Bayesian Learning in Financial Markets
- Testing for the Relevance of Information Precision in Price Discovery *

Nikolaus Hautsch† and Dieter Hess‡

April 2005

Abstract

An important claim of Bayesian learning and a standard assumption in price discovery models is that the strength of the price impact of unanticipated information depends on the precision of the news. In this paper, we test for this assumption by analyzing intra-day price responses of CBOT T-bond futures to U.S. employment announcements. By employing additional detail information besides the widely used headline figures, we extract release-specific precision measures which allow to test for the claim of Bayesian updating. We find that the price impact of more precise information is significantly stronger. The results remain stable even after controlling for an asymmetric price response to 'good' and 'bad' news.

Keywords: Bayesian learning; information precision; macroeconomic announcements; asymmetric price response; financial markets; high-frequency data

JEL classification: E44, G14

*For valuable comments we are grateful to Francis X. Diebold, Robert Engle, Oliver Fabel, Michael Fleming, Alexander Kempf, Christoph Memmel, Stefan Rümzi, David Veredas, and an anonymous referee who greatly helped to improve the paper. The paper has also strongly benefited from comments of participants of the Market Microstructure and High Frequency Data Conference, Sandbjerg, August 2001, the 64th annual meeting of the "Verband der Hochschullehrer für Betriebewirtschaft", Munich, May 2002, the 10th Global Finance Conference, Frankfurt, June 2003, the third "Kölner Finanzmarktkolloquium", Cologne, November 2003, the 40th annual meeting of the Eastern Finance Association, Mystic, April, 2004, the Meeting of the European Financial Management Association, Zürich, June 2004, as well as from comments of workshop and seminar participants at the Universities of Frankfurt, Karlsruhe, Konstanz, Cologne, Odense, St. Gallen and Ulm. Data on analysts' forecasts are obtained from Money Market Services, (MMS, Informa Global Markets) announcement data from the Bureau of Labor Statistics. The authors gratefully acknowledge financial support by the Deutsche Forschungsgemeinschaft (DFG) within the Center of Finance and Econometrics (CoFE). Dieter Hess appreciates a grant by the DFG (project HE 3180/1).

†University of Copenhagen, Institute of Economics, Studiestraede 6, DK-1455 Copenhagen, Denmark, tel: +45 3532 3022 email: nikolaus.hautsch@econ.ku.dk

‡University of Cologne, Corporate Finance Seminar, Albertus-Magnus-Straße, D-50923 Cologne, Germany, tel: +49 (0)221 470 7877, email: hess@wiso.uni-koeln.de
Bayesian Learning in Financial Markets
- Testing for the Relevance of Information Precision in Price Discovery

Abstract

An important claim of Bayesian learning and a standard assumption in price discovery models is that the strength of the price impact of unanticipated information depends on the precision of the news. In this paper, we test for this assumption by analyzing intra-day price responses of CBOT T-bond futures to U.S. employment announcements. By employing additional detail information besides the widely used headline figures, we extract release-specific precision measures which allow to test for the claim of Bayesian updating. We find that the price impact of more precise information is significantly stronger. The results remain stable even after controlling for an asymmetric price response to 'good' and 'bad' news.
1 Introduction

The question of how fundamental information is incorporated into asset prices is one of the most important topics in financial economics. However, empirical research on price discovery is hindered by two major difficulties: First, information is hard to observe. In particular, researchers are confronted with the problem of recording the information flow accurately and of identifying and extracting relevant information driving prices. A second, and even more difficult issue, is to quantify how information is assessed by market participants. Naturally, the valuation of news depends on market participants’ prior expectations and on how these expectations are built up based on the corresponding information sets. Recent research has achieved considerable progress regarding the first problem. Using financial intraday data and headline information conveyed by scheduled macroeconomic releases, several studies\(^1\) were able to identify unanticipated information and to quantify the implied price reaction. The general understanding by now is thus that unanticipated information has a strong and clearly identifiable effect on returns and price volatility. Nevertheless, only little is known about how market participants react to information and how they build their beliefs regarding the meaning and the importance of surprising news. In this context, recent literature focusses on two major aspects. One branch emphasizes the importance of the state of the market in which the information arrives. For example, Veronesi (1999) shows within a rational expectations equilibrium framework that market participants may react quite differently to the same information - depending on their beliefs whether the economy is in a state of low or high growth.\(^2\) An alternative aspect is stressed by the literature on Bayesian learning.\(^3\) This approach is based on the notion that market agents’ reactions are strongly driven by their prior beliefs and the way they


\(^2\)Conrad, Cornell, and Landsman (2002) find empirical evidence for such effects by analyzing stock price reactions to earnings announcements in dependence of the market level.

use new information in order to update these beliefs. In these models, the precision of new information (relative to the precision of information available before an announcement) is of particular importance. Therefore, one main implication of this literature is that price reactions are driven not only by the amount of unexpected information but also by its quality. In periods when released data is perceived to be more precise – relative to prior information – a stronger price reaction should be observed to a given piece of unexpected information.

Until now these aspects have received comparatively little attention in empirical literature. Nevertheless, an important contribution in this field is provided by Krueger and Fortson (2003) who study the influence of U.S. employment news on daily prices of Treasury bonds, but find only limited evidence for a precision effect. One reason for this result could be that on a daily aggregation level, the measurement of price responses is overlaid by a lot of noise which complicates the identification of such effects. Another reason could be that the authors’ approximation of the information quality by a linear time trend which is assumed to capture the increasing precision of announcements over time is presumably too inexact.

To our knowledge no study has yet examined the claim of Bayesian updating using macroeconomic announcements and high-frequency market data. The goal of this paper is to fill this gap and to test the empirical relevance of the role of information precision on an intraday basis. By estimating the price response which is caused by the precision of information, we focus on the following two major research issues:

The first objective concerns the question of whether prices actually respond stronger to more precise news. I.e., is the price reaction stronger if the announced information is perceived to be more precise relative to the precision of the information available before the announcement? An answer to this question provides hints on whether market participants’ valuation and perception of new information is in line with Bayesian learning mechanisms and whether the consideration of such effects significantly contributes to price discovery.
A second question in this paper is related to sign effects, i.e. asymmetries in the price response due to 'good' vs. 'bad' news, since a wide range of papers finds evidence that prices respond stronger to 'bad' news than to 'good' news.\(^4\) In order to preclude that asymmetries in the relative precision of information are driven by spurious correlations between the sign of the news and its precision, we analyze both sign and precision effects. In particular, we test whether prices react stronger to more precise news than to less precise news when the sign of news is explicitly taken into account. Such an analysis provides insights into the question whether information precision can be a further source for asymmetric price reactions.

One obvious reason for the missing empirical evidence in this area is the lack of precision data, in particular the absence of precision measures for released information. Testing for the influence of information quality necessitates data on both the precision of information available prior to a public announcement and the precision of released information. However, both types of precision measures are rarely available at the same time. If analysts’ forecasts are available, as for the headline figures of macroeconomic announcements, a proxy for the (im)precision of prior information can be obtained from the dispersion of analysts’ forecasts.\(^5\) Nevertheless, information on the precision of the released data is virtually unavailable, in particular if the accuracy of announcements varies over time. The unavailability of precision data is not only a problem researchers have to deal with. It often seems to be impossible for market participants as well to infer the precision of a given piece of information at the time of its release.\(^6\)

---


\(^5\)See, for example, Andersen, Bollerslev, Diebold, and Vega (2003) who use the cross-sectional standard deviation of analysts’ forecasts to approximate investors’ uncertainty.

\(^6\)In some cases, researchers try to extract the perceived precision of the data from its impact on posterior beliefs. For example, Kandel and Zilberfarb (1999) compare inflation forecasts for a given period before and after a public announcement.
release-specific precision measures, market participants might try to use supplementary
information to infer the accuracy of the announced data.

In order to extract and to quantify such precision measures, our empirical analysis focusses
on announcements of the U.S. employment report. Besides the fact that this report has a
profound and well documented impact on financial markets\(^7\), it offers a very interesting
second source of information which becomes available at the same time as the widely
awaited headline figures: the revision of the previous month’s nonfarm payrolls figure.
Since revisions reveal measurement errors in the previous reporting period, they may help
traders to assess the reliability of the currently released headline figures, in particular
if these measurement errors contain predictable components. Therefore we propose to
extract a release-specific precision statistic by inspecting the history of (absolute) revisions.
Technically speaking, the one-step-ahead forecast from a volatility model fitted to the time
series of revisions is used to approximate the (im)precision of the released information.
This precision proxy allows us, in connection with the dispersion of analysts’ forecasts, to
construct a measure of the relative precision of announced and prior information.

Based on high-frequency data of the Chicago Board of Trade (CBOT) T-bond futures
covering a twelve year period from 1991 to 2002, we estimate the T-bond futures reactions
in a 90-minute window around the monthly employment releases. This analysis yields the
following results: First of all, we document a significant asymmetry in the price response
to precise vs. imprecise information, providing strong evidence in favor of the catalyzing
effect of information precision. Second, in line with the empirical results of Conrad, Cornell,
and Landsman (2002) for stocks, we find that the T-bond futures market reacts stronger
to ‘bad’ news than to ‘good’ news. Disentangling these two asymmetric price reactions,
we show that the catalyzing effect of information precision is not driven by a possibly

\(^7\)Evidence for its extreme market impact is provided, for example, by Ederington and Lee (1993),
Fleming and Remolona (1999c) or Bollerslev, Cai, and Song (2000). Therefore, the U.S. employment
report is often referred to as the ‘king of announcements’ (see, e.g. Li and Engle 1998, or Andersen and
Bollerslev 1998).
asymmetric price response to 'good' and 'bad' news. In particular, we find that prices respond significantly stronger to precise 'bad' news than to imprecise 'bad' news. The same holds true for precise and imprecise 'good' news.

The remainder of this paper is organized as follows. The subsequent section delineates the role of information precision in determining the strength of the price impact. Section 3 illustrates the main information components in the employment report and explains how to construct appropriate precision estimates. Section 4 describes the high-frequency return data, outlines the estimation procedure, and presents the empirical results. Finally, Section 5 concludes.

2 The role of information precision

Theoretical literature on information processing in financial markets models traders’ reactions to news typically in a Bayesian updating framework. In this literature two fundamental results are evident: Firstly, the price reaction is driven primarily by the amount of unanticipated information, and secondly, the (relative) quality of information acts as a catalyst and determines the strength of this price reaction. Below we present a simple model framework that allows us to pinpoint the basic mechanisms of Bayesian learning.

Suppose that traders have homogeneous beliefs regarding some economic variable $X$ (e.g. the unemployment rate) before some public announcement is made. Let $g(X)$ denote these prior beliefs about $X$ and assume that they are normally distributed, i.e. $g(X) = N(\mu_F, 1/\rho_F)$, where $\mu_F$ represents traders’ mean forecast and $\rho_F$ is the precision of this forecast defined as the inverse of the variance. Moreover, suppose that a public announcement is released which provides traders with a noisy estimate $\mu_A$ of $X$,

---

8See e.g. Holthausen and Verrecchia (1988), Kim and Verrecchia, Blume, Easley, and O'Hara (1994), Kandel and Pearson (1995), and Veronesi (2000), to cite only a few.

9Note that $X$, like the corresponding forecasts and announcements, relate to one specific reporting month $t$, and hence should be indexed by $t$. For ease of exposition, we suppress this index here.
but does not reveal the realization \( X \) itself. We assume an additive error term structure, i.e. \( \mu_A = X + \varepsilon \), where \( \varepsilon \) is a zero mean normally distributed error term with variance \( \text{Var}[\varepsilon] = 1/\rho_A \) and \( \text{E}[X \cdot \varepsilon] = 0 \). Hence the conditional probability density function of \( \mu_A \) given \( X \), \( f(\mu_A|X) \), is \( N(X, 1/\rho_A) \). Note that we abstract from information asymmetries and assume that all market participants know \( \mu_F \) and \( \rho_F \) before the announcement and that the public announcement reveals both \( \mu_A \) and \( \rho_A \).

Let \( g(X|\mu_A) \) denote traders’ posterior beliefs after observing the announced estimate \( \mu_A \). According to Bayes rule, i.e.
\[
g(X|\mu_A) = \frac{f(\mu_A|X)g(X)}{\int_{-\infty}^{\infty} f(\mu_A|X)g(X) dX},
\]
and exploiting the normality of \( \mu_A \) and \( X \), the posterior beliefs are normally distributed with mean
\[
\mu_P := \text{E}[X|\mu_A] = \mu_F \frac{\rho_F}{\rho_F + \rho_A} + \mu_A \frac{\rho_A}{\rho_F + \rho_A} \tag{1}
\]
and precision
\[
\rho_P := \text{Var}[X|\mu_A]^{-1} = \rho_F + \rho_A. \tag{2}
\]
Hence the adjustment of market participants’ mean beliefs induced by the public announcement, \( \mu_P - \mu_F \), is obtained by
\[
\mu_P - \mu_F = (\mu_A - \mu_F) \frac{\rho_A}{\rho_F + \rho_A}. \tag{3}
\]
Thus the shift in traders’ average beliefs is proportional to the deviation of the announcement \( \mu_A \) from its corresponding mean forecast \( \mu_F \). This is typically referred to as unanticipated information in an announcement or as surprise \( S \), i.e.,
\[
S := \mu_A - \mu_F. \tag{4}
\]
Moreover, the strength of this belief revision is also determined by the precision of the announcement, \( \rho_A \), relative to the precision of posterior beliefs, \( \rho_P = \rho_F + \rho_A \).
Assume that the market price $P$ of some risky asset is proportional to traders’ conditional expectations of $X$, i.e.,

$$P = \begin{cases} \nu \cdot \mu_F & \text{before the announcement,} \\ \nu \cdot \mu_p & \text{after the announcement} \end{cases}$$

(5)

with $\nu$ denoting some constant. Then the change in market prices $\Delta P$ induced by a public announcement is given by

$$\Delta P = \nu \cdot \pi \cdot S,$$

(6)

where $\pi$ denotes the so-called 'price-response coefficient'

$$\pi := \frac{\rho_A}{\rho_P} = \frac{\rho_A}{\rho_F + \rho_A}$$

(7)

that determines the strength of the price reaction dependent on the relative precision of the announced data compared to the precision of posterior beliefs.

From the above analysis the following empirically testable implications arise:

(i) Eq. (6) suggests that the immediate price change after an announcement is proportional to the amount of unanticipated information in an announcement. This implication is standard and has been tested in several previous studies, e.g. by Hardouvelis (1988), Dwyer and Hafer (1989), Fleming and Remolona (1999c) and Andersen, Bollerslev, Diebold, and Vega (2003), to name only a few.

(ii) From eq. (6) in connection with the price-response coefficient (eq. 7), it follows that the immediate price impact of a given surprise depends on the relative precision of the announcement compared to prior information. The price reaction is stronger (weaker) if the announced information is perceived to be more (less) precise relative to the precision of information available before the announcement. The two limiting cases emerge when $\rho_F \to 0$ or when $\rho_A \to 0$. In the first case, we observe a maximal

---

10For example, in the models of Kim and Verrecchia or Kandel and Pearson, traders directly receive signals on the asset’s fair value. Then, $\nu = 1$. 7
price reaction due to the fact that prior information is completely unprecise. In the second case, the price response is zero because the announcement itself provides no new information.

Even though the above discussed model framework is rather simple, it nicely illustrates the basic mechanism of Bayesian learning, i.e. that the magnitude of the price response is determined by the amount of unanticipated information and, simultaneously, by the relative precision of information. These fundamental relationships are also found in extended frameworks like, for example, in Kandel and Pearson (1995) and Kim and Verrecchia (1991) who model the frequently observed positive relation between volatility and trading volume or in Veronesi (1999) who explains asymmetries in the price reaction to 'good' versus 'bad' news.

3 Measuring the precision of information

3.1 Major information components in the U.S. employment report

The profound price impact of unanticipated information in the U.S. employment report on various financial markets is well documented.\footnote{Several studies provide strong evidence that unanticipated information in the employment report influences interest rates (e.g. Becker, Finnerty, and Kopecky 1996, Fleming and Remolona 1999c, and Hautsch and Hess 2002), foreign exchange rates (e.g. Hardouvelis 1988, Andersen, Bollerslev, Diebold, and Vega 2003), as well as stock prices (e.g. Boyd, Hu, and Jagannathan 2005). In addition, various studies document that the U.S. employment report influences the volatility of bond prices and foreign exchange rates (e.g. Ederington and Lee 1993, 1995, DeGennaro and Shriives 1997, Andersen and Bollerslev 1998, Jones, Lamont, and Lumsdaine 1998, and Bollerslev, Cai, and Song 2000), bid-ask spreads (e.g. Balduzzi, Elton, and Green 2001) as well as trading volumes (e.g. Fleming and Remolona 1999a).} While this report, which is released by the Bureau of Labor Statistics (BLS), provides a large amount of detailed information, both market participants and researchers focus their attention on a few so-called headline figures, in particular the nonfarm payrolls figure and the unemployment rate figure.\footnote{For example, Dwyer and Hafer (1989) and Prag (1994) focus exclusively on unemployment rates, Fleming and Remolona (1999c) use nonfarm payrolls. Some authors employ both nonfarm payrolls and unemployment rates, e.g. Cook and Korn (1991), Edison (1996), and Balduzzi, Elton, and Green (2001).} Both
figures are disseminated via several news vendors within seconds and provide market participants with a timely and comprehensive estimate of current economic activity. Moreover, they allow some inference about inflationary pressures which might arise from a tightening labor market. In addition, analysts’ forecasts are available for these figures which allow to differentiate between the already anticipated part of a given piece of information and the unanticipated part.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>Nonfarm payroll data used in this study - an example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Release date</td>
<td>Reported total nonfarm payrolls (current month)</td>
</tr>
<tr>
<td>99/01/08</td>
<td>127.156</td>
</tr>
<tr>
<td>99/02/05</td>
<td>127.347</td>
</tr>
<tr>
<td>99/03/05</td>
<td>127.610</td>
</tr>
<tr>
<td>99/04/02</td>
<td>127.678</td>
</tr>
<tr>
<td>99/05/07</td>
<td>127.911</td>
</tr>
<tr>
<td>99/06/04</td>
<td>128.167</td>
</tr>
</tbody>
</table>

Initially reported total nonfarm payrolls (× 1,000) along with first revisions of the previous months’ figures are given in columns 2-3. For example, the May BLS employment report released on June 4, provides a preliminary estimate of May payrolls, i.e. 128,167. The May report also includes a revised April estimate, i.e. 128,156. The announced nonfarm payrolls headline figure ($A_{NF}$) is the change in total payrolls (column 4). This is the difference of the initial May estimate (128,167) and the first revision of the April estimate (128,156). Analysts’ median forecasts provided by Standard & Poors Global Markets (column 5) are used to calculate the unanticipated information (column 6). Such a surprise ($S_{NF}$) is given by the deviation of the reported from the forecasted change (e.g. for the May report $S_{NF} = 11 − 220 = −209$). The revision variable $R_{NF}$ (last column) captures revisions of the previously released total nonfarm payrolls figures. For example, for June 4, $R_{NF}$ is calculated as the difference between the revised and the initial April figure (e.g. $R_{NF} = 128,156 − 127,911 = 245$).

Table 1 provides an example of the released nonfarm payrolls figures. The May 1999 employment report (last row in Table 1) released on June 4, 1999, 8:30 a.m. EST, announced a change in nonfarm payrolls of 11 (thousand).\textsuperscript{13} The so-called 'consensus' forecast was 220. This is the median of analysts’ forecasts polled by Money Market Services (MMS), a

\textsuperscript{13}This is the difference between the preliminary May estimate of the total number of nonfarm jobs (i.e. 128,167 thousand) and the revised April estimate (i.e. 128,156 thousand).
Comparing the announced and the forecasted figure yields a surprise $S_{NF}$ of $-209$. As in previous studies, this figure is used to measure the amount of unanticipated information in the released nonfarm payrolls figure.\(^{15}\)

A particularly interesting feature of the employment report is the fact that the initially released nonfarm payrolls figure is revised in subsequent months.\(^{16}\) The May 1999 report reveals that the preliminary April estimate was revised by 245 (i.e. from the previously disclosed level of 127,911 to 128,156). Primarily, revisions are the result of late responses and follow-up inquiries with nonrespondents.\(^{17}\) In addition, revisions reflect a re-estimation of seasonal adjustment factors and alignments of the employment establishment survey based estimates with the so-called "full universe counts".\(^{18}\) Note that revisions indicate problems in the sampling process, i.e. sampling errors in the previous month’s data. Hence, they are natural indicators for the precision of the previously released information. Therefore, it seems reasonable to assume that market participants exploit this information in order to assess the precision of the released data. This argument is set forth in the following section which shows how such a precision proxy can be constructed.

\(^{14}\) Each Friday, MMS polls analysts’ forecasts of macroeconomic figures to be released during the following week. Survey responses are received over a 3 to 4 hour period every Friday morning via fax or phone. The results of the survey are published at around 1:30 pm EST.

\(^{15}\) The performance of analysts’ forecasts of U.S. macroeconomic headline figures has been scrutinized, for example, by Pearce and Roley (1985), Hardouvelis (1988), Becker, Finnerty, and Kopecky (1996), and Moersch (2001). Based on regressions of released figures ($A_m$) on median forecasts ($F_m$), i.e. $A_m = \alpha + \beta F_m$, where $m$ indexes monthly observations, most studies find only a few series for which the hypothesis of biased forecasts (i.e. $H_0$: $\alpha = 0$, $\beta = 1$) can be rejected. Most importantly, however, none of the studies finds such deficiencies in nonfarm payrolls forecasts.

\(^{16}\) To date and to our knowledge, only Krueger and Fortson (2003) make use of revision information. Using daily data, however, they find no significant price impact of revisions.

\(^{17}\) For example, when a sampled firm goes out of business, most often it simply does not respond to the survey that month, rather than reporting zero employment. The information retrieved by a follow-up is often received too late to be incorporated into initial announcements. See "Technical Notes to Establishment Survey Data Published in Employment and Earnings" by the BLS.

\(^{18}\) The "full universe counts" are derived from administrative records on employees covered by unemployment insurance tax laws.
3.2 Release-specific precision estimates

Since the price impact of an announcement is determined by the relative precision of the announcement compared to pre-announcement expectations, we need two precision estimates in order to approximate the price impact coefficient $\pi$ given in eq. (7): an estimate of the precision of prior information, $\rho_F$, and of the released data, $\rho_A$.

Following Abarbanell, Lanen, and Verrecchia (1995), Mohammed and Yadav (2002), and Andersen, Bollerslev, Diebold, and Vega (2003), among others, we interpret the standard deviation of analysts’ forecasts before an announcement as a measure of the dispersion of prior expectations. To be precise, $s_{F,m}$ denotes the cross-sectional standard deviation of forecasts for a particular month $m$. Then $\rho_{F,m}$ is estimated by $\hat{\rho}_{F,m} = 1/s^2_{F,m}$.

In order to approximate $\rho_{A,m}$, we need release-specific precision estimates of the announced headline figures. Unfortunately, the employment report – like other macroeconomic releases – does not provide a survey-specific sample error estimate which would help traders to assess the quality of released the data at the time of the announcement. Nevertheless, we suppose that traders try to obtain a substitute for such a precision estimate. Particularly for the nonfarm payroll figure, a straightforward measure is obtained from the time series of revisions. A large revision in the currently released report suggests that the quality of the previous month’s headline figure was poor. In order to assess the quality of the currently announced data, traders need to know to what extent this data will be revised next month, i.e. they need a forecast of the magnitude of the subsequent revision. A natural measure for the precision of the current headline figure, and thus the ‘quality’ of the surprise estimate, is the expected variance of the revision.

---

19Sample error estimates provided by the BLS are based on 5-year averages and the reported estimates are updated only once a year.
First revisions of nonfarm payrolls headline figure (in percentage points of the previously announced level of total nonfarm payrolls) for the sample period 01/1980 to 12/2002. Initially released total nonfarm payrolls and first revisions of total nonfarm payrolls are extracted from original announcements of the Bureau of Labor Statistics’ employment report.

In order to analyze whether there are systematic or predictable components in the variance of revisions, we extract revision data for nonfarm payrolls since January 1980 from the original BLS reports. Analyzing the dynamical properties of the revision series, we find insignificant autocorrelations and Ljung and Box (1978) statistics for all lags of percentaged revisions. Hence, signed revisions are actually unpredictable.\textsuperscript{20} In contrast, for squared revisions we find a significant yearly seasonality pattern in (partial) autocorrelations. While the autocorrelation function at lag 12 is highly significant around 0.37, it is virtually zero for all other lags. This pattern is supported by Figure 1 which also reveals distinct seasonalities in the time series of absolute revisions over the analyzed sample period. Such effects may be attributed, for example, to the BLS’s annual benchmark revisions, sam-

\textsuperscript{20}This result is not surprising, since otherwise the BLS would incorporate this information into their preliminary announcements.
pling problems arising from the students’ job market entry in the summer months, as well as firms going out of business and firms creating new businesses. However, from Figure 1 it is also evident that the systematic patterns in absolute revisions do not occur on a completely regular basis. Instabilities in the pattern can arise, for example, from the fact that in many businesses (such as e.g. the building or the gastronomy sector) the yearly fluctuations of staff depend on seasonal weather conditions. Such effects cause shifts of the seasonality pattern within a year.

To capture these effects, we specify a model which does not only allow for seasonality effects in the (conditional) variance of revisions, but also accounts for short-term and long-term dynamics in both the first two moments. Therefore, we model the revisions in terms of an ARMA-GARCH model, where we include a seasonality term in the conditional variance function. Hence, the estimated model is obtained by

\[
\hat{R}_{\text{NF},m} = c + \sum_{j=1}^{p_1} \phi_{1,j} \hat{R}_{\text{NF},m-j} + \sum_{j=1}^{q_1} \phi_{2,j} \varepsilon_{m-j} + \varepsilon_m, \quad \varepsilon_m \sim N(0, g_m)
\]  (8)

\[
g_m = \omega + \sum_{j=1}^{p_2} \psi_{1,j} \varepsilon^2_{m-j} + \sum_{j=1}^{q_2} \psi_{2,j} g_{m-j} + s_m,
\]  (9)

where \( \hat{R}_{\text{NF},m} \) denotes the revision of the nonfarm payroll figure in month \( m \), measured in percentage points of the previously announced level of total nonfarm payrolls, \( g_m \) is the conditional variance of \( \varepsilon_m \) and \( s_m \) denotes a seasonality function which is specified on the basis of a Fourier series approximation as introduced by Gallant (1981) and applied by Andersen and Bollerslev (1998). Assuming a polynomial of degree \( Q \), the non-stochastic seasonal trend term is specified as

\[
s_m := s(\delta^s, \overline{m}, Q) = \delta^s \cdot \overline{m} + \sum_{j=1}^{Q} \left( \delta^s_{c,j} \cos(j \cdot \overline{m} \cdot 2\pi) + \delta^s_{s,j} \sin(j \cdot \overline{m} \cdot 2\pi) \right),
\]  (10)

where \( \delta^s \), \( \delta^s_{c,j} \), and \( \delta^s_{s,j} \) are the seasonal coefficients to be estimated and \( \overline{m} \in [0,1] \) is a normalized time trend.\(^{21}\)

\(^{21}\)\( \overline{m} \) is defined as the number of months from the beginning of a year until month \( m \) divided by 12.
To avoid a possible look-ahead bias, model selection, estimation and forecasting is performed on the basis of a rolling sample window: Firstly, for a particular month \( m \) different ARMA-GARCH models are estimated using the last 10 years of revision data available at that time.\(^{22}\) In order to restrict the computational burden, we select among ARMA-GARCH models of a lag order of one, with and without a seasonality component in the conditional variance equation as given by (10). Secondly, among these models the one with the best in-sample fit according to the Akaike information criterion (AIC) is selected. Thirdly, using the selected model a one-step-ahead forecast of the conditional revision variance, \( \hat{g}_{m+1|m} \), is computed. This forecast is used as a proxy for the precision of the current announcement, i.e. \( \hat{\rho}_{A,m} = 1/\hat{g}_{m+1|m} \).

Table 2 summarizes the goodness-of-fit of the different ARMA-GARCH specifications in the individual rolling sample windows. In nearly all cases the estimated AR and MA parameters\(^{23}\) in the conditional mean function are insignificant which confirms the findings above that (signed) revisions are not autocorrelated. However, interestingly, in most cases we find evidence for significant ARCH and GARCH parameters. On average, we obtain (significant) estimates of the GARCH parameters of \( \hat{\psi}_{1,1} \approx -0.03 \) and \( \hat{\psi}_{2,1} \approx 0.48 \). The positive GARCH parameter indicates that there is a predictable long-run component in the variance of revisions. A possible reason for this finding could be that the reliability of labor market figures is influenced by the (long-run) state of the labor market, and thus by underlying business cycle effects. The negative ARCH parameter\(^{24}\) indicate short-term reversal effects. We attribute this finding to the effect that the yearly systematic fluctuations in squared revisions do not necessarily always take place in the same month but can be shifted by plus/minus one or two months. These patterns cannot be captured by a static seasonality function and require to account for short-term reversals. The finding that

\(^{22}\)I.e. revisions announced in month \( m - 119, m - 118, \ldots, m \)

\(^{23}\)For brevity, we refrain from reporting the individual parameter estimates.

\(^{24}\)Since we do not impose any parameter restrictions, the conditional variance is not restricted to be non-negative. Nevertheless, in our analysis, all specifications produced strictly positive variance forecasts.
in all cases a GARCH(1,1) specification which is augmented by a seasonality component provides the best goodness-of-fit confirms the usefulness of the proposed specification.\textsuperscript{25}

Finally, the two proxy variables for the precision of pre-announcement information ($\hat{\rho}_{F,m}$) and the precision of the announcement ($\hat{\rho}_{A,m}$) enable us to estimate the price-response coefficient $\pi_m$ in eq. (6) for nonfarm payrolls. In Section 4, we will use $\pi_m$ in order to test for the relevance of information precision.

<table>
<thead>
<tr>
<th>Model</th>
<th>Components included in the model</th>
<th>Median value in AIC</th>
<th>Best performing model according to AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>x</td>
<td>-1.023</td>
<td>0</td>
</tr>
<tr>
<td>(b)</td>
<td>x</td>
<td>-1.013</td>
<td>0</td>
</tr>
<tr>
<td>(c)</td>
<td>x</td>
<td>-1.173</td>
<td>0</td>
</tr>
<tr>
<td>(d)</td>
<td>x</td>
<td>-1.072</td>
<td>0</td>
</tr>
<tr>
<td>(e)</td>
<td>x</td>
<td>-1.053</td>
<td>0</td>
</tr>
<tr>
<td>(f)</td>
<td>x</td>
<td>-1.783</td>
<td>88</td>
</tr>
<tr>
<td>(g)</td>
<td>x</td>
<td>-1.702</td>
<td>38</td>
</tr>
<tr>
<td>(h)</td>
<td>x</td>
<td>-1.676</td>
<td>18</td>
</tr>
</tbody>
</table>

In-sample goodness-of-fit of different ARMA-GARCH models for revisions in nonfarm payroll figures in the U.S. employment report released by the BLS. The estimated model is given by $\hat{R}_{NF,m} = c + \sum_{j=1}^{P} \phi_{1,j} \hat{R}_{NF,m-j} + \sum_{j=1}^{Q} \phi_{2,j} \varepsilon_{m-j} + \varepsilon_{m}$, where $\varepsilon_{m} \sim N(0, g_{m})$ and $\hat{R}_{NF,m}$ denotes the revision of the nonfarm payroll figure in month $m$, measured in percentage points of the previously announced level of total nonfarm payrolls. The conditional variance is specified as $g_{m} = \omega + \sum_{j=1}^{P} \psi_{1,j} \varepsilon_{m-j}^2 + \sum_{j=1}^{Q} \psi_{2,j} g_{m-j} + s_{m}$, where $s_{m} = \delta_{s} \cdot m + \sum_{j=1}^{Q} \delta_{s,j} \cos(j \cdot m \cdot 2\pi) + \delta_{s,j} \sin(j \cdot m \cdot 2\pi)$ denotes the seasonality function based on the parameters $\delta_{s}, \delta_{s,j}$, $\delta_{s,j}$, and a normalized time trend $m \in [0,1]$ defined as the number of months from the beginning of a year until month $m$ divided by 12. The lag order of the polynomial is chosen as $Q = 5$.

Within this model class, various AR(MA)-GARCH specifications with and without a seasonality component in the conditional variance equation are estimated. The estimations are performed on the basis of 10-year data windows rolling over the sample period 1/1980 - 12/2002 corresponding to 144 estimations. The goodness-of-fit is evaluated based on the AIC. The table reports the median AIC values for the different specifications over all rolling regressions as well as the number of best performing models for each specification.

\textsuperscript{25}In particular, the GARCH(1,1) model performs best in 88 out of 144 estimations, followed by the AR(1)-GARCH(1,1) model in 38 cases.
4 Empirical Results

4.1 Data

To analyze the price impact of (more precise) information, we use log returns of CBOT T-bond futures in 2-minute intervals during a 90-minute window around the 8:30 employment releases, more precisely from 8:22 to 9:52 a.m. EST. This window is suggested on the one hand by the floor trading hours of the CBOT, which starts at 8:20 a.m. and on the other hand by the release of other macroeconomic announcements at 10:00 a.m. Based on a twelve-year sample, i.e. January 1991 to December 2002, we obtain 128 announcement days after eliminating one day with an inadvertently early release in November 1998 and 15 days with overlapping announcements. Intraday data on CBOT T-Bond futures are obtained from the Futures Industry Institute. Data on analysts’ forecasts, in particular medians and standard deviations of forecasts, are obtained from MMS. Initially released non-revised headline figures as well as revisions are extracted from the original monthly BLS releases. All data are measured in percentage changes.

4.2 Estimation approach

To investigate the effects of variations in the quality of information, we model the log T-bond futures returns using an ARMA specification which is augmented by appropriate explanatory variables. In order to account for (conditional) heteroscedasticity, we include

---

26 Focussing on the most actively traded contract, log returns are calculated on the basis of the last trading price observed during a 2-minute interval. For example, the return associated with the employment release, in this case the 8:30-8:32 return, is computed from the last price before the 8:30 announcement and the last price before 8:32.

27 In the analyzed period, once the GDP report, six times Personal Income and eight times Leading Indicators are announced at the same time. Although most of these reports are of minor importance (see e.g. Fleming and Remolona 1999c) all of these days are eliminated to avoid interference. Moreover, we eliminated one day with an inadvertently early release (see e.g. Fleming and Remolona 1999b). Note, however, that retaining these 16 observations does not change our results substantially.

28 Precisely, nonfarm payrolls surprises are defined as the deviation of the announced number of new nonfarm payrolls from the median of analysts' forecasts divided by the number of total nonfarm payrolls in the previous month (times 100). The unemployment rate figure is already given in percentage points (i.e. the change of the overall unemployment rate from month to month).
ARCH terms and seasonality variables in the conditional variance function. Hence, we assume the following process for 2-minute log returns:

\[
\begin{align*}
    r_t &= c + \sum_{j=1}^{p_1} \phi_{1,j} r_{t-j} + \sum_{j=1}^{q_1} \phi_{2,j} \varepsilon_{t-j} + x_t' \beta + \varepsilon_t, \\
    \varepsilon_t &\sim N(0, h_t) \\
    h_t &= \omega + \sum_{j=1}^{p_2} \psi_j \varepsilon_{t-j}^2 + s_t,
\end{align*}
\]

(11)

where \( t \) indexes the 2-minute intervals around the release of the employment report for month \( m \). Furthermore, \( x_t \) denotes a vector of explanatory variables in the conditional mean function including surprise and revision variables (for more details, see Section 4.3) while \( \beta \) is the corresponding coefficient vector. The seasonality function \( s_t \) in the conditional variance function accounts for heteroscedasticity due to (deterministic) baseline patterns of the volatility around announcements (see e.g. Hautsch and Hess, 2002) and is specified in terms of a flexible Fourier form (see eq. 10) based on the 90-minute time interval from 8:22 to 9:52 a.m. EST.

In contrast to Andersen and Bollerslev (1998), we do not include any daily GARCH components in the variance equation. Since we focus on narrow time windows around monthly announcements instead of analyzing a 24-hour-7-day period it seems reasonable to ignore the daily GARCH component. Nevertheless, there might be a heteroscedasticity component which is ignored here and it is therefore crucial to use robust estimates of the covariance matrix of the parameters. Thus, the AR-ARCH model is estimated by quasi maximum likelihood, where the standard errors are computed based on the Bollerslev and Wooldridge (1992) estimator of the variance covariance matrix.

### 4.3 Information precision and the strength of the price response

To investigate whether the precision of information determines the strength of the price impact of unanticipated information, we test whether the influence of 'precise' informat-
tion is significantly different from that of 'imprecise' information. Estimation results for different specifications of (11) and (12) are given in Table 3.

<table>
<thead>
<tr>
<th>Mean equation</th>
<th>(A)</th>
<th>(B)</th>
<th>(C)</th>
<th>(D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cons</td>
<td>c</td>
<td>-0.006</td>
<td>-0.005</td>
<td>-0.004</td>
</tr>
<tr>
<td>AR(1)</td>
<td>φ₁</td>
<td>-0.087***</td>
<td>-0.089***</td>
<td>-0.089***</td>
</tr>
<tr>
<td>AR(2)</td>
<td>φ₂</td>
<td>0.005</td>
<td>0.004</td>
<td>0.005</td>
</tr>
<tr>
<td>SNFT₁</td>
<td>β₁</td>
<td>-3.145**</td>
<td>-2.877</td>
<td>-2.973</td>
</tr>
<tr>
<td>SNFT₁ × Dᵣₑₗ</td>
<td>β₂</td>
<td>-27.411***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNFT₁ × Dᵣₑₚ</td>
<td>β₃</td>
<td>-18.978***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNFT₁ × Dₚₒₒ₉</td>
<td>β₄</td>
<td>-34.072***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁</td>
<td>β₅</td>
<td>-22.878***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁ × Dₚₒₒ₉</td>
<td>β₶</td>
<td>-34.509***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁ × Dᵣₑₚ × Dₚₒₒ₉</td>
<td>β₷</td>
<td>-14.303***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁ × Dᵣₑₚ × Dᵣₚ₉</td>
<td>β₸</td>
<td>-31.206***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁ × Dᵣₑₚ × Dᵣᵣ₉</td>
<td>β₹</td>
<td>-28.732***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNFT₁ × Dᵣₑₚ × Dᵣᵣ₉</td>
<td>β₁₀</td>
<td>-37.735***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNF₉₂₁</td>
<td>β₀</td>
<td>8.926***</td>
<td>9.080***</td>
<td>8.701***</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₁</td>
<td>-5.571**</td>
<td>-4.824**</td>
<td>-4.767**</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₂</td>
<td>-0.402</td>
<td>-0.483</td>
<td>-0.366</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₃</td>
<td>1.087</td>
<td>1.152</td>
<td>1.007</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₄</td>
<td>2.328</td>
<td>2.046</td>
<td>1.871</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₅</td>
<td>-5.268</td>
<td>-4.858</td>
<td>-4.684</td>
</tr>
<tr>
<td>S₁₂¹</td>
<td>β₆</td>
<td>-0.549</td>
<td>-0.650</td>
<td>-0.633</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variance equation</th>
<th>(A)</th>
<th>(B)</th>
<th>(C)</th>
<th>(D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cons</td>
<td>ω</td>
<td>0.302***</td>
<td>0.299***</td>
<td>0.298***</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>ψ₁</td>
<td>0.108***</td>
<td>0.116***</td>
<td>0.119***</td>
</tr>
<tr>
<td>ARCH(2)</td>
<td>ψ₂</td>
<td>0.054***</td>
<td>0.056***</td>
<td>0.055***</td>
</tr>
<tr>
<td>ARCH(3)</td>
<td>ψ₃</td>
<td>0.035**</td>
<td>0.037**</td>
<td>0.037**</td>
</tr>
</tbody>
</table>

| LR-test | H₀ : β₂ ≥ −β₅ | 80.787*** | (-6198.36) |
|         | H₀ : β₂ₚ ≥ β₂ₚ | 26.511*** | (-6157.97) |
|         | H₀ : β₂ₙ ≥ β₂ₙ | 14.560*** | (-6157.97) |

(continued on next page)
QML estimation of AR(2)-ARCH(3) models for 2-min log returns during the intraday interval 8:22-9:52 a.m. EST at employment announcement days for which no other macroeconomic report is released at the same time. The sample period is Jan. 1991 - Dec. 2002, resulting in 5760 observations (i.e. 128 days with no overlapping announcements × 45 2-min intervals).

The estimated model for log returns $r_t$ is given by

$$r_t = c + \sum_{j=1}^{2} \phi_j r_{t-j} + x_t' \beta + \varepsilon_t,$$

where $\varepsilon_t \sim N(0, h_t)$.

$t$ indexes the first interval after the announcement, 8:30-8:32, $x_t$ denotes a vector of explanatory variables and $\beta$ is the corresponding coefficient vector. $h_t$ is given by

$$h_t = \omega + \sum_{j=1}^{3} \psi_j \varepsilon_{t-j}^2 + s_t,$$

where $s_t = \delta^* \cdot t + \sum_{j=1}^{5} \delta_{c,j} \cos(j \cdot t \cdot 2\pi) + \delta_{s,j} \sin(j \cdot t \cdot 2\pi)$ denotes the seasonality function based on the parameters $\delta^*$, $\delta_{c,j}$, $\delta_{s,j}$ and a normalized time trend $t \in [0, 1]$ given by the elapsed time (in minutes) in the interval 8:22 to 9:52 divided by 90. The estimated seasonality parameters are omitted in the table.

Regressors $x_t$ are the surprise in U.S. nonfarm payrolls, $S_{NF}$, and in unemployment rates, $S_{UN}$, as well as revisions of nonfarm payrolls $R_{NF}$ interacted with time dummies indicating the intervals 8:28-8:30 ($t-1$), 8:30-8:32 ($t$) and 8:32-8:34 ($t+1$). Surprises are computed based on U.S. employment report figures released by the BLS and consensus forecasts provided by MMS. The variables $S_{NF}$ interact with dummy variables $D_{high}$ ($D_{low}$) which takes on the value 1 if estimated price-response coefficient $\hat{\pi}_m$ at month $m$ is higher (lower) than its sample median, and 0 otherwise. $\hat{\pi}_m$ is given by $\hat{\pi}_m = \hat{\rho}_{A,m} / (\hat{\rho}_{F,m} + \hat{\rho}_{A,m})$, where $\hat{\rho}_{A,m} = 1/\hat{g}_{m+1|m} \cdot \hat{g}_{m+1|m}$ is the one-step-ahead prediction of the conditional variance of (percentage) revision of the nonfarm payroll figure in month $m$, $\hat{R}_{NF,m}$, computed based on rolling sample ARMA-GARCH models for the time series of historical revisions, and $\hat{\rho}_{F,m} = 1/\hat{s}_{F,m}^2$ with $\hat{s}_{F,m}$ denoting the cross-sectional standard deviation of MMS forecasts for the employment release for a particular month $m$. In addition, $S_{NF}$ interacts with dummy variables $D^{good} = 1$ if $S_{NF} < 0$ and $D^{bad} = 1 - D^{good}$.

The table reports the R-Squared, the log likelihood (LL), the Akaike information criterion (AIC) and $\chi^2$ statistics of LR tests on the inequality of individual parameters (log likelihood of restricted models in parenthesis). Statistical inference is based on QML standard errors (Bollerslev and Wooldridge 1992). ***, **, and * indicates significance at the 1%, 5%, and 10% level, respectively. Except for the LR tests, the level of significance is based on two-sided tests.

The lag order of the individual autoregressive components is chosen according to the AIC and reveals an AR(2)-ARCH(3) specification with a seasonality component as the preferred model. The conditional mean function includes variables capturing the surprise in nonfarm payrolls, $S_{NF}$, and in unemployment rates, $S_{UN}$, as well as the revision of nonfarm payrolls, $R_{NF}$. In order to account for the timing of the announcement’s price impact, these variables are interacted with time dummies. For instance, $S_{NF,t}$ takes on the value of the surprise variable $S_{NF}$ in the 8:30-8:32 interval and 0 otherwise. Hence the
estimated coefficient of $S_{NF,t}$ captures the immediate price impact of a surprise in nonfarm payrolls. In addition, $S_{NF,t+1}$ accounts for a ‘postponed’ price impact, in the interval 8:32-8:34. Correspondingly, $S_{NF,t-1}$ captures information leakage effects, i.e. a price impact in the interval 8:28-8:30.\footnote{However, leakage effects are very unlikely given the strict lock-up conditions governing the release of the employment report. See, for example, Ederington and Lee (1993) or Fleming and Remolona (1999a,c) for a detailed description of the dissemination procedure.}

As a starting point, model (A) provides a specification which does not account for the relative precision of unanticipated information. The results confirm several major findings of previous studies.\footnote{See, for example, Becker, Finnerty, and Kopecky (1996), Balduzzi, Elton, and Green (2001), Fleming and Remolona (1999a,c), or Hautsch and Hess (2002) for bond markets and Almeida, Goodhart, and Payne (1998) or Andersen, Bollerslev, Diebold, and Vega (2003) for foreign exchange markets.} Firstly, the large values of the highly significant coefficients of $S_{NF,t}$ and $S_{UN,t}$ show that surprising headline information has a strong impact on intraday returns. Secondly, markets process unanticipated headline information very rapidly. As indicated by the insignificant coefficient of $S_{UN,t+1}$ and the relative small coefficient of $S_{NF,t+1}$ (as compared to $S_{NF,t}$), the price reaction is completed within two to four minutes.\footnote{We also analyzed the influence of surprises in the following intervals, in particular $t + 2, ..., t + 5$, but no significant coefficient estimates were obtained.} Thirdly, the directions of observed price reactions are consistent with standard theory: T-bond futures prices rise in response to ‘good’ news from the inflation front, i.e. a lower than expected increase in nonfarm payrolls and a higher than expected unemployment rate. Fourthly, a comparison of the magnitude of the coefficients of $S_{NF,t}$ and $S_{UN,t}$\footnote{Since we measure surprises in both headline figures in percentage points, the magnitudes of the estimated coefficients are directly comparable.} shows that the nonfarm payrolls figure has the strongest price impact. Extending previous studies, we also include revisions of the previously released nonfarm payroll figure into the analysis, i.e. $R_{NF,t-1}$, $R_{NF,t}$ and $R_{NF,t+1}$. However, none of these coefficients is statistically significant. This creates the impression that market participants ignore revisions.

Focussing on precision effects, model (A) already yields some preliminary evidence. Although it does not account for the differences of the relative precision of unanticipated
information over time, it allows us to compare the price impact of headline figures with different average precisions. According to the BLS, the average sampling error of the nonfarm payrolls figure is smaller (0.09%) than the sampling error of the unemployment rate figure (0.13%).\textsuperscript{33} Hence we would expect the more precise nonfarm payrolls figure to have a stronger price impact on average. In fact, the estimated coefficient of $S_{NF,t}$ is significantly higher than the coefficient of $S_{UN,t}$ which is confirmed by a one-sided likelihood ratio (LR).\textsuperscript{34} This result may be interpreted as a first piece of evidence in favor of the claim of Bayesian learning that more precise information should have a stronger price impact.

In order to investigate release-specific precision effects, we extend model (A) by including interaction variables which account for differences in information precision across individual nonfarm payroll announcements (model (B) in Table 3). According to eq. (6) the strength of the price reaction is determined by the (estimated) price-response coefficient at month $m$, $\hat{\pi}_m = \hat{\rho}_{A,m} / (\hat{\rho}_{F,m} + \hat{\rho}_{A,m})$. In order to test this implication we interact the variable $S_{NF,t}$ by a dummy variable $D^{\pi \text{ high}}$ which takes on the value 1 if the proxy for the price-response coefficient $\hat{\pi}_m$ at month $m$ is higher than the sample median of $\hat{\pi}_m$, and 0 otherwise. Correspondingly, $D^{\pi \text{ low}}$ equals 1 if $\hat{\pi}_m$ is lower or equal than the sample median, i.e. $D^{\pi \text{ low}} := 1 - D^{\pi \text{ high}}$.\textsuperscript{35}

The large difference between the estimates $\beta_{2h}$ and $\beta_{2l}$ strongly supports the notion that the relative precision determines the strength of the price impact. The coefficient $\beta_{2h}$ associated with $D^{\pi \text{ high}}$ is almost 50% larger than $\beta_{2l}$ associated with $D^{\pi \text{ low}}$. This suggests that 'precise' announcements move prices much more than 'imprecise' information. In fact,

\textsuperscript{33}See, for example, BLS, Employment and Earnings, June 2000.

\textsuperscript{34}The null hypothesis is $H_0: \beta_2 \geq -\beta_5$, since a higher than expected nonfarm payrolls figure ($S_{NF} > 0$) should have a negative return impact while a higher than expected unemployment rate ($S_{UN} > 0$) should have a positive return impact.

\textsuperscript{35}Note that Abarbanell, Lanen, and Verrecchia (1995) argue that the dispersion of analysts' forecasts may not fully capture investors’ uncertainty before an announcement. Therefore, our proxy of prior information precision could be systematically too high and our price-response coefficient too low. However, since we are not primarily interested in the values of $\hat{\pi}$ itself, but instead use this proxy variable to group our observations into two categories ('precise' vs. 'imprecise' announcements), this bias should have no systematic impact on our results.
on the basis of a one-sided LR test, the null hypothesis that imprecise nonfarm payrolls surprises have a stronger price impact can be rejected at the 1% level.\footnote{Note that due to the negative sign of $\beta_2$ the null hypothesis becomes $H_0 : \beta_2^l \leq \beta_2^h$.} Furthermore, as indicated by the AIC, the inclusion of precision dummies leads to an improvement of the model’s goodness-of-fit.

4.4 Quality of information vs. sign effects?

An alternative candidate to explain asymmetric price reactions is the so-called sign effect, i.e. a stronger price response to ‘bad’ than to ‘good’ news. Several theoretical models justify such asymmetries in the price response, however, mainly only for stock markets and not for bond markets.\footnote{See, for example, Veronesi (1999) Barberis, Shleifer, and Vishny (2002) and Daniel, Hirshleifer, and Subrahmanyam (1998).} Nevertheless, it might be argued that without a more detailed analysis we cannot preclude that our finding of an asymmetric price response to more precise news stems from a spurious correlation between the precision and the sign of information. In order to account for both sign and precision effects, we extend the previous analysis and test whether prices react stronger to more precise ‘bad’ (‘good’) news than to less precise ‘bad’ (‘good’) news.

To perform this test, we interact the variable $S_{NF,t}$ with dummy variables which indicate whether a surprise in this headline figure provides ‘good’ news for the bond market, i.e. $D^{good} = 1$ if $S_{NF} < 0$, or ‘bad’ news, i.e. $D^{bad} = 1 - D^{good}$ (see model (C)). Then, the coefficients $\beta_2^b$ (and $\beta_2^g$) capture the immediate impact of ‘bad’ (‘good’) news, i.e. a higher (lower) than expected nonfarm payrolls figure. In line with the results of Conrad, Cornell, and Landsman (2002) for the stock market, the estimated coefficients indicate that ‘bad’ news has a stronger (negative) price impact than ‘good’ news. In fact, the null hypothesis that $\beta_2^b \geq \beta_2^g$ is rejected on the 1% significance level. Moreover, the difference in the impact of ‘good’ and ‘bad’ news is almost as large as the difference in the impact of
precise and imprecise news (model (B)). Hence, from the comparison of models (B) and (C) we cannot conclude whether asymmetries in the price response are solely due to a 'good' versus 'bad' news effect or a 'precise' versus 'imprecise' news effect or whether both effects are present. Therefore, we interact the 'bad' and 'good' news variables with the precision dummies (model (D)). This analysis clearly shows that both effects are apparent at the same time. On the one hand, the price impact of precise 'bad' news is stronger than the impact of precise 'good' news, i.e. \( \beta_{2 h,b}^2 < \beta_{2 h,g}^2 \) (the same holds true for imprecise 'bad' and 'good' news, i.e. \( \beta_{2 l,b}^2 < \beta_{2 l,g}^2 \)). This is confirmed by a one-sided LR test on the joint hypothesis that the price impact of 'bad' news (either precise or imprecise) is not larger than the price impact of 'good' news, i.e., \( H_0: \beta_{2 h,b}^2 \geq \beta_{2 h,g}^2, \beta_{2 l,b}^2 \geq \beta_{2 l,g}^2 \). This hypothesis is rejected on the 1% level. On the other hand, similar differences can be found between precise and imprecise news. The price impact of precise 'bad' ('good') news is stronger than the impact of imprecise 'bad' ('good') news, i.e. \( \beta_{2 h,b}^2 < \beta_{2 l,b}^2 (\beta_{2 h,g}^2 < \beta_{2 l,g}^2) \).

In fact, the hypothesis that the more precise news does not have a stronger price impact while controlling for 'bad' and 'good' news (i.e. \( H_0: \beta_{2 h,b}^2 \geq \beta_{2 l,b}^2, \beta_{2 h,g}^2 \geq \beta_{2 l,g}^2 \)) is rejected on the 1% level as well.

Overall, these results provide strong evidence in favor of the claim of Bayesian learning that the quality of information plays an important role in determining its price impact. Prices respond stronger to more precise news. Furthermore, we find evidence for a sign effect in the bond market which does not explain the precision effect. Thus, asymmetries in the price response to unanticipated information are driven by differences in the (relative) precision and by the sign of this information.

5 Conclusion

The theory of belief formation in financial markets suggests that the quality of information determines the strength of the price reaction to a given piece of unanticipated
information. Empirical research on the price reaction to information has focused on U.S. macroeconomic announcements since they allow for a fine measurement of the information flow. Unfortunately, due to the unavailability of release-specific data on the precision of information, little evidence in favor of the link between the strength of the price reaction and the quality of information is available. The main objective of this paper is to fill this gap left in the empirical literature. By utilizing additional detail information being released with the headline figures of the employment report, i.e. revisions of previously announced figures, we are able to extract a measure of the quality of the released data. Together with the cross-sectional standard deviations of analysts’ forecasts we obtain a proxy for the release-specific relative quality of the nonfarm payrolls headline figure, which is the most influential information component in the employment report. Since this precision measure is based exclusively on information which is available at the time of an announcement, we assume that it provides a reasonable approximation of the quality of released information on which market participants can base their trading decisions.

The empirical analysis is based on high-frequency data from the CBOT T-bond futures. By using the proposed precision proxies, we find significant evidence in favor of the claim of Bayesian learning that the quality of information acts as a catalyst, i.e. prices respond stronger to more precise news. Our results suggest that traders try to compensate for the lack of official release-specific sample error estimates by extracting release-specific precision signals from additional information related to the widely awaited headline figures.

Analyzing the robustness of this result, the stronger price impact of more precise news remains unchanged, even if we control for the asymmetric price reaction due to 'good' vs. 'bad' news. I.e. precise 'bad' ('good') news lead to stronger downward (upward) price movements than imprecise 'bad' ('good') news. Hence, asymmetries in price responses to news are driven by both the precision and the sign of information.
References


