Do prices respond stronger to more precise news? Testing for the catalyzing effects of precision signals in the U.S. employment report *

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Abstract

It is well documented that the U.S. employment report has a strong price impact in financial markets. Bayesian updating suggests that the information precision acts as a catalyst determining the strength of the price reaction to a given piece of unanticipated information. However, it is difficult to test for this catalyzing effect due to a lack of precision data. Employing additional detail information, we extract release-specific precision measures. Based of these precision proxies, we show that prices respond significantly stronger to more precise information, 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

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1 Introduction

It is well documented that macroeconomic announcements, such as the U.S. employment report, strongly affect the intraday price process in financial markets. Several studies show that prices shift almost instantaneously in response to unanticipated headline information. The theoretical literature on belief formation in financial markets suggests that the strength of this price response can be explained by the magnitude of surprises and the quality of information. Basically, prices should respond stronger to more precise news. However, due to a lack of data on the quality of the released information, little empirical evidence of such a link is available. The primary objective of this paper is to fill this gap in the empirical literature. We suggest that traders can extract release-specific precision signals from additional detail information in the employment report, in particular revisions of previously released headline figures. A test based on these precision proxies reveals that the strength of the immediate price response to unanticipated information is strongly related to the quality of information.

Theoretical models concerning the processing of public information arrival in financial markets are commonly based on Bayesian updating frameworks (e.g. Kim and Verrecchia 1991, Kandel and Pearson 1995, or Veronesi 2000). In these models, price changes are driven mainly by two variables. On the one hand, the amount of unanticipated information in a public announcement determines the price reaction. On the other hand, the precision of the released data (relative to the precision of the information available before an announcement) amplifies this price reaction. Hence, information precision acts as a catalyst. In periods when the released data are perceived to be more precise – or when the information available before an announcement is more diffuse – a stronger price reaction should be observed to a surprise of a given magnitude.

Obviously, testing for the stronger price impact of more precise information necessitates data on both the precision of the information available prior to a public announcement and the precision of the 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 cross-sectional standard deviation of analysts' forecasts.[1] 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. Often also for market participants it seems to be impossible to infer the precision of a given piece of information at the time of its release. [2] Lacking directly observable release-specific precision signals, market participants might try to use information surrounding an announcement to infer the accuracy of the new data. The U.S. employment report 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. Hence, we assume that traders try to extract a release-specific precision statistic by inspecting the history of (absolute) revisions. Technically speaking, the one-step-ahead forecast from a GARCH 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 conjunction with the cross-sectional dispersion of analysts' forecasts, to construct a measure of the relative precision of the new and the prior information. On the basis of this relative precision measure, we

[1] See, for example, Andersen, Bollerslev, Diebold, and Vega (2002) who use this measure to approximate investors' uncertainty.

[2] 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.

are able to test for the claim of Bayesian learning that prices respond stronger to more precise news.

A counterargument to the hypothesis that asymmetries in the price responses can be explained solely by differences in the information precision comes from the recent literature analyzing the impact of companies' earnings announcements on stock prices. For example, the behavioral framework of Barberis, Shleifer, and Vishny (2002) as well as the rational expectations model of Veronesi (1999) implies that stock prices react stronger to 'bad' news than to 'good' news if these news occur in 'good times'.[3] In line with the empirical results of Conrad, Cornell, and Landsman (2002) for stocks, we find that bond markets react stronger to 'bad' news than to 'good' news. Nevertheless, controlling for these effects, the finding of an asymmetry in the price response due to differential precision remains virtually unchanged. For example, we find that prices respond significantly stronger to precise 'bad' news than to imprecise 'bad' news. The same holds for precise and imprecise 'good' news.

The empirical analysis is based on high-frequency data of the Chicago Board of Trade (CBOT) T-bond futures covering a nine year period from January 1991 to December 2002. We focus on the U.S. employment report for several reasons. First of all, we are intrigued by the availability of additional detailed information, which allows a precision inference. Another reason is its profound impact on financial markets which is documented in various studies.[4] In addition, since the employment report is typically released at 8:30 a.m. EST (Eastern Standard Time) on the first Friday of a given month, we do not have to control for day-of-the-week or time-of-the-day effects. Moreover, the overlap with other reports being released at the same time is minimal. Following Hautsch and Hess (2002),

[3] See also Hillier, Mohamed, and Yadav (2002).

[4] 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).

we use a 90-minute window around the monthly employment releases. We estimate the effects of information arrival on the basis of an intraday ARCH model with explanatory variables in both the conditional mean and variance function.

Based on this estimation approach and our relative precision measure, the following results can be summarized. We confirm the findings of previous studies that unanticipated headline information is processed within a few minutes. More importantly, we document a strong asymmetry in the price response to precise vs. imprecise information. In addition, it is shown that this catalyzing effect of information precision is not driven by a possibly asymmetric price response to 'good' and 'bad' news. Moreover, the remarkable robustness of the stronger price impact of more precise information across various alternative model specifications suggests that our relative precision estimate is a meaningful approximation of market participants' behavior in assessing the accuracy of unanticipated information coming with the employment report.

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 characterizes the main information components in the employment report and explains the 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

The literature on information processing in financial markets covers various aspects of the trading process, in particular the variance of price changes around news releases (e.g. Holthausen and Verrecchia 1988), the link between trading volume and volatility (e.g. Holthausen and Verrecchia 1990, Kim and Verrecchia 1991a, b, Harris and Raviv 1993, Kandel and Pearson 1995, and Blume, Easley, and O'Hara 1994), the incentives to acquire private information before a public announcement (e.g. Verrecchia 1982, Kim and

Verrecchia 1997 and Barlevy and Veronesi 2000), or changes in the equity risk premium due to information arrival (Veronesi 2000). Moreover, these models provide important insights into the price adjustment to new information. Since they typically build on a Bayesian updating framework to describe traders belief formation, a common result across various models is that the price reaction is driven primarily by the amount of unanticipated information. At the same time, the (relative) quality of information acts as a catalyst and determines the strength of this price reaction. To delineate this catalyzing effect of the precision of information, we outline the basic principles of Bayesian learning under the normality assumption. As an illustration of the generality of this precision effect, the basic mechanics in the models of Kim and Verrecchia (1991a) and Kandel and Pearson (1995) are briefly discussed thereafter.

Suppose that traders have homogeneous beliefs about 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. $g(X) = N\left(\mu_F, 1/\rho_F^2\right)$. Hence, μ_F represents traders' mean forecast and ρ_F the precision of this forecast (where the precision is defined as the inverse of the variance). Moreover, suppose that a public announcement is made which provides traders with a noisy estimate μ_A of X, but does not reveal the realization X itself. We assume an additive error term structure, i.e. $\mu_A = X + \varepsilon$ where ε is a zero mean normally distributed error term with variance $\mathrm{Var}[\varepsilon] = 1/\rho_A$ and $\mathrm{E}[X \cdot \varepsilon] = 0$. Hence, the conditional p.d.f. of μ_A, $f(\mu_A|X)$ is $N(X, 1/\rho_A)$. Note that we abstract from information asymmetries and assume that all market participants know μ_F and ρ_F before the announcement and that the public announcement reveals both μ_A and ρ_A.

Let $g(X|\mu_A)$ denote traders' posterior beliefs after observing the announced estimate μ_A. According to Bayes rule, i.e.

$$g(X|\mu_A) = \frac{f(\mu_A|X)g(X)}{\int_{-\infty}^{\infty} f(\mu_A|X)g(X)dX} \ ,$$

under the normality assumption, the posterior beliefs are normally distributed with mean

$$\mu_P := \mathrm{E}[X|\mu_A] \quad = \quad \mu_F \frac{\rho_F}{\rho_F + \rho_A} + \mu_A \frac{\rho_A}{\rho_F + \rho_A} \tag{1}$$

and precision

$$\rho_P := \mathrm{Var}[X|\mu_A]^{-1} \quad = \quad \rho_F + \rho_A \ . \tag{2}$$

Hence, the adjustment of market participants' mean beliefs induced by the public announcement, $\mu_P - \mu_F$, is obtained by

$$\mu_P - \mu_F \quad = \quad (\mu_A - \mu_F) \frac{\rho_A}{\rho_F + \rho_A} \ . \tag{3}$$

Thus, the shift in traders' average beliefs is proportional to the deviation of the announcement μ_A from its corresponding mean forecast μ_F. This is typically referred to as the unanticipated information in an announcement or the surprise S, i.e.

$$S \quad := \quad \mu_A - \mu_F. \tag{4}$$

Moreover, the strength of this belief revision is also determined by the precision of the announcement, ρ_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.,

$$P = \begin{cases} \nu \cdot \mu_F & \text{before the announcement} \\ \nu \cdot \mu_p & \text{after the announcement} \end{cases} \tag{5}$$

with ν denoting some constant.[5] Then, the change in market prices ΔP induced by a public announcement is given by

$$\Delta P \quad = \quad \nu \cdot \pi \cdot S, \tag{6}$$

[5]For example, in the models of Kim and Verrecchia or Kandel and Pearson traders directly receive signals about the assets' fair value. Hence, $\nu = 1$.

where π denotes the 'price-response coefficient'

$$\pi \quad := \quad \frac{\rho_A}{\rho_P} \quad = \quad \frac{\rho_A}{\rho_F + \rho_A} \tag{7}$$

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

From the above analysis the following empirically testable implications arise:

1. Eq. (6) suggests that the immediate price change after an announcement is proportional to the amount of unanticipated information in an announcement.

2. From eq. (3) 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 the prior information. The price reaction is stronger (weaker) if the announced information is perceived to be more (less) precise relative to the precision of the information available before the announcement.

In contrast to the simple information structure assumed above, in the model of Kim and Verrecchia (1991a), for example, traders have different pre-announcement beliefs (i.e. different $\mu_{F,i}$ and $\rho_{F,i}$) which stem from their observations of private value signals. Moreover, traders assign different precisions to the announced value signal ($\rho_{A,i}$) and extract additional information from their self-fulfilling price conjectures of the assumed rational expectations equilibrium. These assumptions have important implications for the trading volume, but not for the price response. Trading volume in this model stems primarily from a differential revision of beliefs across traders, whereas the price adjustment to new information is driven by the average shift of beliefs. Hence, also in Kim and Verrecchia (1991a), the price change ΔP is proportional to an average surprise measure $\bar{S}$.[6] However,

[6] This is the deviation of the announced value signal from its expected value given the pre-announcement information set.

due to the assumed uncertainty about aggregate endowment in the economy, the price change is also influenced by a measure of aggregate 'endowment noise' $\bar{N}$:[7]

$$\Delta P = \frac{\bar{\rho}_A}{\bar{\rho}_P}\left(\bar{S} + \bar{N}\right),$$

where $\bar{\rho}_A$ and $\bar{\rho}_P$ denote the corresponding average precisions. More importantly, the price-response coefficient $\bar{\rho}_A / \bar{\rho}_P$ again reflects the precision of posterior relative to prior beliefs, although here the average precisions of the different signals are relevant.

Deviating from the rational expectations literature, Kandel and Pearson (1995) assume that traders do not agree about the interpretation of a publicly available value signal. Instead they believe that the public signal is biased. They believe that $\mu_A = X + \varepsilon$ with $E[\varepsilon] \neq 0$. In addition, this interpretation bias $E[\varepsilon]$ differs across traders. Since traders adjust the announced data by their individual bias perceptions, a non-zero average interpretation bias $\hat{B}$ influences the price change in addition to the surprise component $\hat{S}$:[8]

$$\Delta P = \frac{\hat{\rho}_A}{\hat{\rho}_P}\left(\hat{S} - \hat{B}\right),$$

Hence, also in this framework, the price-response coefficient $\hat{\rho}_A / \hat{\rho}_P$ reflects the relative average precisions of the public signal and the posterior beliefs.

3 Measuring the precision of information

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

The profound impact of unanticipated information in the U.S. employment report on various financial markets is well documented.[9] While this report, which is released by

[7] Basically, this endowment noise term reflects differences in the normalized price signals before and after the announcement.

[8] In the notation of Kandel and Pearson (1995), the 'surprise' $\hat{S}$ is given by the deviation of the announced 'value signal' L from the average prior belief $\hat{X}$, i.e. $\hat{S} = L - \hat{X}$. The interpretation bias $\hat{B}$ is given by the average of traders' mean beliefs of the 'error' in the public signal, i.e. $\hat{\mu}$.

[9] Several studies provide strong evidence that unanticipated information in the employment report moves interest rates (e.g. Edison 1996, Becker, Finnerty, and Kopecky 1996, Fleming and Remolona 1999c, and

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. Both figures provide market participants with a timely and comprehensive estimate of current economic activity.[10] Moreover, they allow some inference about inflationary pressures, which might arise from a tightening labor market.

An important reason for researchers to focus on headline figures is the availability of analysts' forecasts. These forecasts allow one to differentiate between the already anticipated part of a given piece of information and the unanticipated part. This is important because in efficient markets only unanticipated information has an impact on prices.[11] Another reason for the widespread use of headline figures in empirical research is their dissemination via several news vendors within seconds. This comes quite close to an experimental situation where all traders simultaneously receive a certain piece of information and are able to act on it at the same time. Like previous studies of the employment report, we restrict our attention to the nonfarm payrolls figure and the unemployment rate.[12]

[insert Table 1 around here]

A particularly interesting feature of the employment report is the fact that the initially

Hautsch and Hess 2002) as well as foreign exchange rates (e.g. Hardouvelis 1988, Payne 1996, Andersen, Bollerslev, Diebold, and Vega 2002). In addition, various studies document that the U.S. employment report influences the volatility of bond and foreign exchange markets (e.g. Ederington and Lee 1993, 1995, Crain and Lee, DeGennaro and Shrieves 1997, Andersen and Bollerslev 1998 Jones, Lamont, and Lumsdaine, 1998 Fleming and Remolona 1999c and Bollerslev, Cai, and Song) as well as bid-ask spreads (e.g. Fleming and Remolona 1999a and Balduzzi, Elton, and Green 2001) and trading volume (Fleming and Remolona 1999a, Franke and Hess (2000)).

[10] Nonfarm payrolls and unemployment rates are derived from two independent surveys (390,000 establishments and 50,000 households).

[11] Analysts' forecasts of macroeconomic figures are not always unbiased and efficient (see e.g. Becker, Finnerty, and Kopecky 1996). However, in particular for the employment report no systematic inefficiencies can be found (see e.g. Hess 2001).

[12] For example, Hardouvelis (1988), 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, like for example, Cook and Korn (1991), Edison (1996), Balduzzi, Elton, and Green (2001) and Andersen, Bollerslev, Diebold, and Vega (2002).

released nonfarm payrolls figure is revised in the subsequent two months.[13] Table 1 provides an example. The announced nonfarm payrolls headline figure is the change in the level of total nonfarm payrolls from month to month. However, the announced value includes a revision since this change is measured by the difference between the preliminary estimate of total payrolls for the current month (column 2 in Table 1) and the first revision of the previous month's total payrolls (column 3). Take, for example, the May 1999 employment report which was released on June 4, 1999 (last row in Table 1). The preliminary estimate of the total number of nonfarm payrolls in May is $128,167$ (thousand). At the same time, a revised April estimate is disclosed, i.e. the preliminary April estimate is revised upwards by 245 from $127,911$ to $128,156$. The announced change in nonfarm payrolls is 11 (i.e. $128,167 - 128,156$). Analysts had forecasted a change of 220 – this is the so-called 'consensus' forecast or the median of analysts' forecasts polled by MMS. Comparing the announced and the forecasted figure yields a surprise S_{NF} of -209.

Note that this surprise is ambiguous. On the one hand, it could be argued that in the above given example, a lower than expected nonfarm payroll figure is solely due to the fact that the April estimate was revised. If the April figure would have not been revised upwards by 245 a surprise of $+36$ would have been recorded instead of -209. Since the revision is not known in advance of the release, one could argue that the 'true' surprise is $+36$. On the other hand, revisions relate to the previous month's level. In order to properly adjust the announced changes in the nonfarm payrolls level one would need to know how the preliminary level estimate for the current month will be revised. But this information is not available before the next release (i.e. one month later).

However, it seems reasonable to assume that analysts try to forecast the announced headline figure and therefore also try to predict revisions and their impact on the headline figure. This view is in line with the empirical evidence provided by several studies that

[13]To date and to our knowledge, only Krueger (1996) makes use of revision information. Using daily data, however, he finds no significant price impact of revisions.

analysts' forecasts, in particular nonfarm payrolls forecasts, are unbiased estimates of the released headline figures.[14]

3.2 Release-specific precision estimates

While the theoretical literature on the price impact of information emphasizes the importance of the information precision, empirical research into this matter is hindered by a lack of data regarding the precision of information, in particular the precision of the announced figures. The employment report offers a rare opportunity to study this subject since precision proxies can be obtained for both the information available before an announcement and the released data. First, the dispersion of analysts' forecasts before an announcement can be used to approximate the quality of pre-announcement information. Second, a measure of the quality of the released data can be derived from one-step-ahead variance forecasts based on the currently available history of revisions. Since these two measures provide release-specific precision data they are particularly well suited for the empirical analysis of the question whether prices react stronger to more precise information.

Each Friday, Standard & Poors Global Markets (MMS International) polls analysts' forecasts of macroeconomic figures to be released during the coming week.[15] Besides the widely used medians of forecasts, our data set contains the standard deviations of forecasts across analysts. We follow Andersen, Bollerslev, Diebold, and Vega (2002) who interpret the standard deviation of analysts' forecasts as a measure of cross-sectional dispersion of expectations.[16] However, our objective is quite different. Andersen, Bollerslev, Diebold, and Vega

[14]The performance of analysts' forecasts of macroeconomic headline figures has been scrutinized, for example, by Pearce and Roley (1985), Hardouvelis (1988), Becker, Finnerty, and Kopecky (1996), Hess (2001) and Moersch (2001). Based on regressions of released figures (A_i) on median forecasts (F_i), i.e. $A_i = \alpha + \beta F_i$, the hypothesis of biased forecasts (i.e. H_0: $\alpha = 0$, $\beta = 1$) can be rejected only for a few series, in particular for short sample periods. However none of the studies finds such deficiencies in nonfarm payrolls forecasts.

[15]According to MMS, 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 about 1:30 pm EST.

[16]Note that dispersion measures of analysts' forecasts are frequently used in studies measuring stock price

find asymmetries in the price response due to 'bad' news. In order to obtain supplemental evidence, they use these standard deviations as a proxy for the uncertainty regarding the state of the economy and analyze whether pre-announcement uncertainty is higher if previous releases conveyed 'bad' news. In contrast, we want to test for the catalyzing effect of precise information as suggested by eq. (7). Therefore, we use the cross-sectional standard deviation of analysts' forecasts to approximate the precision of prior-information ρ_F, i.e. one of the two variables which determine the price-response coefficient π in eq. (7). Let $\hat{s}_{F,i}$ denote the cross-sectional standard deviation of forecasts for the report in month i, then $\hat{\rho}_{F,i} = 1 \Big/ \hat{s}^2_{F,i}$.

In order to approximate the second input variable of the price-response coefficient, i.e. the precision of the released data ρ_A, we need a release-specific precision estimate of the announced headline figures. Unfortunately, the employment report – like other macroeconomic reports – does not provide something like a survey-specific sample error estimate which could help traders to assess the quality of the released data at the time of the announcement. Nevertheless, we suppose that traders try to obtain a substitute for such a precision estimate.

A straightforward measure is obtained from the revision information. Obviously revisions indicate problems in the current sampling process. However, a large revision in the currently released report only suggests that the quality of the previous month's headline figure was poor. Hence traders have to try to forecast the magnitude of the revision which will be reported next month in order to assess the quality of this month's headline figures. A natural candidate for such a forecast of the magnitude of revisions seems to be the one-step-ahead prediction obtained from a GARCH model fitted to the time-series of revisions (including the currently released one).

reactions to earnings announcements. See e.g. Abarbanell, Lanen, and Verrecchia (1995) or Mohammed and Yadav (2002).

[insert Figure 1 around here]

For this purpose, the history of revisions in the nonfarm payrolls headline back to January 1980 was retrieved from the original BLS reports (see Figure 1). In order to investigate predictability in revisions, several standard models for first as well as second moments are fitted to this time series. Estimation results are provided in Table 2. The first two models (columns 1 and 2 in Table 2) search for predictable patterns in first moments, i.e. the revision series itself. As indicated by the Akaike information criterion (AIC) these models perform quite poorly. Model (1) includes an autoregressive term, model (2) tries to exploit possible seasonal effects. The seasonality function is specified by using the Fourier series approximation proposed by Andersen and Bollerslev (1998) based on the work of Gallant (1981). Assuming a polynomial of degree Q, the non-stochastic seasonal trend term is of the form

$$s(t) = s(\delta^s, \bar{t}, Q) = \delta^s \cdot \bar{t} + \sum_{j=1}^{Q} \left(\delta^s_{c,j} \cos(j \cdot \bar{t} \cdot 2\pi) + \delta^s_{s,j} \sin(j \cdot \bar{t} \cdot 2\pi) \right), \tag{8}$$

where δ^s, $\delta^s_{c,j}$, and $\delta^s_{s,j}$ are the seasonal coefficients to be estimated and $\bar{t} \in [0, 1]$ is a normalized time trend defined as the number of seconds from the beginning of the time interval until t divided by the length of the interval. However, including seasonal components in the mean function of model (2) increases the goodness-of-fit only marginally. In order to test for remaining autocorrelation in the residuals, Breusch/Godfrey LM test for the joint significance of the first 12 lags (i.e. one year) of residuals are performed. The test results suggest that there is no predictability in the revisions itself. In contrast, LM tests against ARCH effects (Engle 1982) up to order 12 indicate strong autocorrelation in second moments (last row in Table 2).

Models (3) to (8) try to account for this heteroskedasticity – and hence for predictability in squared revisions – by including GARCH-terms as well as deterministic seasonal components into the conditional variance function. These models are standard GARCH(1,1) models, however with different explanatory variables in the mean function. As indicated by the AIC values, the inclusion of GARCH terms leads to a slight improvement of the goodness-of-fit. Nevertheless, models (3) to (5) explain only little of the heteroskedasticity in the revisions series. The LM tests against remaining ARCH effects strongly reject the null hypothesis of homoscedasticity.

In order to account for deterministic seasonal patterns in squared revisions, we also include flexible Fourier transforms (as given in eq. 8) into the variance function of models (6) to (8). This changes the results completely. A strong improvement in the AIC is observed. Moreover, the ARCH LM tests can no longer reject the null hypothesis of no autocorrelation in the standardized squared residuals. According to the AIC, model (6) performs best. Hence we use the one-step-ahead variance forecasts of this model to approximate the precision of the nonfarm payrolls headline figure (i.e. to approximate $1/\rho_A$).

[insert Table 2 around here]

Together, the above outlined proxy variables for the precision of pre-announcement information and the precision of the announced data, enable us to approximate the price-response coefficient π in eq. (6) for nonfarm payrolls. On the basis of the estimated price response coefficient π, we discriminate between two types of employment announcements: 'precise' announcements (when a π equal to or above its sample median is observed) and 'imprecise' announcements (i.e. when the estimated π falls below its sample median).

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 should be systematically too high and our price-response coefficient too low. However, since we are not primarily interested in the values of π itself, but instead use this proxy variable to select our observations into two categories (i.e. 'precise' vs. 'imprecise' announcements) this bias should have no serious impact on our results.

3.3 Measuring the average precision across headlines

It should be noted that the Bureau of Labor Statistics (BLS) provides sampling error estimates of the different headline figures. These estimates may serve as a (time invariant) measure of the *average* precision of the released figures. According to the BLS, nonfarm payrolls have the smallest sampling errors, approximately 0.09%. In contrast, the BLS estimates that the standard error of the unemployment rate is about 0.13%.[17] Comparing these sampling error estimates, one would expect that the nonfarm payrolls provides the most reliable information, and hence has on average the strongest impact on market prices.

4 Empirical Results

4.1 Data

We analyze CBOT T-bond futures returns in 2-minute intervals during a 90-minute window around 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. We use log returns calculated on the basis of the last trading price observed in a 2-minute interval.[18] Using a nine-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.[19] Intraday data

[17]Bureau of Labor Statistics, Employment and Earnings, June 2000).

[18]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 announcement and the last price before 8:32. See Hautsch and Hess (2002) for more details.

[19]In the analyzed period, we record one announcement of the GDP report at the same time, six Personal Income releases and eight Leading Indicators announcements. Although most of these reports are of minor

on CBOT T-Bond futures are obtained from the Futures Industry Institute. Intraday transaction volumes are not available. We focus on the front month contract, i.e. the most actively traded contract among the nearby and second nearby contracts.

Data on analysts' forecasts, in particular medians and standard deviations of forecasts, are obtained from Standard & Poors MMS. Initially released non-revised headline figures as well as revisions are extracted from the original monthly BLS releases.[20] Following previous studies, we measure the unanticipated information component in these two headline figures by the deviation of the announced figures from the medians of the corresponding analysts' forecasts. Most previous studies use standardized surprises, i.e. for each headline, surprises are divided by their corresponding sample standard deviation of surprises.[21] In order to exploit the fact that both figures are closely related and to facilitate a comparison of the price impact across headline figures, we measure surprises in both figures in terms of percentage changes.[22]

4.2 Estimation approach

To investigate the effects of variations in the quality of information, we follow Hautsch and Hess (2002) and estimate an AR-ARCH model including explanatory variables in the conditional mean and in the conditional variance function. Hence, we assume the following process for 2-minute log returns:

$$r_t = x_t'\beta + \varepsilon_t, \qquad \varepsilon_t \sim N(0, h_t) \tag{9}$$

importance (see e.g. Fleming and Remolona 1999c) we eliminate all of these days to avoid an interference. Moreover, we eliminate 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.

[20] Medians and standard deviations of analysts forecasts are proprietary MMS data and must be obtained from them. Historical time series of initially released headline figures and revisions are available from different sources, for example, the BLS's 'Monthly Labor Review'.

[21] See, for example, Andersen, Bollerslev, Diebold, and Vega (2002) or Hautsch and Hess (2002).

[22] 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)

with

$$h_t = w_t'\gamma + \sum_{j=1}^{p} \phi_j \varepsilon_{t-j}^2. \tag{10}$$

x_t denotes the vector of explanatory variables in the conditional mean function including the above described surprise and revision variables (see Section 4.3 for details) while β is the corresponding coefficient vector. Covariates in the conditional variance function, γ, include seasonality variables that capture deterministic seasonality effects over the analyzed time window (see eq. 8) as well as announcement variables.

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 7-day-24-hour period it seems to be reasonable to ignore the daily GARCH component. Nevertheless, there might be a heteroskedasticity 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 (QML) while the standard errors are based on the Bollerslev and Wooldridge (1992) estimator of the variance covariance matrix.

4.3 Estimation results: Information precision and the strength of the price response

The central question of our paper is whether the precision of information determines the strength of the price impact of unanticipated information as it is suggested by the standard Bayesian learning framework. We investigate this issue by testing whether the estimated coefficients capturing the price impact of 'precise' information are significantly different from those coefficients capturing the price impact of 'imprecise' information. To analyze the robustness of our results we estimate several alternative specifications of eq. (9) and (10).

[insert Table 3 around here]

Estimation results for five different specifications of eq. (9) are given in Table 3. The variance function includes three ARCH terms as well as flexible Fourier transforms of order $Q = 5$ to account for intraday seasonal effects. Besides lagged returns (r_{t-1} and r_{t-2}), the conditional mean function includes variables accounting for a surprise in nonfarm payrolls S_{NF} and unemployment rates S_{UN} as well as a revision of the previously released nonfarm payrolls figure R_{NF}. In order to account for the timing of the impact of announcements, 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, i.e. the 2-min interval following immediately the release of the employment report, 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, i.e. in the interval 8:32-8:34. $S_{NF,t-1}$ captures information leakage effects, i.e. a price impact in the interval 8:28-8:30.[23]

As a starting point, model (1) provides a specification which does not account for time variations of the relative precision of unanticipated information. The results confirm several major findings of previous studies.[24] First, the large values of the highly significant coefficients of $S_{NF,t}$ and $S_{UN,t}$ show that surprising headline information has a strong and significant impact on intraday returns. Second, 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 a few minutes.[25] Third, 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

[23]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, 1995 or Fleming and Remolona 1999a, c for a detailed description of the dissemination procedure.

[24]See, for example, Becker, Finnerty, and Kopecky (1996), Balduzzi, Elton, and Green (2001), Fleming and Remolona (1999a, b, c), or Hautsch and Hess (2002) for bond markets and Almeida, Goodhart, and Payne (1998) or Andersen, Bollerslev, Diebold, and Vega (2002) for foreign exchange markets.

[25]We have also analyzed the influence of surprises in the following intervals, in particular $t+2$, ..., $t+5$, but no significant coefficient estimates were obtained.

unemployment rate. Fourth, a comparison of the magnitude of the coefficients of $S_{NF,t}$ and $S_{UN,t}$ shows that the nonfarm payrolls figure has the strongest price impact. Extending previous studies, we also include revisions into the analysis, in particular $R_{NF,t-1}$, $R_{NF,t}$ and $R_{NF,t+1}$. However, none of these coefficients is statistically significant. This creates the impression that market participants ignore revisions.

Overall, model (1) strongly confirms previous results of a consistent, sharp, and rapid price reaction to unanticipated information. However, it seems to provide no clear-cut answer to the question whether information precision determines the strength of the price reaction, since it does not account for the differences of the relative precision of unanticipated information over time. Nevertheless, it allows us to compare the price impact of headline figures with different *average* precisions (see section 3.3). According to the BLS, the average sampling error of the nonfarm payrolls figure is smaller (i.e. 0.09%) than the sampling error of the unemployment rate figure (i.e. 0.13%).[26] Hence, we would expect that the more precise nonfarm payrolls figure should have a stronger price impact *on average*. In fact, the estimated coefficients of $S_{NF,t}$ is about three times as large as the coefficient of $S_{UN,t}$.[27] This is confirmed on the basis of a one-sided likelihood ratio (LR) test of the null hypothesis that a surprise in the unemployment figure moves prices more than a comparable surprise in the nonfarm payrolls headline, which is rejected at the 1% level. Note that the null hypothesis is H_0: $\beta_4 \geq -\beta_7$, since a larger than expected nonfarm payrolls figure ($S_{NF} > 0$) should have a negative return impact while a larger than expected unemployment rate ($S_{UN} > 0$) should have a positive return impact. The result of this LR test 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.

[26] See, for example, BLS, Employment and Earnings, June 2000.

[27] Surprises in both the nonfarm payrolls and the unemployment headline figure, ($S_{NF,t}$ and $S_{UN,t}$, resp.) indicate unanticipated changes in (un)employment, however, based on two independent surveys. Nevertheless, since we measure surprises in both headline figures in percentage points, the magnitudes of the estimated coefficients are directly comparable.

In order to investigate the effects of release-specific precisions, we extend model (1) by including interaction variables which account for differences in the information precision across announcements (columns (2) to (4)). According to eq. (6) the strength of the price reaction is determined by the relative precision of the announced data compared to the pre-announcement information, i.e. the price-response coefficient[28] $\pi = \rho_A \,/ (\rho_F + \rho_A)$. As outlined above, a precision estimate of the announced information ($\hat{\rho}_A$) is derived from the variance forecast based on the time series of observed revisions (including the currently announced revision of the of previously released headline figure) while the precision of the pre-announcement information ($\hat{\rho}_F$) is obtained from the dispersion of analysts' forecasts. According to eq. (6), a high value of π should result in a more pronounced belief revision and hence in a stronger price reaction. In order to test this implication we split up the variable $S_{NF,t}$ by introducing an interaction variable which accounts for high (low) values of π. To be precise, the dummy variable $D^{\pi\ high}$ takes on the value 1 if the proxy for the price-response coefficient $\hat{\pi}_i$ of the ith announcement is larger than the sample median of $\hat{\pi}$, and 0 otherwise. $D^{\pi\ low}$ equals 1 if $\hat{\pi}_i$ is lower or equal than the sample median, i.e. $D^{\pi\ low} := 1 - D^{\pi\ high}$.

The large difference between the estimated coefficients strongly supports the notion that the relative precision determines the strength of the price impact. The coefficient ${\beta_4}^h$ associated with $D^{\pi\ high}$ is almost 50% larger than ${\beta_4}^\ell$ associated with $D^{\pi\ low}$. This suggests that 'precise' announcements move prices much more than 'imprecise' information. In fact, 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. Note that due to the negative sign of β_4 the null hypothesis becomes $H_0 : {\beta_4}^\ell \leq {\beta_4}^h$. In addition, comparing the goodness-of-fit of model (1) and (2) based on the AIC suggests that the inclusion of precision dummies leads to an improvement of the model's goodness-of-fit.

[28] To be precise, π stands for the price-response coefficient associated with the i-th announcement in our sample (π_i). However, to simplify the notation we drop the index i.

In model (2) we allow solely for a precision dependent asymmetric impact of the immediate price impact of nonfarm payrolls by interacting only $S_{NF,t}$ with the above defined 'precision' dummy variables. By also interacting $S_{NF,t+1}$ in model (3) we explore whether this asymmetric price response carries on to the second interval. In fact, also in the second 2-min interval the price impact of precise information is significantly stronger than of imprecise information ($H_0 : {\beta_5}^{\ell} \leq {\beta_5}^{h}$ is rejected at the 5 % level).

Finally, dropping the insignificant variables in specification (4), we obtain a more parsimonious model. In particular, we drop the insignificant unemployment rate variables $S_{UN,t-1}$ and $S_{UN,t+1}$, the revision variables $R_{NF,t-1}$, $R_{NF,t}$ and $R_{NF,t+1}$, as well as the twice lagged return variable r_{t-2}. The fact that no substantial change in the remaining coefficients is recorded underlines the robustness of the results.

4.4 Quality of information vs. 'bad' news effects?

Several models imply asymmetries in the price response to 'good' and 'bad' news (see Andersen, Bollerslev, Diebold, and Vega 2002 for a recent overview). For example, the rational expectations model of Veronesi (1999) suggests that 'bad' news may have a stronger impact on stock prices than 'good' news, in particular if 'bad' news occurs in 'good' times. Comparable results are obtained in a behavioral framework by Barberis, Shleifer, and Vishny (2002). Therefore, without a more detailed analysis we cannot preclude that our results might be driven by an asymmetric price impact of 'good' vs. 'bad' news. Note however that our intension is not to provide a formal test of the above mentioned models. Besides that these models analyze stock price reactions rather than bond market prices, the main reason is that most of our sample period falls into the prolonged expansionary phase which started early 1991 and ended in the middle of 2001. Therefore we find only a few 'bad times', and more severe, only two turning points. Hence, we can only test wether T-bond future prices react more pronounced to 'not as good as expected' news than to 'better than expected' news. We are unable to test whether the impact of 'bad news' is stronger in 'good times' than in 'bad times', as suggested by Veronesi (1999).

However, in order to analyze whether a possibly asymmetric price impact of 'good' and 'bad' news drives our results, we estimate some modifications of the parsimonious model (4) given in Table 3. Basically, we interact nonfarm payroll surprises with dummy variables accounting for the sign of surprises. Precisely, the variables capturing the immediate price impact of unanticipated information in the nonfarm payrolls figure ($S_{NF,t}$) are interacted 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. $D^{bad} = 1 - D^{good}$). In other words, we split up the regressor $S_{NF,t}$ into a variable accounting for positive surprises and a separate variable for negative surprises. Hence, the coefficients ${\beta_4}^{\cdot,b}$ (and ${\beta_4}^{\cdot,g}$) capture the immediate impact of 'bad' ('good') news, i.e. a larger (lower) than expected nonfarm payrolls figure. Estimation results are reported in Table 4.

[insert Table 4 around here]

In order to facilitate a comparison, model (5) provides a parsimonious versions of model (1). This specification ignores both the precision and the sign of $S_{NF,t}$. Model (6), which is identical to model (4), accounts for the precision but not for the sign. In contrast, model (7) ignores the precision of information, but accounts for 'bad' vs. 'good' news. Finally, model (8) accounts for both effects. In line with Conrad, Cornell, and Landsman (2002), the estimation results for model (7) indicate that 'bad' news has a stronger (negative) price impact than 'good' news. In fact, the null hypothesis that ${\beta_4}^b \geq {\beta_4}^g$ can be rejected at the 1% significance level. Moreover, the difference in the impact of 'good' and 'bad' news is very similar to the difference in the impact of precise and imprecise news (specification 6). Hence, from the comparison of models (6) and (7) we cannot conclude whether asymmetries in the price response are solely due to a 'good' versus 'bad' 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 in model (8). This analysis clearly shows that both effects are at work 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. ${\beta_4}^{h,b} < {\beta_4}^{h,g}$ (the same holds for imprecise 'bad' and 'good' news, i.e. ${\beta_4}^{\ell,b} < {\beta_4}^{\ell,g}$). 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: ${\beta_4}^{h,b} \geq {\beta_4}^{h,g}$, ${\beta_4}^{\ell,b} \geq {\beta_4}^{\ell,g}$. This hypothesis can be rejected at the 1% level.

On the other hand, similar differences are found between precise and imprecise news. The price impact of precise 'bad' news is stronger than the impact of imprecise 'bad' news, i.e. ${\beta_4}^{h,b} < {\beta_4}^{\ell,b}$ (the same holds for precise and imprecise and 'good' news, i.e. ${\beta_4}^{h,g} < {\beta_4}^{\ell,g}$). In fact, on the basis of a one-sided LR test the hypothesis that the more precise news does not have a stronger price impact after controlling for an asymmetric price response to 'bad' vs. 'good' news (i.e. H_0: ${\beta_4}^{h,b} \geq {\beta_4}^{\ell,b}$, ${\beta_4}^{h,g} \geq {\beta_4}^{\ell,g}$) is rejected at the 1% level, as well.

Overall, these results provide strong evidence in favor the claim of Bayesian learning that the quality of information plays an important role in determining its price impact. Asymmetries in the price response to unanticipated information are driven by differences in the (relative) precision *and* by differences in the sign of this information (i.e. 'good' versus 'bad' news) as suggested by Veronesi (1999) and others.

4.5 Robustness under alternative variance specifications

Hautsch and Hess (2002) present evidence that unanticipated information has an impact on both first and second moments of the price process. Therefore, we evaluate the robustness of our results under alternative specifications of the conditional variance function. So far, we have accounted for ARCH effects as well as seasonal effects in the conditional variance function. Now in addition, variables describing the news flow are included in the vector of explanatory variables w_t for the variance function. In particular, we include absolute surprises and revisions, i.e. $|S_{NF}|$, $|S_{UN}|$ and $|R_{NF}|$, as well as the above discussed proxies for the (im)precision) of the prior information and the announced information, i.e. σ_F and σ_A, resp. Note that $|S_{NF}|$, $|S_{UN}|$, $|R_{NF}|$, and σ_A are set to zero before 8:30 in order to account for the unavailability of this information prior to the release.

In addition to providing a simple robustness check of our results, we want to analyze another implication of the Bayesian learning framework. Eq. (2) shows that the precision of posterior beliefs about the equilibrium price level is increasing with the precision of the pre-announcement information as well as in the precision of the announced data. If traders are less certain about the equilibrium price level, we would expect to record larger unsystematic price fluctuations, i.e. price fluctuations which cannot be explained by the amount, sign and precision of the unanticipated information. In other words, the conditional volatility of unexplained returns should be increasing in both σ_F and σ_A.

[insert Table 5 around here]

Estimation results for the parsimonious specification of the mean function of model (8) are given in Table 5. To facilitate the comparison, the first column of Table 5 re-displays model (8). In addition, model (9) includes absolute surprises and revisions, model (10) includes the dispersion measures, and model (11) both sets of additional variables. First of all, note that the magnitude as well as the significance of the estimated coefficients in the mean function remains virtually unchanged. This underlines the robustness of the results. Confirming the results of Hautsch and Hess (2002), the estimation results for model (9) show that uncertainty is increasing in the amount of unanticipated information, i.e. the volatility of unexplained returns is proportional to the magnitude of unanticipated information in both headline figures (i.e. S_{NF} and S_{UN}). Surprisingly, revisions itself seem have no significant impact on volatility. Model (10) indicates that – as predicted by eq. (2) – a larger dispersion of the prior information produces more uncertainty. However, the estimated coefficient for σ_F is significant only at the 10% level and the significance fades away when the surprise and revisions variables are included (model 11). Moreover, according to eq. (2) one would expect that a higher imprecision of the announced information also increases the volatility. However, no significant influence of σ_A is found (neither in specification 10 nor 11). Nevertheless, evaluating the alternative models on the basis of the AIC, indicates that model (11), which includes both the imprecision and the surprise variables performs best. Hence, the goodness-of-fit is increased by including the imprecision proxies in the conditional variance specification.

Overall, mixed evidence with respect to the volatility impact of information (im)precision according to eq. (2) is found. Nevertheless, in the sense of a simple robustness check of the asymmetric mean impact of different information precision across alternative specifications of the conditional variance function, the results of this analysis underline the stability of the catalyzing mean effect of precise 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 into 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 primary objective of this paper is to fill this gap left in the empirical literature. Utilizing additional detail information being released with the headline figures of the employment report, i.e. revisions of previously announced figures, 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 an approximate measure 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 the released information on which market participants can base their trading decisions.

The empirical analysis based on this precision proxy provides strong evidence in favor of the claim of Bayesian learning that the quality of information acts as a catalyst. Prices respond stronger to more precise news. Analyzing the stability of this result, we find evidence that some part of this asymmetric price response is due to a 'good' versus 'bad' news effect. However, asymmetries in the price response are not driven exclusively by the latter effect. While prices respond significantly stronger to 'bad' news than to 'good' news, the precision of the information amplifies these price reactions. For example, precise 'bad' news has a significantly stronger price impact than imprecise 'bad' news. Moreover, the finding of a catalyzing effect of information precision is remarkably robust against various alternative specifications of the mean and the variance function.

Overall, 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. Such a precision proxy allows them to assess the quality of the released information and hence respond more aggressively to more precise unanticipated information.

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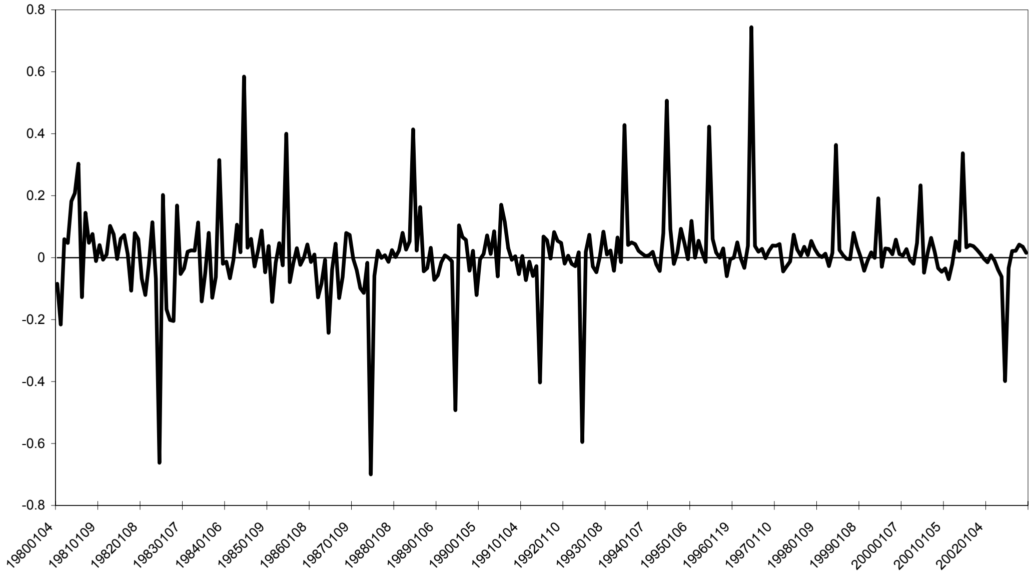
Figure 1: History of nonfarm payrolls revisions since 1980



First revisions of nonfarm payrolls headline figure (in percentage points) for the sample period Jan. 1980 until Dec. 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.

Table 1: Nonfarm payroll data used in this study - an example

(1)	(2)	(3)	(4)	(5)	(6)	
Release date	Reported total nonfarm payrolls prel. estimate (current month)	1st revision (previous month)	Announced change A_{NF}	Forecasted change F_{NF}	Regression variables S_{NF}	R_{NF}
99/04/02	127,678	127,632	46	163	-117	22
99/05/07	127,911	127,677	234	225	9	-1
99/06/04	128,167	128,156	11	220	-209	245

Initially reported total nonfarm payrolls ($\times$ 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 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 2: Time series models fitted to historical revisions (1980-2002)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean equation								
$cons$	0.0144**	0.0589	0.0134**	0.0061	0.0981*	0.0123***	0.0049*	-0.0367
$AR(1)$	0.0374	0.0293		0.0306**	0.0101		0.1836***	0.1180**
$\bar{t}$		-0.0825			-0.1715			0.0917
$sin(1 \cdot \bar{t}\, 2\,\pi)$		-0.0363			-0.0585*			0.0144
$sin(2 \cdot \bar{t}\, 2\,\pi)$		-0.0140			-0.0301*			0.0092
$sin(3 \cdot \bar{t}\, 2\,\pi)$		-0.0176			-0.0276**			0.0031
$sin(4 \cdot \bar{t}\, 2\,\pi)$		-0.0100			-0.0141*			-0.0050
$sin(5 \cdot \bar{t}\, 2\,\pi)$		-0.0045			-0.0082			0.0019
$cos(1 \cdot \bar{t}\, 2\,\pi)$		-0.0083			0.0103			-0.0227
$cos(2 \cdot \bar{t}\, 2\,\pi)$		0.0255***			0.0275***			0.0132*
$cos(3 \cdot \bar{t}\, 2\,\pi)$		0.0079			0.0248*			-0.0130
$cos(4 \cdot \bar{t}\, 2\,\pi)$		0.0043			0.0038			0.0003
$cos(5 \cdot \bar{t}\, 2\,\pi)$		-0.0046			0.0097			-0.0294*
Variance equation								
$cons$			0.0010***	0.0012***	0.0027**	0.0025	-0.0009	0.0038
$ARCH(1)$			-0.0406***	-0.0412***	-0.0357***	-0.0011***	0.0057***	0.0156***
$GARCH(1)$			0.9883***	0.9763***	0.8798***	0.9800***	0.9520***	0.8381***
$\bar{t}$						-0.0039	0.0028	-0.0032
$sin(1 \cdot \bar{t}\, 2\,\pi)$						-0.0013	0.0105	0.0059
$sin(2 \cdot \bar{t}\, 2\,\pi)$						-0.0337*	-0.0106	-0.0086
$sin(3 \cdot \bar{t}\, 2\,\pi)$						-0.0009	-0.0002	-0.0020
$sin(4 \cdot \bar{t}\, 2\,\pi)$						-0.0327***	0.0083***	0.0072***
$sin(5 \cdot \bar{t}\, 2\,\pi)$						-0.0008	-0.0107*	-0.0099*
$cos(1 \cdot \bar{t}\, 2\,\pi)$						-0.0047	-0.0072	-0.0076
$cos(2 \cdot \bar{t}\, 2\,\pi)$						0.0011	0.0176*	0.0160*
$cos(3 \cdot \bar{t}\, 2\,\pi)$						-0.0381**	-0.0250*	-0.0213
$cos(4 \cdot \bar{t}\, 2\,\pi)$						0.0006	0.0171***	0.0148***
$cos(5 \cdot \bar{t}\, 2\,\pi)$						-0.0707***	-0.0099	-0.0086
LL	154.7944	158.4468	179.1398	176.0257	173.0003	342.6355	337.0985	338.2955
AIC	1.1153	1.0617	1.2737	1.2484	1.1460	2.3828	2.3438	2.2722
B/G LM	14.9745	13.0373	15.3290	14.9190	14.1024	15.3600	20.0216*	15.9378
ARCH LM	43.9773***	36.6526***	73.3178***	64.8624***	49.6632***	8.6484	13.3781	16.5339

Estimated time series models for revisions in the nonfarm payrolls. The sample period is 1/1980 - 12/2002 (264 observations). The mean function includes a constant and an AR(1) term, the variance function includes one ARCH and one GARCH term. Moreover, in both the mean and variance function flexible Fourier transforms of order $Q = 5$ are included to account for seasonal patterns (see eq. 8). For each model, the log likelihood (LL) is reported. The goodness-of-fit of the models is evaluated according to the Akaike information criterion (AIC). The last two lines report statistics of LM tests against autocorrelation in the residuals according to Breusch and Godfrey (B/G) and results of LM test against ARCH effects (see, Engle 1982). Both types of LM tests are based on 12 lags, i.e. one year. ***, **, and * indicates significance at the 1%, 5%, and 10% level, respectively.

Table 3: Price impact of unanticipated information dependent on the relative precision:

		(1)	(2)	(3)	(4)
Mean equation					
cons	β_0	-0.005	-0.005	-0.005	-0.006
r_{t-1}	β_1	-0.089***	-0.090***	-0.091***	-0.089***
r_{t-2}	β_2	0.004	0.004	0.003	
$S_{NF,t-1}$	β_3	-3.044*	-2.977**	-2.943**	-2.823**
$S_{NF,t}$	β_4	-27.155***			
$S_{NF,t} \times D^{\rho\, low}$	${\beta_4}^{\ell}$		-23.171***	-23.185***	-22.784***
$S_{NF,t} \times D^{\rho\, high}$	${\beta_4}^{h}$		-32.048***	-31.783***	-32.788***
$S_{NF,t+1}$	β_5	-5.192**	-4.971**		
$S_{NF,t+1} \times D^{\rho\, low}$	${\beta_5}^{\ell}$			-2.086	-2.726
$S_{NF,t+1} \times D^{\rho\, high}$	${\beta_5}^{h}$			-8.484***	-8.666***
$S_{UN,t-1}$	β_6	-0.402	-0.483	-0.485	
$S_{UN,t}$	β_7	8.926***	9.082***	9.094***	9.686***
$S_{UN,t+1}$	β_8	1.087	1.115	1.249	
$R_{NF,t-1}$	β_9	2.328	2.061	2.078	
$R_{NF,t}$	β_{10}	-5.268	-5.068	-5.113	
$R_{NF,t+1}$	β_{11}	-0.549	-0.634	-0.524	
Variance equation					
cons	ω_0	0.298***	0.299***	0.298***	0.302***
ε^2_{t-1}	ϕ_1	0.118***	0.119***	0.119***	0.110***
ε^2_{t-2}	ϕ_2	0.055***	0.055***	0.055***	0.054***
ε^2_{t-3}	ϕ_2	0.036**	0.036**	0.037**	0.035**
R-sq.		0.2370	0.2404	0.2425	0.2328
LL		-6157.97	-6153.50	-6151.66	-6166.42
AIC		-2.1476	-2.1464	-2.1461	-2.1491
LR-tests					
$H_0: \ \beta_4 \geq -\beta_7$		80.7879***			
		(-6198.36)			
$H_0: {\beta_4}^h \geq {\beta_4}^{\ell}$			8.9381***	8.6106***	11.4608***
			(-6157.97)	(-6155.96)	(-6172.16)
$H_0: {\beta_5}^h \geq {\beta_5}^{\ell}$				3.6828**	3.0753**
				(-6153.50)	(-6167.96)

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 $\times$ 45 2-min intervals). The conditional variance equations also include seasonal components as described in eq. (8), i.e. flexible Fourier transforms of order $Q = 5$, whose estimated coefficients are omitted here. For each model, the R-Squared, the log likelihood (LL), and the Akaike information criterion (AIC) are reported. In addition, χ^2 statistics of LR tests on the inequality of selected parameters are given at the bottom (log likelihood of restricted models in parenthesis). Inference is based on QML standard errors (Bollerslev and Wooldridge 1992). ***, **, and * indicates significance at the 1%, 5%, and 10% level, respectively. Except for LR tests, significance is based on two-sided tests.

Table 4: Asymmetric price impact of 'good' news versus 'bad' news?

		(5)	(6)	(7)	(8)
Mean equation					
$cons$		-0.006	-0.006	-0.004	-0.004
r_{t-1}		-0.088***	-0.089***	-0.088***	-0.088***
$S_{NF,t-1}$		-2.975**	-2.823**	-2.814**	-2.921**
$S_{NF,t}$	β_4	-27.362***			
$S_{NF,t} \times D^{\pi\, low}$	β_4^ℓ		-22.784***		
$S_{NF,t} \times D^{\pi\, high}$	β_4^h		-32.789***		
$S_{NF,t} \times D^{good}$	${\beta_4}^g$			-22.184***	
$S_{NF,t} \times D^{bad}$	${\beta_4}^b$			-35.764***	
$S_{NF,t} \times D^{\pi\, low} \times D^{good}$	${\beta_4}^{\ell,g}$				-19.107***
$S_{NF,t} \times D^{\pi\, high} \times D^{good}$	${\beta_4}^{\ell,b}$				-26.126***
$S_{NF,t} \times D^{\pi\, low} \times D^{bad}$	${\beta_4}^{h,g}$				-29.648***
$S_{NF,t} \times D^{\pi\, high} \times D^{bad}$	${\beta_4}^{h,b}$				-41.487***
$S_{NF,t+1} \times D^{\pi\, low}$		-2.660	-2.726	-2.900	-2.901
$S_{NF,t+1} \times D^{\pi\, high}$		-8.892***	-8.666***	-7.789***	-7.279***
$S_{UN,t}$		9.559***	9.686***	9.217***	9.333***
Variance equation					
$cons$		0.302***	0.302***	0.301***	0.301***
ε^2_{t-1}		0.108***	0.110***	0.112***	0.113***
ε^2_{t-2}		0.054***	0.054***	0.055***	0.054***
ε^2_{t-3}		0.035**	0.035**	0.036**	0.036**
R-sq.		0.2287	0.2328	0.2350	0.2384
LL		-6172.16	-6166.42	-6162.03	-6156.96
AIC		-2.1507	-2.1491	-2.1476	-2.1465
LR-test					
$H_0 : {\beta_4}^{h,\cdot} \geq {\beta_4}^{\ell,\cdot}$			11.4608***		10.1299***
			(-6172.16)		(-6162.03)
$H_0 : {\beta_4}^{\cdot,b} \geq {\beta_4}^{\cdot,g}$				20.2563***	18.9254***
				(-6172.16)	(-6166.42)

Re-estimation of the parsimonious specification (4) given in Table 3 in order to analyze a possibly asymmetric price impact of 'good' and 'bad' news. Model (5) is a simplification of model (4) since it ignores both precision and 'bad' news effects. Model (6) is identical to model (4). It accounts for differential information precision by interacting the regressor capturing the immediate price impact of unanticipated information in the nonfarm payrolls figure, $S_{NF,t}$, with dummy variables capturing the precision of this information ($D^{\pi\, low}$ and $D^{\pi\, high}$). In model (7) $S_{NF,t}$ is interacted with dummy variables which indicate whether a surprise provides 'good' news for the bond market (i.e. $D^{good} = 1$ if $S_{NF} < 0$) or 'bad' news (i.e. $D^{bad} = 1 - D^{good}$). Model (8) accounts for both precision and 'bad' vs. 'good' news effects. All other variables remain unchanged. Parameter estimates of flexible Fourier transforms ($Q = 5$) are omitted. χ^2 statistics of one-sided LR tests are given at the bottom (log likelihood of restricted model in parenthesis). Inference is based on QML standard errors (Bollerslev and Wooldridge 1992). ***, **, and * indicates significance at the 1%, 5%, and 10% level, respectively. Except for LR tests, significance is based on two-sided tests.

Table 5: Robustness of the results against alternative variance specifications:

		(8)	(9)	(10)	(11)
Mean equation					
$cons$		-0.004	-0.002	-0.004	-0.002
r_{t-1}		-0.088***	-0.090***	-0.089***	-0.090***
$S_{NF,t-1}$		-2.921**	-2.870**	-2.935**	-2.885**
$S_{NF,t} \times D^{\pi\, low} \times D^{good}$	${\beta_4}^{g,\ell}$	-19.107***	-19.202***	-19.075***	-19.192***
$S_{NF,t} \times D^{\pi\, high} \times D^{good}$	${\beta_4}^{g,h}$	-26.126***	-26.115***	-26.133***	-26.118***
$S_{NF,t} \times D^{\pi\, low} \times D^{bad}$	${\beta_4}^{b,\ell}$	-29.648***	-29.623***	-29.619***	-29.609***
$S_{NF,t} \times D^{\pi\, high} \times D^{bad}$	${\beta_4}^{b,h}$	-41.487***	-42.097***	-41.658***	-42.218***
$S_{NF,t+1} \times D^{\pi\, low}$		-2.901	-2.933	-2.907	-2.934
$S_{NF,t+1} \times D^{\pi\, high}$		-7.279***	-7.244***	-7.266***	-7.229***
$S_{UN,t}$		9.333***	9.369***	9.344***	9.368***
Variance equation					
$cons$		0.301***	0.308***	0.248***	0.281***
ε^2_{t-1}		0.113***	0.112***	0.113***	0.112***
ε^2_{t-2}		0.054***	0.045***	0.053***	0.045***
ε^2_{t-3}		0.036**	0.035**	0.037**	0.036**
$\bar{t}$		0.618***	0.496***	0.635***	0.511***
$sin(1 \cdot \bar{t}\, 2\,\pi)$		0.774***	0.740***	0.781***	0.744***
$sin(2 \cdot \bar{t}\, 2\,\pi)$		0.596***	0.576***	0.597***	0.578***
$sin(3 \cdot \bar{t}\, 2\,\pi)$		0.263***	0.251***	0.265***	0.253***
$sin(4 \cdot \bar{t}\, 2\,\pi)$		-0.047**	-0.053***	-0.043**	-0.051***
$sin(5 \cdot \bar{t}\, 2\,\pi)$		-0.117***	-0.121***	-0.117***	-0.122***
$cos(1 \cdot \bar{t}\, 2\,\pi)$		0.331***	0.335***	0.332***	0.333***
$cos(2 \cdot \bar{t}\, 2\,\pi)$		-0.150***	-0.148***	-0.149***	-0.148***
$cos(3 \cdot \bar{t}\, 2\,\pi)$		-0.346***	-0.343***	-0.348***	-0.345***
$cos(4 \cdot \bar{t}\, 2\,\pi)$		-0.281***	-0.275***	-0.281***	-0.276***
$cos(5 \cdot \bar{t}\, 2\,\pi)$		-0.063***	-0.057***	-0.061***	-0.056***
$\lvert S_{NF}\rvert$			0.551***		0.537***
$\lvert S_{UN}\rvert$			0.235***		0.238***
$\lvert R_{NF}\rvert$			-0.069		-0.085
$\hat{\sigma}_A$				-0.099	-0.133
$\hat{\sigma}_F$				1.483*	0.878
R-sq.		0.2384	0.2382	0.2383	0.2382
LL		-6156.96	-6138.56	-6152.06	-6135.90
AIC		-2.1465	-2.1412	-2.1455	-2.1409
LR-test					
$H_0 : {\beta_4}^{h,\cdot} \geq {\beta_4}^{\ell,\cdot}$		10.1299***	10.5222***	10.3279***	10.6601***
		(-6162.03)	(-6143.82)	(-6157.22)	(-6141.23)
$H_0 : {\beta_4}^{\cdot,b} \geq {\beta_4}^{\cdot,g}$		18.9254***	19.3738***	19.0357***	19.4788***
		(-6166.42)	(-6148.24)	(-6161.57)	(-6145.64)

ML estimation of 2-min log returns during the intraday interval 8:22-9:52a.m. EST at employment announcement days (sample period Jan. 1991 - Dec. 2002, 5760 observations). AR(1)-ARCH(3) models with different sets of explanatory variables in the conditional variance equation are estimated, in particular seasonal components (see eq. 8), absolute surprises and revisions, and imprecision proxies. χ^2 statistics of one-sided LR tests are given at the bottom (log likelihood of restricted model in parenthesis). Inference is based on pseudo ML standard errors (Bollerslev and Wooldridge 1992). ***, **, and * indicates significance at the 1%, 5%, and 10% level, respectively. Except for LR tests, significance is based on two-sided tests.