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The Processing of Non-Anticipated Information in Financial Markets: Analyzing the Impact of Surprises in the Employment Report

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Abstract. This paper delineates the simultaneous impact of non-anticipated information on mean and variance of the intraday return process by including appropriate variables accounting for the news flow into both the mean and the variance function. This allows us to differentiate between the consistent price reaction to surprising news and the traders' uncertainty about the precise price impact of this information. Focussing on the US employment report, we find that headline information is almost instantaneously incorporated into T-bond futures prices. Nevertheless, large surprises, and 'bad' news in particular, create considerable uncertainty. In contrast, if surprises in related headlines cross-validate each other, less room for differences of opinion is left and hence volatility is decreased.

Key words: high-frequency data, information processing, macroeconomic announcements, Treasury bond futures, trading process, volatility.

JEL classification codes: E44, G14.

1. Introduction

This paper investigates the processing of macroeconomic news in financial markets, in particular surprises in headline figures of the US employment report. We model simultaneously two effects of public news arrival: On the one hand, non-anticipated information in public news induces a shift in traders' beliefs about the equilibrium price level which should result in a sharp and immediate price reaction. While average beliefs shift instantaneously, on the other hand, traders do not have to agree about the precise price impact of a given piece of information. Uncertainty about the new equilibrium price level causes prices to fluctuate more widely around the new equilibrium level until a new consensus is reached. We disentangle these effects by controlling for the impact of non-anticipated information on both the mean and the variance function of the return process.

As it is well known from previous literature on this topic, information arrival has an impact on both prices and volatility in financial markets (see e.g., Goodhart and O'Hara 1997 for an overview).[1] Nevertheless, previous empirical studies on announcement effects have either focused on the impact of scheduled announcements on signed returns (e.g. Berkman 1978, Urich and Wachtel 1984, Hardouvelis 1988, Fleming and Remolona 1997, and Hess 2001) or on the volatility of returns (e.g. Harvey and Huang 1991, Ederington and Lee 1993, Fleming and Remolona 1999a, and Franke and Hess 2000a), neglecting relations between the impact of non-anticipated information on the first and second moments of the return process.[2] We close this apparent gap in the literature by modelling the impact of announcements on both the mean and the variance function simultaneously. Our approach provides some interesting insights into the processing of information. It enables us to distinguish between a volatility shock arising from a news induced shift of the price to a new equilibrium and a situation in which prices are just bouncing around, for example because traders' opinions diverge widely.

We use high-frequency data of the Chicago Board of Trade (CBOT) T-bond future in order to investigate the effects of news arrival. One problem in this context is the simultaneous occurrence of releases. To avoid an interference of effects caused by multiple releases, we analyze situations in which only one report is announced at a time. In particular, we focus on the employment report, which is typically released at 8:30 a.m. ET (Eastern Time). Besides being the most influential report,[3] it has the nice property that the overlap with other announcements is minimal. During the five-year sample used here, i.e. January 1995 to December 1999, only 7 out of the 60 employment announcement days are lost due to an announcement of other releases at the same time. In order to keep the results free from the influence of announcements made later on the same day (in particular at 10:00 a.m.), we focus on a 90-minute window in which information processing should be dominated by the release of the employment report.[4] In contrast to Andersen and Bollerslev (1998), who model the 24-hour volatility pattern in the foreign exchange market and try to identify the main components of 'overall' volatility, we focus on 90-minute subsamples around announcements in order to analyze the processing of important macroeconomic information and in particular its simultaneous impact on the mean and the variance of T-bond futures returns.

[1] There is also some tradition using volatility as a proxy for information arrival. See, e.g. Lamoureux and Lastrapes (1990) or Franke and Hess (2000b).

[2] Note that a few studies investigate both signed returns and absolute returns, as well as some other variables such as trading volume or bid-ask spreads. For example, Fleming and Remolona (1997) run separate regressions of signed returns on surprises as well as of absolute returns and trading volume on announcement dummies and absolute surprises. See also Balduzzi et al. (1997). Nevertheless, these studies do not model the simultaneous impact of announcements on first and second moments.

[3] Several studies document that the employment report has by far the highest impact on the mean function (e.g. Balduzzi et al. 1997, Hess 2001) as well as on the variance function (Ederington and Lee 1993, Fleming and Remolona 1997).

[4] To provide a simple robustness check for the results, we also analyze information processing around some other important reports (i.e. the announcement of the NAPM index, consumer prices, and housing starts).

The effects of information arrival are analyzed by means of an intraday ARCH model with multiplicative heteroskedasticity on 2-minute returns. Explanatory variables which capture the time pattern and the impact of surprises are included in the mean function as well as in the variance specification. In order to analyze the explanatory power of the different model components, their predictive performance is evaluated separately. This allows us to differentiate between the explanatory power of the implemented ARCH component, the variables capturing deterministic time patterns and the additional explanatory variables (i.e. surprises in headline figures).

Based on this estimation approach, we provide the following main findings: Non-anticipated information leads to a sharp and consistent price reaction, suggesting that traders' average beliefs shift almost instantaneously. Nevertheless, after controlling for the effect on the mean, we still find a strong and persistent increase in volatility which points to considerable disagreement among traders about the precise implications of macroeconomic news. These differences of opinion are only slowly resolved. Furthermore, we delineate the different modes of impact of non-anticipated information on volatility: We provide some evidence that traders' differences of opinion increase with the magnitude of a surprise (absolute volatility impact). 'Bad' news creates considerably more uncertainty among traders than 'good' news (asymmetric impact). Surprises in related headline figures pointing in the same direction reinforce the price signal and thus leave less room for differences of opinion (reinforcement effect).

The remainder of this paper is organized as follows. The subsequent section reviews the related literature. Section 3 characterizes the major information components of the employment report. Moreover, several hypotheses are derived concerning the processing of outstanding information. Section 4 describes the data, explains the estimation procedure, and presents the empirical results. In Section 5 we analyze the information processing around some other announcements in order to check the robustness of the results. Section 6 concludes.

2. Previous Studies – A Synthesis

The previous literature on announcement effects can be divided into two branches, one focusses on the impact of news on first moments, the other focusses on second moments of the price process. The first branch analyzes the signed price impact of non-anticipated information. The main question of this literature is which types of announcements significantly affect the equilibrium price level. Usually, these studies measure the magnitude of surprises employing survey data on analysts' forecasts for certain headline figures contained in macroeconomic reports. Nonanticipated information is then measured by the deviation of a given headline figure (A_τ), announced at time τ, from the median of analysts' forecasts (F_τ). Hence, the surprise in the ith headline figure is given as $S_{i,\tau} = A_{i,\tau} - F_{i,\tau}$. Typically, the impact on the return in period t is investigated by regressing signed log returns r_t on surprises in some sets of macroeconomic announcements ($i = 1, \ldots, n$), i.e.

$$r_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i S_{i,\tau} D_{i,t=\tau} + \epsilon_t,$$

where $D_{i,t=\tau}$ denotes headline specific dummy variables which take on the value 1 if announcement i is made during the interval t and 0 else. In addition, lagged returns or variables controlling for seasonalities, such as day-of-the-week effects, may be included in such an analysis.[5] Heteroskedasticity in the error term ϵ_t is usually not explicitly modelled. Instead, heteroskedasticity consistent variance-covariance estimators are applied.

While early studies analyze daily returns,[6] more recent studies regress returns in narrow intraday windows around the announcements on surprises in headline figures in order to separate the impact of scheduled announcements from other not explicitly observed news, which may arrive occasionally over the course of a trading day. Following this approach, Becker et al. (1996), Fleming and Remolona (1997, 1999b), and Hess (2001), among others, find that several US announcements have a significant influence on bond market prices. Evidence of announcement effects in the foreign exchange spot market is provided, for example, by Almeida et al. (1998) and Dominguez (1999).[7] Overall, studies on first moments suggest a significant and immediate adjustment of the level of prices to non-anticipated information. In particular, surprising information in the employment report (especially in the nonfarm payrolls figure) triggers the most pronounced price responses in both bond and foreign exchange markets.

A second string of the literature on announcement effects analyzes volatility shocks due to news arrival. First of all, these studies show that scheduled macroeconomic announcements stand out from the steady flow of information which hits financial markets. Fleming and Remolona (1997) find that out of the 25 largest intraday price changes in the U.S. treasury market, all but one occurred after such an announcement, in particular after the release of employment reports. This is confirmed by Bollerslev et al. (2000) for T-bond futures. Dominguez (1999) obtains similar results for the Deutsche Mark-US Dollar spot rate.[8]

[5] See, for example, Fleming and Remolona (1997) or Hess (2001).

[6] See, for example, Berkman (1978), and Urich and Wachtel (1981, 1984) who analyze money growth announcements. Cook and Korn (1991) and Prag (1994) focus on employment reports. Hardouvelis (1988), Dwyer and Hafer (1989), and Edison (1996), among others, investigate several releases.

[7] See also Goodhart et al. (1993) who analyze the influence of two single news events on high-frequency British Pound–US Dollar exchange rates.

[8] However, it is not clear whether these findings are due to consistent price reactions to new information or just volatility shocks, since these approaches do not explicitly control for shifts of the mean function.

In contrast to studies focussing on the mean function, the literature on second moments usually does not account for surprises in releases. In general, the impact of the mere existence of an announcement is investigated, for example, by regressing absolute log returns, $|r_t|$, on the above defined dummy variables which account only for the timing of announcements, i.e.[9]

$$|r_t| = \alpha_0 + \sum_{i=1}^{n} \alpha_i D_{i,t=\tau} + \nu_t.$$

Based on such specifications, several studies document that quite a number of different types of releases have a significant impact on (intraday) volatility, for example, Ederington and Lee (1993) and Franke and Hess (2000a) for T-bond futures, Fleming and Remolona (1997) and Balduzzi et al. (1997) for the interdealer T-bond market, and Harvey and Huang (1991) and Ederington and Lee (1993, 1995) for foreign exchange spot and futures markets.

The persistence of volatility after such an announcement is another issue which has gained widespread attention. Analyzing daily returns, Jones et al. (1998) as well as Jones (1998) apply a switching GARCH model and find no significantly higher interday volatility persistence after the release of the employment report and the producer price index. In contrast, disentangling dynamic GARCH effects and announcement effects on the basis of a filtered GARCH model, Li and Engle (1998) are able to reject the hypothesis that volatility persistence that stems from announcement days is the same as from non-announcement days. Ederington and Lee (1993), for example, analyze the sample variance in 5-minute intervals across announcement days and find that volatility is significantly higher in the period associated with the announcement and that it declines rapidly afterwards. This is confirmed for several markets by various other studies (e.g. Ederington and Lee 1995, Crain and Lee 1995, Balduzzi et al. 1997, Fleming and Remolona 1999a, and Franke and Hess 2000a).[10]

A detailed characterization of different volatility components, including calendar features, scheduled announcement effects, as well as persistent volatility (ARCH) components, in the Deutsche Mark-US Dollar foreign exchange spot market is provided by Andersen and Bollerslev (1998). They assume that the mean adjusted return process is given by

$$R_{t,d} - E[R_{t,d}] = \sqrt{h_{t,d}}u_{t,d}, t = 1, \ldots, T, d = 1, \ldots, D, \tag{1}$$

where $R_{t,d} = \exp(r_{t,d})$ denotes gross returns and $u_{t,d}$ is an i.i.d. zero mean unit variance error term. Since Andersen and Bollerslev explicitly specify daily ARCH-

[9] See, for example, Ederington and Lee (1993) or Fleming and Remolona (1997). In general, seasonalities in volatilities such as day-of-week or time-of-the-day effects are controlled for by including appropriately defined additional dummy variables.

[10] Volatility seems to persist somewhat longer in more liquid instruments (see Christie-David and Chaudhry 1999).

effects, the index d is introduced to denote trading days. The variance process is specified by

$$h_{t,d} = \sigma_{t,d}^2 \cdot s_{t,d}^2, \tag{2}$$

where $\sigma_{t,d}^2$ collects the persistent volatility components which are modelled based on GARCH processes on a daily and intradaily level[11] and $s_{t,d}^2$ represents intraday and interday seasonality components, including announcement effects.

Andersen and Bollerslev (1998) illustrate the identification and estimation of the different volatility components and evaluate their explanatory power. By discussing the major driving forces of the volatility process, they conclude that announcement effects are of minor importance when the overall volatility in the 24-hour foreign exchange market is modelled. Nevertheless, they show that major announcements lead to the largest returns and induce a strong response of the price process immediately after the release.[12]

Overall, studies focusing on volatility do not account for the consistent price reaction to non-anticipated information arrival which is well documented by studies on the mean process. Usually, second moments studies are concerned with volatility forecasting, mainly from a pre-announcement perspective, or with the identification of volatility components in order to characterize the driving forces of the overall volatility process. However, an important question is whether the observed volatility spike after macroeconomic announcements is merely due to a news induced jump of the price to a new equilibrium level.

In contrast to Andersen and Bollerslev (1998) or Bollerslev et al. (2000), our major objective is not the characterization of the different components of overall volatility. Instead we focus on the processing of non-anticipated information in scheduled announcements. Therefore, our approach differs with respect to two aspects: First, we control for the price impact of non-anticipated information by including appropriate news flow variables into the mean function. Second, we do not study the 24-hour trading process. Instead, we cut out narrow time periods around announcements in which we can identify the dominant news items. Only those periods are used in which an interference with other news releases is avoided. We utilize information on the timing of the news arrival but also on the amount and the sign of surprises. We assume the following process for 2-minute log returns:

$$r_t - \mathrm{E}[r_t] = \sqrt{h_t} \cdot u_t, \tag{3}$$

with

$$h_t = \sigma_t^2 + s_t^2, \tag{4}$$

[11] In particular, Anderson and Bollerslev model $\sigma_{t,d}^2$ based on a daily GARCH process which is assumed to be constant over a trading day. Hence, $\sigma_{t,d}^2 = \sigma_d^2 / T$.

[12] Based on this framework (see also Andersen and Bollerslev 1997), Bollerslev et al. (2000) investigate intraday seasonality patterns in volatility after controlling for interday GARCH effects and find supporting evidence for the T-bond futures market.

where, following the notation of Andersen and Bollerslev (1998), s_t^2 and σ_t^2 capture ARCH and announcement effects, respectively. The expected return is specified by $\mathrm{E}[r_t] = x_t'\beta$, where β is a coefficient vector and x_t denotes the corresponding vector of explanatory variables (see Section 4 for more details on the specific definition of the variables). In contrast to Andersen and Bollerslev (1998), we do not include any daily GARCH effects in the variance equation since we do not focus on a 24-hour period but on narrow time windows around announcements.[13] Ignoring the daily GARCH component seems to be reasonable because we analyze announcements on a monthly schedule.[14] Moreover, the announcement effects are very large relative to the interdaily GARCH effects. However, there is a heteroskedasticity component which is ignored in this analysis and thus it is crucial to use robust inference techniques. σ_t^2 is simply specified by

$$\sigma_t^2 = \sum_{j=1}^{p} \phi_p \epsilon_{t-j}^2,$$

accounting for intradaily ARCH effects. The volatility component s_t^2 is specified as $s_t^2 = \exp(w_t'\gamma)$, including absolute surprises as well as signed surprises in the individual headline figures of the employment report (see Section 4 for more details). Estimating equations (3) and (4) simultaneously, our approach may be viewed as a synthesis of the previous literature on the mean and the variance of the return process.

3. Information Diffusion in Efficient Markets

What is it that makes markets react so sharply to macroeconomic announcements? How does the price adjustment process to non-anticipated information work? In order to analyze these and other questions, first the information content of the major headline figures of an employment report is analyzed. Hypotheses concerning the impact of this information on the mean and variance of returns are presented thereafter.

3.1. THE INFORMATION CONTENT OF THE EMPLOYMENT REPORT

Several studies have documented that the monthly report on the U.S. employment situation prepared by the Bureau of Labor Statistics (BLS) is the most influential macroeconomic release for financial markets.[15] Its importance stems from the fact that it is an extremely timely and comprehensive measure of economic activity. Nonfarm payroll employment, for example, is commonly seen as a coincident

[13] For this reason we drop the daily index d.

[14] For more details see Section 4.

[15] See, for example, Bollerslev et al. (2000) or Fleming and Remolona (1999a) for its impact on intraday volatility and Fleming and Remolona (1997) or Hess (2001) for its intraday price impact.

indicator of the business cycles.[16] Moreover, both payroll employment and the unemployment rate provide a measure for the tightness of the labor market and thus an indication of price pressures in probably the most important input factor, i.e. labor.

The employment report is a rather voluminous document containing a large amount of detailed information. This is one of the reasons why previous studies have focused on headline figures which summarize this information. Another reason is the availability of so-called consensus forecasts of these figures which allow one to measure the non-anticipated part of information arrival.[17] Previous studies of the employment report restrict their attention to two headline figures, the nonfarm payroll measure and the unemployment rate.[18] In addition to these, we use a third headline figure, i.e. average hourly earnings.[19]

Payroll employment and the (un)employment rate are strongly related, since both convey information about overall economic activity, consumers spending power, as well as price pressures arising from the labor market. Therefore, it may be argued that using one of these figures is enough to capture most of the information. However, it is important to note that they are derived from different sources. While the (un)employment rate is derived from the household survey, the payroll measure (like hourly earnings) is based on the much larger establishment survey.[20] Hence, in the short run they can move in opposite directions. Although it is often argued that market participants consider the nonfarm payroll figure to be more important, since changes in nonfarm payrolls are less volatile than changes in unemployment rates,[21] inspecting both figures might allow market participants to better assess the probability of measurement errors.

As mentioned above, financial markets also try to infer from employment figures whether inflationary pressures are building up which may arise from an increased bargaining power of employees in a tight labor market. Related but more

[16] See, for example, Rogers (1998, Chap. 1).

[17] Analysts' forecasts of macroeconomic figures are not always unbiased and efficient (see e.g. Becker et al. 1996). However, there seems to be no systematic inefficiencies across different sample periods (see e.g. Hess and Moersch 2001).

[18] For example, Hardouvelis (1988), Dwyer and Hafer (1989), and Prag (1994) analyze surprises in unemployment rates, Fleming and Remolona (1997) use nonfarm payrolls, and Cook and Korn (1991), Edison (1996), Balduzzi et al. (1997), and Hess (2001) use both headlines.

[19] A fourth headline figure, the average workweek, receives attention from time to time. This measure is not employed here since MMS does not provide survey data for this figure until October 1998. Hence, only a few data points are available.

[20] Based on interviews conducted with approximately 50,000 households, the (un)employment rate measures civilian noninstitutional employees including agricultural workers as well as self-employed persons. In contrast, the nonfarm payrolls figure draws from the payroll records of approximately 390,000 establishments and counts jobs added in nonagricultural industries. See, for example, Rogers (1998, Chap. 1), or Niemira and Zukowski (1998, Chap. 10).

[21] In fact, during our sample period the standard deviation of relative month-over-month changes in nonfarm payrolls turns out to be 0.119%, in unemployment rates 0.161% and in hourly earnings 0.244%. See also Hess and Moersch (2001).

direct information is obtained from average hourly earnings. Obviously, this figure provides a straightforward reading of price changes in the input factor labor. However, while hourly earnings primarily measure current price pressures, trends in employment may allow market participants to foresee wage increases down the road. Hence, hourly earnings add to the picture of price trends sketched by payrolls and unemployment rates by providing a look back.

Due to the differences in the information content of headline figures described above, one would expect that surprises in any of these three headline figures contribute to the explanation of returns observed after an announcement. This is stated by hypothesis H1.

H1: Informativeness of headline figures

> After an announcement, prices react significantly to non-anticipated information in headline figures. Since all three headline figures are informative, they contribute to the explanation of returns.

3.2. EFFICIENT PROCESSING OF NON-ANTICIPATED INFORMATION

According to the well-known efficient market hypothesis, one would expect that prices adjust immediately to public news arrival if this information is regarded to be important. However, only non-anticipated information can move prices because in an efficient market, prices already reflect widely anticipated events. The unique dissemination procedure of statistical agencies in the US guarantees that macroeconomic reports are released precisely according to the schedule.[22] Reporters are allowed to analyze the data in advance but they are not allowed to communicate until the official release time. When the phone lines are turned on at exactly 8:30 a.m., headline figures are transmitted almost immediately to traders on the floor, as well as to other market participants via news agencies. Thus, the most obvious non-anticipated information, i.e. surprises in headline figures, should be incorporated into prices within a few minutes (hypothesis H2). The time span until this information is fully incorporated into prices may serve as a measure of market efficiency in terms of the speed of information diffusion.

H2: Immediate price impact of headline information

> In an efficient market, prices adjust immediately to non-anticipated information in the widely awaited headline figures. Thus, no systematic impact is found after a few minutes.

Hypotheses H1 and H2 refer to the impact of information arrival on the mean function of the return process. The following section deals with the implications for the volatility process.

[22] See, for example, Ederington and Lee (1993, 1995) or Fleming and Remolona (1997, 1999a) for a detailed description of these procedures.

3.3. THE VOLATILITY IMPACT OF INFORMATION ARRIVAL

The sharply increased volatility immediately after macroeconomic announcements, as well as its persistence, is well documented (see e.g. Ederington and Lee 1993, Crain and Lee 1995, Fleming and Remolona 1997, 1999a, and Franke and Hess 2000a). In order to delineate the impact of macroeconomic announcements on volatility, we differentiate between four components: (1) The impact of the mere existence of new information, i.e. the baseline volatility time pattern related to the announcement of the employment report, (2) the magnitude of non-anticipated information in this report, i.e. absolute surprises in headline figures, (3) the asymmetric impact of good and bad news on volatility, i.e. signed surprises, and (4) the 'reinforcement' effect of surprises in related headline figures, i.e. whether surprises in newly created jobs (payrolls) and the overall (un)employment rate convey the same message.

The first component captures a volatility increase due to an acceleration of the speed of information diffusion after an announcement. This component accounts for the well-known effect that information arrival is associated with higher trading volume as well as higher volatility (for a comprehensive overview see e.g. Karpoff 1987 or Goodhart and O'Hara 1997). Note that this component does not account for specific details concerning the type of information, the magnitude, or the direction of surprises. Hence, it captures the deterministic time pattern of volatility around announcements as a baseline. One argument for a persistently higher volatility after announcements stems from the mixture of distribution hypothesis (Clark 1973, Harris 1987), stating that both volume and volatility are driven by the rate of information arrival. Clusters in news then lead to a positively autocorrelated volatility. Considering that an employment report contains a load of detailed information besides the exposed headline figures and assuming that this information is only gradually processed, the mixture of distribution hypothesis provides one explanation for volatility clustering after such a report. A somewhat related argument is provided by the sequential information arrival model (Copeland 1976, 1987), which assumes that not all market participants receive the information at the same time.[23] Another argument is that even if market participants have the same access to the information at the same time, differences of opinion about its price impact can persist for quite some time (e.g. Varian 1985, Kandel and Pearson 1995, or Harris and Raviv 1993). Market participants may interpret the data differently, either if they have additional private information, different prior beliefs, or if they use different models to evaluate the impact of news. Hypothesis H3 summarizes these arguments:

[23] This view is supported for example by Dacorogna et al. (1993) and Müller et al. (1997), who argue that different market participants have different time horizons to process information and to act upon it. This leads to waves in trading activity and thus to waves in price volatility.

H3: Baseline volatility after an announcement

Volatility increases after an employment report release and declines only slowly due to (1) the huge amount of detailed information contained in this report, (2) traders' different response horizons, and/or (3) differences of opinion about the precise price impact of new information.

The effect of an awaited employment announcement on the volatility before this event is less clear. On the one hand, there is some evidence that trading volume declines before such an announcement.[24] Then, the well-documented positive volume-volatility relation (see e.g. Karpoff 1987) would suggest that volatility before an announcement is lower. However, a possible counterargument arises from the liquidity of markets. If speculative trading dries out, liquidity trades may have a higher price impact. This would increase volatility before an announcement.[25] Hypothesis H4 follows the first line of reasoning, suggesting a 'calm before the storm' effect.

H4: Baseline volatility before an announcement

Volatility is depressed before an announcement.

The second component in the variance specification accounts for the magnitude of non-anticipated information in a report and is measured by the deviation of announced headline figures from analysts' 'consensus' forecasts. It seems to be unclear why large surprises should lead to higher volatility, especially if one controls for the direct impact of surprises on the mean function. Since these surprises have high visibility, i.e. market participants get the information very fast via news vendors such as Bloomberg or Reuters, one would expect an immediate and consistent price reaction rather than a prolonged stage of random fluctuations. One explanation for a persistently high volatility could be that a surprise in a headline figure increases the probability that there are also surprises in other less exposed figures and that it is not easy for market participants to find out what else might be affected. Therefore, market participants may have more difficulties in assessing the precise price impact of larger surprises. In addition, surprises leave more room for differences of opinion if one considers the possibility of imprecise measurements. For example, it may be unclear whether a surprise is due to a measurement error (i.e. market participants may disagree about the precision of the signal). Extreme surprises may even call the reliability of forecast models into question. This is stated by hypothesis H5.

24 Fleming and Remolona (1999a), for example, report that trading volume in U.S. Treasuries is slightly but insignificantly lower before an announcement. Franke and Hess (2000a) find that Bund future trading volume is significantly lower in the 5-minute interval preceding 8:30 announcements and insignificantly lower before releases scheduled at 9:15 and 10:00 ET.

25 See, for example, Franke and Hess (2000a).

H5: Volatility impact of the magnitude of surprises

Larger surprises give rise to more pronounced differences of opinion. Hence, volatility increases with the magnitude of surprises.

The third volatility component allows us to investigate whether good' or 'bad' news have a different impact on volatility (hypothesis H6). An asymmetric volatility response coupled with an asymmetric mean response may be interpreted as evidence in favor of the time-varying risk premium hypothesis (see e.g. Pindyck 1984 and French et al. 1987). If risk is priced and traders anticipate that negative news will produce a stronger increase in volatility, a higher required rate of return leads to a stronger decline in prices. While this effect has been studied in particular for stock markets, it should be observed for bond prices too.[26] On the basis of daily data, Li and Engle (1998), for example, report strong asymmetric effects of scheduled announcements on the T-bond future. They find that positive shocks depress volatility on consecutive days and vice versa. While Li and Engle define 'good' and 'bad' news on the basis of the observed daily return reactions, we directly exploit the sign of analysts' forecast errors in the headline figures to assess whether a surprise provides 'good' or 'bad' news.[27] This allows us to investigate asymmetric effects for each of the headline figures separately.

H6: Asymmetric volatility impact of surprises

Traders' uncertainty, and thus volatility, is higher for 'bad' news than for 'good' news.

The fourth volatility component is included in order to investigate a possible interaction between surprises in headline figures in more detail. Recall that both the nonfarm payrolls figure and the (un)employment rate may indicate future price pressures arising from a tight labor market. Since these two figures are closely related, market participants can use them to cross-validate each other. If both headline figures convey the same message, e.g. a surprisingly high increase in nonfarm payrolls and a lower than expected unemployment rate, the room for differences of opinion about a tight labor market is reduced. A large surprise in one headline figure might be interpreted as a measurement error. If large surprises in both figures occur which point in the same direction, then the possibility of a measurement error is reduced. In this case, one would expect a sharp initial price reaction, but on the other hand volatility afterwards should be comparatively low. In other words, we should observe a more moderate increase in volatility if large surprises in nonfarm

[26] Although obviously not applicable to bonds, there is a second explanation for the asymmetric volatility response in the stock market which draws on the leverage effect (see e.g. Black 1976, and Christie 1982). A drop in stock prices causes an increase of the market price of debt relative to the market price of equity. This increase in the financial leverage makes the stock riskier, and thus increases its volatility.

[27] Li and Engle (1998) define, for example, 'big negative news' as news corresponding with (daily) returns lower than the 33% quantile. In contrast, here, 'had' news is given by a higher than expected nonfarm payrolls figure ($S1^{+}$), a lower than predicted unemployment rate ($S2^{-}$), and a higher than forecasted average hourly earnings announcement ($S3^{+}$).

payrolls and the unemployment rate cross-validate each other.[28] Hence, the fourth component examines whether multiple surprises pointing in the same direction reduce the room for differences of opinion (hypothesis H7).

H7: Reinforcement effect of surprises in related figures

Volatility is lower if large surprises in the related nonfarm payrolls figure and the unemployment rate mutually confirm their messages, i.e. if both provide either ‘good’ or ‘bad’ news, since then less room is left for differences of opinion. Moreover, this effect is more pronounced for negative surprises given the existence of asymmetric effects (H6).

4. Empirical Analysis

4.1. DATA

We analyze Chicago Board of Trade (CBOT) T-bond futures returns in 2-minute intervals, during 90-minute windows around employment releases (more precisely from 8:22 a.m. to 9:52 a.m. ET). This window is suggested, on the one hand, by the floor trading hours of the CBOT, which start at 8:20 a.m.[29] and, on the other hand, by the release of other macroeconomic announcements at 10:00 a.m. Log returns are calculated on the basis of the last trading price observed in a given 2-minute interval. For example, the return associated with the employment release, i.e. the 8:30–8:32 return, is computed from the last price before the 8:30 a.m. announcement and the last price before 8:32 a.m. Since the employment report is released almost always on Fridays, we do not have to account for day-of-the-week effects.[30] We only use those days on which no other macroeconomic report is released during the 90-minute period. Using a five-year sample, i.e. January 1995 to December 1999, we obtain 53 announcement days.[31] CBOT T-Bond futures data is obtained from the Futures Industry Institute. This is ‘tick-by-tick’ data, containing a time-stamped record whenever a price change is observed. Transaction volumes are not recorded. Like in previous studies, the front month contract is analyzed, i.e. the most actively traded contract among the nearby and second nearby contract.[32]

[28] A ‘large’ surprise will be defined as a surprise exceeding one standard deviation.

[29] The definition of 2-minute returns does not allow us to calculate a return for the 8:20–8:22 interval since no price is observed before 8:20.

[30] Typically, the employment report is released on the first Friday after the end of the month it refers to. During the sample period, 3 reports were announced on a Thursday since the first Friday was a holiday. Moreover, after controlling for the impact of announcements, Li and Engle (1998) do not find a significant difference between Thursdays and Fridays. This is in line with the findings of Ederington and Lee (1993), Franke and Hess (2000a) and others, suggesting that most of the day-of-week and time-of-the-day effects in bond markets can be explained by the announcement schedule.

[31] Seven days are removed at which either leading indicators, personal income or gross domestic product were released at the same time.

[32] See, for example, Ederington and Lee (1995) or Franke and Hess (2000a).

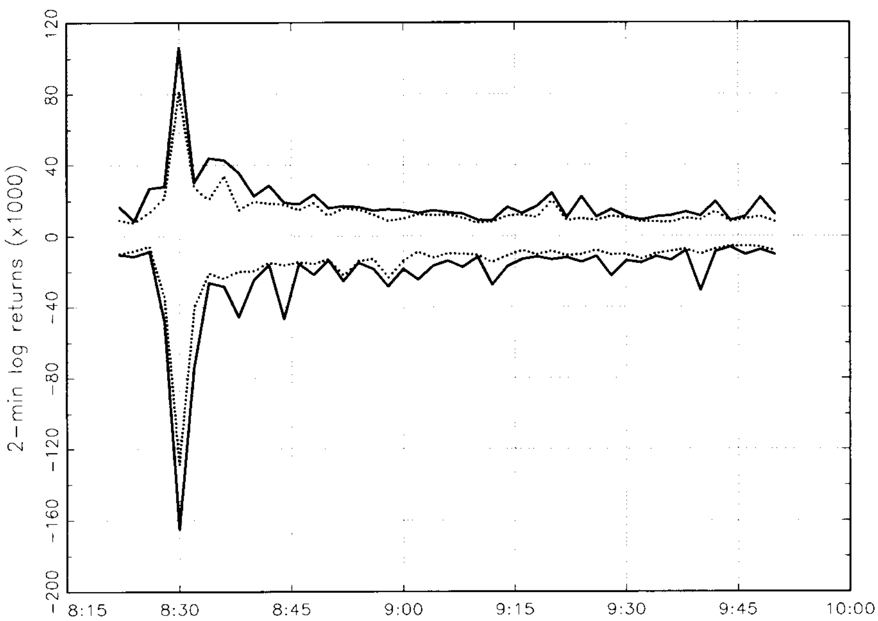

Figure 1. Descriptive statistics of 2-minute log returns ($\times 10,000$) during the interval 8:22–9:52 a.m. ET on employment announcement days are reported. The sample period is from January 1995 to December 1999, resulting in 53 days, on which no other macroeconomic report is released along with the employment report. 1% and 99% percentiles (solid lines) are displayed as well as 5% and 95% percentiles (dotted lines).

As an illustration for the impact of announcements, the 1% and 99% as well as the 5% and 95% fractiles of 2-minute log returns are shown in Figure 1.

To explore the effect of the bid-ask bounce on the results, some experiments are conducted using log returns computed on the basis of so-called 'pseudo equilibrium prices' as suggested by Ederington and Lee (1995). These are the averages of the last two prices in an interval. However, the results do not change in any meaningful aspect using 'pseudo equilibrium prices'. Neither coefficients in the mean nor in the variance function are affected substantially. Although this is somewhat in contrast to the results reported by Ederington and Lee (1995), it is not surprising since a higher aggregation level is used. The influence of the bid-ask spread on returns in very narrow 10-second intervals is much more pronounced since price changes are much smaller as compared to 2-minute intervals.[33] In addition, there seems to be a trade-off between the bias induced by the bid-ask spread and the bias induced by averaging over lagged prices especially during periods of dense information arrival.

Non-anticipated information is measured on the basis of survey data on analysts' forecasts, provided by Standard & Poors Global Markets (MMS). Initially

[33] The impact of the bid-ask spread depends on the size of the bid-ask bounce relative to average (absolute) price changes in a given interval. In an extremely liquid market, like the T-bond futures market, 2-minute intervals seem to be enough to eliminate the influence of the bid-ask spread largely.

released non-revised figures were extracted from the original monthly releases. Surprises are defined as the difference between initially announced figures and the median of analysts' forecasts. To facilitate a comparison between the headline figures, standardized surprises are used, i.e. for each headline, surprises are divided by the sample standard deviation of surprises.

4.2. SPECIFICATION OF THE MEAN FUNCTION

In this subsection we focus on the mean function of the return process and estimate eq. (3) without already specifying the (conditional) variance h_t (eq. (4)). Here it is assumed to be time-invariant, i.e. $h_t = h$.[34] With r_t denoting 2-minute log returns ($\times 10,000$), we estimate

$$r_t - \mathrm{E}[r_t] = \sqrt{h} \cdot u_t, \quad \text{where} \quad \mathrm{E}[r_t] = x_t'\beta. \tag{5}$$

The response of the price process to non-anticipated information is analyzed based on the explanatory variables x which capture surprises in headline figures (see Section 2). Surprises in nonfarm payrolls, unemployment rates, and hourly earnings are denoted by $S1$, $S2$, and $S3$, respectively. In addition, time dummies are defined which take on the value 1 for a given interval and zero else, i.e.

$$D_\tau = \begin{cases} 1 & \text{if } t = \tau \\ 0 & \text{else,} \end{cases}$$

where $t = 1, \ldots, 45$ denotes the 2-minute intervals between 8:22 a.m. and 9:52 a.m. Moreover, surprise dummies are defined for each 2-minute time interval such that the surprise variables interact multiplicatively with the dummy variables, i.e.

$$S_\tau = D_\tau S, \quad \text{with} \quad S \in \{S1, S2, S3\}.$$

For example, the interaction term $S2_{8:32\text{–}8:34} = D_{8:32\text{–}8:34} \times S2$ captures the impact of a surprise in headline 2 on the return in the interval 8:32–8:34. In addition, lagged 2-minute log returns are included in the regressions.

In a first step, we analyze the impact of the different types of information separately by running simple OLS regressions of 2-minute log returns on different sets of the corresponding surprise variables. In all regressions the above defined dummy variables cover the interval from 8:28 a.m. to 8:36 a.m.[35]

As a benchmark, the first regression, i.e. specification (1) in Table I, includes only a constant and lagged returns. In addition, the second regression (specification (2)) includes variables capturing detailed information concerning the first headline figure, i.e. nonfarm payrolls ($S1$). The following findings can be summarized:

[34] This requires the use of heteroskedasticity robust inference techniques.

[35] We also included dummies capturing further intervals before and after the announcement, but did not find any significant impacts.

Table I. Mean function estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Const	−0.126	0.225	0.073	0.135	0.164	0.282*
r_{t-1}	−0.027	−0.098**	−0.033	−0.027	−0.095**	−0.089**
$S1_{8:28–8:30}$		−3.625**			−4.495**	−3.684*
$S1_{8:30–8:32}$		−28.692***			−27.897***	−26.507***
$S1_{8:32–8:34}$		−7.577***			−8.338***	−7.323***
$S1_{8:34–8:36}$		0.092			0.906	
$\|S1_{8:28–8:30}\|$		−1.625			−1.538	
$\|S1_{8:30–8:32}\|$		−11.494*			−11.262	−3.000
$\|S1_{8:32–8:34}\|$		−7.093***			−10.391***	−7.035***
$\|S1_{8:34–8:36}\|$		1.391			1.377	
$S2_{8:28–8:30}$			−1.279		−2.809	
$S2_{8:30–8:32}$			26.156***		20.004	18.867***
$S2_{8:32–8:34}$			1.002		0.490	
$S2_{8:34–8:36}$			1.852		2.086	
$\|S2_{8:28–8:30}\|$			−2.395		−3.385	
$\|S2_{8:30–8:32}\|$			−1.164		3.560	
$\|S2_{8:32–8:34}\|$			−2.256		0.179	
$\|S2_{8:34–8:36}\|$			1.924		1.549	
$S3_{8:28–8:30}$				2.476	0.673	
$S3_{8:30–8:32}$				−16.348*	−28.342	−23.907***
$S3_{8:32–8:34}$				1.861	−3.131	
$S3_{8:34–8:36}$				0.082	0.640	
$\|S3_{8:28–8:30}\|$				−2.567	2.586	
$\|S3_{8:30–8:32}\|$				−7.250	11.540	
$\|S3_{8:32–8:34}\|$				−4.016	6.542	
$\|S3_{8:34–8:36}\|$				1.360	−1.238	
$\bar{R}^2$	0.001	0.181	0.136	0.058	0.324	0.312
Regular F-test	0.360	6.045***	2.200**	0.788	4.346***	12.137***
BIC	−0.004	0.023	0.022	0.022	0.076	0.019

OLS regressions of 2-minute log returns on employment report announcement days. The sample period is from January 1995 to December 1999. Fifty-three days are used, on which no other report is announced along with the employment report. For each of these days, the intraday interval 8:22–9:52 a.m. ET is analyzed. The adjusted coefficient of determination ($\bar{R}^2$) is given as well as the results of a regular F-test on the hypothesis of a zero coefficient vector. The Bayes information criterion (BIC) is also provided. Inference is based on heteroskedasticity robust standard errors.
***, ** and * indicates significance at the 1%, 5%, and 10% level, respectively.

First, the estimated coefficients provide evidence for a significant impact of the surprise on the price, i.e. the higher the difference between the announced number and the corresponding forecast, the stronger the resulting decline of the price.[36] The strikingly high coefficient of the 8:30–8:32 surprise dummy ($S1_{8:30–8:32}$) supports

[36] Note that a higher than expected outcome of nonfarm payrolls as well as of hourly earnings is 'bad news' and should lead to an increase in interest rates and a decline in T-bond futures prices. In

hypothesis H1, which states that the arrival of non-anticipated information causes sharp price reactions.

Second, the significant coefficients of the absolute nonfarm payroll surprise dummies (in particular $|S1_{8:32\text{–}8:34}|$) suggest an asymmetric response to 'good' and 'bad' news. The asymmetry in the response to surprises is particularly pronounced in the second interval:[37] 'Bad' news still has quite a negative impact on returns in the 8:32–8:34 interval, while 'good' news of the same size has almost no impact.[38] Note, however, that a significant asymmetric response is found only for the nonfarm payrolls figure, but not for the other headline figures.

Third, focusing on the time pattern of the price response induced by the payrolls surprise, we find significant price movements between two minutes before ($S1_{8:28\text{–}8:30}$) and four minutes after the announcement ($S1_{8:30\text{–}8:32}$ and $S1_{8:32\text{–}8:34}$ as well as $S1_{8:30\text{–}8:32}$ and $|S1_{8:32\text{–}8:34}|$). The significant price reaction in the 8:28–8:30 interval provides some evidence for slight leakage effects. This result is quite surprising, since in the US, strict lock-up conditions should rule out any leakage of information.[39] However, the largest price reaction is observed within the 8:30–8:32 interval. This reaction sharply declines between 8:32–8:34 and disappears within the following 2-minute interval. These results indicate that the T-bond futures market rapidly advances towards a new equilibrium level after the arrival of non-anticipated information. Thus, the finding of a fast information diffusion strongly supports hypothesis H2.

The analysis described above is repeated for the remaining two headline figures, i.e. the unemployment rate $S2$ and hourly earnings $S3$. Regression results are given in columns (3) and (4) of Table I. Again, surprises in these headline figures cause strong price responses within the 8:30–8:32 interval, coinciding with the announcement.

Since after 8:32 no statistically significant influence is found, nonanticipated information associated with the unemployment rate and hourly earnings seems to be processed even more rapidly. The adjustment is basically completed within two minutes after the release. Moreover, note that the signs of the estimated coefficients for signed surprise dummies ($S2_{8:30\text{–}8:32}$, $S3_{8:30\text{–}8:32}$) support the hypothesized price reactions. T-bond futures prices rise in response to 'good' news from the inflation front, i.e. a lower than expected increase in nonfarm payrolls, a higher than expected unemployment rate and a lower than expected average hourly earnings

contrast, a lower than expected unemployment rate is also considered to be 'bad news' for T-bond futures.

[37] The asymmetric response in the 8:30–8:32 interval is only slightly significant in specification (2). It becomes insignificant when the other headline figures are included (see spec. (5), Table I).

[38] For example, a surprise of plus one standard deviation ($S1_{8:32\text{–}8.34} = |S1_{8.32\text{–}8:34}| = +1$) lowers returns in the 8:32–8:34 interval by around 0.15%, i.e. $(-7.577 - 7.093)/10000$. In contrast, a surprise of minus one standard deviation ($S1_{8:32\text{–}8:34} = -1$ and $|S1_{8:32\text{–}8:34}| = +1$) increases returns only slightly $(+7.577 - 7.093)/10000$.

[39] However, note that if we model the mean and the variance simultaneously, the significance of this effect is reduced. See the results provided in the following section.

figure. In contrast to the nonfarm payrolls, there is no indication of an asymmetric response to surprises in these figures since the $|S2|$ and $|S3|$ coefficients are insignificant.[40]

In regressions (5) and (6), the joint impact of the different types of non-anticipated information is evaluated. A very important result is that the estimated coefficients remain relatively stable when the corresponding explanatory variables associated with surprises in the other headline figures are included. In general, the significance of the variables is nearly unchanged which illustrates the robustness of the results. These findings indicate that each of the different types of nonanticipated information contributes to the explanation of the return process, which provides strong evidence in favor of hypothesis H1. Thus, market participants do not only assign weight to nonfarm payrolls but also pay attention to unemployment rates and hourly earnings.

In order to achieve a more parsimonious representation of the mean function, in regression (6), only those surprise variables are included which turned out to be significant in the previous regressions, i.e. (1) to (5). Note that no substantial change in the estimated coefficients is recorded, except for the insignificant $|S1_{8:30-8:32}|$ variable.

The analysis of the explanatory power of the particular models, based on the adjusted coefficient of explained variation $\bar{R}^2$, yields some interesting insights: First, accounting for autocorrelation in returns without including surprise variables (column 1) explains virtually nothing ($\bar{R}^2 = 0.1\%$). Second, including surprise variables associated only with one of the headline figures results in a substantial increase of the explanatory power (nonfarm payrolls +18.0%, unemployment rates +13.5%, and hourly earnings +5.7%).[41] Third, including all three headline figures (column (5)) explains 32.4% of the total variation, which is a quite satisfying result for an intraday return process. The strongly reduced model, which includes only the significant variables (column (6)), explains 31.2% of the variation.

4.3. SPECIFICATION OF THE VARIANCE FUNCTION

Besides the analysis of the price impact, a further major issue in this paper is the investigation of the variance impact of the arrival of nonanticipated information. To analyze the time pattern of the volatility response, we use an ARCH specification

[40] In contrast to $S1$, for which signed and absolute surprises are virtually uncorrelated ($Corr(S1, |S1|) = 0.04$), the correlation of $S2$ and $|S2|$ is -0.37 and that of $S3$ and $|S3|$ is 0.46. Hence, including both signed and absolute variables causes multicollinearity effects. This becomes evident by the changes of the coefficient signs of the insignificant $S2$ and $S3$ variables (compare columns (3) and (5), and (4) and (5), respectively).

[41] While the employment release is often referred to as ‘the king of announcements’ (see, for example, Li and Engle 1998, or Andersen and Bollerslev 1998), the results of these regressions suggest that the nonfarm payroll component ‘wields the scepter’. Nevertheless, the regularly neglected hourly earnings figure still has some explanatory power.

with multiplicative heteroskedasticity. While in the previous section the variance h_t was assumed to be time-invariant, now it is modelled as (eq. (4))

$$h_t = \sigma_t^2 + s_t^2 = \phi\epsilon_{t-1}^2 + \exp(w_t'\gamma),$$

where w_t is a vector of explanatory variables consisting of the surprise variables and time dummies, entering the variance specification collectively as multiplicative heteroskedasticity. w includes a constant term which can be interpreted as a baseline volatility level. γ is the corresponding coefficient vector.

As discussed in Section 2, we neglect any daily GARCH components since we focus on 90-minute windows around announcements of the employment report which is released on a monthly schedule. Moreover, we are primarily interested in the variance response due to surprise effects and not in the volatility persistence. Therefore, only three ARCH terms are included.[42] This seems to be appropriate to capture the variance dynamics within the particular 90-minute windows. However, since we neglect a possible volatility component, we use a robust inference based on pseudo ML estimates of the variance-covariance matrix (see Bollerslev and Wooldridge 1992).

The mean function is modelled based on the specification of column (6) in Table I. The estimation results for the complete model are given in Table II.

As a starting point, a simple ARCH(3) specification is given in column (1) of Table II. It illustrates the existence of a significant first order serial dependence in the variance function, with an ARCH coefficient of 0.521. Note that for all models the significance of the ARCH(2) coefficients is substantially lower and the ARCH(3) term is insignificant.

Columns (2) to (6) show the results of ARCH models with multiplicative heteroskedasticity. The model given in column (2) accounts for the deterministic pattern of volatility by including a set of time dummies covering the period from 8:26 a.m. to 9:40 a.m.[43] The variance peaks out in the interval just after the announcement (8:30–8:32) and declines almost monotonically until about one hour after the event. After this period, we do not find significant differences compared to the volatility level of the base category. Since the explanatory variables enter the variance equation exponentially, at its peak between 8:30 and 8:32, the conditional variance is more than 50 times higher than the variance in the base period, while it drops to a factor of around 9 in the following interval. 30 minutes after the announcement, the conditional variance is just about twice as high as in the base period. Thus, an extreme volatility response immediately after the announcement is found, followed by a relatively strong decline within the first minutes and a more slowly decaying

[42] Note that the implementation of a GARCH effect would lead to an inclusion of the explanatory variables in the model dynamics which would complicate the interpretation of the results.

[43] The base category is the time before the announcement (8:22–8:26) and the last 12 minutes of the analyzed time interval (9:40–9:52). This categorization is quite reasonable as it allows us to analyze the variance response due to announcement effects compared with the variance level before and a longer time after the announcement.

Table II. Simultaneous estimation of the mean and variance function

	(1)	(2)	(3)	(4)	(5)	(6)
Mean:						
const	0.325	0.161*	0.186*	0.207**	0.209**	0.213**
r_{t-1}	−0.119***	−0.101***	−0.102***	−0.104***	−0.104***	−0.106***
$S1_{8:28–8:30}$	−14.742**	−3.586**	−3.455**	−3.116**	−3.051*	2.830*
$S1_{8:30–8:32}$	−33.079***	−24.799***	−22.937***	−23.769***	−22.398***	−22.744***
$S1_{8:32–8:34}$	−5.898	−4.860*	−4.252**	−4.816**	−4.169**	−4.779*
$\|S1_{8:30–8:32}\|$	−2.267	−1.112	−1.075	−1.006	−1.450	−0.479
$\|S1_{8:32–8:34}\|$	−8.093*	6.607***	6.289***	−6.983***	−6.375***	−6.913***
$S2_{8:30–8:32}$	18.670**	20.417***	19.254***	19.398***	19.255***	18.036***
$S3_{8:30–8:32}$	−19.893***	−24.634***	−24.839***	−23.790***	−24.267***	−21.683***
Variance:						
const	3.934***	3.047***	2.513***	2.989***	2.608***	2.560***
ϵ^2_{t-1}	0.502**	0.113***	0.096***	0.082***	0.084***	0.085***
ϵ^2_{t-2}	0.037	0.045**	0.027*	0.033**	0.024*	0.022*
ϵ^2_{t-3}	0.032	0.027*	0.020	0.025	0.020	0.016
$D_{8:26–8:28}$		0.692**	0.712**	0.633**	0.684***	0.686**
$D_{8:28–8:30}$		2.000***	2.000***	1.979***	1.967***	1.949***
$D_{8:30–8:32}$		4.140***	4.091***	4.076***	4.072***	4.154***
$D_{8:32–8:34}$		2.125***	2.246***	2.229***	2.283***	2.365***
$D_{8:34–8:36}$		1.045***	1.240***	1.136***	1.270***	1.341***
$D_{8:36–8:38}$		2.275***	2.358***	2.271***	2.339***	2.373***
$D_{8:38–8:40}$		1.649***	1.610***	1.638***	1.645***	1.693***
$D_{8:40–8:42}$		1.212***	1.192***	1.239***	1.223***	1.255***
$D_{8:42–8:44}$		1.120***	1.152***	1.095***	1.130***	1.169***
$D_{8:44–8:50}$		1.256***	1.231***	1.230***	1.244***	1.269***
$D_{8:50–9:00}$		0.757***	0.821***	0.746***	0.802***	0.833***
$D_{9:00–9:10}$		0.417***	0.475***	0.437***	0.474***	0.518***
$D_{9:10–9:20}$		0.322*	0.365***	0.313**	0.358**	0.377***
$D_{9:20–9:30}$		0.217	0.199	0.230	0.210*	0.243*
$D_{9:30–9:40}$		−0.076	−0.019	−0.070	−0.027	−0.024
$\|S1\|$			0.158**		0.161***	0.217***
$\|S2\|$			0.083*		0.073	0.090*
$\|S3\|$			0.462***		0.281***	0.269***
$S1$				0.223***	0.174***	0.212***
$S2$				−0.021	−0.008	−0.013
$S3$				0.271***	0.167***	0.167***
$I^{S1^{++}S2^{--}}_{8:30–8:38}$						−1.674***
$I^{S1^{++}S2^{--}}_{8:38–9:20}$						−0.475*
BIC	7.235	6.820	6.795	6.798	6.793	6.795
α_0	43.606***	−4.354	−4.584	−5.337	−4.566	−11.330
α_1	0.477***	1.024	1.040	1.046	1.039	1.126***
$F_{\alpha_0=0,\alpha_1=1}$	7.619***	0.569	0.302	0.295	0.203	0.447
R^2	0.060	0.229	0.242	0.249	0.250	0.287

Maximum likelihood estimation of 2-minute log returns on employment report announcement days (sample period: January 1995 to December 1999, i.e. 53 non-overlapping employment announcement days). For each day the intraday interval 8:22–9:52 a.m. ET is analyzed. The Bayes information criterion (BIC) as well as the R^2 from the regression $\hat{\epsilon}_t^2 = a_0 + a_1 \hat{h}_t + \nu_t$ is given along with the results of an F-test on the joint hypothesis of $a_0 = 0$ and $a_1 = 1$ ($F_{\alpha_0=0,\alpha_1=1}$). Inference is based on pseudo ML standard errors (Bollerslev and Wooldridge 1992).

structure a longer time after the news arrival. Hence, these findings strongly support hypothesis H3.

Furthermore, some empirical evidence is obtained indicating that volatility starts to rise between 8:26 to 8:28 and shows a strong increase just before the announcement. Therefore, hypothesis H4 is clearly rejected. The detection of a pre-announcement surge in volatility is in line with the results of Ederington and Lee (1995), Fleming and Remolona (1999a), Franke and Hess (2000a) and others.

A further important finding is a significant decrease of the ARCH coefficients compared to specification (1), which indicates that the volatility response due to the arrival of non-anticipated information seems to be a major source of autocorrelation in the volatility process.

In regressions (3) and (4), both variables accounting for the deterministic time pattern and the surprise variables are included. Note that these variables enter the variance specification multiplicatively, i.e. the surprise variables interact with the complete set of time dummies, leading to proportional downward or upward shifts of the variance function. In column (3), variables capturing the magnitude of surprises in the three headline figures are added, i.e. absolute surprises ($|S1|$, $|S2|$, and $|S3|$). We find significantly positive coefficients, thus large surprises lead to higher variances which supports hypothesis H5. Column (4) allows to investigate asymmetric effects by adding signed surprises ($S1$, $S2$, and $S3$). The results suggest a significant positive impact of 'bad' news for $S1$ and $S3$ which confirms hypothesis H6.[44] No significant asymmetric influence is found for $S2$.

The model in column (5) includes both signed as well as absolute surprise variables. Note that the coefficients and corresponding standard errors remain quite stable, indicating the robustness of the results. This confirms the preliminary results of model (3) and (4). Hence, we obtain empirical evidence for the existence of absolute effects (H5) and asymmetric effects (H6) of surprises in nonfarm payrolls and hourly earnings.[45]

Finally, specification (6) includes two interaction terms between surprises in nonfarm payrolls and unemployment rates, in order to test for the reinforcement effect stated by hypothesis H7. $I^{S1^{++}S2^{--}}$ takes on the value one if a large[46] positive value for $S1$ and, at the same time, a large negative value for $S2$ is observed and zero else. This dummy variable is interacted with the time dummies, creating a separate variable for the interval from 8:30 to 8:38, in which volatility is extremely high, i.e., $I^{S1^{++}S2^{--}}_{8:30\text{–}8:38}$, and another variable for the subsequent phase of rather moderately increased volatility, i.e., $I^{S1^{++}S2^{--}}_{8:38\text{–}9:20}$. As hypothesized by H7, a strong and highly significant reduction of volatility is found if both headline figures convey

44 Recall that positive surprises in $S1$ and $S3$ cause negative price movements. In contrast, negative price movements are caused by negative surprises in $S2$.

45 Similar asymmetric effects associated with scheduled announcements have also been found by Li and Engle (1998) based on daily data. However, Li and Engle define 'negative' news indirectly on the basis of the observed price reaction rather than including the signed surprise.

46 Here, large is defined as exceeding one standard deviation.

extremely bad news and thus mutually reconfirm their messages.[47] This indicates that the room for differences of opinion is significantly reduced if reconfirmation of 'bad' news reduces the possibility of a measurement error. Then volatility is substantially decreased.

Analyzing the goodness-of-fit of the particular specifications based on the Bayes Information Criterion (BIC) reveals that the inclusion of time dummies leads to the strongest improvement. This result illustrates the importance of accounting for the time pattern of the volatility response due to announcement effects. Further improvements of the model are reached by the inclusion of the particular surprise variables. The lowest BIC value is obtained based on specification (5).

In order to evaluate the goodness-of-fit of the different volatility specifications based on in-sample predictions, we follow Pagan and Schwert (1990) and regress the 2-minute squared residuals $\hat{\epsilon}_t^2$ on the corresponding variance forecasts $\hat{h}_t$ based on the individual specifications (1 to 6), i.e. $\hat{\epsilon}_t^2 = a_0 + a_1 \hat{h}_t + \nu_t$. Then, the goodness-of-fit is evaluated based on the coefficient of explained variation R^2 associated with this regression as well as on the estimates $\hat{a}_0$ and $\hat{a}_1$.[48] Results of this estimation are given in the last four lines of Table II. They show that the predictive performance increases substantially when explanatory variables are included which capture the volatility response due to the announcement schedule. This confirms the findings based on the BIC. Again, the goodness-of-fit is only slightly improved when the particular surprise variables are taken into account. For the complete model, i.e. specification (6), the highest R^2 is obtained (0.287) corresponding to a correlation between squared residuals and variance predictions of $Corr(\hat{\epsilon}_t^2, \hat{h}_t) = 0.536$. However, the fact that the estimated slope coefficient a_1 is significantly larger than 1 indicates that specification (6) yields slightly biased predictions. Moreover, we obtain a higher BIC value than for specification (5). Hence, highly significant coefficient estimates indicate the existence of reinforcement effects, whereas the BIC criterion and the in-sample forecast tests suggest that the overall model performance is not increased.

5. Stability of the Results – A Look at Other Announcements

To complete the analysis and to provide a simple robustness test, we analyze the processing of non-anticipated information contained in three other, quite different, macroeconomic releases: the report of the National Association of Purchasing Managers (NAPM), consumer prices (CPI) and housing starts (HS).[49] Analysts'

[47] We also analyzed positive reinforcement effects, i.e. extremely 'good' news in the two headline figures, but these did not turn out to be significant.

[48] Note that unbiased predictions imply values of $\hat{a}_0 = 0$ and $\hat{a}_1 = 1$.

[49] The NAPM index provides even more timely information about economic activity than the employment report since it is typically released a few days earlier. In contrast, the BLS's CPI report is announced around one week later, and another week later, the Commerce Department's housing start figures. While the NAPM index and housing starts allow market participants to gauge the strength of

forecasts are available for one headline figure of the NAPM report (i.e. the overall index) and the HS report (i.e. the total number of residential construction starts), as well as for two headline figures of the CPI report (i.e. the overall CPI and the core CPI, which excludes volatile food and energy prices). Although two CPI headlines are available, in contrast to the employment report's unemployment and payroll figures, the CPI figures do not originate from different surveys. Since the core CPI only removes some prices from the overall CPI's basket, a considerable overlap remains in what is measured by the two figures. Consequently, a high correlation coefficient between surprises in the total CPI and the core CPI is found, i.e. 0.61.[50] This leads to multi-collinearity problems, especially if we include both signed and absolute surprise variables into the analysis. Besides the high correlation, the fact that the CPI figures are not based on different surveys, and hence, do not allow traders to gain much evidence about the occurrence of measurement errors, precludes an analysis of the reinforcement effect. Therefore, we perform the analysis for each headline figure separately. Nevertheless, we are able to check the robustness of the remaining results reported in the previous section.

Again, we measure surprises as deviations from MMS forecasts and apply a 90-minute window around the release of each report.[51] Analyzing unique announcements, we exclude those days on which other reports are announced in this interval. While the overlap with other announcements is minimal for the employment report, we loose considerably more observations for the other three announcements, in particular for the NAPM and CPI report (see Table III).

Estimation results for the simultaneous mean and variance impact of the individual headline figures are given in Table III. First, focussing on the mean function the following results can be summarized: Again, non-anticipated information is processed rather rapidly.[52] With the exception of the NAPM index, the highest impact is found in the announcement interval ($S1_{8:30–8:32}$). Nevertheless, the magnitude of this impact is considerably lower as compared to the employment report. There seems to be some lagged response to the NAPM release (but also a leakage effect), which may be due to a less strict announcement procedure of this non-government report. However, for the other reports the processing of non-anticipated

economic activity, and hence possible inflation pressures, the CPI report provides a direct reading of price changes. For more details see, for example, Rogers (1998).

50 This is due to the fact that announced changes in the total and core CPI figures are highly correlated, i.e. 0.55. In contrast, announced changes in unemployment rates and nonfarm payrolls are almost uncorrelated, i.e. –0.18.

51 Surprises are standardized by their sample standard deviation. For the NAPM report, which is released at 10:00 ET, we use the window from 9:52 to 11:22. Since the other reports are announced at 8:30 ET, we apply the same window as for the employment report, i.e. 8:22–9:52.

52 The signs of the estimated surprise variables are in accordance with standard theory: A higher than expected NAPM or HS reading indicates higher economic activity which might lead to higher expected real interest rates and/or to higher expected inflation rates. CPI figures provide a direct measure of (past) inflation rates. Hence, surprises in the four headline figures should have a negative impact on T-bond futures returns.

Table III. Simultaneous estimation of the mean and variance response to the announcement of the NAPM index, consumer prices, and housing starts

	(1) NAPM	(2) Overall CPI	(3) Core CPI	(4) HS
Mean:				
const	0.123	−0.006	−0.019	0.015
r_{t-1}	0.081**	−0.173***	−0.171***	−0.176
$S1_{8:28–8:30}$	−4.806**	−0.453	−1.241**	−0.175
$S1_{8:30–8:32}$	−7.156*	−6.953***	−6.116***	−8.282
$S1_{8:32–8:34}$	−10.701***	−3.555*	−2.000	−0.389
$\|S1_{8:30–8:32}\|$	−2.735	−5.479***	−2.093	1.777
$\|S1_{8:32–8:34}\|$	−9.098***	−6.295**	−2.704*	1.204*
Variance:				
const	2.963***	2.153***	2.131***	2.362
ϵ^2_{t-1}	0.042	0.104***	0.092***	0.064**
ϵ^2_{t-2}	−0.029	0.047*	0.045	0.019
ϵ^2_{t-3}	0.057	0.018	0.030	−0.003
$D1_{8:26–8:28}$	0.815	0.582**	0.627**	−0.496**
$D1_{8:28–8:30}$	0.941**	−0.251	−0.478	0.176
$D1_{8:30–8:32}$	2.324***	2.255***	2.209	2.109***
$D1_{8:32–8:34}$	2.062***	2.482***	2.649	0.958***
$D1_{8:34–8:36}$	1.634***	1.275***	1.171***	1.111***
$D1_{8:36–8:38}$	0.722	0.598*	1.053**	−0.185
$D1_{8:38–8:40}$	1.098**	2.081***	2.111	0.687***
$D1_{8:40–8:42}$	0.186	1.251***	1.249	0.195
$D1_{8:42–8:44}$	−0.445	1.029**	0.927**	0.018
$D1_{8:44–8:50}$	0.374	0.390	0.389	0.311**
$D1_{8:50–9:00}$	−0.015	0.499**	0.484**	0.255*
$D1_{9:00–9:10}$	−0.037	0.027	−0.022	−0.158
$D1_{9:10–9:20}$	−0.731**	0.141	0.098	0.031
$D1_{9:20–9:30}$	−0.761***	−0.205	−0.211	−0.400***
$D1_{9:30–9:40}$	−0.251	0.076	0.098	−0.266**
$\|S1\|$	0.554**	0.195**	0.221***	0.172***
$S1$	0.791***	0.083*	0.102**	0.075**
BIC	6.205	5.892	5.890	5.616
α_0	17.727***	−3.410	−0.718	−2.277*
α_1	0.384***	1.189**	1.053	1.142**
$F_{\alpha_0=0,\alpha_1=1}$	6.422***	0.262	0.031	0.253
R^2	0.040	0.219	0.201	0.209

Maximum likelihood estimation of 2-minute log returns during 90-minute intervals around the announcements of the National Association of Purchasing Managers (NAPM) index, consumer prices (CPI) and housing starts (HS). The CPI report contains two headline figures, i.e. the overall index and a core index. During the sample period, January 1995 to December 1999, we observe 12 NAPM, 17 CPI, and 41 HS announcements without an overlap with other releases. For further details see Table II.

information is completed within the first two minutes after the announcements. Moreover, similar to the nonfarm payrolls figure, indications of an asymmetric mean response are found for all the four headline figures. Overall, a similar reaction of the conditional mean function of the return process to non-anticipated information in these figures is observed, although the reaction to employment figures is much more pronounced. Nevertheless, this finding strongly confirms the above reported results with respect to the mean impact.

In addition, the impact of the four figures on the variance process also resembles the variance impact of the employment headlines. Again, only small but mostly highly significant ARCH(l) coefficients are found, while only one ARCH(2) and no ARCH(3) term are significant, when surprise variables are included into the specification. Moreover, the estimated deterministic volatility pattern is quite similar. It shows a strong increase of volatility after the announcement, followed by a rapid decline to the base level. However, the volatility peak is not quite as high (e.g. when NAPM is released, volatility is 'only' 10 times higher than the base level) and volatility returns faster to the base level (i.e. within about 30 minutes).[53] More importantly, the results concerning the impact of surprises on the volatility are strongly confirmed. For all the four figures a (highly) significant positive impact of absolute surprises is found. In addition, the estimated coefficients of the surprise variables are of comparable magnitudes, only absolute NAPM surprises seem to have a somewhat stronger impact. The results for the asymmetric volatility response are also confirmed: For all the four headline figures we find again that 'bad' news, i.e. positive surprises which have a negative impact on returns, raise the volatility.

Overall, these results suggest that the simultaneous mean and variance impact of non-anticipated information in the employment report is not a unique phenomenon. Non-anticipated information in widely awaited macroeconomic headline figures is incorporated very rapidly into T-bond future prices suggesting that traders' average beliefs about the new equilibrium price level shift almost instantaneously. But surprises also create uncertainty. Volatility is higher after large surprises, in particular after 'bad' news, indicating that traders' opinions about the precise price impact are more dispersed. Although these effects on first and second moments are quite similar across individual releases, the employment report is special in the sense that it allows market participants to cross-validate information provided by its headline figures. This is due to the fact that nonfarm payrolls and unemployment rates are derived from two independent surveys. Therefore, the employment report allows market participants a better assessment of the probability of measurement errors. In situations where measurement errors can be ruled out, less room for differences of opinion is left, and hence volatility is reduced.

[53] This is in line with the findings of Bollorslev et al. (2000) that the deterministic volatility pattern around employment releases is higher and more persistent in comparison to other releases.

6. Conclusions

This paper scrutinizes the processing of information contained in the U.S. employment report. The impact of non-anticipated information arrival on both first and second moments of the return process is analyzed. This allows some interesting insights into the creation of uncertainty by the release of macroeconomic news.

In contrast to the previous literature, which investigates volatility while refraining from including variables into the mean function that account for surprises, we control for the consistent price reaction to non-anticipated information. With a completely specified mean function, the volatility function receives a different interpretation: Rather than capturing just the fluctuations of squared returns, the volatility function describes market participants' uncertainty about the precise price impact of new information, while the mean function describes the shift in average beliefs about the new equilibrium price level induced by the arrival of non-anticipated information.

The main results derived on the basis of this estimation approach are as follows. First, surprises in all three headline figures have a distinct impact on the level of prices, with the nonfarm payrolls figure having the strongest impact. Second, non-anticipated information leads to an almost instantaneous price reaction which is completed within the first two to four minutes. This indicates that the market advances very rapidly to a new equilibrium price level. Third, volatility is slightly higher before the announcement, which might be due to a temporary illiquidity before the announcement. Volatility surges immediately afterwards. In particular, volatility peaks out in the 2-minute interval associated with the announcement and is substantially reduced in the following interval, though remaining elevated for about one hour. The high volatility after the announcement suggests that there is considerable uncertainty about the precise price impact of new information. Forth, strong magnitude effects of surprises are found to have an impact on volatility, i.e. larger surprises do not only lead to a more pronounced price reaction, they also create more uncertainty. Fifth, there are strong asymmetric effects, i.e. 'bad' news measured in terms of the surprises contained in headline figures raise the volatility substantially, while good' news reduces traders' uncertainty. This suggests that market participants have more difficulties to assess the precise price impact of news when negative shocks occur. Last but not least, a strong interaction is detected between headline figures with a related information content. Pointing in the same direction, extremely bad news in the nonfarm payrolls figure reinforces the signal of a devastating unemployment rate reading. This cross-validation of extreme signals leaves less room for traders' differences of opinion and hence decreases volatility.

Analyzing the stability of these results, similar effects are found for other scheduled announcements. This suggests some regularities in the processing of non-anticipated macroeconomic information. However, the fact that the main employment headlines are derived from two independent surveys distinguishes the employment report to some extent from other releases. This dual-survey sampling allows market participants a more accurate assessment of the probability of measurement errors and hence a more precise assessment of the price impact of the survey results.

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