

It is clear that there is an error term in (2.7) that will make estimation of $\tau\left(\overrightarrow{z}_t\right)$

imprecise but still unbiased.

In practice, direct estimation of (2.6) is difficult as the macro variables are not defined on the same high frequency basis as the returns. Recognizing that the macroeconomy is slowly evolving, we use a partially non-parametric estimator to model the low frequency component of volatility. This has the great advantage that it can be used for any series without requiring specification of the economic structure. Then the estimated low frequency volatilities can be projected onto the macroeconomic variables:

$$\tau^{1/2} = \sum_k \beta_k z_{k,t} + \mu_t, \tag{2.8}$$

and this model can be entertained for forecasts or policy analysis. This Spline-GARCH model is introduced in the next section.

2.3 A New Time Series Model for High and Low Frequency Volatility

In this section, we introduce the Spline-GARCH model that extends the GARCH(1,1) model introduced by Bollerslev (1986) offering a more flexible specification of low frequency volatility based on a semi-parametric framework. To motivate our model, consider a specification for unexpected returns that follows the familiar GARCH(1,1) model:

$$r_t - E_{t-1}(r_t) = \sqrt{h_t}\varepsilon_t, \tag{2.9}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{2.10}$$

where ε_t is the innovation term assumed to be distributed with mean 0 and variance 1, the expectation E_{t-1} is conditional on an information set Φ_{t-1} including historical past returns up to time $t-1$, and h_t characterizes the corresponding conditional variance. Now, let us concentrate on the long run properties of this model. For example, we can rewrite Equation (2.10) in terms of the unconditional variance as follows:

$$h_t = \sigma^2 + \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(h_{t-1} - \sigma^2) \tag{2.11}$$

where $\sigma^2 = \omega(1-\alpha-\beta)^{-1}$ is the unconditional variance. When $\alpha+\beta < 1$, the conditional variance reverts to its mean value σ^2 at a geometric rate of $\alpha + \beta$. This structure allows mean reversion at a reasonable rate only if $\alpha+\beta$ is very close to unity. For a long horizon T, the T days ahead volatility forecast will be the same constant σ no matter if the forecast is made at day t or at day $t - k$, $k > 0$. Therefore, despite the empirical success of this model in describing the dynamics of conditional volatility in financial markets (particularly in the short run), its ability to account for more permanent and/or slow moving patterns of volatility is limited.[1] This feature does not seem to be consistent with the time series behavior of realized (and implied) volatilities of stock market returns where volatility can be abnormally high or low for a decade. Consequently, we need a model flexible enough to generate an expected volatility that captures the low frequency patterns observed in the data. Allowing for "slow" time variation in σ seems to be the natural extension. However, this change induces a number of theoretical and practical questions. What are the statistical and economic properties of the new term? How can we identify it from the other elements describing the dynamics of volatility? What is the appropriate functional form?

The component GARCH model introduced by Engle and Lee (1999) provides a parametric approach to answer these questions. Their model involves a decomposition of the volatility process into two separate components. One describes the short run dynamics of conditional volatility associated with transitory effects of volatility innovations. The other characterizes slower variations in the volatility process associated with more permanent effects. An additive decomposition is motivated by replacing σ^2 in Equation (2.11) with a stochastic component describing the long memory features of the volatility process. This long memory component determines the unconditional volatility and might be interpreted as a trend around which the conditional volatility fluctuates. For identification, this component is assumed to have a much slower mean-reverting rate

[1] See Andersen and Bollerslev (1998a) for details on the empirical success of the GARCH(1,1) model in fitting and forecasting financial volatilities.

than the short run component.[2] In this regard, the component GARCH model relaxes parameter restrictions for the unconditional volatility and the speed of mean reversion in the standard GARCH(1,1) model; however, the slow moving trend is mean reverting to a fixed value and the conclusion that the volatility process reverts eventually to a constant level remains unchanged.[3]

In this paper, we go beyond and relax the assumption that the slow moving trend in the volatility process, named here low frequency volatility, reverts to a constant level. In addition, we take a non-parametric approach that allows the data to provide the functional form of this low frequency volatility. Moreover, instead of using an additive decomposition, we separate the high and low frequency components of the volatility process using a multiplicative decomposition motivated by the economic model of volatility presented in Section 2.2. Specifically, we modify the standard GARCH(1,1) model by introducing a trend in the volatility process of returns. This trend describes the low frequency component of the volatility process associated with slowly varying deterministic conditions in the economy, or random variables that are highly persistent and move slowly. We approximate this unobserved trend non-parametrically using an exponential quadratic spline, which generates a smooth curve describing this low frequency volatility component based exclusively on data evidence. The exponential functional form guarantees that the low frequency component of volatility is always positive. The quadratic form is motivated by the requirement to obtain smoothness through continuity of at least one derivative at a minimum cost in terms of degrees of freedom. Our Spline-GARCH model for stock returns implements Equation (2.6) as follows:

$$r_t - E_{t-1}(r_t) = \sqrt{\tau_t g_t}\varepsilon_t, \;\; where \;\;\; \varepsilon_t|\Phi_{t-1} \sim N(0,1) \tag{2.12}$$

$$g_t = (1-\alpha-\beta) + \alpha\left(\frac{(r_{t-1} - E_{t-2}(r_{t-1}))}{\tau_{t-1}}\right) + \beta g_{t-1} \tag{2.13}$$

[2]Maheu (2004) finds that moderate to large datasets are needed to accurately identify the two components.

[3]Another interesting approach that allows for stochastic time variation in the parameters of a GARCH specification is the Markov Regime Switching GARCH approach introduced by Cai (1994) and Hamilton and Susmel (1994) for the ARCH case. This approach leads to time varying unconditional volatilities that change according to the volatility regime. However, the estimation process might become more complicated and data demanding.

$$\tau_t = c \exp\left(w_0 t + \sum_{i=1}^{k} w_i \left((t - t_{i-1})_+ \right)^2 + z_t \gamma \right) \tag{2.14}$$

where Φ_t denotes an extended information set including the history of returns up to time t and weakly exogenous or deterministic variables z_t,

$$(t - t_{i-1})_+ = \begin{cases} (t - t_{i-1}) & if \ \ t > t_i \\ 0 & Otherwise \end{cases}$$

and $\{t_0 = 0, t_1, t_2, ..., t_k = T\}$denotes a partition of the time horizon T in k equally-spaced intervals. $\Theta = \{\alpha, \beta, c, w_0, w_1, ..., w_k\}$includes the parameters estimated in the model. Since k, the number of knots in the spline model, is unspecified, we can use an information criterion to determine an "optimal" choice for this number, which in fact governs the cyclical pattern in the low frequency trend of volatility. Large values of k imply more frequent cycles. The "sharpness" of each cycle is governed by the coefficient, $\{w_i\}$. Notice that the normalization of the constant term in the GARCH equation implies that the unconditional volatility depends exclusively on the coefficients of the exponential spline. In fact, a special feature of this model is that the unconditional volatility coincides with the low frequency volatility, i.e.,

$$E\left[(r_t - E_{t-1}(r_t))^2 \right] = \tau_t E\left(g_t \right) = \tau_t. \tag{2.15}$$

Our semi-parametric approach has the potential to capture both short and long term dynamic behavior of market volatility. Equation (2.13) characterizes the short term dynamics keeping the nice properties of GARCH models in fitting and forecasting volatility processes at high and medium frequencies. Equation (2.14) describes non-parametrically low frequency volatility changes, which can be associated with volatility dynamics at longer horizons, using a smooth differentiable curve including $k-1$ changes in curvature that (naturally) capture cyclical patterns.

Figure 2.1 and Table 2.1 illustrate the model with Gaussian innovations for the US, based on S&P500 data during the period 1955-2003. Table 2.1 reports the estimates for the Spline-GARCH specification with 7 knots, which is selected by the BIC among specifications with the number knots varying between 1 and 15. The coefficients of the GARCH component are statistically significant and standard in terms of magnitude. This will be discussed with more detail in the next section. The knot coefficients are also statistically significant for the six interior knots suggesting changes in the curvature of the time trend in February 1962, April 1969, April 1976, May 1983, May 1990 and June 1997. Figure 2.1 shows how this Spline-GARCH model fits high and low frequency patterns of volatility during the sample period. The volatility trend suggested by the data reveals a cyclical behavior that may be associated with the business cycle. In addition, the graph shows that the assumption that volatility reverts towards a constant is not appealing to describe the volatility behavior over long horizons. More examples and further discussion on the specifics of the estimation of the Spline-GARCH model will be presented in the following section.

2.4 Time Series Estimation of Low Frequency Volatilities Using the Spline-GARCH Model

2.4.1 Returns Data

The first part of our empirical analysis considers stock market returns. Using the index associated with the main stock exchange, we collect daily data of several countries on stock market returns from Datastream and Global Financial Data.[4] Our sample includes all developed countries and most emerging markets that experienced significant liberalization during the 1980's and 1990's, as described in Bekaert and Harvey (2000). Table 2.2 lists these countries, the names of the exchanges and market indices, their IFC country classification as developed or emerging markets, as well as general exchange features, such as average values for the number of listed companies and market capitalization.

The sample windows vary for each exchange since we tried to maximize the number of daily observations used in the estimation. In other words, data availability, mainly

[4] We only included countries for which daily stock market data and quarterly macroeconomic data are available.

associated with the age of each particular exchange, determined the sample periods. Columns 2 and 3 of Table 2.3 show the starting date and the number of observations used in the time series estimation for each country. In all the cases, the ending point is on June 30th, 2003.

2.4.2 Estimation of Low Frequency Volatilities Based on Global Equity Markets

For each country, we use its daily returns time series and estimate the Spline-GARCH model introduced in Section 2.3 assuming Gaussian innovations. We use the BIC to select the optimal number of knots associated with the spline component. Figure 2.2 presents some examples. These graphs illustrate the two volatility components associated with the short run conditional volatility and the slow moving trend that characterizes the low frequency volatility. In addition, annual realized volatilities are included to illustrate how realized volatility, as a consistent estimator of unconditional volatility, lies close to the estimated trend.

Table 2.3 summarizes the estimation results for all the countries included in our analysis. In column 1, the optimal number of knots in the Spline-GARCH model is presented. Variation in this number is associated with both country specific volatility patterns and the length of the sample period. The number of observations per knot, presented in column 4, is used as an indicator of the cyclical pattern observed in the low frequency volatility component for each country. Table 2.4 presents a more detailed description of the distributional features of this variable. The results indicate that the average number of observations per knot in developed markets is almost three times that number in emerging markets (including transition economies). Therefore, emerging markets show on average almost three times more cycles than developed economies.

To explore possible changes in the dependence structure of the Spline-GARCH model, we estimate a standard GARCH(1,1) model and compare the coefficients associated with temporal dependence in both models. The ARCH effects (alphas) in the Spline-GARCH and GARCH (1,1) models are presented in columns 5 and 6 of Table

2.3, respectively. The results suggest little variation between the two models in terms of these effects. In fact, the mean values are 0.17 and 0.16 for the Spline-GARCH and GARCH(1,1) models, respectively. Moreover, the first panel of Figure 2.3 shows that the number of knots does not seem to have an effect on this conclusion. Regarding the GARCH effects (betas), columns 7 and 8 of Table 2.3 present the estimated coefficients over the countries in our sample for the two models. The mean values suggest slightly less persistence in the Spline-GARCH model (0.73 compared with 0.80 of the GARCH(1,1)). The second panel of Figure 2.3 shows that this pattern is roughly independent of the number of knots. Overall, these results suggest that the Spline-GARCH model observes a slightly shorter memory ARMA structure in the squared innovations, which is a feature shared by other GARCH family models that relax the parameter restrictions for the unconditional variance, such as the component GARCH model described above.

Now, to show the improved performance of the Spline-GARCH model over the simple GARCH(1,1), we use the BIC and the likelihood ratio test. The two criteria suggest that the Spline-GARCH model is clearly preferred over the GARCH(1,1) model for all the countries where the optimal number of knots is larger than one. Moreover, even for the one-knot cases, where we would expect more difficulties in rejecting the assumption of mean reversion in volatility to a fixed value, we reject the GARCH(1,1) specification for all the cases but France. The BIC and LR statistics are shown in columns 11-13 of Table 2.3.

2.5 Economic Determinants of Low Frequency Volatilities

A second goal of this study is providing an explanation on what are the economic determinants of low frequency volatility. We approach this question by providing both cross-sectional and time series evidence along the countries included in our sample. We focus on macroeconomic fundamental variables and variables related to the market structure of each exchange. Economic theory and previous empirical evidence motivate the selection of such variables.

2.5.1 Data

The sources for our macroeconomic variables are Global Insight/WRDS, Global Financial Data, and the Penn World Tables. These variables include: GDP, inflation indices (Consumer Price Indices are used to measure inflation), exchange rates, and short term interest rates. The set of countries with available macroeconomic data is smaller than the set with available financial time series data. Thus, we are left with a reduced sample of 48 countries.

We also collect information for different years on the size and diversification of each market associated with the counties listed in Table 2.2, such as market capitalization and the number of listed companies. The former is obtained from Global Financial Data and the official web pages of the exchanges. The sources for the latter are: the World Federation of Exchanges, the Ibero-American Federation of Exchanges (FIAB), and official web pages of the exchanges.

2.5.2 Variables Discussion

We start with a description of the dependent variable. In this regard, given that volatilities are not directly observed, we need to define a measure of low frequency volatilities to construct our dependent variable.[5] For each country, we use the Spline-GARCH model introduced in Section 2.3 to fit its daily time series of market returns considering the sample periods described in Table 2.3. As mentioned in Section 2.4, we use the BIC to select the optimal number of knots associated with the spline component. In each case, we obtain the low frequency volatility component described in Equation

[5]Andersen, Bollerslev, Diebold, and Labys (2003) argue that under suitable conditions, realized volatilities can be thought as the observed realizations of volatility. We present estimation results for this alternative measure of long term volatilities in Section 2.7).

(2.14). Thus, a measure of the low frequency volatility can be defined as the average of the daily low frequency volatilities over a long term horizon, namely one year.

We appeal to economic theory and previous empirical evidence to select the potential determinants of low frequency volatilities. Levels as well as fluctuations of fundamental variables are the natural candidates. Previous research has pointed out the relation between volatilities and the business cycle; for example, Schwert (1989) and Hamilton and Lin (1996) find economic recessions as the most important factor influencing the US stock return volatility. We consider the growth rate of real GDP as a variable accounting for changes in real economic activity.

Volatility and uncertainty about fundamentals are also potential factors affecting market volatility. For example, Gennotte and Marsh (1993) derive returns volatility and risk premia based on stochastic volatility models of fundamentals; David and Veronesi (2004) identify inflation and earnings uncertainty as sources of stock market volatility and persistence. We consider measures of macroeconomic volatility to account for this uncertainty. Specifically, we construct a proxy for inflation volatility based on our CPI quarterly time series. We obtain the absolute values of the residuals from an AR(1) model, and then we compute their yearly average.

$$\begin{aligned} \Delta \log(y_t) &= c + u_t, \;\; u_t = \rho u_{t-1} + e_t \\ \sigma^2_{y,t} &= \frac{1}{4}\sum_{j=t-2}^{t+1} |e_j| \,. \end{aligned} \tag{2.16}$$

Following the same setup, we construct proxies for country economic uncertainty linked to fundamentals. In particular, we estimate volatilities of real GDP, interest rates (without logs) and exchange rates based on the residuals of fitted autoregressive models. Exchange rates are measured as US$ per unit, and interest rates are based on short term government bonds.

Some country-based empirical studies have suggested that market development is an important element in explaining differences in market volatilities across countries. For example, De Santis and Imrohoroglu (1997) find higher conditional volatilities, as well as larger probabilities of extreme events, in emerging markets relative to developed markets. Moreover; Bekaert and Harvey (1997) find that market liberalizations increase the correlation between the local market and the world market, but they do not find significant effects on market volatilities. In order to capture the effect of market development in our analysis we construct two dummy variables for emerging markets and transition economies. The emerging market classification comes from the IFC; we define transition economies as the former socialist economies, such as the Central European and Baltic countries in our sample.

To explain further variations in the cross-sectional stock market volatilities it is important to account for other factors associated with market liberalizations, for example macroeconomic reforms relevant for both increasing efficiency in risk sharing and increasing market liquidity. In emerging economies many macroeconomic reforms are intended to improve institutional control of inflation and to open the economies to international trade. Bekaert, Harvey, and Lundblad (2006) find that a larger inflation rate, as well as a larger external sector, is positively related to consumption and GDP growth volatility. Since we are interested in variables explaining volatility of fundamentals, we account for the effect of inflation rates, which are measured as the growth rate of the CPI.

Cross-sectional variation in market volatilities may also be related to the size of the markets and/or the size of the economies. We would expect that larger markets have advantages in terms of offering broader diversification opportunities and probably lower trading costs. We consider two different variables to account for these size effects. The first one is the log of the annual market capitalization of each exchange. The second one is the log of nominal GDP in US dollars. Having these variables in logs allows for testing the effect of the stock market size as a proportion of the overall value of the economy (ratio of market capitalization to GDP). This ratio can be used as a measure of how developed is the stock market and as a proxy for the degree of integration in terms of foreign investment.[6] All of these variables are converted to US dollars using annual exchange rates. Finally, we consider the number of listed companies on each

[6]Bekaert and Harvey (1997) consider the ratio market capitalization to GDP and the size of the trade sector as measures of the country's degree of financial and economic integration that affect the intertemporal relation between domestic market volatilities and world factors.

exchange as a variable proxying the market size and the span of market diversification opportunities. Table 2.5 summarizes the variables of our analysis.

2.5.3 Cross-Sectional Analysis of Low Frequency Volatilities

In this subsection, we describe our cross-sectional analysis of expected long term market volatilities. Before describing the general setup, it is important to point out some data issues and conventions. First, we relate long term periods with annual intervals.[7] Thus, for each of the variables introduced above, we construct annual averages. Next, for each country, we have to match the annual low frequency volatility time series with several macroeconomic time series. This process leads to country-specific sample windows, and therefore to an unbalanced panel of countries. Moreover, the number of countries increases with time, since recent data is available for most of the countries, and also because many markets started operations during the 1990's (e.g. transition economies). Therefore, in order to keep a relatively large number of countries in the cross-sectional dimension, we consider a panel that covers 1990-2003.[8] This data structure can be summarized in a system of linear equations projecting, for each year, the low frequency volatility estimated from the Spline-GARCH model on the explanatory variables described in Table 2.5. Following the discussion in Section 2.5.2, the annualized low frequency volatility for year t and country i is the following sample average:

$$Lvol_{i,t} = \frac{1}{M_{i,t}} \sum_{d=1}^{M_{i,t}} (\tau_{i,t,d})^{1/2} \, , \tag{2.17}$$

where $M_{i,t}$ represents the number of trading days in country i at year t, and $\tau_{i,t,d}$ is the daily low frequency volatility in Equation (2.14) observed in country i at trading day d

[7] This convention has no effect in our framework. We could have taken a different horizon and followed the same process.

[8] Note that, for some countries, variables constructed from dynamic models, such as low frequency volatilities and macroeconomic volatilities, might have involved longer sample periods in the estimation process (see Table 2.3 for details).

of year t.[9] Thus, the system of linear equations can be specified as follows:

$$Lvol_{i,t} = \underline{z}_{i,t}\beta_t + \mu_{i,t}, \;\; t = 1, 2, ..., T, \quad i = 1, 2, ..., N_t, \tag{2.18}$$

where $\underline{z}_{i,t}$ is a vector of explanatory variables associated with country i and year t, and $\mu_{i,t}$ is the error term assumed to be contemporaneously uncorrelated with $\underline{z}_{i,t}$.[10]

The next task is to find an econometric approach that efficiently accounts for the features observed in the structure of our data. We start by looking at the correlation structure of the data across time. In particular, we select a sub-panel from 1997-2003 to have an almost balanced structure. We look at the correlation across years of low frequency volatilities, regressors, and residuals coming from individual regressions for each year. Tables 2.6 and 2.7 present such correlations for low frequency volatilities and residuals, respectively. These tables show high correlation of the residuals, suggesting that unobservable factors affecting expected volatilities are likely to be serially correlated across time. In addition, even higher correlation is observed on the dependent variable suggesting little variation across time. Similarly, it is observed that many of the explanatory variables are also highly correlated across time, showing again little time variability. Some exceptions that show lower correlation across time are the real GDP growth rate and the exchange rate volatility.

The observation of these features motivates our econometric approach. As usual in cross sectional studies, we assume that the errors are uncorrelated in the cross-section.[11] However there is clear autocorrelation. A method that efficiently handles autocorrelation in the unobserved errors is appealing. The Seemingly Unrelated Regressions (SUR) model developed by Zellner (1962) provides a framework that imposes no assumptions on the correlation structure of the errors and easily incorporates restrictions on the coefficients. The presence of large autocorrelations across the disturbances, as suggested in Table 2.7, implies important gains in efficiency from using FGLS in a SUR system as

[9]Note that in this section the sub-index t refers to years, not to days as in Sections 2.3 and 2.4.

[10]The assumption $E\left(\underline{z}_{i,t}\mu_{i,t}\right) = 0$, $t = 1, 2, ..., T$, $i = 1, 2, ..., N_t$ does not rule out non contemporaneous correlation; so, the error term at time t may be correlated with the regressors at time $t+1$. Therefore, in this setup financial volatility can cause macroeconomic volatility, as is suggested in Schwert (1989). However when SUR estimation is used, the assumption of exogeneity will be maintained.

[11]Cross sectional dependence will generally not give inconsistency in our model, but inference and efficiency could be improved if a factor structure is assumed as in Pesaran (2006).

well as improved standard errors. Standard panel data approaches that impose further restrictions could be considered; however, their underlying assumptions and estimation features seem to be less attractive based on the features of our data. For example, the low variation over time observed in many of the explanatory variables indicates that fixed effects models can lead to imprecise estimates (see Wooldridge (2002)). On the other hand, even though the standard random effects model allows for some time correlation, the structure of the covariances is restrictive in the sense that it comes exclusively from the variance of the individual effects, which is assumed to be constant across time. This feature does not seem appealing based on the evidence in Table 2.7. Therefore, more general panel data approaches that deal more efficiently with serial correlation would be desirable. We will explore one possibility in the robustness section. Nevertheless, given that the SUR method allows for time fixed effects and flexible autocorrelation structure, we take this approach as our main specification for the cross sectional analysis. We assume that the coefficients, other than the intercept, remain constant over time.

Using this SUR modeling strategy, we start our cross sectional analysis by exploring the relationship between low frequency volatilities and each of the explanatory variables, one at a time. Table 2.8 presents the estimation results of the system of cross sectional regressions on single explanatory variables.[12] From this preliminary analysis, we observe positive relations among low frequency market volatilities and each of the following variables: emerging markets, log nominal GDP, inflation rate, and macroeconomic volatilities (associated with interest rates, exchange rates, GDP, and inflation). In contrast, the following variables show a negative relation with long term market volatility: transition economies, growth rate of GDP and market size variables, such as log market capitalization, and number of listed companies. The results are significant for most variables except for transition economies and log nominal GDP in current US dollars.

Next, we estimate the full system of equations described in (2.18), which includes all the explanatory variables. The corresponding results are presented in the first column of Table 2.9. From this analysis, we observe that emerging markets show larger expected volatility compared to developed markets. The effect is significant and consis-

[12]The constant term is allowed to vary across years.

tent with the empirical evidence about volatility of emerging markets (see Bekaert and Harvey, 1997). It is however much smaller than in the univariate regressions. Transition economies have only slightly larger volatility than developed economies. Market size variables show different results. Whereas log market capitalization has a significant negative effect (at the 10% level), log nominal GDP in current US dollars is positive and significant (at the 5% level). The positive effect dominates, suggesting that larger market sizes are associated with larger expected volatilities. In contrast, the number of listed companies in the exchange has a negative effect on volatility. This suggests that markets with more listed companies may offer more diversification opportunities, reducing the overall expected volatility.

In regard to real economic activity variables, the results show that economic recessions increase low frequency volatilities, and inflation rates also affect them positively. These results indicate that countries experiencing low or negative economic growth observe larger expected volatilities than countries with superior economic growth. Similarly, countries with high inflation rates experience larger expected volatilities than those with more stable prices. Although the effect is not significant for real GDP growth, the effect is larger and highly significant for inflation rates.

In relation to volatility of macroeconomic fundamentals, the results suggest that volatility of inflation, as well as volatility of real GDP, are strong determinants of low frequency market volatility. Both variables are associated with significant positive effects. The coefficient on interest rate volatility is also positive and significant but small in magnitude. The effect of exchange rate volatility is negative, small and quite insignificant. This evidence encourages theoretical work relating volatility of fundamentals to causes of fluctuations in market volatility at long horizons.

We also consider plausible dimension reductions based on the significance of the explanatory variables. We estimate different model specifications based on a reduction process that drops the least significant variable one at a time. In this process, the goodness of fit in each model is given by the concentrated likelihood, and therefore by the determinant of the residual covariance. In addition, to select an optimal reduction, we take an information criterion approach; in particular, we select a BIC type of penalization for increasing the number of parameters. In column 2 of Table 2.9, we present the "best" reduction in which the BIC favors a specification for which volatility of exchange rates (first) and real GDP growth (second) are omitted. Therefore, the reduction process leads to a model with nine explanatory variables.

2.6 Country Heterogeneity

We start this section with a diagnostic analysis estimating the benchmark SUR model excluding from the sample one country at a time. Figures 2.4 and 2.5 show the coefficients associated with each regressor and the t-statistics respectively. Each point in the horizontal axis represents the country that is dropped from the sample following the order presented in Table 2.2. For instance, the first point corresponds to the estimation without Argentina, and the last point corresponds to the estimation without Venezuela. From Figure 2.5, we observe that the significance of some explanatory variables remains strong no matter which country is taken out of the sample. Indeed, this is the case for emerging, number of listings, log nominal GDP, and volatility of real GDP, which also preserve the same sign (see panels 1, 4, 5, and 10, Figures 2.4 and 2.5). In contrast, a surprising result arises with respect to real GDP growth and volatility of inflation. When we remove Argentina from the sample, volatility of inflation is no longer significant and changes sign (see panel 11, Figures 2.4 and 2.5); at the same time, real GDP growth becomes significant with a considerably larger negative sign (see panel 6, Figures 2.4 and 2.5).

Argentina seems to be an influential observation for other variables as well. For instance, volatility of interest rates becomes highly significant when this country is dropped from the sample. Moreover, although other observations such as Czech Republic and Russia seem to be influential for the significance of this variable (see panel 8, Figure 2.5).

In results not reported, the effect of these countries is no longer influential once Argentina is taken out of the sample. Thus, without Argentina, volatility of interest rate is significant at 5% level no matter which other country is omitted. Something similar occurs with inflation; indeed, the apparent influential effects on the significance of inflation of countries such as Lithuania, Peru, and Turkey are drastically diminished once Argentina is out of the sample.[13]

Column 4 of Table 2.9 presents estimation results of the SUR model when Argentina is removed from the sample. As shown in Figures 2.4 and 2.5, the main differences with respect to column 1 include the loss of log market capitalization and volatility of inflation as significant explanatory variables, and the gain of real GDP growth as a significant variable. From these diagnostics we find that the results for six variables, namely emerging, log nominal GDP, number of listings, inflation, volatility of interest rates, and volatility of real GDP growth, are quite robust. Regarding real GDP growth and volatility of inflation, the results presented in the previous section should be taken with caution given the sensitivity of the corresponding estimates to the inclusion of Argentina in the sample.

However, dropping Argentina from the sample might be unsatisfactory not only because this country is an important emerging market in which the relation between macroeconomic environment and financial volatility might be of particular interest (especially during the period surrounding the recent Argentine crisis, 2001-2002), but also because looking at the macroeconomic time series of Argentina, we did not find a conclusive argument to support the deletion of this country.

Therefore, we explore the possibility of giving more structure to the unobserved individual country effects in order to evaluate their possible impacts in our results. Specifically, we estimate an alternative panel data model that accounts for individual country random effects, keeping the time fixed effects, and allows for serial correlation in the remainder error term using a simple first order autoregressive process.[14] In fact, this reflects the effect of unobserved variables that are serially correlated across time. Thus, the error term in Equation (2.18) is modeled as follows:

$$\mu_{i,t} = \lambda_t + \eta_i + v_{i,t}, \tag{2.19}$$

[13]Inflation remains significant at 5% when either Lithuania or Turkey is dropped from the sample without Argentina. For Peru, the variable is significant only at 13%.

[14]References for panel data models with serial correlation include Lillard and Willis (1978), Baltagi and Li (1991), and Chamberlain (1994).

where

$$
\begin{aligned}
\lambda_t &= time \quad fixed \quad effects \\
\eta_i &= iid(0, \sigma_\eta^2) \\
v_{i,t} &= \rho v_{i,t-1} + \varepsilon_{i,t} \\
\varepsilon_{i,t} &\sim iid(0, \sigma_\varepsilon^2) \\
\varepsilon_{i,t} &\perp \eta_i .
\end{aligned}
$$

Estimation results for this model are shown in the last column of Table 2.9. We confirm the robustness of our results with respect to the six variables mentioned above. Moreover, in this case neither real GDP growth nor volatility of inflation is significant. Interestingly, even though all countries were included in the sample, these results look quite similar to those in column 4, corresponding to the SUR model without Argentina. Therefore, modeling random country effects seems to account for the effect of unobservables associated with influential observations.[15]

2.7 Realized Volatility

We continue our robustness analysis by comparing the estimation results of the cross-sectional expected volatility model with alternative measures of long term volatilities. First, we estimate a system of equations using the annual realized volatility instead of the Spline-GARCH low frequency volatility. Following Equation (2.7), the annualized realized volatility can be expressed as:

$$
Rvol_{i,t} = \left(\sum_{d=1}^{M_{i,t}} r_{i,t,d}^2 \right)^{1/2}, \tag{2.20}
$$

where $M_{i,t}$ is the number of trading days observed in country i at year t, and $r_{i,t,d}^2$ denotes the daily square return observed in country i at day d of year t. Thus, we can specify the

[15]Specifications with fixed country effects were also considered; however, as we expected from our earlier discussion about the little time variability observed in most of our explanatory variables, the Hausman (1978) test rejected in general fixed effects specifications in favor of random effects models.

system of linear equations for annual realized volatilities as follows:

$$Rvol_{i,t} = \underline{z}_{i,t}\beta_t + \upsilon_{i,t}, \ \ t = 1, 2, ..., T, \quad i = 1, 2, ..., N_t, \tag{2.21}$$

where the same explanatory variables are included, and the error term $\upsilon_{i,t}$ satisfies the same conditions mentioned in Section 2.5. The estimation results for realized volatilities are presented in column 1 of Table 2.10. We observe the same signs for most of the variables with exception of volatility of inflation. Specifically, volatility of inflation shows a negative and insignificant effect on realized volatilities, contrasting with the low frequency volatility case, in which the effect was positive and highly significant.

Column 2 of Table 2.10 shows estimation results for the "best" reduction based on the same criterion described in the previous section. Specifically, for realized volatilities, the least significant variable is the indicator of transition, followed by volatility of inflation, and inflation rate. In this case, our information criterion suggests that omitting these three variables is optimal. Hence, in contrast with the low frequency volatility from the Spline-GARCH model, the realized volatility shows almost no responsiveness to inflation variables but is significantly negatively affected by the real GDP growth, a variable that is characterized by its low correlation across time with respect to other explanatory variables.

As in the case of low frequency volatilities, we perform a diagnostic analysis by reestimating the SUR model dropping from the sample one country at a time. Figures 2.6 and 2.7 present the estimates and t-statistics respectively. In this case, Argentina also seems to be an influential observation for volatility of inflation and real GDP growth (see panels 6 and 11, Figures 2.6 and 2.7). Nevertheless, volatility of inflation is never significant and real GDP growth is always significant. Figure 2.7 suggests that five variables, namely emerging, log nominal GDP, real GDP growth, volatility of interest rates, and volatility of real GDP growth, are always significant at 5% level no matter which country is deleted from the sample. On the other hand, number of listings is sensitive to the inclusion of the UK, and log market capitalization is sensitive to the inclusion of Chile, India, Poland, and South Africa. The last two columns of Table 2.10 confirm this description. The results from a SUR model without Argentina do not change too much with respect to the results in column 1 (including all countries). However, when random country effects are introduced, number of listings and log market capitalization are no longer significant. Just the five variables named above remain significant. Note that four of them, namely emerging, log nominal GDP, volatility of interest rates, and volatility of real GDP growth, coincide with the "robust" variables in the low frequency volatility case. Nevertheless, the main difference with respect to this case is maintained. Real GDP growth is always relevant for realized volatility but not for low frequency volatility; and inflation is always significant for low frequency volatility but never for realized volatility. Moreover, number of listings is also always significant for low frequency volatility, but it is not for realized volatility in the random effects model.

Furthermore, we observe that among the SUR specifications, the determinant of the residual covariance is smaller for the models with low frequency volatility as dependent variable. This may suggest that low frequency volatility fits better in terms of the concentrated likelihood. In addition, Table 2.11 shows the R-squares for each equation in the SUR system for both low frequency and realized volatility. The results point to the same direction that the model using low frequency volatility shows better fit than that using realized volatility. In summary, as it is illustrated in Figure 2.2, discrepancies in the results between the spline and realized volatility might be due to the fact that the latter is a noisier measure of low frequency volatility.

We also compare the results in levels from the previous sections with the results from a model in logs. Specifically, we estimate two systems of equations, in which the log of both the low frequency volatility from the Spline-GARCH model and the annual realized volatility are the dependent variables for each year, respectively. Column 3 in Tables 2.9 and 2.10 presents estimation results for these cases. Note that for most of the variables the signs do not change with respect to the models in levels. The only exception is the real GDP growth rate for low frequency volatility, whose coefficient turns positive, albeit it is the least significant variable. In fact, our reduction process suggests that omitting only this variable leads to the "best" specification.

2.8 Concluding Remarks

We introduce a new model to characterize the long term pattern of market volatility in terms of its low frequency component. Keeping the attractiveness of a GARCH framework, we model the slow moving trend of volatility taking a non-parametric approach that leads to a smooth curve that describes the low frequency volatility. A special feature of this model is that the unconditional volatility coincides with the low frequency volatility.

After proposing a method to estimate the low frequency volatility component, a deeper question arises: what influences this low frequency volatility? We answer this question empirically. We perform a cross-sectional analysis of low frequency volatility to explore its macroeconomic determinants by considering evidence from international markets.

Our empirical evidence suggests that long term volatility of macroeconomic fundamentals, such as GDP and interest rates, are primary causes of low frequency market volatility. These variables show a strong positive effect in the cross sectional analysis. In addition, volatility of inflation also presents a positive effect, but in this case, the result is sensitive to the inclusion of one country, Argentina. Countries with high inflation and countries with low real growth rate have higher volatility although the importance of real growth also depends on Argentina.

In line with other empirical studies, we find that market development is also a significant determinant. Emerging markets show higher levels of low frequency market volatilities. An explanation may be that emerging markets are typically associated with larger inflation rates.

Market size variables are also important. The number of listed companies, as an indicator of the span of local diversification opportunities, reduces low frequency market volatility. In addition, the size of the economies measured by the log of GDP in US dollars increases low frequency volatilities; bigger countries have more volatility.

After performing some diagnostic analyses, we conclude that the results are robust for all variables except volatility of inflation and real GDP growth for which statistical significance is sensitive to influential observations.

We compare our results with the results of annual realized volatility as an alternative measure of low frequency volatility. We find changes in significance due to the fact that realized volatility is a noisier measure of low frequency volatility than the spline volatility. Inflation variables are no longer good predictors of annual realized volatilities.

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The text of this chapter is adapted from *The Spline GARCH Model for Low Frequency Volatility and its Global Macroeconomic Causes*, Robert F. Engle and Jose Gonzalo Rangel, 2006, Unpublished Manuscript.

2.9 Figures

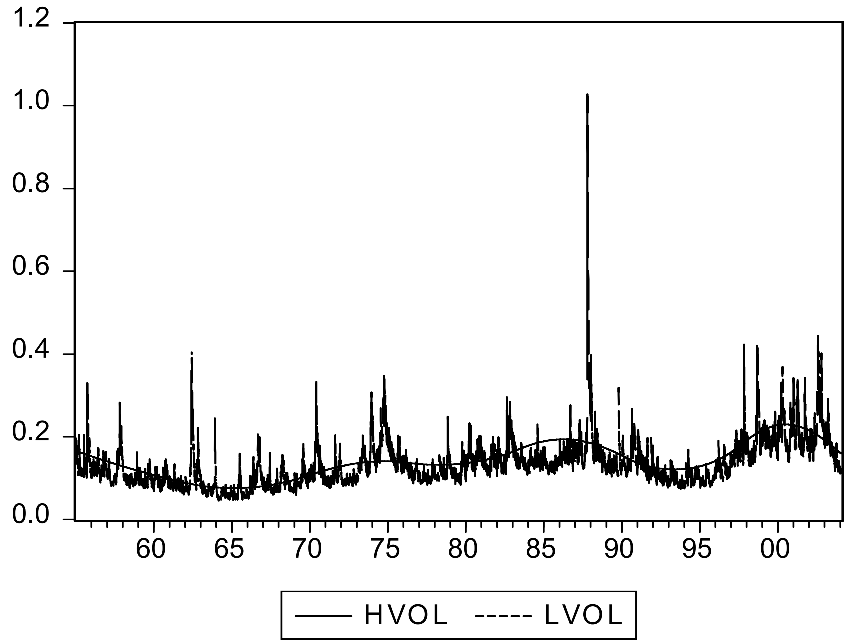

Figure 2.1: High and Low Frequency Volatility SP500

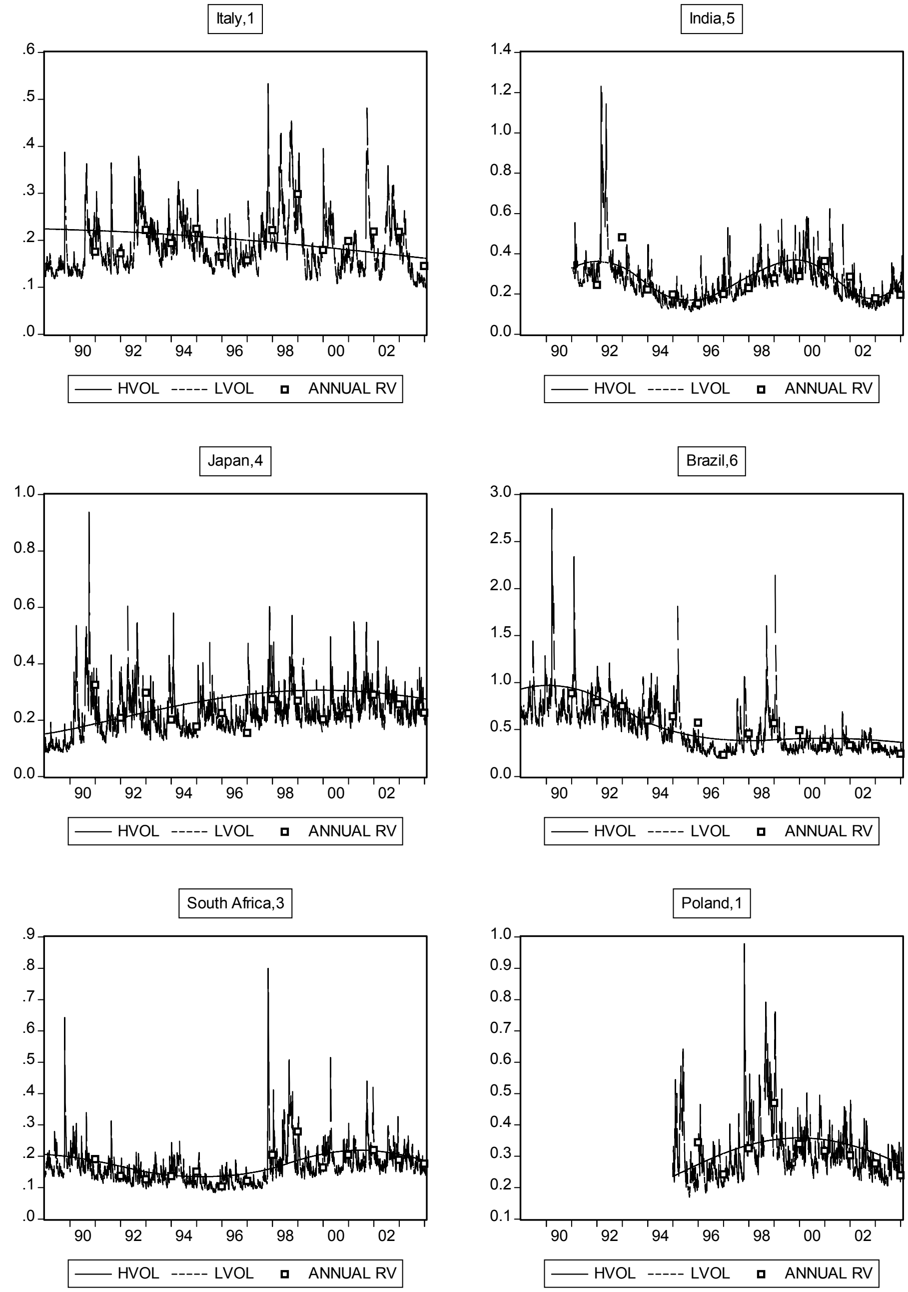

Figure 2.2: High Frequency, Low Frequency, and Realized Volatilities of Selected Countries

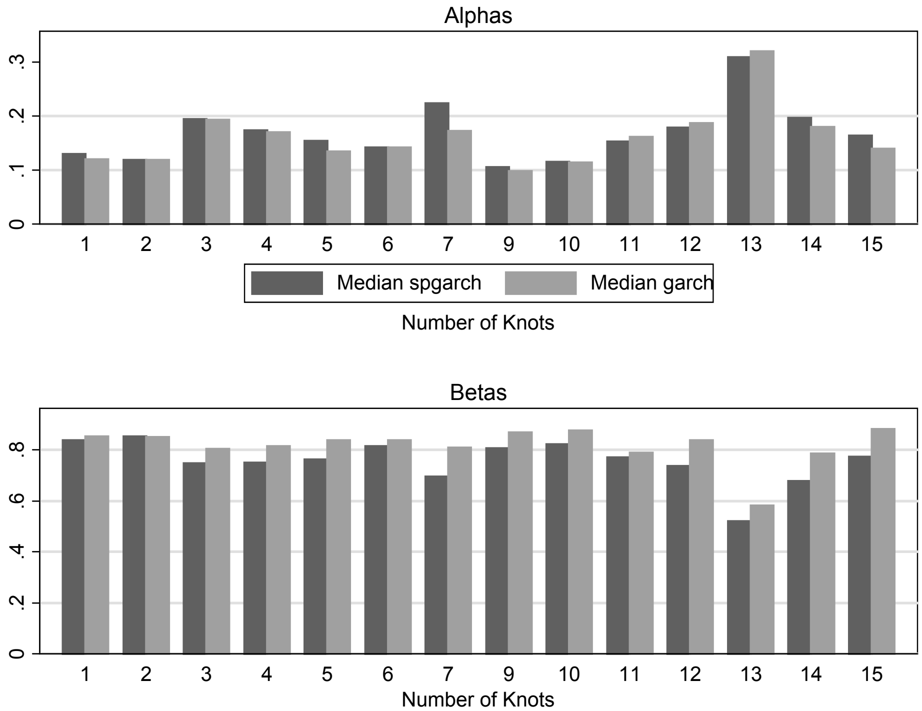

Figure 2.3: Dependence Structure in the Spline-GARCH and GARCH(1,1) Models

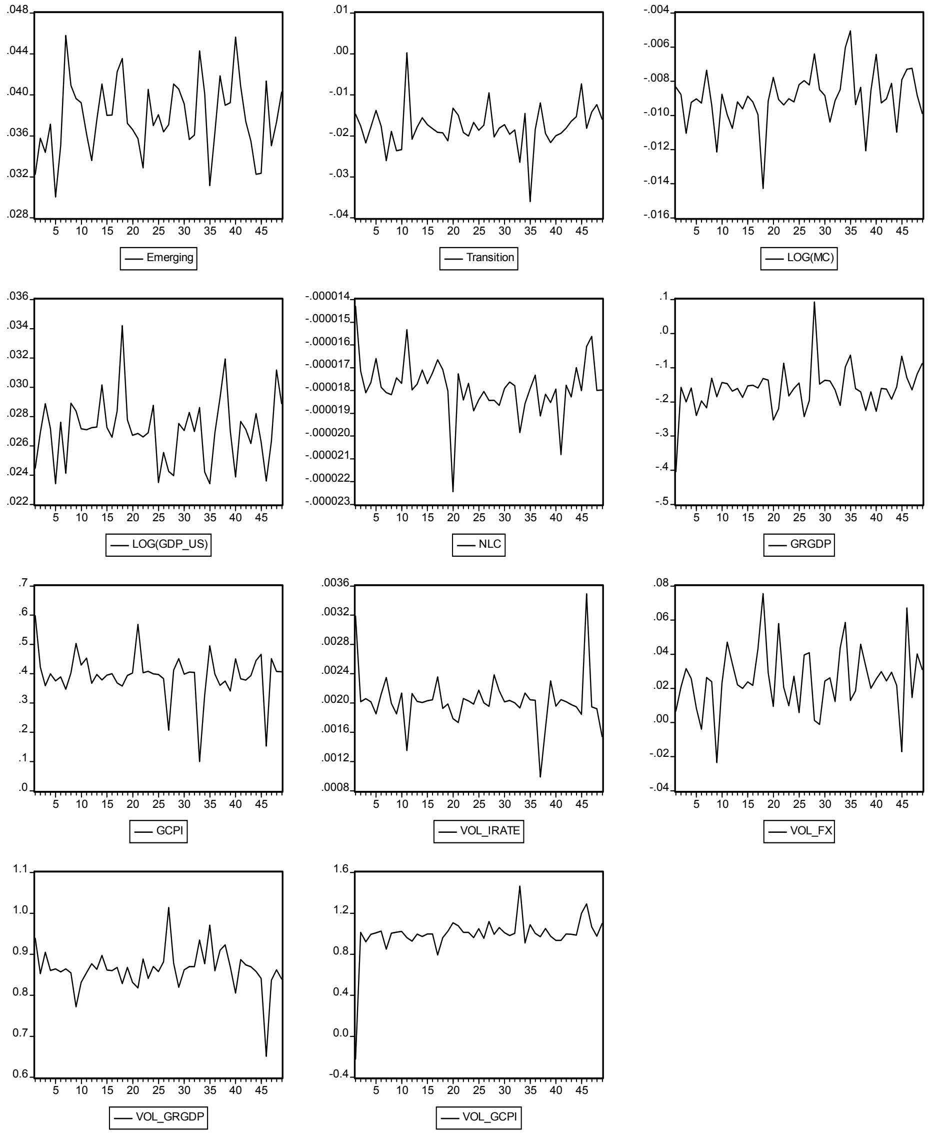

Figure 2.4: Estimates for Low Frequency Volatility: Dropping One Country at a Time

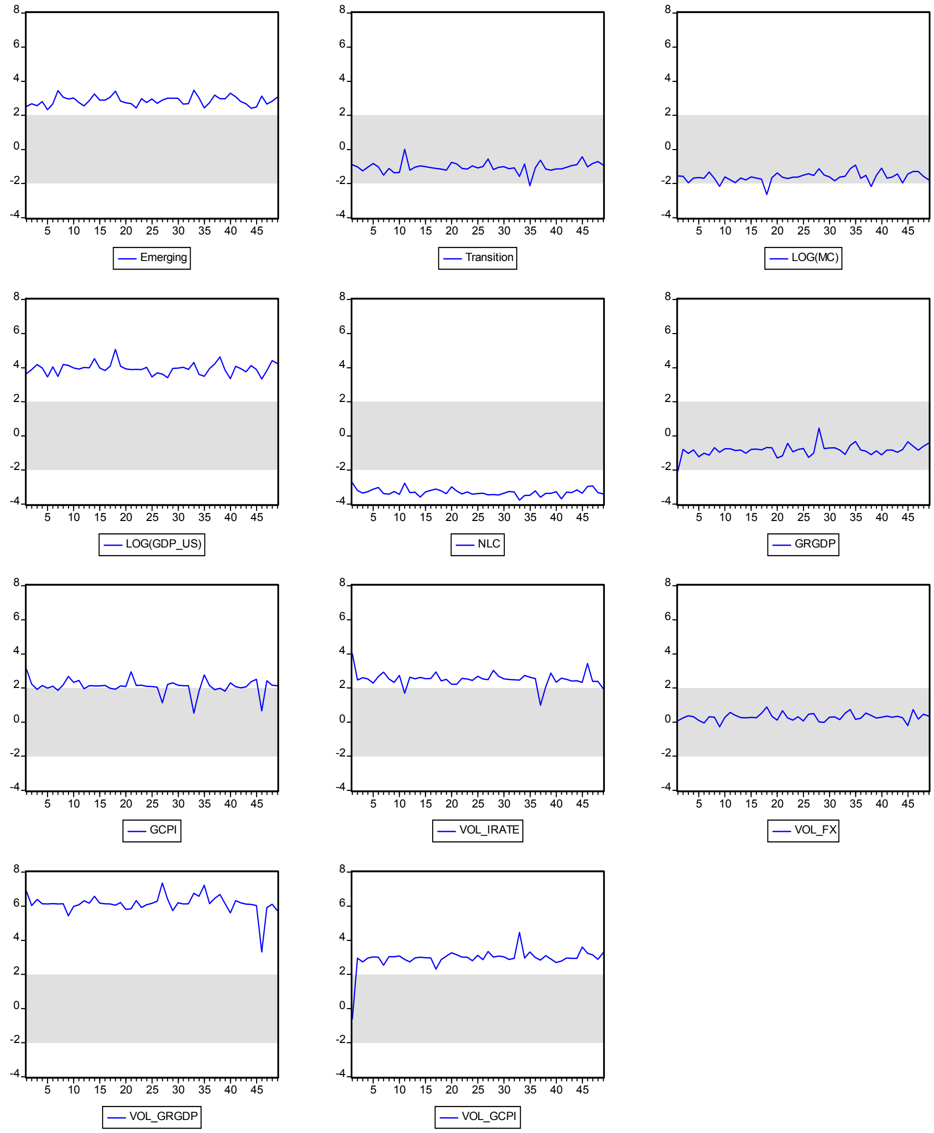

Figure 2.5: T-Statistics for Low Frequency Volatility: Dropping One Country at a Time

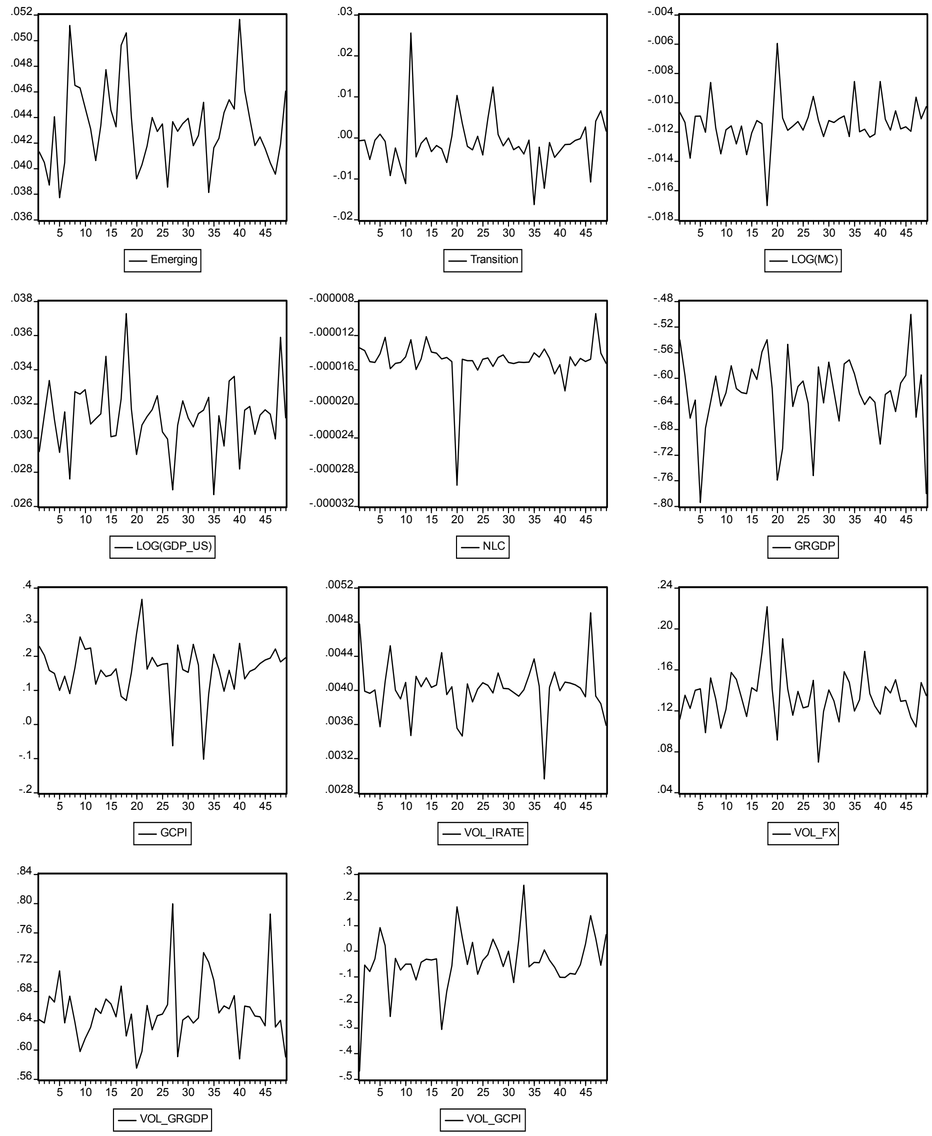

Figure 2.6: Estimates Realized Volatility: Dropping One Country at a Time

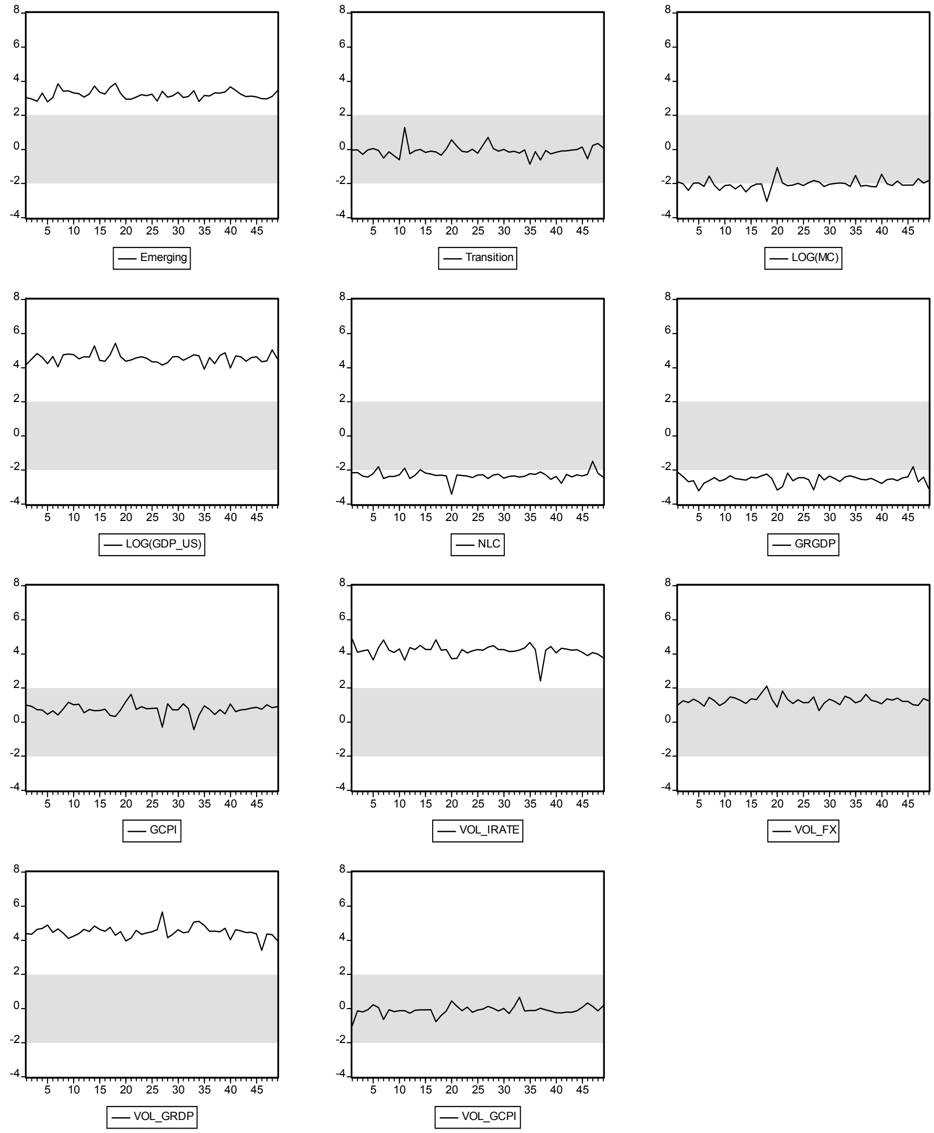

Figure 2.7: T-Statistics for Realized Volatility: Dropping One Country at a Time

2.10 Tables

Table 2.1: Estimation Results for the SP500 (1955-2004)

	Coefficient	Std. Error
c	1.1373	0.0436
w_0	-0.0003	7.5E-05
w_1	-1.9E-08	2.6E-08
w_2	2.7E-07	2.9E-08
w_3	-4.4E-07	3.9E-08
w_4	3.3E-07	5.4E-08
w_5	-4.0E-07	5.4E-08
w_6	6.0E-07	5.9E-08
w_7	-8.0E-07	9.9E-08
α	0.0895	0.0024
β	0.8810	0.0046
Log likelihood	-15733.51	
BIC	2.5348	

a) Estimation based a model with Gaussian Innovations. See model Specification in Equations (2.12), (2.13) and (2.14).

Table 2.2: Countries Included in the Sample

Country	Market Clasification	Exchange	Name of the Index	Average No. of Listings	Average Market Capitalization
Argentina	emerging	Buenos Aires	IVBNG	143	35352.96
Australia	developed	Australian	ASX	1236	295354.2
Austria	developed	Wiener Börse	ATX	137	31104.35
Belgium	developed	Euronext	CBB	1229	128803.2
Brazil	emerging	Sao Paulo	BOVESPA	513	155037
Canada	developed	TSX Group	S&P/TXS 300	1633	501122.3
Chile	emerging	Santiago	IGPAD	261	54529.27
China	emerging	Shanghai Stock Exchange	SSE-180	370	216199.3
Colombia	emerging	Bogota	IGBC	109	11480.09
Croatia	emerging	Zagreb	CROBEX	57	2406
Czech Republic	emerging	PSE	SE PX-50 Index	563	13319.22
Denmark	developed	Copenhagen	KAX All-Share Index	241	72720.3
Finland	developed	Helsinki	HEX	106	113409
France	developed	Euronext	CAC-40*	1229	752041.9
Germany	developed	Deutsche Börse	DAX	880	759628.3
Greece	developed	Athens	Athens SE General Index	224	56050.52
Honk Kong	developed	Hong Kong	Hang Seng Composite Index	637	389810
Hungary	emerging	Budapest	Budapest SE Index*	53	9728.453
India	emerging	Mumbai	Mumbay SE-200 Index	5696	128732.4
Indonesia	emerging	Jakarta	Jakarta SE Composite Index	243	36744.79
Ireland	developed	Irish	ISEQ Overall Price Index	89	69934.38
Israel	emerging	Tel-Aviv	TA SE All-Security Index	563	41720.75
Italy	developed	Borsa Italiana	Milan MIB General Index	263	374715.4
Japan	developed	Tokyo	Nikkei 225	1911	2930639
Korea	emerging	Korea	KOSPI	708	163264.7
Lithuania	emerging	National SE of Lithuania	Lithuania Litin-G Stock Index	174	3190.185
Malaysia	emerging	Bursa Malaysia	KLSE Composite	610	141464.6
Mexico	emerging	Mexico	IPC	208	119904.7
Netherlands	developed	Euronext	AEX	1229	366983.1
New Zealand	developed	New Zealand	New Zealand SE All-Share Capital Index	190	23119.93
Norway	developed	Oslo	Oslo SE All-Share Index	175	50232.67
Peru	emerging	Lima	Lima SE General Index	235	8892.879
Philippines	emerging	Philippine	Manila SE Composite Index	205	33072.59
Poland	emerging	Warsaw	Poland SE Index (Zloty)	129	15687.93
Portugal	developed	Euronext	Portugal PSI General Index*	1229	32279.57
Russia	emerging	Russian Exchange	Russia AKM Composite	169	52182.45
Singapore	developed	Singapore	SES All-Share Index	336	114633.9
Slovak Republic	emerging	Bratislava	SAX Index	764	3909.196
South Africa	emerging	JSE South Africa	FTSE/JSE All-Share Index	618	200916.7
Spain	developed	Spanish Exchanges (BME)	Madrid SE General Index	3119	315363.5
Sweden	developed	Stockholmsbörsen	SAX All-Share index	242	206177.8
Switzerland	developed	Swiss Exchange	Switzerland Price Index	431	463321.4
Taiwan	emerging	Taiwan	Taiwan SE Capitalization Weighted Index	410	237885.5
Thailand	emerging	Thailand	SET General Index	369	68325.18
Turkey	emerging	Istanbul	Istanbul SE IMKB-100 Price Index	227	41548.86
United Kingdom	developed	London	FTSE-250*	2497	1739880
United States	developed	NYSE	S&P500	2298	6805999
Venezuela	emerging	Caracas	Caracas SE General Index	71	7718.482

Source: Global Financial Data and Datastream*
Yearly Averages over the period 1990-2003
Units market capitalization: USD millions

Table 2.3: Estimation Results: Spline-GARCH and GARCH(1,1) Models

	1	2	3	4	5	6	7	8	9	10	11	12	13
Country	Knots[a]	Starting Year[b]	Obs	obs/knot[c]	Alpha[d]		Beta[e]		Log likelihood		BIC		LRT[f]
					spgarch	garch	spgarch	garch	spgarch	garch	spgarch	garch	
ARGENTINA	3	Jan-67	9,240	3,080	0.21	0.19	0.76	0.83	-8785.2	-8879.7	1.9085	1.9252	189.0
AUSTRALIA	1	Jan-58	11,682	11,682	0.23	0.17	0.71	0.84	-14244.6	-14396.8	2.4427	2.4674	304.4
AUSTRIA	11	Jan-86	4,574	416	0.15	0.12	0.77	0.87	-5733.3	-5816.8	2.5346	2.5495	166.9
BELGIUM	2	Jan-91	3,370	1,685	0.12	0.12	0.85	0.85	-4153.7	-4167.6	2.4796	2.4813	27.6
BRAZIL	6	Jan-72	8,220	1,370	0.14	0.14	0.82	0.87	-9705.7	-9775.2	2.3724	2.3820	139.0
CANADA	10	Jan-76	7,182	718	0.11	0.11	0.82	0.87	-8892.1	-8957.4	2.4897	2.4946	130.7
CHILE	4	May-76	7,003	1,751	0.36	0.37	0.52	0.55	-8819.5	-8963.8	2.5289	2.5638	288.6
CHINA	7	Jan-95	2,266	324	0.25	0.17	0.59	0.81	-2786.2	-2927.2	2.4966	2.5950	282.0
COLOMBIA	13	Jan-92	2,971	229	0.46	0.49	0.30	0.36	-3752.1	-3854.5	2.5715	2.6037	205.0
CROATIA	3	Jan-97	1,723	574	0.20	0.21	0.64	0.76	-2020.2	-2072.5	2.3752	2.4201	104.7
CZECHREP	1	Sep-94	2,405	2,405	0.15	0.13	0.78	0.86	-3143.9	-3168.1	2.6307	2.6443	48.3
DENMARK	5	Jan-79	6,344	1,269	0.22	0.16	0.65	0.81	-8220.0	-8305.9	2.6038	2.6231	171.8
FINLAND	4	Jan-87	4,379	1,095	0.15	0.12	0.76	0.88	-4979.5	-5069.3	2.2896	2.3216	179.6
FRANCE	1	Sep-87	4,385	4,385	0.09	0.09	0.88	0.89	-5715.2	-5716.4	2.6163	2.6136	2.6
GERMANY	6	Sep-59	11,208	1,868	0.14	0.14	0.82	0.84	-13953.2	-14022.9	2.4982	2.5050	139.4
GREECE	7	Oct-88	3,926	561	0.20	0.19	0.69	0.81	-4910.6	-4978.9	2.5247	2.5433	136.7
HONGKONG	1	Nov-69	8,528	8,528	0.15	0.15	0.84	0.85	-10237.0	-10249.5	2.4061	2.4072	25.1
HUNGARY	4	Feb-91	3,496	874	0.22	0.18	0.66	0.79	-4224.4	-4292.2	2.4354	2.4632	135.6
INDIA	5	Jan-91	3,157	631	0.14	0.13	0.78	0.85	-3994.5	-4038.8	2.5536	2.5671	88.4
INDONESIA	15	Apr-83	5,204	347	0.20	0.17	0.75	0.87	-4539.6	-4779.5	1.7759	1.8421	479.6
IRELAND	9	Jan-87	4,348	483	0.11	0.10	0.80	0.87	-5539.7	-5602.2	2.5732	2.5833	125.1
ISRAEL	11	Jun-81	5,665	515	0.14	0.16	0.77	0.79	-7423.5	-7510.1	2.6437	2.6565	173.3
ITALY	1	Jan-75	7,421	7,421	0.09	0.09	0.89	0.89	-9702.5	-9712.2	2.6209	2.6214	19.3
JAPAN	4	Jan-55	13,759	3,440	0.17	0.16	0.78	0.84	-16702.2	-16824.7	2.4334	2.4479	245.0
KOREA	15	Jan-62	12,136	809	0.13	0.11	0.80	0.90	-11875.8	-12034.8	1.9718	1.9858	318.0
LITHUANIA	6	Jun-98	1,536	256	0.16	0.17	0.64	0.52	-2081.3	-2126.4	2.7578	2.7831	90.2
MALAYSIA	14	Jan-80	6,057	433	0.19	0.19	0.67	0.78	-6942.0	-7050.7	2.3158	2.3305	217.4
MEXICO	12	Jan-85	4,859	405	0.14	0.12	0.74	0.85	-5940.6	-6010.4	2.4731	2.4797	139.7
NETHERLANDS	1	Jan-83	5,433	5,433	0.11	0.11	0.87	0.88	-6607.8	-6613.7	2.4404	2.4398	11.7
NEWZEALAND	3	Jul-86	4,512	1,504	0.19	0.20	0.73	0.78	-5708.5	-5745.5	2.5434	2.5529	73.9
NORWAY	4	Jan-83	5,385	1,346	0.18	0.19	0.73	0.76	-6886.8	-6928.7	2.5705	2.5786	83.9
PERU	11	Jan-82	5,580	507	0.27	0.30	0.65	0.70	-6349.4	-6451.1	2.2990	2.3173	203.4
PHILIPPINES	13	Jan-86	4,580	352	0.16	0.15	0.74	0.80	-5693.5	-5820.3	2.5143	2.5444	253.6
POLAND	1	Jan-95	2,338	2,338	0.11	0.11	0.83	0.84	-3121.4	-3127.5	2.6867	2.6865	12.3
PORTUGAL	7	May-88	4,216	602	0.28	0.09	0.56	0.90	-5133.7	-5315.6	2.4571	2.5282	363.8
RUSSIA	14	Jan-95	2,338	167	0.20	0.17	0.68	0.79	-2825.9	-2870.8	2.3374	2.3560	89.9
SINGAPORE	7	Jul-65	9,917	1,417	0.22	0.21	0.74	0.79	-11694.1	-11851.3	2.3686	2.3931	314.4
SLOVAKREP	5	Oct-93	2,507	501	0.16	0.14	0.74	0.82	-2942.7	-3000.9	2.3757	2.4043	116.4
SOUTHAFRICA	3	May-86	4,618	1,539	0.12	0.11	0.82	0.86	-5988.7	-6011.4	2.6064	2.6095	45.6
SPAIN	5	Aug-71	7,454	1,491	0.14	0.11	0.81	0.86	-9477.8	-9559.3	2.5538	2.5688	163.0
SWEDEN	4	Jun-86	4,525	1,131	0.12	0.12	0.82	0.85	-5737.8	-5765.6	2.5509	2.5545	55.6
SWISS	6	Jan-69	8,862	1,477	0.14	0.14	0.81	0.83	-11011.8	-11099.1	2.4954	2.5082	174.7
TAIWAN	3	Jan-67	10,650	3,550	0.10	0.09	0.88	0.91	-12893.4	-12949.8	2.4260	2.4334	112.7
THAILAND	12	May-75	7,271	606	0.18	0.19	0.75	0.84	-7852.8	-7992.7	2.1778	2.2007	279.7
TURKEY	3	Nov-87	4,143	1,381	0.22	0.20	0.72	0.76	-5433.3	-5450.4	2.6370	2.6378	34.1
UK	1	Jan-87	4,563	4,563	0.17	0.17	0.76	0.80	-5742.2	-5799.8	2.5261	2.5482	115.1
US	7	Jan-55	12,455	1,779	0.09	0.08	0.88	0.92	-15733.5	-15811.2	2.5348	2.5412	155.3
VENEZUELA	12	Jan-94	2,492	208	0.35	0.33	0.34	0.64	-3103.2	-3203.7	2.5407	2.5817	201.1

a) Optimal number of knots in the Spline-GARCH model.

b) Starting date in the Sample Period. Ending date is June 31, 2006.

c) Number of Observations per Knot in the Spline-GARCH model (Ratio of Column 3 to Column 1).

d) ARCH effects in the Spline-GARCH model (spgarch) and the GARCH(1,1) model (garch).

e) GARCH effects in the Spline-GARCH model (spgarch) and the GARCH(1,1) model (garch).

f) Statistic of Likelihood Ratio Test: GARCH(1,1) vs Spline-GARCH.

Table 2.4: Descriptive Statistics on the Distribution of the Number of Observations per Knot in the Spline-GARCH Model[a]

	Country Classification		
	Developed	Emerging[b]	Transition Econ.
Number of Countries	23	18	7
Minimum	415.82	207.67	167.00
Maximum	11682.00	3550.00	2405.00
Mean	2795.39	1002.03	1016.53
Standard Deviation	2951.17	969.33	953.54
Quantiles			
25%	1094.75	352.31	256.00
50%	1490.80	560.46	574.33
75%	4385.00	1381.00	2338.00

a) The variable "Observations per Knot" is presented in column 4 of Table 2.3.
b) Emerging markets excluding emerging transition economies.

Table 2.5: Explanatory Variables

Name	Description
emerging	Indicator of Market Development (1=Emerging, 0=Developed)
Transition	Indicator of Transition Economies (Central European and Baltic Countries)
log(mc)	log Market Capitalization ($US)
log(gdp_dll)	Log Nominal GDP in Current $US
nlc	Number of Listed Companies in the Exchange
grgdp	GDP Growth Rate
gcpi	Inflation Rate
vol_irate	Volatility of Short Term Interest Rate*
vol_forex	Volatility of Exchange Rates*
vol_grgdp	Volatility of GDP*
vol_gcpi	Volatility of Inflation*

*Volatilities are obtained from the residuals of AR(1) models

Table 2.6: Correlation Low Frequency Volatilities Across Years

	LVOL1997	LVOL1998	LVOL1999	LVOL2000	LVOL2001	LVOL2002	LVOL2003
LVOL1997	1	0.76800	0.79614	0.71752	0.64246	0.66100	0.74651
LVOL1998	0.76800	1	0.91144	0.71398	0.52270	0.49749	0.58763
LVOL1999	0.79614	0.91144	1	0.88333	0.72605	0.68825	0.70021
LVOL2000	0.71752	0.71398	0.88333	1	0.93833	0.87955	0.84312
LVOL2001	0.64246	0.52270	0.72605	0.93833	1	0.94249	0.87678
LVOL2002	0.66100	0.49749	0.68825	0.87955	0.94249	1	0.91471
LVOL2003	0.74651	0.58763	0.70021	0.84312	0.87678	0.91471	1

Table 2.7: Correlation of Residuals from Yearly Regressions (1997-2003)

	RES97	RES98	RES99	RES00	RES01	RES02	RES03
RES97	1	0.72148	0.58690	0.63573	0.52845	0.51425	0.66501
RES98	0.72148	1	0.76567	0.70793	0.50636	0.46868	0.49255
RES99	0.58690	0.76567	1	0.76222	0.49994	0.54647	0.47898
RES00	0.63573	0.70793	0.76222	1	0.90622	0.82757	0.78706
RES01	0.52845	0.50636	0.49994	0.90622	1	0.89690	0.82175
RES02	0.51425	0.46868	0.54647	0.82757	0.89690	1	0.85353
RES03	0.66501	0.49255	0.47898	0.78706	0.82175	0.85353	1

Table 2.8: Individual SUR Regressions[a]

	Coefficient	Std. Error	t-Statistic	Prob.	Det Residual Covariance
emerging	0.0957	0.0176	5.4528	0.0000	6.45E-39
transition	-0.0077	0.0180	-0.4284	0.6685	1.53E-38
log(mc)	-0.0093	0.0032	-2.9345	0.0035	3.76E-38
log(gdp_dll)	0.0015	0.0055	0.2740	0.7842	2.18E-37
nlc	-1.29E-05	0.0000	-2.3706	0.0181	1.23E-37
grgdp	-0.6645	0.1255	-5.2945	0.0000	3.89E-38
gcpi	0.6022	0.0418	14.4181	0.0000	1.64E-38
vol_irate	0.0089	0.0006	14.4896	0.0000	8.59E-39
vol_forex	0.5963	0.0399	14.9468	0.0000	2.47E-38
vol_grgdp	1.1192	0.1008	11.1056	0.0000	8.71E-39
vol_gcpi	0.9364	0.0848	11.0375	0.0000	2.84E-38

a) SUR estimation of annual low frequency volatilities on each individial variable (see Equation 2.18).

Table 2.9: Estimation Results for Low Frequency Volatilities

	SUR Models				Panel Specification[a]
	All Countries	Opt. Reduction	Logs	Without Arg	Random Country Effects
emerging	0.0376	0.0387	0.2079	0.0322	0.0478
	(0.0131)**	(0.0128)**	(0.0592)**	(0.0128)**	(0.0212)**
transition	-0.0178	-0.0164	-0.0332	-0.0147	-0.0258
	(0.0171)	(0.0167)	(0.0741)	(0.0163)	(0.0304)
log(mc)	-0.0092	-0.0085	-0.0345	-0.0083	-0.0046
	(0.0055)*	(0.0053)	(0.0235)	(0.0054)	(0.0067)
log(gdpus)	0.0273	0.0271	0.1156	0.0245	0.0175
	(0.0068)**	(0.0066)**	(0.0302)**	(0.0067)**	(0.0099)*
nlc	-1.8E-05	-1.8E-05	-8.1E-05	-1.4E-05	-1.7E-05
	(5.4E-06)**	(5.3E-06)**	(2.3E-05)**	(5.2E-06)**	(8.6E-06)**
grgdp	-0.1603		0.0962	-0.4046	-0.2094
	(0.1930)		(0.7474)	(0.1984)**	(0.2258)
gcpi	0.3976	0.3915	1.1459	0.5985	0.6114
	(0.1865)**	(0.1641)**	(0.7755)	(0.1939)**	(0.2229)**
vol_irate	0.0020	0.0022	0.0061	0.0032	0.0034
	(0.0008)**	(0.0008)**	(0.0031)*	(0.0008)**	(0.0009)**
vol_gforex	0.0222		0.0185	0.0068	-0.0221
	(0.0844)		(0.3383)	(0.0878)	(0.0959)
vol_grgdp	0.8635	0.8373	2.5808	0.9392	0.9019
	(0.1399)**	(0.1352)**	(0.6138)**	(0.1371)**	(0.1862)**
vol_gcpi	0.9981	1.0983	3.1467	-0.2243	-0.0849
	(0.3356)**	(0.3208)**	(1.3431)**	(0.3627)	(0.3917)
d1990	0.1532	0.1471	-1.8546	0.1638	0.0252
	(0.04835)**	(0.0472)**	(0.2068)**	(0.0470)**	(0.0185)
d1991	0.1488	0.1427	-1.8687	0.1569	0.0160
	(0.0480)**	(0.0468)**	(0.2058)**	(0.0465)**	(0.0173)
d1992	0.1314	0.1245	-1.9539	0.1407	0.0004
	(0.0472)**	(0.0459)**	(0.2037)**	(0.0457)**	(0.0170)
d1993	0.1435	0.1362	-1.9398	0.1447	0.0000
	(0.0498)**	(0.0485)**	(0.2118)**	(0.0480)**	(0.0159)
d1994	0.1244	0.1169	-2.0181	0.1314	-0.0138
	(0.0498)**	(0.0484)**	(0.2144)**	(0.0481)**	(0.0152)
d1995	0.1230	0.1150	-2.0304	0.1320	-0.0236
	(0.0490)**	(0.0477)**	(0.2115)**	(0.0476)**	(0.0141)*
d1996	0.1177	0.1087	-2.0580	0.1274	-0.0276
	(0.0491)**	(0.0479)**	(0.2120)**	(0.0476)**	(0.0134)**
d1997	0.1371	0.1284	-1.9570	0.1483	-0.0068
	(0.0495)**	(0.0482)**	(0.2124)**	(0.0479)**	(0.0124)
d1998	0.1831	0.1763	-1.7804	0.1951	0.0455
	(0.0506)**	(0.0493)**	(0.2150)**	(0.0490)**	(0.0121)**
d1999	0.2028	0.1938	-1.7047	0.2164	0.0648
	(0.0517)**	(0.0503)**	(0.2197)**	(0.0502)**	(0.0114)**
d2000	0.1941	0.1851	-1.7241	0.2049	0.0562
	(0.0499)**	(0.0486)**	(0.2135)**	(0.0484)**	(0.0104)**
d2001	0.1762	0.1683	-1.7837	0.1866	0.0406
	(0.0493)**	(0.0479)**	(0.2110)**	(0.0477)**	(0.0094)**
d2002	0.1619	0.1540	-1.8487	0.1701	0.0242
	(0.0487)**	(0.0473)**	(0.2090)**	(0.0471)**	(0.0076)**
d2003	0.1358	0.1272	-1.9588	0.1456	0.0213
	(0.0505)**	(0.0490)**	(0.2167)**	(0.0487)**	(0.1032)
Det residual covariance	2.3E-38	3.8E-39	4.2E-22	1.6E-39	
BIC	-88.067	-88.15	-48.89	-89.00	

Standard errors reported in parentheses.
* Denotes significance at 10%.
**Denotes significance at 5%.
a) Estimated autocorrelation coefficient: **ρ** = 0.4731 (See Equation 2.19 for assumptions on the error term).

Table 2.10: Estimation Results for Realized Volatilities

	SUR Models				Panel Specification
	All Countries	Opt. Reduction	Logs	Without Arg	Random Country Effects
emerging	0.0434	0.0408	0.0964	0.0413	0.0373
	(0.0134)**	(0.0124)**	(0.0317)**	(0.0136)**	(0.0199)*
transition	-0.0013		-0.0084	-0.0007	0.0018
	(0.0182)		(0.0417)	(0.0183)	(0.0282)
log(mc)	-0.0116	-0.0112	-0.0256	-0.0107	-0.0042
	(0.0055)**	(0.0052)**	(0.0130)**	(0.0056)*	(0.0074)
log(gdpus)	0.0314	0.0309	0.0730	0.0292	0.0245
	(0.0068)**	(0.0066)**	(0.0162)**	(0.0069)**	(0.0101)**
nlc	-1.5E-05	-1.4E-05	-3.8E-05	-1.3E-05	-1.3E-05
	(6.4E-06)**	(6.2E-06)**	(1.5E-05)**	(6.2E-06)**	(8.8E-06)
grgdp	-0.6222	-0.6568	-0.9639	-0.5400	-1.0773
	(0.2442)**	(0.2322)**	(0.5277)*	(0.2517)**	(0.2939)**
gcpi	0.1598		0.2366	0.2286	0.4299
	(0.2159)		(0.4840)	(0.2312)	(0.2630)
vol_irate	0.0040	0.0043	0.0059	0.0048	0.0056
	(0.0010)**	(0.0008)**	(0.0021)**	(0.0010)**	(0.0011)**
vol_gforex	0.1329	0.1649	0.2807	0.1120	0.1040
	(0.1057)	(0.0894)*	(0.2247)	(0.1105)	(0.1203)
vol_grgdp	0.6500	0.7002	1.3278	0.6414	0.6728
	(0.1437)**	(0.1277)**	(0.3378)**	(0.1463)**	(0.1989)**
vol_gcpi	-0.0432		-0.1124	-0.4683	-0.5073
	(0.3978)		(0.9042)	(0.4700)	(0.4799)
d1990	0.4158	0.4133	-0.9029	0.4187	0.0640
	(0.0512)**	(0.0471)**	(0.1172)**	(0.0515)**	(0.0193)**
d1991	0.3726	0.3702	-0.9944	0.3751	0.0189
	(0.0489)**	(0.0447)**	(0.1142)**	(0.0491)**	(0.0180)
d1992	0.3583	0.3551	-1.0306	0.3610	0.0045
	(0.0493)**	(0.0451)**	(0.1156)**	(0.0494)**	(0.0179)
d1993	0.3492	0.3457	-1.0560	0.3492	0.0008
	(0.0500)**	(0.0455)**	(0.1172)**	(0.0501)**	(0.0168)
d1994	0.3616	0.3570	-1.0243	0.3584	0.0187
	(0.0502)**	(0.0454)**	(0.1173)**	(0.0504)**	(0.0163)
d1995	0.3439	0.3403	-1.0681	0.3406	-0.0083
	(0.0513)**	(0.0464)**	(0.1193)**	(0.0514)**	(0.0151)
d1996	0.3194	0.3186	-1.1212	0.3202	-0.0368
	(0.0502)**	(0.0452)**	(0.1176)**	(0.0504)**	(0.0145)**
d1997	0.4102	0.4090	-0.9139	0.4127	0.0503
	(0.0509)**	(0.0458)**	(0.1184)**	(0.0511)**	(0.0135)**
d1998	0.4656	0.4630	-0.8042	0.4693	0.1095
	(0.0515)**	(0.0464)**	(0.1190)**	(0.0517)**	(0.0134)**
d1999	0.4136	0.4117	-0.9067	0.4168	0.0527
	(0.0524)**	(0.0471)**	(0.1218)**	(0.0526)**	(0.0128)**
d2000	0.4276	0.4259	-0.8772	0.4330	0.0630
	(0.0512)**	(0.0460)**	(0.1191)**	(0.0513)**	(0.0121)**
d2001	0.4157	0.4131	-0.8969	0.4193	0.0481
	(0.0505)**	(0.0454)**	(0.1177)**	(0.0507)**	(0.0114)**
d2002	0.4068	0.4048	-0.9206	0.4088	0.0415
	(0.0504)**	(0.0456)**	(0.1173)**	(0.0506)**	(0.0097)**
d2003	0.3616	0.3589	-1.0160	0.3657	-0.0904
	(0.0518)**	(0.0467)**	(0.1209)**	(0.0521)**	(0.0978)
Det residual covariance	3.6E-37	3.6E-37	1.8E-27	3.0E-37	
BIC	-83.58	-83.63	-61.25	-83.75	

Standard errors reported in parentheses.
* Denotes significance at 10%.
**Denotes significance at 5%.
a) Estimated autocorrelation coefficient: **ρ** = 0.4731 (See Equation 2.19 for assumptions on the error term).

Table 2.11: R-Squared Statistics for Each Equation in the SUR System Including All Countries

	Low Frequency Vol[a]	Realized Vol[b]
1990	0.5816	0.4019
1991	0.6435	0.5786
1992	0.7293	0.3640
1993	0.6463	0.5102
1994	0.5798	0.5577
1995	0.6689	0.4982
1996	0.7040	0.7218
1997	0.5700	0.4172
1998	0.5608	0.4835
1999	0.4481	0.3878
2000	0.3908	0.2442
2001	0.3477	0.2556
2002	0.3636	0.0985
2003	0.3968	0.2026
Average	**0.5451**	**0.4087**

a) Values correspond to system in Equation (2.18).

b) Values correspond to system in Equation (2.21).

Chapter 3

Macroeconomic Announcements, Price Discovery, and Order Flow Effects in the Stock Market: Evidence from Daily Data and Multiple Financial Markets

3.1 Introduction

Asset prices are affected by revisions in expectations about changing economic conditions driven by macroeconomic news, such as output, employment and inflation surprises. Because the objectives of monetary policy are expressed in terms of the same macroeconomic variables, the response of the stock market to macroeconomic news is linked to market assessments of future Fed actions and/or future states of the economy. In this context, it remains an intriguing question the empirical distinction of the link between market beliefs and the mechanisms through which macroeconomic information enters the price process.

The impacts of macroeconomic news on asset prices have been analyzed under two main approaches. The most common, known as the "asset pricing approach", is based on symmetric information. This approach supports the view that public information is fully and nearly instantaneously incorporated into prices since all agents observe the same piece of information, and interpret any asset pricing implication the same way. Therefore, the implied mechanism suggests that asset prices jump to their new equilibrium values nearly immediately after an announcement is released.[1] The second approach has been less explored. It is based on asymmetric information, which is associated with heterogeneous interpretation of public announcements. The asymmetric information approach points out that although real time macroeconomic information is publicly observed, economic agents might differ in their interpretations of the relevance of specific news for asset prices. This approach recognizes that some agents might have better models or superior information with which they can make more accurate predictions of the economy than the rest of the agents. As a result, the price impact of a macroeconomic surprise might not be instantaneous, but rather it might take some time for the market to aggregate heterogeneous beliefs and learn about the "true" price impact of the economic news. The microstructure literature suggests the mechanism in which this learning process occurs is through trading. Therefore, the price formation process is sensitive to the underlying information structure.

Homogeneous assessments imply different reactions than heterogeneous revisions. However, the empirical literature on announcement effects has mostly ignored asymmetric information effects, and the two approaches described above have largely followed two separate lines of research. Combining the two underlying mechanisms is crucial for a complete understanding of news effects in financial markets. Micro effects of macro announcements are only partially understood if one does not take into account relevant issues, such as heterogeneity of beliefs, the process of aggregating heterogeneous information, and news effects on revisions of expectations about long run states of the economy.

In the present paper, I contribute to reduce the gap between these lines of research by combining key elements of the two approaches in a structural microstructure model. Specifically, the goal of this paper is to jointly explore these two mechanisms to evaluate the extent to which heterogeneity in the market assessment of public fundamental

[1] A nearly instantaneous adjustment in prices can be interpreted as a case where information affects prices with little or no trading activity, and the fundamental price impact is fully revealed at most a few minutes (or seconds) after the announcement.

information explains the stock market responses to such information. I do so by including two distinct components in the fundamental price. The first component is consistent with the standard “asset pricing view” and describes instantaneous responses (jumps) of the fundamental price to macroeconomic news, while the second component accounts for possible asymmetric information (measured by permanent order flow price impacts) on “announcement” days due to aggregation of heterogeneous private information, or heterogeneous interpretation of public information.

The effects of macroeconomic surprises on asset prices have been analyzed in a number of recent empirical studies. Most of these papers consider the symmetric information view. Based on different data sets and data frequencies, some of these studies address the conditional mean effects of macroeconomic news using event-study analyses. For instance, Bernanke and Kuttner (2005) and Boyd, Jagannathan, and Hu (2005) analyze the stock market; Balduzzi, Elton, and Green (2001) and Fleming and Remolona (1999) study the bond market; and Andersen, Bollerslev, Diebold, and Vega (2003) analyze exchange rates. Other studies examine news effects on market volatility. For example, Flannery and Protopapadakis (2002) and Bomfim (2003) study stock returns; Andersen and Bollerslev (1998b) analyze exchange rates; Li and Engle (1998) and Jones, Lamont, and Lumsdaine (1998) examine bonds. News effects at a multi-market level are investigated in Andersen, Bollerslev, Diebold, and Vega (2005) and Faust, Rogers, Wand, and Wright (2003).

The less explored approach of asymmetric information, under a microstructure framework, has most of its theoretical foundations in the seminal papers of Kyle (1985), and Glosten and Milgrom (1985). Heterogeneous responses to public announcements are theoretically discussed in Kim and Verrecchia (1991a) and Kim and Verrecchia (1991b). Empirical studies accounting for asymmetric information (order flow) effects in asset prices linked to public announcements include Evans and Lyons (2005) (for exchange rates) and Brandt and Kavajecz (2004) (for yields).

Like Andersen, Bollerslev, Diebold, and Vega (2005), this paper analyzes simultaneous reactions of prices to macroeconomic news in several markets. However, I go beyond their analysis by introducing an asymmetric information component described in terms of price impacts of the order flow on announcement days. Indeed, I estimate a microstructure model that captures jointly instantaneous news effects and permanent order flow effects, which might have some nontrivial implications for "observed" volatility and market liquidity. In my empirical analysis, I use daily observations to proxy microstructure measures. Specifically, following the Markov chain Monte Carlo (MCMC) approach for microstructure models with unobserved latent variables suggested in Hasbrouck (2004) and Hasbrouck (2005), I estimate the microstructure parameters from closing prices and trading volume.[2] I extend the Hasbrouck model by introducing news effects on the fundamental (unobserved efficient) price and average differential effects of order flows on announcement regimes versus the non-announcement regime. In addition, I use evidence from other financial markets as a robustness analysis. Specifically, I analyze to what extent the interest rate component, or other primitive components, such as growth rate expectations and risk premia, explain reactions to news in the stock market.

My empirical analysis estimates the effect on the stock market of 19 macroeconomic announcements. In line with the empirical literature, the results suggest instantaneous news effects are important for macroeconomic variables related to real activity, investment, inflation, and monetary policy. In addition, my results support the presence of both instantaneous news impacts and order flow effects on employment announcement days. This evidence, along with other measures of liquidity based on daily data such as liquidity ratios, indicates liquidity decreases in equity markets on employment announcement days. My theoretical motivation and features of observed trading volume suggest that the combination of asymmetric information with either increases in the volatility of the fundamental price or decreases in the precision of the asset price implication of the news, are likely reasons for explaining the increment in the asymmetric information component on employment announcement days.

My multi-market analysis suggests that this increase in asymmetric information in the stock market is driven by the interest rate component. In fact, I find evidence of excess sensitivity of long term interest rates to employment news in terms of both news

[2]The main motivation for implementing Bayesian MCMC methods in these cases is the analytical and computational convenience in dealing with the unobserved trade direction.

effects and order flow effects. This complements the results of Gurkaynak, Sack, and Swanson (2005) in the sense that, not only do private agents revise their expectations of future Fed policies and/or long run states of the economy, but also their revisions might be heterogeneous. Therefore, the asymmetric information effect comes from uncertainty about long term interest rates due to heterogeneous assessments of future Fed responses to employment shocks. This argument is also consistent with the two theoretical reasons discussed above: decreases in the precision of asset price implications of employment news and increases in stock market volatility when employment information arrives.

These results are important for several reasons. On a fundamental level, they contribute to a better understanding of the link between macroeconomic information and the price formation process, which is one of the main functions of financial markets. In addition, the implications for returns, volatility and liquidity are of great relevance not only for portfolio and risk management decisions of market participants, but also for policy decisions, such as government and central bank policies, concerning financial system stability. Indeed, practitioners and policy makers can benefit from new methods for measuring impacts of output and inflation shocks in financial markets. Moreover, the analysis of both mechanisms permits us to evaluate the heterogeneity in the market assessment of economic news and future Fed policies, and provides a more general view of the information structure in financial markets.

This paper is organized as follows. Section 3.2 presents a theoretical review of the asset pricing approach and a microstructure theoretical framework in the context of public macroeconomic announcements. Section 3.3 describes the data. Section 3.4 presents the structural model and the econometric estimation strategy. Section 3.5 reports my empirical findings. Section 3.6 presents a robustness analysis based on information from other financial markets, and Section 3.7 concludes.

3.2 Theoretical Economic Framework

3.2.1 Macroeconomic Information and the Asset Pricing Approach

In this subsection, I provide intuition on how macroeconomic fundamental variables affect asset prices under a standard rational expectations equilibrium framework consistent with a structure in which the interpretation of macroeconomic news is common knowledge. Following the standard consumption-based model with nominal prices, I obtain the familiar pricing equation:

$$p_t = E_t\left[\left(\beta\frac{u'(c_{t+1})}{u'(c_t)}\frac{\Pi_t}{\Pi_{t+1}}\right)x_{t+1}\right] = E_t\left[\Lambda_{t+1}x_{t+1}\right], \tag{3.1}$$

where $u'(c_t)$ denotes the marginal utility of consumption c_t, Π denotes the nominal price level (CPI), β is the discount rate, and x_{t+1} represents the future payoff (dividends and principal). Under constant relative risk aversion (CRRA) utility with parameter $\gamma > 0$, and taking the equilibrium condition $c_{t+1} = x_{t+1}$, the stochastic discount factor takes the form:

$$\Lambda_{t+1} = \beta\left(\frac{x_{t+1}}{x_t}\right)^{-\gamma}\frac{\Pi_t}{\Pi_{t+1}} \tag{3.2}$$

Moreover, Equation (3.1) can be rewritten as follows:

$$p_t = E_t\left[\Lambda_{t+1}\right]E_t\left[x_{t+1}\right] + cov_t\left(\Lambda_{t+1}, x_{t+1}\right) \tag{3.3}$$

Equations (3.2) and (3.3) permit us to analyze the effects of macroeconomic shocks on the different components of the price. For instance, the expected value of the stochastic discount factor, which sets the price of a zero-coupon bond and determines the risk-free rate, decreases with positive output shocks, as well as with positive inflation shocks.[3] In contrast, a positive output shock will increase the current expected payoff (rate of growth), which is represented by $E_t\left[x_{t+1}\right]$. Therefore, the interest rate and the expected growth rate components react to output (and inflation) shocks in opposite directions. Moreover, the reaction of the covariance term (risk premium) to macroeconomic shocks is also ambiguous. This leaves the overall effect of macroeconomic shocks on stock prices as an important empirical question. Nevertheless, using data from other

[3]The effect of inflation shocks on Λ_{t+1} is not sensitive to the assumption of power utility.

financial markets, such as bond markets, might give more insights in determining which effect dominates.

3.2.2 A Microstructure Asymmetric Information Model

Under the risk-neutral probability measure, the fundamental asset price in Equation (3.1) satisfies the martingale property, and has a random walk representation. Moreover, even with respect to the actual probability measure, the random walk representation works well on a daily basis due to the little change in consumption and risk aversion at daily or higher frequencies. Thus, under symmetric information, the fundamental price can be expressed as follows:

$$m_t = m_{t-1} + u_t \tag{3.4}$$

where u_t reflects innovations in the fundamental price over the interval $(t-1, t]$ due to the arrival of public information, including macroeconomic announcements. Here, information is instantaneously incorporated in the fundamental price.

Under asymmetric information, an additional component is added to the fundamental price due to revisions in expectations of the market maker(s) conditional on either an order arrival or the aggregated order flow. Glosten and Milgrom (1985) and Kyle (1985) provide formal theoretical derivations of asymmetric information models in a context of insider trading. However, in a context of public announcements, it is convenient to restate the motivation. Indeed, after an announcement release, some trades might be based on superior information associated, for instance, with the presence of better informed agents who are able to process public news in superior ways that lead to better predictions of the asset price impact of such news. Moreover, since this informed trading is based on private models, heterogeneous assessments of the price implication of such public news among informed traders present a natural scenario that describes how information asymmetry might arise when public announcements are released. As mentioned earlier, the situation of facing informed trading hidden in standard liquidity demands creates an order flow adverse selection problem for market makers, and motivates their revisions in expectations, which make permanent the asymmetric information effect on the fundamental price.[4]

Several specifications that include permanent effects of orders on prices are available in the literature. Hasbrouck (2005) presents one in which the fundamental (efficient) price takes the following form:

$$m_t = m_{t-1} + \widetilde{\lambda} Q_t + \varepsilon_t, \tag{3.5}$$

where t indexes equally-spaced intervals, and Q_t is a measure of the cumulative signed order flow over the interval $(t-1, t]$. For instance, if $\widetilde{q}_k$ is defined as an indicator of the trade direction corresponding to the k trade, where it takes the value of 1 if a transaction was initiated by a buyer (ask), and -1 if a transaction is initiated by a seller (bid), then Q_t can be defined as $\sum\limits_{k=1}^{N_t} \widetilde{q}_k$, where N_t represents the number of trades in the interval. Alternatively, the order flow can be proxied using signed trading volume. In this case, Q_t can be replaced in Equation (3.5) by $V_t q_t$, where V_t denotes the dollar trading volume (or a function of it), and q_t represents the sign of Q_t.[5] Therefore, Equation (3.5) can be replaced by:

$$m_t = m_{t-1} + \widetilde{\lambda} V_t q_t + \varepsilon_t \tag{3.6}$$

The second term in Equation (3.6) characterizes the asymmetric information (spread) component as a function of the order sizes, which are approximated by a function of the volume variable.[6] Other related specifications also account for this size effect. For instance, Glosten and Harris (1987) characterize the asymmetric information spread component as an affine function of the order size. Theoretical motivation about why this component should increase with the quantity traded can be found in Kyle (1985) and Easley and O'Hara (1987), in a general context. In the particular context of public releases, Appendix C1 provides further economic motivation and gives insights to ex-

[4]Appendix C1 provides a more formal economic intuition by analyzing asymmetric information effects when announcements are released. The theoretical framework is based on an extension of Kyle (1985) in a simple one-period context. In this extension, I accommodate multiple informed traders who receive noisy signals about the price impact of a piece of news.

[5]Hasbrouck (2005) interprets q_t as the trade direction associated with the last trade of the corresponding interval. This study also finds similar results using either cumulative order flow or signed volume.

[6]See Glosten and Harris (1987) and Hasbrouck (2004) for a complete representation of the components of the bid-ask spread.

plain possible changes in the marginal effect of order flows. For instance, the marginal order flow impact might increase when any of the following situations occur: the variance of the fundamental price increases, the variance of liquidity demands decreases, the precision of the signal that informed agents obtain about the price implication of an economic news decreases (provided the number of informed agents is sufficiently large), and the number of informed agents decreases (provided the number of informed agents is sufficiently large).

3.3 Data

Jointly analyzing the fields of market microstructure and asset pricing has proven difficult. Hasbrouck (2005) argues that these difficulties arise from differences in the data samples and frequencies favored by each area. Asset pricing models require data at daily or lower frequencies due to various reasons, such as large sample requirements to estimate risk factors, and the fact that daily data might be the highest frequency at which prices keep their convenient martingale properties. On the other hand, microstructure models require intradaily trades and quotes data, which favors analyses of other important issues, such as intraday price dynamics, price discovery, impacts of transaction costs, inventory effects, among others; however, the data samples are small (covering only recent periods), and they are difficult obtain, particularly in multi-market setups. These issues, combined with the importance of linking the asset pricing and microstructure areas, as well as the possibility of inferring microstructure characteristics from daily data (as suggested by Hasbrouck), motivate the use of daily data in the present study.

In particular, I use daily closing prices and trading volume data for the S&P 500 index, obtained from the Center for Research in Security Prices (CRSP) database. I also use futures daily closing prices and trading volume data for contracts associated with stocks, exchange rates, and bonds at different maturities, obtained from Global Financial Data and Datastream. Specifically, I consider the S&P 500, $US/Yen, US 5-Year Note and US 10-Year Note futures contracts. My sample period covers from January 1992 through December 2003.

I analyze the effect on asset prices of 19 macroeconomic announcements, classified into seven categories, namely real activity, investment, consumption, trade, price level, forward looking, and monetary policy.[7] The real activity group includes: industrial production, retail sales, nonfarm payroll employment, unemployment rate, capacity utilization, personal income, and consumer credit; the investment group includes: durable goods orders, construction spending, and business inventories; the consumption group includes: new home sales and personal consumption expenditures; the trade group is composed of the goods and services trade balance; the price level group includes: the consumer price index and the producer price index; the forward looking group includes: the index of leading indicators, the National Association of Purchasing Managers (NAPM) index, and housing starts; and finally, the monetary policy category includes only the Federal Open Market Committee (FOMC) announcements.[8] Data on the corresponding macroeconomic releases are obtained from the Bureau of Labor Statistics.[9] Macroeconomic forecasts are obtained from the Money Market Services (MMS) survey, which includes data from telephone surveys conducted normally one week or less before any macroeconomic news release.[10] Based on this information, a surprise for release k on day t is calculated as follows:

$$S_{kt} = \frac{Y_{kt} - \widehat{Y}_{kt}}{\sigma_k} \tag{3.7}$$

where Y_{kt} is the realization of variable k, $\widehat{Y}_{kt}$ is the corresponding median forecast, and σ_k is the standard deviation of the forecast error.

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).[11] Therefore, these instruments can be used to compute monetary

[7] In this clasification, we followed Andersen, Bollerslev, Diebold, and Vega (2005).

[8] All these announcements are released monthly, except the FOMC announcements that occur approximately every six weeks.

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

[10] This data was kindly provided by Informa Global Markets/MMS. Balduzzi, Elton, and Green (2001) conclude 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.

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

policy surprises surrounding FOMC announcements as follows:

$$S_{it} \equiv i_t - E_{t-1} i_t = \left(\frac{D}{D-d} \Delta f f_t \right) \tag{3.8}$$

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.

Table 3.1 presents a preliminary analysis using liquidity measures constructed from daily data on the S&P500 and the S&P500 futures contract. These measures are computed for subsamples of different announcement days and non-announcement days. Announcement days are grouped based on the clasification described above and, within each category, they are listed in chronological order of their release. For the S&P500, the first column reports the square-root variant of the Amihud (2002) illiquidity ratio, which is the average (over the subsample days) of the square-root of the ratio between the absolute daily return and the daily (dollar) trading volume.[12] As mentioned in Hasbrouck (2005), this measure loosely corresponds to $\widetilde{\lambda}$ in Equation (3.5), but it captures the absolute return impact of a cumulative unsigned volume rather than the return impact of a comulative order flow. A larger value of this measure indicates less liquidity and larger impacts of the trading acativity. The second column reports a T-test of equality of means between the group of type-k announcement days and the group of non-announcement days. These measures and tests suggest that employment days as well as retail sales days exhibit significant less liquidity than non-announcement days. The last two columns of Table 3.1 report the same measures for the S&P500 futures contract. The results indicate that employment, construction spending, and NAPM days are significantly less liquid than non-announcement days.

This preliminary analysis suggests that announcement days might show diferences in liquidity. More intestingly, in both markets employment announcement days show evidence of a drop in liquidity linked in general to larger price impacts and/or bid-ask spreads that might be associated with increases in asymmetric information costs.

[12]Using square-root variants of liquidity ratios is suggested in Hasbrouck (2005) to smooth the extreme values exhibited by the original measures.

The following section presents a structural analysis to further evalute these preliminary findings.

3.4 Model Specification and Econometric Approach

I extend the version of the augmented Roll (1984) model with trade effects on the fundamental price presented in Hasbrouck (2004, 2005). Although this microstructure framework has been motivated in the spirit of sequential trade models, the economic intuition of the strategic trade model presented in Appendix C1 remains valid, and the estimated asymmetric information spread component, given by the order flow parameters, can be related to the "$Kyle's\ lambda$" type parameter discussed in this appendix.[13] The extensions included here are the following. First, I introduce macroeconomic news effects on the fundamental price, which allows for jumps on announcement days. Second, I introduce differentiated (average) order flow effects on the fundamental price associated with different regimes linked to announcement and non-announcement days. In this context, the model can be stated as follows. Let the fundamental price in Equation (3.6) take the following form:

$$m_t = m_{t-1} + (\widetilde{\lambda} + I_{k,t} a_k) V_t q_t + u_t, \tag{3.9}$$

where $q_t \in \{1, -1\}$ denotes the trade direction (1 if the t trade is a buy order, -1 if the t trade is a sell order), $q_t \sim Bernoulli(1/2)$, V_t is an affine function of trading volume, and $I_{k,t}$ is an indicator of type-k announcement regime. As described in Section 3.2, $V_t q_t$ represents signed volume as a proxy of order flow. Moreover, the term $(\widetilde{\lambda} + I_{k,t} a_k) V_t q_t$ characterizes the asymmetric information spread component. In addition, u_t reflects new public information as follows:

$$u_t = \varepsilon_t + \beta S_{k,t}, \tag{3.10}$$

[13] Back and Baruch (2004) find that the bid-ask spread in the Glosten and Milgrom (1985) model is approximately twice the order size multiplied by the "Kyle's lambda" when the order size is not too big.

where $\varepsilon_t \sim iidN(0, \sigma_\varepsilon^2)$, and $S_{k,t}$ represents the news variables (or a function of the news variables) defined in Equations (3.7) and (3.8). The permanent-transitory decomposition is completed by specifying an equation for the observed (log) trade price:

$$p_t = m_t + cq_t \tag{3.11}$$

Although the original setup of this model refers to intradaily price dynamics, the model has the same form under time aggregation, as pointed out by Hasbrouck (2005). This allows us to infer the microstructure parameters from estimation based on daily data. In terms of interpretation of the structural model, parameters $\widetilde{\lambda}$ and a_k characterize the order flow effects associated with the asymmetric information aspects discussed in Section 3.2; parameter β_k measures the direct impact of (*type-k*) public news on the fundamental price, capturing the fundamental news effects discussed in the beginning of Section 3.2; and parameter c characterizes the average spread as a measure of aggregated transaction costs (excluding asymmetric information costs). Even though the goal of this study is not the analysis of these transaction costs, as it is in the simplest version of Roll's model, I maintain the structural form of the model and direct my attention to the asymmetric information parameters and the news effects.

Based on this setup, the returns and their properties can be associated with contemporaneous news effects and market microstructure features. Indeed, from Equations (3.9)-(3.11), the model implies observed returns:

$$\Delta p_t = c\Delta q_t + (\widetilde{\lambda} + I_{k,t}a_k)V_t q_t + \beta_k S_{k,t} + \varepsilon_t, \tag{3.12}$$

which leads to the following expression for the conditional variance, given some information set Φ_{t-1}.[14]

$$\begin{aligned} Var\left(\Delta p_t | \Phi_{t-1}\right) \;&=\; 2c^2 + (\widetilde{\lambda} + I_{k,t}a_k)^2 E(\textit{volume}_t^2 | \Phi_{t-1}) + c(\widetilde{\lambda} + I_{k,t}a_k) \\ &\quad\; E(\textit{volume}_t | \Phi_{t-1}) + \beta_k^2 Var(S_{k,t} | \Phi_{t-1}) + \sigma_\varepsilon^2 \end{aligned} \tag{3.13}$$

To estimate this model, I follow the Bayesian approach of Hasbrouck (2004), which

[14]Recall that q_t is assumed to be independent of V_t and $E\left(q_t^2 | \Phi_t\right) = 1$.

was motivated by the power of MCMC techniques for accommodating latent data. In this setup, the parameters of the model are included in $\Theta = \left\{c, \widetilde{\lambda}, a_k, \beta_k, \sigma_\varepsilon^2\right\}$. The latent data include the sequence of trade direction indicators $q = \{q_1, q_2, ..., q_N\}$ over the sample period.[15] Given the assumptions described above, it is possible to directly sample iteratively from all the complete conditional distributions, which makes the MCMC algorithm a Gibbs sampler. The following steps describe the Gibbs sampler procedure that I use to obtain a sequence of draws from the unattainable desired posterior $F(\Theta, q|\Omega)$ given a vector of initial values $\left(\Theta^{(0)}, q^{(0)}\right)$, where Ω denotes the set of observed data, which includes closing prices, trading volume, announcement indicators, and news variables.

Step 1 Draw $\Theta^{(1)}$ from $P\left(\Theta|q^{(0)}, \Omega\right)$

Step 2 Draw $q^{(1)}$ from $P\left(q|\Theta^{(1)}, \Omega\right)$

Step 3 Continue in this fashion until generate a sequence of random variables $\left\{\Theta^{(j)}, q^{(j)}\right\}_{j=1}^{J}$ whose limiting distribution is the desired posterior.

To fully describe the algorithm, the following proposition characterizes the conditional distributions on steps 1 and 2.

Proposition 3.1. Consider the model and underlying assumptions described in Equations (3.9)-(3.11). Assuming normal/inverted gamma priors on $\Theta = \left\{\left(c, \widetilde{\lambda}, a_k, \beta_k\right), \sigma_\varepsilon^2\right\}$, then the conditional posterior $P(\Theta|q, \Omega) \sim MVN/IG$, as in the standard Bayesian multivariate regression model.

Moreover, the conditional posterior distribution for the latent trade direction at time t is defined as follows:

$$P(q_t|q_{-t}, \Theta, \Omega) \propto \phi\left(M_t^*, \sqrt{\frac{\sigma_\varepsilon^2}{2}}\right) \times$$

$$\frac{\exp\left\{\frac{-\left(m_{t-1} - m_{t+1} + \widetilde{\lambda}_t V_{t+1} q_{t+1} + \beta S_{k,t+1} + \widetilde{\lambda}_t V_t q_t + \beta S_{k,t}\right)^2}{4\sigma_\varepsilon^2}\right\}}{\exp\left\{\frac{-\Psi_{1,t}^2}{4\sigma_\varepsilon^2}\right\} + \exp\left\{\frac{-\Psi_{2,t}^2}{4\sigma_\varepsilon^2}\right\}},$$

---

[15] Although the sequence of efficient prices $m = \{m_1, m_2, ..., m_N\}$ represents also a vector of unobserved latent variables, the structural Equation (3.11) pins down its values once q and c are known.

where ϕ denotes the normal pdf, $q_{-t} = \{q_1, q_2, ..., q_{t-1}, q_{t+1}, ..., q_N\}$, $M_t^* = \frac{1}{2}(m_{t-1} + \widetilde{\lambda}_t V_t q_t + \beta_k S_{k,t} + m_{t+1} - \widetilde{\lambda}_{t+1} V_{t+1} q_{t+1} - \beta_k S_{k,t+1})$, $\Psi_{1,t} = m_{t-1} - m_{t+1} + \widetilde{\lambda}_t V_{t+1} q_{t+1} + \beta S_{k,t+1} + \widetilde{\lambda}_t V_t + \beta S_{k,t}$, $\Psi_{2,t} = m_{t-1} - m_{t+1} + \widetilde{\lambda}_t V_{t+1} q_{t+1} + \beta S_{k,t+1} - \widetilde{\lambda}_t V_t + \beta S_{k,t}$, $\widetilde{\lambda}_t = (\varphi + I_{k,t} a_k)$ and $m = p - cq$.

The first part of Proposition 1 is straightforward from Equation (3.12), which, once q is known, fits in the standard Bayesian multivariate regression framework where the result is well known. The second part is developed in Appendix C2. Proposition 1 is the basis of the Gibbs sampler procedure used for estimation of the parameters in the structural microstructure model. Empirical estimation results are discussed in the next section.

3.5 Estimation Results

I estimate the model described above considering an affine function of volume in the order flow term of Equation (3.9).[16] Thus, $V_t = (1,$*trading volume at day* $t)'$, $\widetilde{\lambda} = (\lambda_0, \lambda_1)$, and $a_k = (a_{0,k}, a_{1,k})$. Table 3.2 presents descriptive statistics for the S&P 500 trading volume on non-announcement and announcement days.[17] In addition, I consider asymmetric news effects by accounting for differential effects associated with positive and negative shocks. Therefore, the model can be summarized from the specifications for fundamental and observed prices in Equations (3.9) and (3.11):

$$m_t = m_{t-1} + (\widetilde{\lambda} + I_{k,t} a_k) V_t q_t + u_t,$$

$$p_t = m_t + c q_t$$

However, in lieu of Equation (3.10), the following equation describes the public information term:

$$u_t = \beta_{1,k} S_{k,t}^{+} + \beta_{2,k} S_{k,t}^{-} + \varepsilon_t, \tag{3.14}$$

[16] Glosten and Harris (1987) suggest a linear affine function of the number of traded shares to characterize the order size effect on the asymmetric information spread.

[17] The types of announcement days included in this table correspond to the announcements that show significant effects for the index in my estimation results (see Table 3.2).

where

$$S^{+}_{k,t} = \begin{cases} S_{k,t} & \text{if } S_{k,t} \geq 0 \\ 0 & Otherwise \end{cases}$$

$$S^{-}_{k,t} = \begin{cases} |S_{k,t}| & \text{if } S_{k,t} < 0 \\ 0 & Otherwise \end{cases},$$

and therefore, Equation (3.12) becomes:

$$\Delta p_t = c\Delta q_t + (\widetilde{\lambda} + I_{k,t}a_k)V_t q_t + \beta_{1,k}S^{+}_{k,t} + \beta_{2,k}S^{-}_{k,t} + \varepsilon_t \tag{3.15}$$

Considering these modifications and applying Proposition 1, Table 3.3 presents estimation results for the S&P500.[18] As mentioned in Section 3.4, I focus on the interpretation of the asymmetric information coefficient vectors, $\widetilde{\lambda}$ and a_k, and those corresponding to the direct news impacts, $\beta_{1,k}$ and $\beta_{2,k}$. For reasons of space, I present results only for the announcements that show significance on the coefficients of interest. The results in columns (1) and (2) show that news effects are important for variables regarding real activity, such as non farm employment payrolls, the unemployment index, and retail sales; investment, such as construction spending; prices, such as the consumer price index; and monetary policy, such as the federal funds rate. In terms of output surprises in real activity and investment, the effects indicate that positive shocks decrease returns and negative shocks increase returns. These results are in line with Andersen, Bollerslev, Diebold, and Vega (2005) and Boyd, Jagannathan, and Hu (2005) given that most of the years included in the sample period correspond to expansions, where bad news has a puzzling positive impact due to a dominant discount rate effect. In contrast, positive inflation surprises show the expected negative effect in the stock index, and lower than expected interest rates show a positive impact.

Regarding asymmetric information effects, I find significant order flow effects as a general feature of all trading days. In line with the empirical evidence on price impacts, the asymmetric information effect associated with $\widetilde{\lambda}$ is significant. Columns (3) and (4) in Table 3.3 show that the effect is mostly driven by the slope coefficient λ_1. Indeed,

[18] I also consider the possibility of structural breaks in the volatility of the efficient price by applying the group of tests presented in Andreou and Ghysels (2002). This procedure indicates two likely breaking points, one corresponding to 10/24/1995 and the other to 3/26/1997.

while the slope coefficient λ_1 is highly significant for all the cases, the intercept coefficient λ_0 is only weakly significant. This is illustrated by the first panel of Figure 3.1 that shows an increasing cumulative order flow effect, $\lambda_0 + \lambda_1 \mathit{volume}_t$, as well as confidence intervals for the relevant range of trading volume in the sample.

In relation to announcements days, although I find that the order flow impact is not significant for most of the announcements, the analysis provides an interesting result in terms of the economic content of employment news. Besides the direct news effects, which are consistent with the empirical literature, I find a significant increase in the asymmetric information spread on employment announcement days. Columns (6) and (7) in Table 3.3 indicate that the intercept coefficient of the incremental asymmetric information term is significant. The slope coefficient does not suggest any significant increase in λ_1 on these event days. This pattern is illustrated in Figure 3.1, where the second panel shows how the incremental cumulative effect on employment announcement days, $a_0 + a_1 \mathit{volume}_t$, is driven by the significant intercept term; and the third panel shows how the cumulative effect shifts upwards on employment days. An interesting point in these graphs is the average effect, which refers to the cumulative impact when these affine functions are evaluated on the average trading volume. Columns (5) and (8) of Table 3.3 show that the average effect of order flow on employment announcement days almost duplicates the average effect of about 0.35 basis points on non-announcement days. Moreover, the size of the average (incremental) order flow effect suggests that the asymmetric information component is of the same order of magnitude as the fundamental news effect on employment announcement days.

Table 3.4 presents F-tests regarding the coefficients on the specification with employment news. The first column suggests that all of the coefficients in the returns equation are jointly significant; the tests in the second column reject the null of a zero intercept coefficient in the order flow component; the tests in the third column confirm that the slope parameter is not driving the effect; and the tests in the last column indicate that the two employment order flow coefficients are jointly significant.

These results suggest that employment information has particular characteristics that make the mechanism through which it is incorporated into stock prices different. To understand the reason for the increase in the order flow effect on employment announcement days, it is useful to review the motivation provided in Section 3.2 and Appendix C1, where increases in the level of asymmetric information could be associated with one (or a combination) of the following reasons: increases in the volatility of the fundamental price, decreases in the volatility of liquidity demands, decreases in the precision of the signal for a sufficiently large number of informed traders, or decreases in the number of these informed traders. In the context of employment announcement days, some of these reasons seem less likely than others. For instance, it would be difficult to believe that on employment announcement days there is a drop in the number of informed traders compared to days in which other macroeconomic announcements are released. Such a case seems neither economically nor empirically feasible. Regarding liquidity trading, Table 3.2 reports descriptive statistics of the trading volume on employment and non-employment days. Neither the mean nor the standard deviation are significantly different on employment announcement days (see the last two columns in Table 3.2). Indeed, based on the variance ratio test presented in Table 3.2, I cannot reject the null hypothesis of equal variances on employment and non-employment days. Thus, a drop in the volatility of liquidity demands on employment announcement days also seems unlikely. Therefore, the most likely explanations are related to the informative content of the news. In fact, a decrease in the precision of the interpretation of employment news implications for asset prices, and/or an increase in the volatility of the fundamental price due to the information arrival process, are potential (interrelated) explanations for the incremental order flow impact observed on employment announcement days. Moreover, they are in line with the argument that interpretation of public news might be heterogeneous due to uncertainty about future policy decisions and economic conditions.

These empirical results might be conservative given the daily time aggregation considered in the estimation of the structural model. The fact that most of the announcements are released in the morning, combined with the use of closing prices and a structure that links the order flow component with the last trading activity of a day, indicate that the model is capturing permanent effects in stock prices several hours after the news arrival. Indeed, an important part of the intradaily adjustments is missed with this time aggregation and, therefore, my specification might find difficulties in accounting for other permanent impacts that might be reversed or smoothed during the day due to the arrival of other information. If this is the case, the news effects might be underestimated in my analysis.[19]

The asymmetric information effects observed on employment announcement days are also relevant to explain empirical patterns in conditional volatility. Equation (3.13) suggests that employment announcement days present larger conditional volatility in terms of observed returns due to the incremental asymmetric information effect. This result is consistent with recent empirical studies that provide evidence of larger stock market volatility on employment announcement days; examples of such studies include Flannery and Protopapadakis (2002) and Rangel (2004).

In the following section, I present a robustness analysis of my empirical results based on a revision of reactions in other financial markets (futures markets), and I provide further discussion of the economic intuition behind my findings for employment announcement days.

3.6 Robustness: A Multi-market analysis

To confirm the empirical evidence obtained in Section 3.5, I estimate the structural model summarized in Equation (3.15) using data on the S&P 500 futures contract. This is convenient since using this data permits us to avoid possible concerns about the aggregation of trading volume in the actual index. Table 3.5 presents descriptive statistics for the daily (dollar) volume of the S&P 500 futures contract on announcement and non-announcement days. Table 3.6 shows the estimation results for this market. The first two columns confirm the results obtained in the previous section in terms of fundamental news impacts. Indeed, sizes and signs of the estimated effects are fully consistent with those obtained for the actual index (see Table 3.3). Moreover, columns (5) and (8)

[19] An additional issue is how accurate are the daily proxies of microstructure features. Comparing daily and intradaily estimates for individual stocks, Hasbrouck (2005) finds correlations around .94 for transaction costs and around .75 for price impacts of trades.

in Table 3.6 also confirm the presence of significant incremental order flow effects on employment announcement days.[20] Interestingly, in this market the slope coefficient, $a_{1,k}$, is driving the effect (see columns (6) and (7)). This suggests that the order flow impact is stronger in days with large levels of trading volume. Figure 3.2 illustrates this point by showing the changes in slope between the cumulative asymmetric information effect (on all days) and the incremental asymmetric information effect (on employment announcement days). Despite the difference in the structure of the asymmetric information component showed in Figures 3.1 and 3.2, results from the futures market reinforce the empirical findings discussed in the previous section.

To explore further the nature of the reactions in stock markets implied by the structural specification discussed in Section 3.4, I study reactions to macroeconomic news in other financial markets. For instance, an analysis of bond markets describes the behavior of the interest rate component of asset prices. Moreover, it provides a barometer indicating the market evaluation of future Fed actions when macroeconomic shocks occur. Similarly, foreign exchange markets can lend insight into the effect of output shocks on expectations of future growth.

An exploration of futures data on these markets suggests that taking into account the seasonality in trading volume is important. Figure 3.3 presents the pattern of trading (dollar) volume for the 5-Year and 10-Year US Treasury Note contracts. The evident seasonal components are associated with the contract months, namely March, June, September, and December. Given that changes in volume associated with this contract design do not stem from informational asymmetries, I include an indicator variable for these contract months in the order flow term of Equation (3.9), as follows[21]:

$$m_t = m_{t-1} + (\widetilde{\lambda} + \widetilde{\lambda}_{cm} I_{cm,t} + a_k I_{k,t}) V_t q_t + u_t, \tag{3.16}$$

where $I_{cm,t}$ is an indicator of the contract months of the Treasury notes.[22] In addition,

[20] Also, note that, in this market, days of FOMC meetings are also associated with a significant increment in the order flow effect. This new finding might add more support to the argument that reactions in the stock market are linked to revisions in expectations of private agents (that might be heterogeneous) in response to Fed actions. Further discussion is presented at the end of this section.

[21] This specification was also estimated for the case of the S&P 500 futures contract. No significant changes in the results were found.

[22] u_t is described in Equation (3.14), $V_t = (1, \mathit{volume}_t)$, and the order flow coefficients, $\widetilde{\lambda}$, $\widetilde{\lambda}_{cm}$, and a_k,

I perform tests for structural breaks in the variance of the fundamental price innovation in the same fashion as in the previous section.[23]

Table 3.7 shows the estimation results for the two bond futures contracts, considering employment announcements.[24] The first two columns indicate that instantaneous fundamental news effects are highly significant, and they are consistent with the predictions of the asset pricing view described in Section 3.2, under power utility. Thus, employment shocks related to positive output shocks affect bond prices negatively (or interest rates positively). In contrast, employment shocks associated with negative output shocks (like increases in the unemployment rate) impact bond prices positively (or interest rates negatively). More remarkable is the finding that order flow effects are also highly significant for both contracts. In this case, the intercept and slope coefficients drive the asymmetric information effect, whose average value is more than three times that of a non-announcement day.

These results suggest that the reactions observed in the stock market on employment announcement days are driven in an important part by the interest rate component. This is the case not only for the order flow effect, but also for the fundamental news impacts. The finding that bad news for employment is good news for stocks in expansionary periods has been justified in Boyd, Jagannathan, and Hu (2005) and Andersen, Bollerslev, Diebold, and Vega (2005) arguing that information about interest rates dominates during expansions. Nevertheless, the new empirical contribution of the present study consists in pointing out that the unexplored order flow effects in the stock market observed on employment announcement days are also driven by asymmetric information regarding the behavior of long term interest rates.

In addition, the interest rate effect can be described using the argument of Gurkaynak, Sack, and Swanson (2005) about the excess sensitivity of long term interest rates to

are 2×1 vectors.

[23]I find three breaks for each contract. One matches in both contracts and corresponds to 09/08/1998. The other occurs in the same year and month, but at a different day: 12/29/2000 for 5-Year notes and 12/19/2000 for 10-Year notes. And the last one does not match: 08/02/96 for 5-Year notes and 08/03/95 for 10-Year notes. However, the results are not highly sensitive to accounting for these changing points, particularly the breaks that do not match in both contracts.

[24]Results on the other 17 announcements are not presented in order to conserve space, but they are available upon request.

macroeconomic fundamental news. They find that long term interest rates react significantly to news that would be expected to have only transitory effects on the short-term interest rate. They argue that this phenomenon is due to adjustments in private agents' expectations of the long run inflation target. My findings support that there is, indeed, excess sensitivity of long term interest rates in response to employment news, and complement the results found in Gurkaynak, Sack, and Swanson (2005) by suggesting that, not only do private agents revise their expectations about future Fed actions, but also their revisions are heterogeneous. This result is also consistent with the implications of the theoretical model presented in Appendix C1. Indeed, revisions of private agents' expectations about future states of the economy can be associated with increases in volatility of the fundamental price, and heterogenous revisions can be associated with decreases in the precision of the news implication for stock prices.

Table 3.8 presents estimation results for a currency market, the $US/YEN futures contract. In line with Andersen, Bollerslev, Diebold, and Vega (2005), I find that positive employment (output) shocks appreciate the dollar (see columns (1) and (2) in Table 3.8). However, additional order flow effects on employment announcement days are not present.[25] This suggests that the impact of employment news on the asset pricing component associated with growth rate expectations (future payoffs) is not responsible for the asymmetric information effect. Therefore, my conclusion that this last effect comes from the interest rate component is maintained.[26]

3.7 Concluding Remarks

This paper explores two mechanisms that describe the process through which macroeconomic information enters stock prices, in order to evaluate heterogeneity in the market assessment of public announcements. One mechanism is related to the fundamental price impact of a surprise, which is reflected as a direct instantaneous reaction of stock

[25]The order flow effect in currency markets on regular days has been studied by Evans and Lyons (2004).

[26]Further analysis would be required to isolate the effect of employment news in the risk premium component. I leave this extension for future work.

prices to the news. The second is related to the process of aggregating heterogeneous information in the market stemming from heterogeneous beliefs about the price impact of a macroeconomic surprise. This latter effect is reflected in a permanent post announcement impact of order flow in the fundamental price. Heterogeneity of beliefs, associated with heterogeneous assessments of agents about future Fed policies and/or future states of the economy, makes the news implication for stock prices less precise. I provide theoretical motivation and empirical support for the presence of both effects on announcement days.

A modified version of the structural microstructure model introduced by Hasbrouck (2004) is the basis of my empirical analysis. Announcement effects, and differential order flow impacts associated with announcement regimes, are allowed to have a permanent effect on the fundamental price. The analysis is based on daily observations of closing prices and trading volume. I follow the econometric approach of Hasbrouck (2004, 2005) to estimate the microstructure parameters from incomplete data using the Gibbs sampler.

In addition to fundamental news impacts associated with announcements on real activity (including employment), investment, inflation and monetary policy, order flow effects also are present on employment announcement days. Moreover, they are the same order of magnitude as fundamental news effects. Futures markets provide further evidence of this incremental asymmetric information effect. Along with other measures of liquidity based on daily data such as Amihud illiquidity ratios, these results add more evidence of liquidity decreases in equity markets on employment announcement days. From a theoretical perspective, increases in the price impact of order flow on employment announcement days could more likely be explained by either increases in the dispersion of the news interpretation in terms of its asset price implications, or increases in volatility of fundamental prices. Both reasons are consistent with heterogeneity of beliefs.

An analysis of bond and currency markets suggests that the asymmetric information effect observed in the stock market might be driven by the interest rate component of stock prices. Excess sensitivity of long-term interest rates to employment news is found in terms of both instantaneous fundamental news impacts and order flow effects. This confirms the argument that the asymmetric information effect observed on employment announcement days is due to heterogeneous beliefs and/or revisions about long-run Fed policies driven by employment surprises. This finding is also consistent with a decrease in the precision of the news implication for stock prices when employment surprises arrive.

The incremental asymmetric information effect observed on employment announcement days also provides an explanation for (at least part of) the excess of returns volatility observed on such days, according to recent empirical evidence. This opens interesting questions regarding the contribution of this effect to the excess of volatility relative to the contribution associated with the volatility of the symmetric information term. In this context, an intradaily analysis will provide a richer dynamic framework to explain this phenomenon. Moreover, introducing specifications that allow more general time varying news and order flow impacts are also appealing to help get a better understanding of the dynamics of these two mechanisms characterizing the information structure on announcement days. I leave these extensions for future research.

3.8 Figures

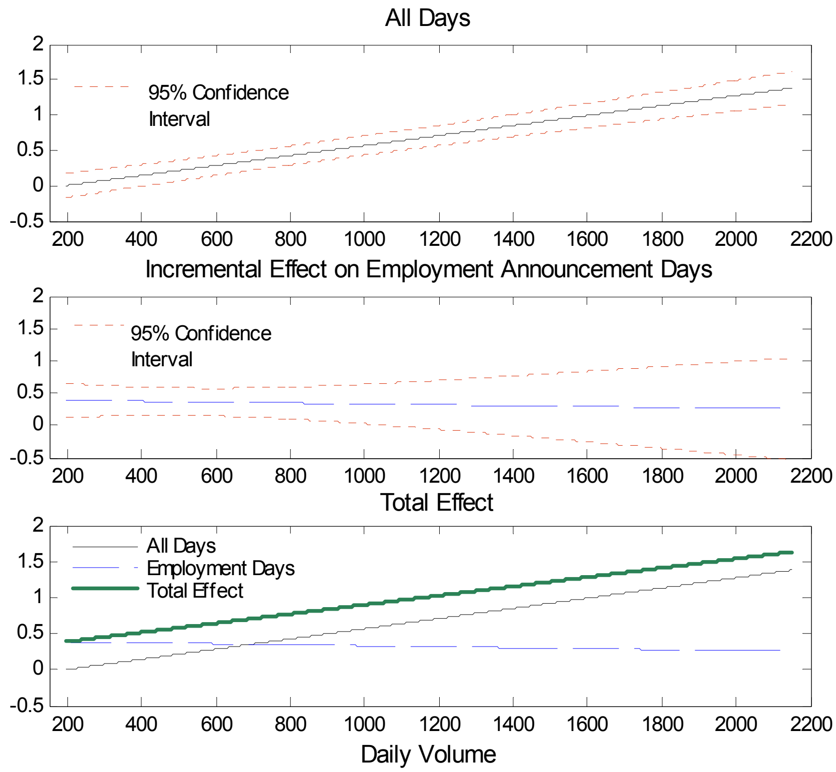

Figure 3.1: Cumulative Effect SP500

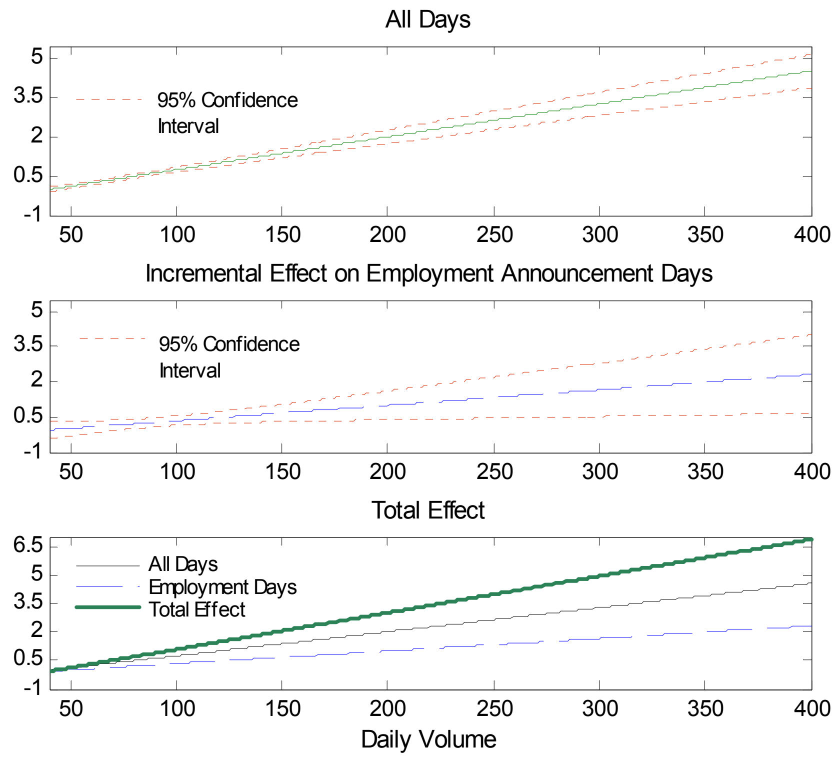

Figure 3.2: Cumulative Effect Futures SP500

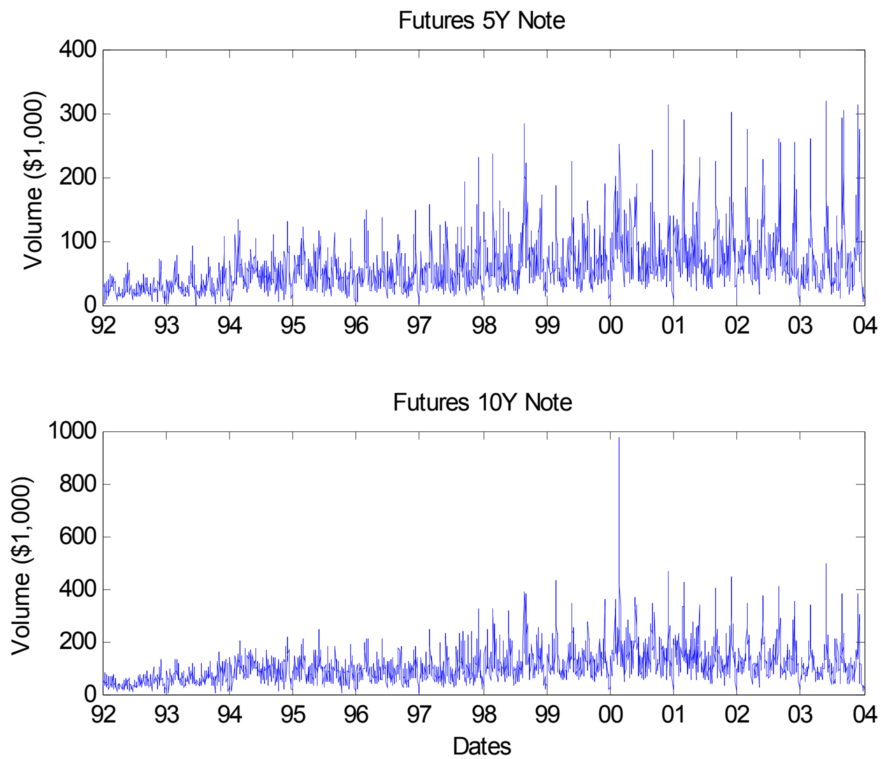

Figure 3.3: Trading Volume Futures Bond Markets

3.9 Tables

Table 3.1: Liquidity Measures Based on Daily Data (1992-2003)

	S&P500		Futures S&P500	
Day	*Amihud*[a]	*t-stat*[b]	*Amihud*[a]	*t-stat*[b]
Non_announcement	0.00000321		0.0002905	
Real Activity				
Unemp./Nonfarm Payroll Emp.	**0.0000037**	-3.16	**0.00032**	-2.42
Retail Sales	**0.0000035**	-2.16	0.00028	0.93
Industrial Production	0.0000032	0.36	0.00027	1.73
Capacity Utilization	0.0000032	0.21	0.00027	1.60
Personal Income	0.0000033	-0.58	0.00031	-1.57
Consumer Credit	0.0000033	-0.36	0.00027	1.60
Consumption				
New Home Sales	0.0000032	0.21	0.00029	-0.16
Personal Consumption Expenditure	0.0000033	-0.58	0.00031	-1.57
Investment				
Durable Goods Orders	0.0000031	0.69	0.00030	-1.21
Construction Spending	0.0000032	-0.17	**0.00034**	-3.49
Business Inventories	0.0000030	1.27	0.00027	1.87
Trade				
Goods and Services Trade Balance	0.0000033	-0.66	0.00029	0.27
Prices				
Producer Price Index	0.0000031	0.61	**0.00027**	2.10
Consumer Price Index	0.0000032	-0.03	0.00028	0.95
Forward Looking				
NAPM	0.0000033	-0.36	**0.00034**	-3.90
Housing Starts	0.0000031	0.64	0.00028	1.12
Leading Indicators	0.0000030	1.69	0.00030	-0.73
FOMC				
Target Federal Funds Rate	0.0000033	-0.56	0.00031	-1.30

a) Square-root variant of Amihud (2002) illiquidity ratio: $mean\left(\sqrt{\frac{|r_t|}{vol_t}}\right)$

b) Bold: significant at 5% level.

Table 3.2: Descriptive Statistics for SP500 Trading Volume

Type of Announcement Day	Obs	Mean	Std. Dev.	95% Conf. Interval for Mean		T-Test	F-Test
Non-Announcement	2892	695.22	457.01	678.56	711.88		
CPI	132	763.62	488.94	679.43	847.80	-1.68*	0.87
Employment	141	708.96	441.91	635.39	782.54	-0.29	1.02
FFR (FOMC)	102	723.29	556.68	613.95	832.63	-0.56	0.67*
Retail Sales	142	703.65	430.53	632.23	775.08	-0.15	1.14
Construction Spending	141	714.83	455.47	638.99	790.66	-0.44	1.01

Source: Data from The Center for Research in Security Prices (CRSP)
Sample Period: From January 1, 1992 to December 31, 2003
Notes: Volume is given in millions of shares. T-Test denotes a test for equality of means with respect to Non-Announcement days, i.e., Ho: Mean(Non-Announcement Days) = Mean(Announcement Days). F-Test denotes a variance ratio test for Ho: Std. Dev(Non-Announcement) = Std. Dev(Announcement) against Ha: Std. Dev(Non-Announcement) > Std. Dev.(Announcement). A size of 5% is used in both tests (*p<.05).

Table 3.3: Estimation Results for SP500

Announcement	News Effects		Asymmetric Information Coefficients					
			$\tilde{\lambda}$			a_k		
REAL ACTIVITY	$\beta_{1,k}$	$\beta_{2,k}$	λ_0	λ_1	*Average Effect*‡	a_0	a_1	*Average Effect*‡
Nonfarm Payroll	-0.2711*	-0.0047	-0.1385	0.00071*	0.3601*	0.3996*	-0.00007	0.3514*
	-0.1233	-0.1148	-0.0946	-0.00008	-0.0636	-0.1632	-0.00023	-0.1106
Unemployment	0.035	0.0202	-0.1659**	0.00072*	0.3404*	0.4255*	-0.00018	0.3013*
	-0.1288	-0.0969	-0.0954	-0.00008	-0.0647	-0.1651	-0.00025	-0.1101
Retail Sales	-0.0585	0.3172*	-0.1831**	0.00072*	0.3241*	0.1215	-0.00055	-0.2632
	-0.1185	-0.1306	-0.0998	-0.00008	-0.0698	-0.3715	-0.00083	-0.4136
INVESTMENT								
Construction Spending	-0.0122	0.2165*	-0.1641	0.00069*	0.3262*	-0.1199	0.00032	0.1093
	-0.0994	-0.1088	-0.1095	-0.00008	-0.0764	-0.2035	-0.00024	-0.1242
PRICES								
CPI	-0.4613*	0.1197	-0.1733**	0.00072*	0.3355*	0.0905	-0.00051	-0.3138
	-0.1341	-0.0934	-0.105	-0.00008	-0.0735	-0.2984	-0.00066	-0.3367
MONETARY POLICY								
FFR	-0.1003	0.1792**	-0.1772**	0.00070*	0.3150*	-0.0816	0.00027	0.122
	-0.1831	-0.0955	-0.1032	-0.00008	-0.0735	-0.4266	-0.00035	-0.2335

Source: Data from The Center for Research in Security Prices (CRSP)

Sample Period: From January 1, 1992 to December 31, 2003

Notes: Estimates correspond to the fundamental price specification $m_t = m_{t-1} + (\tilde{\lambda} + a_k I_{k,t}) V_t q_t + \beta_{1,k} S^{+}_{k,t} + \beta_{2,k} S^{-}_{k,t} + \varepsilon_t$,

where $\tilde{\lambda} = (\lambda_0, \lambda_1)$, $a = (a_0, a_1)$, $V_t = (1, volume_t)'$.

Estimates for transaction costs and volatilities are not reported, but they are available upon request.

Standard errors in parentheses.

*) 5% Significant.

**) 10% Significant.

‡) $\lambda_0 + \lambda_1 Avg\ (volume)$

$a_0 + a_1 Avg\ (volume)$

Table 3.4: Coefficient Tests

Announcement	**F Tests**			
	$B=0$‡	$\alpha_{0,k}=0$	$\alpha_{1,k}=0$	F2&F3
REAL ACTIVITY	F1	F2	F3	F4
Nonfarm Payroll	67.37*	14.05*	0.77	16.04*
	(12.32)	(6.95)	(1.38)	(5.52)
Unemployment	62.78*	15.87**	1.73	14.32*
	(11.35)	(8.28)	(2.58)	(5.84)

Standard errors in parentheses.
*) 5% significant.
**) 10% significant.
‡) $B=(c, \lambda_0, \lambda_1, \alpha_{0,k}, \alpha_{1,k}, \beta_{1,\kappa}, \beta_{2,\kappa})$

Table 3.5: Descriptive Statistics for Futures SP500 Trading Volume

Type of Announcement Days	Obs	Mean	Std. Dev.	95% Conf. Interval for Mean		T-Test	F-Test
Non-Announcement	2865	82.41	41.42	80.89	83.92		
CPI	132	101.82	53.33	92.64	111.00	-5.19*	0.60*
Employment	140	88.10	36.60	81.98	94.21	-1.39	1.34
FFR (FOMC)	101	82.21	44.86	73.35	91.06	0.26	0.88
Retail Sales	142	100.05	55.50	90.85	109.26	-4.88*	0.55*
Construction Spending	140	80.44	34.52	74.67	86.21	0.81	1.52

Source: Thomson Financial Datastream/Chicago Mercantile Exchange.
Sample Period: From January 1, 1992 to December 31, 2003.
Notes: Units are expressed in terms of dollar volume ($1000). T-Test denotes a test for equality of means with respect to Non-Announcement days, i.e., Ho: Mean(Non-Announcement Days) = Mean(Announcement Days). F-Test denotes a variance ratio test for Ho: Std. Dev(Non-Announcement) = Std. Dev(Announcement). CPI and Retail Sales days favor the alternative Ha: Std. Dev(Non-Announcement)<Std. Dev.(Announcement) at the 5% level (*p<.05).

Table 3.6: Estimation Results for Futures SP500

Announcement	News Effects		Adverse Selecction Coeff					
			$\widetilde{\lambda}$			a_k		
REAL ACTIVITY	$\beta_{1,k}$	$\beta_{2,k}$	λ_0	λ_1	*Average Effect**	a_0	a_1	*Average Effect**
Nonfarm Payroll	-0.3107*	0.0084	-0.5191*	0.0127*	0.5349*	-0.3226	0.0066*	0.2614*
	-0.1193	-0.106	-0.078	-0.001	-0.0403	-0.2696	-0.0027	-0.0973
Unemployment	-0.0255	-0.04	-0.5280*	0.0127*	0.5281*	-0.3601	0.0067*	0.2330*
	-0.1217	-0.0914	-0.0793	-0.001	-0.0419	-0.2972	-0.0029	-0.1083
Retail Sales	-0.0229	0.2892*	-0.5651*	0.0131*	0.5276*	0.3325	-0.0064	-0.3091
	-0.1057	-0.1306	-0.0807	-0.001	-0.0424	-0.3877	-0.0046	-0.3106
INVESTMENT								
Construction Spending	0.2008	0.2963**	-0.5163*	0.0127*	0.5448*	-0.9472	0.0131**	0.1095
	-0.1358	-0.1542	-0.0779	-0.001	-0.0409	-0.6363	-0.0077	-0.0995
PRICES								
CPI	-0.4868*	0.1043	-0.5393*	0.0131*	0.5493*	0.062	-0.0028	-0.2191
	-0.1445	-0.0935	-0.079	-0.0009	-0.0409	-0.2534	-0.0034	-0.1894
MONETARY POLICY								
FFR	-0.1729	0.1744*	-0.5298*	0.0127*	0.5238*	-0.4713*	0.0087*	0.2460*
	-0.2075	-0.0846	-0.0802	-0.001	-0.0425	-0.2345	-0.0026	-0.1029

Source: Thomson Financial Datastream/Chicago Mercantile Exchange

Sample Period: From January 1, 1992 to December 31, 2003.

Notes: Estimates correspond to the fundamental price specification $m_t = m_{t-1} + (\widetilde{\lambda} + a_k I_{k,t})V_t q_t + \beta_{1,k} S^{+}_{k,t} + \beta_{2,k} S^{-}_{k,t} + \varepsilon_t$,

where $\widetilde{\lambda} = (\lambda_0, \lambda_1)$, $a = (a_0, a_1)$, $V_t = (1, volume_t)'$.

Estimates for transaction costs and volatilities are not reported, but they are available upon request.

Standard errors in parentheses.

*) 5% Significant.

**) 10% Significant.

‡) $\lambda_0 + \lambda_1 Avg\ (volume\ )$

$a_0 + a_1 Avg\ (volume\ )$

Table 3.7: Employment Effects on Bond Futures Markets

Announcement	News Effects		Asymmetric Information Coefficients					
			$\widetilde{\lambda}$			a_k		
REAL ACTIVITY	$\beta_{1,k}$	$\beta_{2,k}$	λ_0	λ_1	*Average Effect*‡	a_0	a_1	*Average Effect*‡
				5Y Notes				
Nonfarm Payroll	-0.2403*	0.1818*	-0.1196*	0.1273*	0.0518*	0.1626*	-0.0354*	0.1047*
	-0.038	-0.0527	-0.0207	-0.0088	-0.0131	-0.0448	-0.0212	-0.0245
Unemployment	0.1493*	-0.0713*	-0.1244*	0.1277*	0.0475*	0.1768*	-0.0341**	0.1214*
	-0.0439	-0.0314	-0.0204	-0.0088	-0.0129	-0.0435	-0.0208	-0.024
				10Y Notes				
Nonfarm Payroll	-0.3839*	0.1743*	-0.2288	0.2194	0.0719*	0.2754*	-0.0782*	0.1465*
	-0.0466	-0.0522	-0.0321	-0.0136	-0.0197	-0.0662	-0.0323	-0.0341
Unemployment	0.1739*	-0.1389*	-0.2398*	0.2215*	0.0637*	0.3222*	-0.0844*	0.1840*
	-0.0645	-0.0474	-0.0324	-0.0137	-0.0201	-0.0671	-0.0331	-0.0344

Source: Thomson Financial Datastream/Chicago Mercantile Exchange.
Sample Period: From January 1, 1992 to December 31, 2003.
Notes: Estimates correspond to the fundamental price specification $m_t = m_{t-1} + (\widetilde{\lambda} + a_k I_{k,t})V_t q_t + \beta_{1,k} S^{+}_{k,t} + \beta_{2,k} S^{-}_{k,t} + \varepsilon_t$,
where $\widetilde{\lambda} = (\lambda_0, \lambda_1)$, $a = (a_0, a_1)$, $V_t = (1, volume_t)'$.
Estimates for transaction costs and volatilities are not reported, but they are available upon request.
Standard errors in parentheses.
*) 5% Significant.
**) 10% Significant.
‡) $\lambda_0 + \lambda_1 Avg\ (volume\ )$
$a_0 + a_1 Avg\ (volume\ )$

Table 3.8: Estimation Results for Futures FX US/YEN

Announcement	News Effects		Asymmetric Information Coefficients					
			$\widetilde{\lambda}$			a_k		
REAL ACTIVITY	$\beta_{1,k}$	$\beta_{2,k}$	λ_0	λ_1	*Average Effect**	a_0	a_1	*Average Effect**
Nonfarm Payroll	*-0.1794***	0.036	-0.2324*	0.0220*	0.2494*	0.1924	-0.0156	-0.2167
	-0.1073	-0.0748	-0.0372	-0.001	-0.027	-0.1394	-0.0104	-0.2836
Unemployment	0.0985	-0.1183**	-0.2543*	0.0236*	0.2634*	0.2328	-0.0168**	-0.2076
	-0.0945	-0.07	-0.0367	-0.001	-0.0273	-0.1487	-0.0096	-0.2661

Source: Thomson Financial Datastream/Chicago Mercantile Exchange.

Sample Period: From January 1, 1992 to December 31, 2003.

Notes: Estimates correspond to the fundamental price specification $m_t = m_{t-1} + (\widetilde{\lambda} + a_k I_{k,t})V_t q_t + \beta_{1,k} S^{+}_{k,t} + \beta_{2,k} S^{-}_{k,t} + \varepsilon_t$,
where $\widetilde{\lambda} = (\lambda_0, \lambda_1)$, $a = (a_0, a_1)$, $V_t = (1, volume_t)'$.

Estimates for transaction costs and volatilities are not reported, but they are available upon request.

Standard errors in parentheses.

*) 5% Significant.

**) 10% Significant.

‡) $\lambda_0 + \lambda_1 Avg(volume)$

$a_0 + a_1 Avg(volume)$

3.10 Appendix C1

3.10.1 A Simple Microstructure Model of Price Determination

To provide economic intuition on the impact of trades on fundamental prices due to heterogeneous private information, I present an extension of the Kyle (1985) model that includes noisy signals and more than one agent with superior information.[27] For expositional convenience, I present results for the simple one period model.[28]

Let p_0 represent the starting price of an asset observed before an announcement is released. Now, let v denote the post announcement fundamental value of the same asset. Assume v is normally distributed with mean p_0 and variance σ^2. Suppose I have M informed agents who get noisy signals, s_m $(m = 1, 2, ..., M)$, about the "true" price impact of a news on a particular announcement day. Specifically, $s_m = v + \varepsilon_m$, where v and ε_m are independent, and $\{\varepsilon_m\}_{m=1}^{M}$ are iid zero mean normal random variables with variance σ_ε. After obtaining her signal, the informed trader m demands x_m units of the asset. In addition, there are noise traders whose aggregated demand u is normal with mean zero and variance σ_u. There is also a market maker who observes the global order flow and sets prices. I am interested in Nash equilibria with linear pricing. As I show below, linear equilibrium has the advantage that symmetric informed agents will behave in a similar fashion. Accordingly, the informed traders conjecture that the market maker uses a linear pricing rule:

$$p^* = \lambda Q + \mu, \tag{3.17}$$

where

$$Q = u + \sum_{m=1}^{M} x_m$$

denotes the global order flow observed by the market maker.

Informed trader m chooses her demand to maximize expected profits given her signal and the conjectured pricing rule. Symmetry implies that, given a linear pricing by

[27] Holden and Subrahmanyam (1992) extend the Kyle (1985) model allowing for multiple privately informed agents who strategically exploit their long-lived informational advantage.

[28] Although the batch auction nature of Kyle's model is a simplification, Back and Baruch (2004) have shown that it converges to the more realistic sequential trade models.

the market maker, the only possible equilibrium between the informed traders is one in which they choose identical demands, which are linear in their signals. The market maker makes zero profits and prices satisfy a market efficiency condition:

$$p^* = E(v \mid Q) = E\left(v \mid u + \sum_{m=1}^{M} x_m\right) \tag{3.18}$$

The following proposition characterizes the unique linear equilibrium price.

Proposition 3.2. Given $v \sim N(p_o, \sigma^2)$, $\{\varepsilon_m\}_{m=1}^{M}$ $iidN(0, \sigma_\varepsilon)$, $\varepsilon_m \perp v, u \sim N(0, \sigma_u)$, and the market efficiency condition in Equation (3.18), there exists a unique linear equilibrium in which the price satisfies Equation (3.17), and the order flow impact on the security price is given by:

$$\lambda = \frac{\sigma^2 \left[M(\sigma^2 + \sigma_\varepsilon^2)\right]^{1/2}}{\sigma_u \left[(M+1)\,\sigma^2 + 2\sigma_\varepsilon^2\right]} \tag{3.19}$$

Proof. The profits of the informed agent m, given a linear price conjecture, are:

$$\pi_m = (v - p^*)x_m = \left[s_m - \varepsilon_m - \lambda\left(u + \sum_{m=1}^{M} x_m\right) - \mu\right] x_m$$

Moreover, her expected profits given her signal take the following form:

$$E_m\left[\pi_m | s_m\right] = \left[s_m - E_m\left(\varepsilon_m | s_m\right) - \lambda x_m - \mu\right] x_m - \lambda\left(\sum_{k \neq m} E_m(x_k | s_m)\right). \tag{3.20}$$

She maximizes her expected profits by choosing her optimal demand x_m. To solve her demand optimization problem, the following two intermediate results are needed:

1) $E_m\left(\varepsilon_m | s_m\right) = \frac{\sigma_\varepsilon^2 (s_m - p_0)}{\sigma_\varepsilon^2 + \sigma^2}$

This follows from the assumption of normality: $\binom{\varepsilon_m}{v} \sim N\left[\binom{0}{p_0}, \begin{pmatrix}\sigma_\varepsilon^2 & 0 \\ 0 & \sigma^2\end{pmatrix}\right]$ implies that $\binom{\varepsilon_m}{s_m} \sim N\left[\binom{0}{p_0}, \begin{pmatrix}\sigma_\varepsilon^2 & \sigma_\varepsilon^2 \\ \sigma_\varepsilon^2 & \sigma_\varepsilon^2 + \sigma^2\end{pmatrix}\right]$, and 1) is the conditional mean associated with this bivariate normal.

2) $E_m\left(s_k | s_m\right) = \frac{\sigma^2 (s_m - p_0)}{\sigma_\varepsilon^2 + \sigma^2} + p_0$

This also follows from the assumption of normality, where
$\binom{s_k}{s_m} \sim N\left[\binom{p_0}{p_0}, \begin{pmatrix}\sigma_\varepsilon^2 + \sigma^2 & \sigma^2 \\ \sigma^2 & \sigma_\varepsilon^2 + \sigma^2\end{pmatrix}\right]$.

Given the symmetry among informed traders, they conjecture that the other informed agents have a linear demand in their particular signals, $x_k = \alpha + \beta s_k$. Thus, $E_m(x_k|s_m) = \alpha + \beta E_m(s_k|s_m)$. Using this relation, and the results in 1) and 2), the FOC of maximizing the expression in Equation (3.20) with respect to x_m takes the following form:

$$\left\{\frac{\sigma^2}{\sigma_\varepsilon^2+\sigma^2}s_m + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma^2}p_0 - 2\lambda x_m - \lambda\sum_{k\neq m}\left(\alpha+\beta\left[\frac{\sigma^2(s_m-p_0)}{\sigma_\varepsilon^2+\sigma^2}+p_0\right]\right)\right\} = 0$$

Thus, the optimal demand of informed trader m is:

$$\begin{aligned} x_m \;&=\; \left(\frac{\sigma^2-\lambda(M-1)\beta\sigma^2}{2\lambda\left(\sigma_\varepsilon^2+\sigma^2\right)}\right)s_m + \\ &\frac{\sigma_\varepsilon^2}{2(\sigma_\varepsilon^2+\sigma^2)}\left(\frac{1-\beta\lambda(M-1)}{\lambda}\right)p_0 - \left(\frac{\mu+\lambda(M-1)\alpha}{2\lambda}\right)\end{aligned}$$

To satisfy the linear conjecture, $x_m = \alpha + \beta s_m$, the coefficients of s_m is equalized to β, and the following expression for λ is obtained:

$$\lambda = \frac{\sigma^2}{\beta\left[\left(M+1\right)\sigma^2+2\sigma_\varepsilon^2\right]} \tag{3.21}$$

On the other hand, the market maker makes zero profits, and prices satisfies the market efficiency condition in Equation (3.18). Given that $Q = u + \sum_{m=1}^{M} x_m = u + M\alpha + \beta M v + \sum_{m=1}^{M}\varepsilon_m$, and $\left\{v, u, \sum_{m=1}^{M}\varepsilon_m\right\}$ are mutually independent, the vector $\binom{v}{Q} \sim N\left(\binom{p_0}{M(\alpha+\beta)p_0}, \begin{pmatrix}\sigma^2 & M\beta\sigma^2\\ M\beta\sigma^2 & \sigma_u^2+\beta^2M^2\sigma^2+\beta^2M\sigma_\varepsilon^2\end{pmatrix}\right)$. Thus, Equation (3.18) takes the following form:

$$p^* = E\left(v\mid Q\right) = \frac{M\beta\sigma^2\left(Q-M\alpha-M\beta p_0\right)}{\sigma_u^2+\beta^2M^2\sigma^2+\beta^2M\sigma_\varepsilon^2}$$

This is consistent with the linear conjecture in Equation (3.17) provided

$$\lambda = \frac{\beta M\sigma^2}{\sigma_u^2+\beta^2M^2\sigma^2+\beta^2M\sigma_\varepsilon^2}. \tag{3.22}$$

Equalizing Equations (3.21) and (3.22) implies that $\beta = \frac{\sigma_u}{\sqrt{(M(\sigma^2+\sigma_\varepsilon^2))}}$. Substituting this value in Equation (3.21) leads to the result for λ. $\square$

A simple exercise of comparative statics suggests that λ increases with the variance of the fundamental price (σ^2) and decreases the variance of liquidity demands (σ_u^2). The relation with respect to the other parameters is non-monotonic. For instance, when the precision of the signal (σ_ε^{-2}) decreases, λ increases provided $\sigma_\varepsilon^2 < \frac{(M-3)\sigma^2}{2}$. This condition is likely to hold when the number of informed agents is not too small. Similarly, λ decreases with the number of informed agents for large enough M $\left(M > 1 + \frac{2\sigma_\varepsilon^2}{\sigma^2}\right)$. Given these complicated relations, explaining empirically changes in the λ parameter is not straightforward. There might be many possibilities or interactions. However, some scenarios seem more likely than others in the context of scheduled releases of public information. The empirical part of this study presents further discussion on the interpretation of changes in λ (expressed in terms of changes in $\widetilde{\lambda}$ in Equations 3.5 and 3.6), and estimates proxies of this trade price-impact parameter in different regimes associated to "announcement" and "regular" days.

3.11 Appendix C2

Proof. **of Proposition 1:**

This proof follows the appendix of Hasbrouck (2004). Define the subsequent notation:

$p = (p_1, p_2, ..., p_T)$

$q_{-t} = (q_1, ..., q_{t-1}, q_{t+1}, ..., q_T)$

Equations (3.9)-(3.11) can be summarized as follows:

$p_t = m_t + cq_t$

$m_t = m_{t-1} + \widetilde{\lambda}_t V_t q_t + \beta_k S_{k,t} + \varepsilon_t,$

where $\widetilde{\lambda}_t = (\varphi + a_k I_{k,t})$

To conserve space, all densities are conditioned on $\Theta = \left\{(c, \varphi, a_k, \beta_k), \sigma_\varepsilon^2\right\}$ and the observed data $\{S_{k,t}, I_{k,t}, V_t\}_{t=1}^T$.

Thus, the conditional distribution of the latent variables is given by:

$P(q_t|p, q_{-t}) = P(q_t|p_t, m_{t-1}, m_{t+1}, q_{t+1})$

Moreover, from Bayes rule

$P(q_t|p_t, m_{t-1}, m_{t+1}, q_{t+1}) = \frac{f(p_t|q_t, m_{t-1}, m_{t+1}, q_{t+1}) P(q_t|m_{t-1}, m_{t+1}, q_{t+1})}{f(p_t|m_{t-1}, m_{t+1}, q_{t+1})},$

which implies:

$$P(q_t|p_t, m_{t-1}, m_{t+1}, q_{t+1}) \propto f(p_t|q_t, m_{t-1}, m_{t+1}, q_{t+1}) P(q_t|m_{t-1}, m_{t+1}, q_{t+1}) \quad (3.23)$$

Now, consider the second term in Equation (3.23) and apply Bayes rule:

$P(q_t|m_{t-1}, m_{t+1}, q_{t+1}) = \frac{f(m_{t+1}|m_{t-1}, q_t, q_{t+1}) P(q_t|m_{t-1}, q_{t+1})}{P(m_{t+1}|m_{t-1}, q_{t+1})}$

Given that $P(q_t|m_{t-1}, q_{t+1}) = \frac{1}{2}$,

$$P(q_t|m_{t-1}, m_{t+1}, q_{t+1}) \propto f(m_{t+1}|m_{t-1}, q_t, q_{t+1}) = f(\varepsilon_t + \varepsilon_{t+1}), \quad (3.24)$$

where $\varepsilon_t = m_t - m_{t-1} - (\widetilde{\lambda}_t V_t q_t + \beta_k S_{k,t})$ and $\varepsilon_{t+1} = m_{t+1} - m_t - (\widetilde{\lambda}_{t+1} V_{t+1} q_{t+1} + \beta_k S_{k,t+1})$.

Now, given the assumption that $\varepsilon_t \sim iidN(0, \sigma_\varepsilon^2)$, Equation (3.24) can be written as:

$P(q_t|m_{t-1}, m_{t+1}, q_{t+1}) \propto$

$\int_{-\infty}^{\infty} \exp\left\{-\left(\frac{\left(m_t - m_{t-1} - (\widetilde{\lambda} V_t q_t + \beta_k S_{k,t})\right)^2}{2\sigma_\varepsilon^2} + \frac{\left(m_{t+1} - m_t - (\widetilde{\lambda} V_{t+1} q_{t+1} + \beta_k S_{k,t+1})\right)^2}{2\sigma_\varepsilon^2}\right)\right\} dm_t$

Solving the integral:

$P(q_t|m_{t-1},m_{t+1},q_{t+1}) \propto \exp\left\{-\frac{\left(m_{t-1}-m_{t+1}+\widetilde{\lambda}V_{t+1}q_{t+1}+\beta_k S_{k,t+1}+\widetilde{\lambda}V_t q_t+\beta_k S_{k,t}\right)^2}{4\sigma_\varepsilon^2}\right\}$,
and defining
$\Gamma_t = \exp\left\{-\frac{\left(m_{t-1}-m_{t+1}+\widetilde{\lambda}V_{t+1}q_{t+1}+\beta_k S_{k,t+1}+\widetilde{\lambda}_t V_t+\beta_k S_{k,t}\right)^2}{4\sigma_\varepsilon^2}\right\}$
$+\exp\left\{-\frac{\left(m_{t-1}-m_{t+1}+\widetilde{\lambda}q_{t+1}+\beta_k S_{k,t+1}-\widetilde{\lambda}_t V_t+\beta_k S_{k,t}\right)^2}{4\sigma_\varepsilon^2}\right\}$,
I obtain the normalized conditional density:

$$P(q_t|m_{t-1},m_{t+1},q_{t+1}) = \frac{\exp\left\{-\frac{\left(m_{t-1}-m_{t+1}+\widetilde{\lambda}V_{t+1}q_{t+1}+\beta_k S_{k,t+1}+\widetilde{\lambda}V_t q_t+\beta_k S_{k,t}\right)^2}{4\sigma_\varepsilon^2}\right\}}{\Gamma_t} \tag{3.25}$$

Now, consider the first term in Equation (3.23),
$f(p_t|q_t,m_{t-1},m_{t+1},q_{t+1}) = f(m_t+cq_t|q_t,m_{t-1},m_{t+1},q_{t+1})$
$= f(m_t|q_t,m_{t-1},m_{t+1},q_{t+1}) \propto f(m_{t+1}|m_t,q_{t+1})f(m_t|m_{t-1},q_t)$
$= \exp -\left\{\frac{\left(m_t-m_{t-1}-(\widetilde{\lambda}V_t q_t+\beta_k S_{k,t})\right)^2}{2\sigma_\varepsilon^2}+\frac{\left(m_{t+1}-m_t-(\widetilde{\lambda}V_{t+1}q_{t+1}+\beta_k S_{k,t+1})\right)^2}{2\sigma_\varepsilon^2}\right\}$
Simplifying:
$f(p_t|q_t,m_{t-1},m_{t+1},q_{t+1}) \propto$
$\exp\left\{\frac{-\left[m_t-\frac{1}{2}\left(m_{t-1}+\widetilde{\lambda}V_t q_t+\beta_k S_{k,t}+m_{t+1}-\widetilde{\lambda}V_{t+1}q_{t+1}-\beta_k S_{k,t-1}\right)\right]^2}{2\left(\sqrt{\frac{\sigma_\varepsilon^2}{2}}\right)^2}\right\}$
or,

$$f(p_t|q_t,m_{t-1},m_{t+1},q_{t+1}) = \phi_{p_t-cq_t}\left(M_t^*,\sqrt{\frac{\sigma_\varepsilon^2}{2}}\right), \tag{3.26}$$

where $M_t^* = \frac{1}{2}(m_{t-1}+\widetilde{\lambda}V_t q_t+\beta_k S_{k,t}+m_{t+1}-\widetilde{\lambda}V_{t+1}q_{t+1}-\beta_k S_{k,t+1})$, and ϕ denotes the normal pdf with respect to the random variable m_t.

Finally, the result follows from substituting Equations (3.25) and (3.26) into Equation (3.23).

□

Note that we need some modifications for the endpoints. The following expressions provide the conditional densities for such points.

First point:

$$P(q_1|m_2,q_2,p_1) = \frac{\exp\left\{\frac{-\left(p_1-cq_1-(m_2-\widetilde{\lambda}V_2q_2-\beta_k S_{k,2})\right)^2}{2\sigma_\varepsilon^2}\right\}}{\exp\left\{\frac{-\left(p_1+c-(m_2-\widetilde{\lambda}V_2q_2-\beta_k S_{k,2})\right)^2}{2\sigma_\varepsilon^2}\right\}+\exp\left\{\frac{-\left(p_1-c-(m_2-\widetilde{\lambda}V_2q_2-\beta_k S_{k,2})\right)^2}{2\sigma_\varepsilon^2}\right\}}$$

Last point:

$$P(q_T|m_{T-1}, q_{T-1}, p_T) = \frac{\exp\left\{\frac{-\left(p_T - cq_T - (m_{T-1} + \widetilde{\lambda} V_T q_T + \beta_k S_{k,T})\right)^2}{2\sigma_\varepsilon^2}\right\}}{\exp\left\{\frac{-\left(p_T + c - (m_{T-1} + \widetilde{\lambda} V_T q_T + \beta_k S_{k,T})\right)^2}{2\sigma_\varepsilon^2}\right\} + \exp\left\{\frac{-\left(p_T - c - (m_{T-1} + \widetilde{\lambda} V_T q_T + \beta_k S_{k,T})\right)^2}{2\sigma_\varepsilon^2}\right\}}.$$

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