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Price Adjustment to News with Uncertain Precision

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Abstract

Bayesian learning provides a core concept of information processing in financial markets. Typically it is assumed that market participants perfectly know the quality of released news. However, in practice, news' precision is rarely disclosed. Therefore, we extend standard Bayesian learning allowing traders to infer news' precision from two different sources. If information is perceived to be imprecise, prices react stronger. Moreover, interactions of the different precision signals affect price responses nonlinearly. Empirical tests based on intra-day T-bond futures price reactions to employment releases confirm the model's predictions and reveal statistically and economically significant effects of news' precision.

Keywords: Bayesian learning, information quality, precision signals, macroeconomic announcements

JEL classification: E44, G14

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1 Introduction

Rumours, analysts' comments or official press releases – financial markets are subject to a huge information flow which needs to be evaluated by market participants. However, information is of different precision and may contain errors. In such a noisy environment, Bayesian learning models are frequently used to explain how prices in financial markets react to news releases. Most importantly, these models suggest that prices react more strongly to more precise information. However, in practice, the precision of an individual piece of new information is rarely disclosed along with the information itself. Consequently, traders face severe uncertainty on the reliability of news which in turn affects their trading strategy.

This paper analyzes theoretically and empirically how market participants process information when its precision is uncertain. In particular, we extend standard Bayesian learning models by taking into account that traders use different sources to infer the precision of the released information. This explains non-linear price reactions to unanticipated information. By confirming empirically that price reactions depend crucially on traders' perception of news' precision, we provide new insights into price discovery and market participants' learning behavior in an uncertain environment.

Among macroeconomic announcements, employment figures have the most pronounced impact on financial markets (see, e.g., Andersen, Bollerslev, Diebold, and Vega, 2003). Given their importance for macroeconomic predictions and their distinct influence on asset prices, it is crucial for market participants to assess whether a potentially high surprise is reliable or whether it is rather driven by noise or sampling errors. Such an assessment naturally determines to which extent portfolios have to be reallocated and thus affects the ultimate price reaction. Another example of information shocks are companies' earnings announcements which often lead to sharp stock price adjustments.

Although a company report contains lots of detail information about the earning power of a company, market participants are left alone in making a judgement regarding its reliability, i.e. its precision. Recent empirical evidence suggests that market participants consider additional sources of information to assess news' precision. For the employment report, Hautsch and Hess (2007) show that revisions of the headline figure provide information which can be exploited for such a purpose. Furthermore, for company reports, Sloan (1996), Feltham and Pae (2000), and Richardson, Sloan, Soliman, and Tuna (2005), among others, show that accruals provide information about the quality of stated earnings.

Our paper shows how to incorporate such effects in a Bayesian learning framework. Basic Bayesian learning models relying on normally distributed variables with known parameters imply that prices react linearly in response to surprises. Moreover, the strength of this price adjustment depends on the relative precision of the announced data compared to the precision of prior beliefs. This standard model is quite restrictive, since it assumes news' precision to be known and additionally requires perfect knowledge of all underlying distributions. Subramanyam (1996) relaxes these assumptions by including parameter uncertainty about news' precision. In this framework, traders try to infer the precision of news from the magnitude of the surprise component in an announcement. Due to this strict link between the expected precision and the signal magnitude, large surprises result in relatively weak price reactions which may be even smaller than for medium surprises. Consequently, surprisingly good news may be interpreted as *too good to be true*, as recently analyzed by Mattsson, Voorneveld, and Weibull (2007).[1] This results in S-shaped price reactions to unexpected news, i.e. price reactions are relatively strong for small surprises, while they are relatively weak for large

[1]In an early contribution, Milgrom (1981) has already studied this effect and provided conditions for monotonicity of price reactions in the announced information. These monotonicity results based on a monotone likelihood ratio criterion were recently generalized by Mattsson, Voorneveld, and Weibull (2007) in a discrete choice model under uncertainty.

surprises. A restrictive assumption in this setting is that market participants assess the reliability of news solely based on the released figures' magnitudes and ignore any other potentially available information on precision. This is rather unrealistic in practice and can induce severe misinterpretations of the announced figures. Indeed, large surprises may as well be very precise and thus should generate strong price reactions.

A key assumption in this paper is that traders do not only evaluate the news itself but employ further sources of information to assess news' quality. For instance, before deciding which trading strategy to choose after a news release, market participants are assumed to gather general information on the news provider, the general economic environment, the underlying data source or the reliability of recent news releases. This assumption is empirically supported by Hautsch and Hess (2007). Their results provide evidence that traders can extract the release-specific precision of unanticipated headline information in the employment report from additional detail information. In particular, traders may derive such a precision estimate by inspecting revisions of previously announced data. Taking into account such effects, Hautsch and Hess (2007) show that prices in the T-bond futures market indeed react more strongly to employment information which is perceived to be more precise.

Connecting both types of precision signals, we develop a learning model which brings together the approaches of Hautsch and Hess (2007) and Subramanyam (1996). In this setting, traders use two different kinds of information as precision signals. Firstly, so-called 'external' precision signals – such as the sample size of a survey or the reputation of an auditing company – directly influence the perception of information precision. Secondly, the released information itself serves as an 'internal' precision signal. In accordance with Subramanyam (1996) this implies that the probability for news to be imprecise increases with its magnitude (i.e. these news are believed to be *too large to be true*).We show that such learning behavior implies non-linear, S-shaped price response functions, i.e. the price response coefficient becomes smaller for large absolute surprises. Additionally, the model predicts stronger reactions to news which are perceived to be more precise. In this case, the curvature of the price response function becomes even more pronounced and strongly deviates from linearity for surprises of high magnitude. We also show that our results hold in a framework where the precision of the prior distribution itself is uncertain and are valid for a wide class of distributional assumptions.

In an empirical analysis of the price reactions of CBOT T-bond futures to the release of U.S. employment data we provide strong evidence in favor of Bayesian learning under these two types of precision signals. From data revisions in employment releases, we extract release-specific external precision measures, which do not depend on the surprise itself. The estimated price response curves clearly reveal that prices (i) respond non-linearly with an S-shaped pattern and, (ii) react significantly different depending on the external precision signal. Also from an economic perspective, our results are strongly significant. We show that ignoring the available precision signals leads to severe estimation errors when determining the price impact of a news release. Altogether, our empirical study provides strong evidence in favor of the claim of Bayesian learning that the *perceived* quality of information plays an important role in determining its price impact.

The remainder of this paper is organized as follows. The following section presents a theoretical Bayesian learning framework which allows the precision of arriving news to be unknown and allows for uncertainty in the prior distribution. Section 3 describes the high-frequency return data and outlines the estimation procedure. The empirical results are presented and discussed in Section 4. Finally, Section 5 concludes.

2 A Bayesian Learning Model

2.1 Standard Bayesian Learning

Bayesian learning models provide a framework to analyze how new information is incorporated into expectations and prices, while both prior information as well as incoming news contain uncertainty. Throughout our analysis we assume that all market participants have the same information just before the release of some public announcement. Each participant is equipped with the same utility function and the same endowment of assets including a risky asset. The price P of this risky asset is assumed to be proportional to traders' expectations of an economic variable X with proportionality factor ν, i.e. $P = \nu \cdot E[X]$. The beliefs on X prior to the announcement are assumed to be normally distributed with known parameters, i.e. $X \sim N(\mu_F, 1/\rho_F)$, where μ_F is the mean of the prior information on X in the market, and ρ_F denotes their precision, defined as the inverse of the variance. This prior information represents the market's forecasted probability distribution of the variable X given all available information including for example all publicly released analysts' forecasts. Empirical research on the impact of scheduled announcements typically assumes that the distribution of prior beliefs in the market may be approximated by the distribution of analysts' forecasts. Hence, it is implicitly assumed that analysts' forecasts are unbiased for X and together with their cross-sectional dispersion they provide a consistent estimate of market's prior information.[2]

Now an announcement is released providing a noisy estimate of X. It is assumed that the released figure includes an additive error, i.e. $A = X + \varepsilon$, where ε is a zero mean normally distributed error term with variance $Var[\varepsilon] = 1/\rho_\varepsilon$ and $E[X \cdot \varepsilon] = 0$. Consequently,

[2] See e.g. Abarbanell, Lanen, and Verrecchia (1995), Mohammed and Yadav (2002), Andersen, Bollerslev, Diebold, and Vega (2003) and Hautsch and Hess (2007).

traders receive an unbiased estimate of the underlying variable X whose precision is reflected by ρ_ε. The additive error term structure implies that the unconditional variance of the news release exceeds the variance of the market's prior information. Accordingly, the announcement A is distributed as $A \sim N(\mu_F, 1/\rho_A)$. After observing the public announcement, traders adjust their beliefs according to Bayes' rule. Then, traders' posterior beliefs are normally distributed with

$$\mu_P := E[X \mid A] = \mu_F + (A - \mu_F)\frac{\rho_A}{\rho_F} = \mu_F + (A - \mu_F)\frac{\rho_\varepsilon}{\rho_F + \rho_\varepsilon} \tag{1}$$

and

$$\rho_P := Var[X \mid A]^{-1} = \rho_F + \rho_\varepsilon. \tag{2}$$

Consequently, after traders observe the signal A, the market price of the risky asset changes as

$$\Delta P = \nu \cdot (\mu_P - \mu_F) = \nu \cdot S \cdot \pi, \tag{3}$$

where π denotes the so-called 'price-response coefficient'

$$\pi := \frac{\rho_A}{\rho_F} = \frac{\rho_\varepsilon}{\rho_\varepsilon + \rho_F}. \tag{4}$$

Hence, the main model implication is that price changes are proportional to the surprise $S := A - \mu_F$, where the proportionality factor π depends on the relative precision of announcements and the market's forecast.

2.2 Surprises as an 'Internal' Signal on the Precision of Releases

Announcements such as employment figures are usually released without an associated precision measure which contradicts the assumptions of the standard Bayesian learning model. Subramanyam (1996) relaxes the latter framework by treating news' precision to be unknown and assuming that the announcement is conditionally normally distributed given the true precision, i.e. $A|\rho_A \sim N(\mu_F, \rho_A)$. Formally, Bayesian updating of traders works similar as in the basic framework yielding

$$\mu_P = E[X \mid A] = \mu_F + (A - \mu_F)\frac{E[\rho_A \mid A]}{\rho_F} = \mu_F + S \cdot \pi(S), \tag{5}$$

with $E[\rho_A|A]$ representing traders' conditional expectation of the signal precision given its realization. Hence, it turns out that the price response coefficient, $\pi(S)$, is no longer constant but depends on the absolute surprise. Consequently, the latter serves as an 'internal' signal on news' precision. As shown by Subramanyam (1996) and illustrated in a more general framework in the next section, this generates a nonlinear relationship between the magnitude of the surprise and the implied update of traders' beliefs. In particular, if traders observe high absolute values of unanticipated information, they conclude that these stem from an announcement with low precision. This reduces their adjustment of beliefs in absolute terms which (in the extreme case) may even generate negative marginal contributions of surprises resulting in an S-shaped price response curve. However, this direct link between the amount of unanticipated information and the expected precision is relatively restrictive since it implies that large surprises are always *too large to be true*. Even in an environment when the information precision is high large surprises may occur occasionally. Then, we would expect to observe a strong price reaction.

2.3 'External' Signals on the Precision of Releases

Extending the previous setting we assume that traders do not only evaluate the released information itself, but employ other data sources. For instance, for the U.S. employment report, Hautsch and Hess (2007) show that traders may infer on the precision of announced employment figures by inspecting the time series of historical revisions of the headline figure. Since revisions in announcements reflect (ex post) sampling errors, a natural precision measure arises from their conditional variance.

Suppose that market participants are able to observe such a so-called *external* signal $\hat{\rho}_A$ for the precision of the announcement ρ_A. Here, 'external' refers to the case when the signal is not directly linked to the announced figure itself. For example, $\hat{\rho}_A$ might be information on the sample size of a survey, the reliability of data collection or a precision estimate based on (past) revisions as in Hautsch and Hess (2007).

Let this additional precision signal follow a conditionally normal distribution given the true precision ρ_A, i.e. $\hat{\rho}_A \mid \rho_A \sim N(\rho_A, \sigma^2_{\hat{\rho}_A})$. Moreover, we assume that the announcement A and the precision signal $\hat{\rho}_A$ are conditionally independent given the true precision ρ_A. Then, the precision signal and the news release are only linked indirectly via the true precision. If $\sigma^2_{\hat{\rho}_A}$ reaches zero, the signal reveals the true precision of the announcement. In this case, the surprise itself does no longer serve as an internal precision signal and we are back in the standard Bayesian learning model. If $\sigma^2_{\hat{\rho}_A}$ is different from zero, both precision signals are taken into account by market participants. Analogously to the updating equations given above, traders form their beliefs as[3]

$$\mu_P = E\left[X \mid A, \hat{\rho}_A\right] = \mu_F + (A - \mu_F)\frac{E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\rho_F} = \mu_F + S \cdot \pi(S, \hat{\rho}_A). \tag{6}$$

As before, adjustments in traders' beliefs depend symmetrically on the sign of news. However, now the market incorporates additional information into its price formation. This is reflected by the price response coefficient $\pi(\cdot)$ depending not only on S but also on $\hat{\rho}_A$. As shown in Appendix A, the conditional expectation of the precision $E\left[\rho_A \mid A, \hat{\rho}_A\right]$ is computed by

$$E\left[\rho_A \mid A, \hat{\rho}_A\right] = \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}, \tag{7}$$

where $f(\cdot)$ denote the corresponding conditional and unconditional p.d.f.'s and the support S_A of $f(\rho_A)$ is given by $S_A \in (\rho_F, \infty)$. Hence, it turns out that the expected

[3] For a formal derivation, see Appendix A.

precision does not only depend on $\hat{\rho}_A$ and A, but also on the unconditional prior distribution of the precision, $f(\rho_A)$.

In Proposition 1, we will show in accordance with Subramanyam (1996) that the amount of unanticipated information influences the expected precision of the announcement negatively. This result holds irrespective of the choice of the underlying prior distribution $f(\rho_A)$:

Proposition 1 *The price response coefficient* $\pi(S, \hat{\rho}_A)$ *is strictly decreasing in the absolute magnitude of the surprise* $|S|$ *for any prior distribution* $f(\rho_A)$*, i.e.* $\partial\pi(S, \hat{\rho}_A)/\partial|S| < 0$.

Proof: *See Appendix A.*

Hence, prices react relatively strongly to news with small surprises and relatively weakly to news with a high surprise component. Consequently, there are two effects determining the change in beliefs $(\mu_P - \mu_F)$ after an announcement is made: Firstly, given the price response coefficient $\pi(\cdot)$, a high (low) surprise $S = A - \mu_F$ strengthens (weakens) the price reaction linearly. Secondly, according to Proposition 1, it decreases (increases) the expected signal precision and thus decreases (increases) $\pi(\cdot)$. As shown in Proposition 2, the latter effect induces price reactions which are S-shaped in absolute surprises:

Proposition 2 *The marginal impact of the surprise* S *on investors' updates of beliefs,* $\mu_P - \mu_F$*, is given by* $\partial(\mu_P - \mu_F)/\partial S = \pi(S, \hat{\rho}_A) - S^2\rho_F^{-1}Var[\rho_A \mid A, \hat{\rho}_A]$.

Proof: *See Appendix A.*

Hence, investors update their expectations in the direction with the sign of the surprise as long as $\pi(S, \hat{\rho}_A) - S^2\rho_F^{-1}Var[\rho_A \mid A, \hat{\rho}_A] > 0$. However, if $|S|$ becomes large, the relation may even reverse and the marginal effect of absolute surprises may as well become negative, i.e. $\partial(\mu_P - \mu_F)/\partial S < 0$. These effects are enforced if ρ_F is small and $Var[\rho_A \mid A, \hat{\rho}_A]$ is large. Consequently, we obtain an S-shaped price reaction as graphically illustrated in Figure 1. Note that in case of a degenerated prior distribution $f(\rho_A)$, we get a linear response as in the basic model. Hence the results of an S-shaped relation between surprises and traders' updates of expectations according to Subramanyam (1996) still holds also in this extended framework.

However, the following proposition shows that traders' conditional expectations of news' precision depend positively on the external precision signal $\hat{\rho}_A$. Hence, traders positively (negatively) update their conditional expectations if $\hat{\rho}_A$ increases (decreases). Consequently, $\hat{\rho}_A$ affects the price response coefficient $\pi(S, \hat{\rho}_A)$ in opposite direction than $|S|$.

Proposition 3 *The price response coefficient $\pi(S, \hat{\rho}_A)$ and the absolute signal response $|\mu_F - \mu_P|$ are strictly increasing in the observed value of the precision signal $\hat{\rho}_A$ for any prior distribution $f(\rho_A)$, i.e. $\partial\pi(S, \hat{\rho}_A)/\partial\hat{\rho}_A > 0$ and $\partial|\mu_p - \mu_F|/\partial\hat{\rho}_A > 0$.*

Proof: *See Appendix A.*

The proposition also states that a central implication of standard Bayesian learning is maintained even if the true precision parameter of news is replaced by a noisy signal: Market prices react more strongly to news which is perceived to be more precise, whereas news which appear to be imprecise induce rather moderate market reactions. However, as shown in Figure 1, the existence of an 'external' precision measure $\hat{\rho}_A$ induces an additional effect which even amplifies the S-shape. A higher ρ_A leads to a straightening of the price response curve for surprises near zero but to more pronounced S-shaped price responses to large surprises.

2.4 Accounting for Uncertainty into the Prior Distribution

So far we assumed that traders have normally distributed prior beliefs on the distribution of the variable X with perfectly known parameters. However, traders generate their views for example by relying on analysts' forecasts and thus face estimation errors. In practice, traders might approximate the precision of prior information by the dispersion of different analysts' forecasts. However, the quality of such estimates is itself subject to uncertainty. In order to capture uncertainty in the precision of prior information we assume that the latter is random and follows a distribution $f(\rho_F)$. Then, X is assumed to be conditionally normally distributed given ρ_F, i.e. $X \mid \rho_F \sim N(\mu_F, 1/\rho_F)$. This results in a scale mixture distribution for the prior yielding

$$f(X) = \int_{S_F} f(X \mid \rho_F) f(\rho_F) d\rho_F \tag{8}$$

with $S_F \in (0, \infty)$. Nevertheless, as shown in Proposition 4, all previous results still hold:

Proposition 4 *If the prior distribution of traders follows a scale mixture of normal distributions, Propositions 1, 2 and 3 still hold.*

Proof: *See Appendix A.*

Obviously, this proposition states that our analysis is not restricted to the case of normally distributed variables but holds for a wide class of distributions, including e.g. also fat-tailed prior distributions.

2.5 Testable Implications of the Model

The learning model outlined above yields hypotheses on how traders' expectations adjust to new information. Assuming that prices are proportional to traders expectations of the observed market variable, the following testable hypotheses arise:

(1) The standard Bayesian learning model with perfectly known normal distributions as presented in Section 2.1 implies a linear price response function,

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

Here, a higher magnitude of surprises implies higher absolute price reactions, since the price response coefficient, π, is a constant *and* known parameter which does not depend on the revealed unanticipated information, S. Then, the price response coefficient is determined by the precision of the announcement and the precision of the released data.

(2) As shown in Section 2.2, the model suggested by Subramanyam (1996) implies

$$\Delta P = \nu \cdot S \cdot \pi(S).$$

Here, news precision is unknown and is inferred from the magnitude of surprises. Since large surprises serve as a signal for a low precision of news, the price response coefficient $\pi(S)$ is decreasing in the absolute size of the surprise $|S|$ implying an S-shaped relationship between ΔP and S.

(3) Allowing for additional external precision signals $\hat{\rho}_A$ as in Section 2.3, we get

$$\Delta P = \nu \cdot S \cdot \pi(S, \hat{\rho}_A).$$

Then, the previous result of an S-shaped price response curve still holds but we observe the additional effect of a positive relation between ΔP and $\hat{\rho}_A$. In this case, both effects might work in opposite directions and the S-shape of the price response curve is even amplified if news' precision is high.

These implications will be empirically tested in the next sections.

3 Data and Empirical Framework

3.1 Data

Note that we do not estimate the model outlined above in a structural way since this would require additional structural assumptions in order to estimate $E[\rho_A|A, \hat{\rho}_A]$. We rather test for the implications summarized above in reduced form by estimating the shape of the price reaction curve in dependence of S and the perceived precision of news $|\hat{\rho}_A|$. We use intraday returns of CBOT T-bond futures, corresponding to one of the most liquid futures markets, to monthly releases of the U.S. employment report. The latter is by far the most influential scheduled macroeconomic release and its impact on financial markets is investigated in a wide range of studies.[4] While the employment report contains various detail information on the employment situation in the U.S., market participants focus in particular on two headline figures: the nonfarm payrolls figure and the unemployment rate figure. The disclosure of this information offers a rare opportunity to analyze Bayesian learning effects in price adjustment processes, since both the amount of unanticipated information *and* a release-specific precision measure can be obtained.

Hautsch and Hess (2007) document the importance of news' precision in a framework where traders are assumed to use external information to infer on the precision of news. To facilitate a comparison with these results, we employ a similar data set based on two minutes log returns of T-bond futures in 90-min windows around employment announcements.[5] However, our dataset covers an extended sample period of 15 years,

[4]Several empirical studies provide evidence that unanticipated information in the employment report has a strong influence on bond market prices (e.g. Becker, Finnerty, and Kopecky (1996), Fleming and Remolona (1999c), and Hautsch and Hess (2002)), but also on 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)).

[5]Log returns are calculated on the basis of the last trading price observed during a 2-minute interval. We use the same time window, i.e. 8:22-9:52 a.m. EST. Since trading starts at 8:20, the first return

i.e. Jan. 4, 1991 to Dec. 2, 2005. These high frequency T-bond data are obtained from the Chicago Board of Trade (via their Time & Sales records). During our sample period we obtain 161 event windows in which no other major information event occurs besides the release of the employment report.[6] Thus information processing during these event windows is only driven by employment figures. Like previous studies, we use so-called consensus estimates, i.e., medians of analysts' forecasts, to approximate the anticipated part of information in the employment headline figures. These analysts' forecasts are obtained from Informa Global Markets (formerly S&P Money Market Services, MMS). The announcement data are extracted from the original (i.e. unrevised) employment releases of the Bureau of Labour Statistics (BLS). In accordance with other studies, we concentrate on the headline information in the employment report, i.e., surprises in the nonfarm payrolls figure, S_{NF}, and the unemployment rate, S_{UN}.[7] Note that nonfarm payrolls are revised in the subsequent month. We include this revision information, $R_{NF,m}$, into our analysis. In order to facilitate a direct comparison across the information components, all surprise and revision variables are measured in percentage changes.

In order to extract release-specific precision measures for the monthly employment releases, we employ the procedure suggested by Hautsch and Hess (2007): Firstly, as a precision measure for the prior information, the dispersion of analysts' forecasts before

can be calculated for interval 8:22-8:24. In order to avoid that other announcements, being released at 10:00 a.m. EST., influence our results, only price observations up to 9:52 a.m. EST are used. Like most previous studies, we focus on the front month contract, i.e. the most actively traded contract among the nearby and second nearby contracts.

[6]We eliminate 15 days in which other reports where released during our 90-min window, in particular releases of Leading Indicators, Personal Income, and Gross Domestic Product. Furthermore, we eliminate one inadvertently early employment release in November 1998 (Fleming and Remolona 1999b) and another 3 releases which were presumably affected by the temporary shutdown of federal agencies due to the budget dispute during the Clinton administration (see Hess, 2004). This leaves us with a total of 161 observations.

[7]The unanticipated information contained in the releases of month m is then measured as the difference between the announced figure $A_{.,m}$ and its median forecast $\mu_{F,.,m}$. For instance, the surprise in a non-farm payrolls figure,$S_{NF,m}$, is determined as $S_{NF,m} = A_{NF,m} - \mu_{F,NF,m}$.

an announcement is used.[8] In particular, the standard deviation of analysts' forecasts, $\hat{s}_{F,m}$, for a particular month m is interpreted as a measure of the cross-sectional dispersion of expectations and serves as a proxy for the precision of prior information, i.e. $\hat{\rho}_{F,m} = 1 \Big/ \hat{s}^2_{F,m}$. Secondly, in order to obtain a measure for the precision of the announced information itself, a one-step-ahead prediction of the (conditional) variance of revisions is used. Using revisions in nonfarm payrolls is based on the idea that a large revision of the previous month's figure (as reported in the current report) indicates that the precision of that figure obviously has been poor. Hautsch and Hess (2007) illustrate that the magnitude of revisions, and thus the size of estimation errors in announced figures, are autocorrelated. Hence, the size of revisions as a proxy for news' precision is predictable. Corresponding forecasts are obtained from an ARMA-GARCH model fitted to the time series of revisions. Then, $\hat{\rho}_{\varepsilon,m}$ is obtained by $\hat{\rho}_{\varepsilon,m} = \widehat{Var}[R_{NF,m}|R_{NF,m-1}, R_{NF,m-2}, \ldots]^{-1}$.[9]

In order to reduce the impact of estimation noise in the quantification of news' precision and to avoid the necessity to impose additional assumptions on the functional relationship between the precision measure and the induced price reaction, we restrict our analysis to a distinction between precise and imprecise news. These two states are identified based on a proxy of the price response coefficient $\hat{\pi}_m = \hat{\rho}_{\varepsilon,m}/(\hat{\rho}_{\varepsilon,m} + \hat{\rho}_{F,m})$. Then, we define news to be precise if $\hat{\pi}_m$ is equal to or above its sample median and imprecise otherwise. Estimating the relationship between price changes, the surprise S and the derived precision dummy allows us to test for the implications of the generalized Bayesian learning framework outlined above.

[8] This is in accordance with Abarbanell, Lanen, and Verrecchia (1995), Mohammed and Yadav (2002), Andersen, Bollerslev, Diebold, and Vega (2003) and Hautsch and Hess (2007), among others. However, note that the information set of all publicly available prior information may be even much larger. Furthermore, as for example Ottaviani and Sorensen (2006) argue, forecasts may be announced strategically depending on the forecaster's loss function, e.g. as the median of a distribution.

[9] For more details, see Hautsch and Hess (2007).

3.2 Specification of Price Response Curves

Using 2-minute log returns r_t in the described 90-minute-windows around the employment release we estimate alternative ARMA-ARCH specifications augmented with appropriate sets of explanatory variables x_t, i.e.

$$r_t = c + \sum_{j=1}^{p_1} \phi_{1,j} r_{t-j} + \sum_{j=1}^{q_1} \phi_{2,j} \varepsilon_{t-j} + x_t' \beta + \varepsilon_t, \qquad \varepsilon_t \sim N(0, h_t), \tag{9}$$

with

$$h_t = \omega + \sum_{j=1}^{p_2} \psi_{1,j} \varepsilon_{t-j}^2 + z_t' \theta. \tag{10}$$

Here, t indexes the 2-minute intervals around the release of the employment report for a given month m. In particular, $t = 0$ indicates the interval following immediately after the announcement, i.e. 8:30 - 8:32 a.m. EST and $t = 1$ denotes the 8:32 - 8:34 interval. For simplicity, the index m is suppressed.

The conditional variance equation (10) captures ARCH effects. In addition, z_t (with corresponding parameter vector θ) consists of regressors $\{\bar{t}, \sin(2 \cdot r \cdot \pi \cdot \bar{t}), cos(2 \cdot r \cdot \pi \cdot \bar{t})\}$ with $r = 1, \ldots, R$ associated with a Fourier series approximation of order R defined over the interval $\bar{t} \in (0, 1)$ capturing the used 90-minutes window around the announcement. The latter allow us to control for (deterministic) seasonal volatility patterns around news releases. Preliminary studies show that such a specification captures most variations in conditional variances during the analyzed 90-minute interval.[10]

To test for the different implications of the Bayesian learning model discussed above, we use alternative specifications of the vector x_t. In particular, to impose the standard Bayesian learning model in accordance with Section 2.1, a dummy variable $D_{8:30}$ indicating the interval 8:30 - 8:32 and a linear term in the surprise $D_{8:30} \cdot S_{NF}$ are included

[10]Nevertheless, there might be heteroscedasticity components which are still ignored in our specification. Therefore, we use robust standard errors according to Bollerslev and Wooldridge (1992).

(among other variables) as regressors in x_t:

$$x_t' = [\ldots,\ D_{8:30}\ ,\ D_{8:30} \cdot S_{NF}\ , \ldots]\ ,$$

where $S_{NF,m}$ contains the unexpected component in the nonfarm payrolls figure for month m. Obviously, this specification implies a linear price relationship between nonfarm payroll surprises and the implied return.

In order to capture the impact of an internal precision signal (in accordance with Section 2.2), we allow for non-linear price responses to news in nonfarm payrolls by including power functions of this figure into the set of explanatory variables. To keep the model tractable, we allow for this flexibility only in the interval 8:30-8:32, where typically most of the price movements after announcements are realized. Correspondingly, we model the impact of surprises in nonfarm payrolls based on the regressors

$$x_t' = \left[\ldots,\ D_{8:30}\ ,\ D_{8:30} \cdot S_{NF}\ ,\ D_{8:30} \cdot S_{NF}^2\ ,\ D_{8:30} \cdot S_{NF}^3\ , \ldots\right].$$

To estimate the most general (unrestricted) model allowing for both internal and external precision signals (in accordance with Section 2.3) we differentiate between precise vs. imprecise announcements by interacting the corresponding regressors with a dummy variable $D^{\pi low}$ which takes on the value one if the external precision signal is below its sample median and zero otherwise:

$$\begin{aligned} x_t' = \quad & \Big[\ldots,\ D_{8:30} \cdot D^{\pi low},\ D_{8:30} \cdot D^{\pi high}, \\ & D_{8:30} \cdot S_{NF} \cdot D^{\pi low},\ D_{8:30} \cdot S_{NF} \cdot D^{\pi high}, \\ & D_{8:30} \cdot S_{NF}^2 \cdot D^{\pi low},\ D_{8:30} \cdot S_{NF}^2 \cdot D^{\pi high}, \\ & D_{8:30} \cdot S_{NF}^3 \cdot D^{\pi low},\ D_{8:30} \cdot S_{NF}^3 \cdot D^{\pi high}, \ldots\Big], \end{aligned}$$

where $D^{\pi high} = 1 - D^{\pi low}$. This approach is flexible enough to allow for a wide variety of shapes of the price response function. Starting with the linear specification, the conventional constant price impact coefficient is obtained as a reference case. Increasing the order of included polynomials, allows us to test whether more non-linear terms are needed to describe the price response function appropriately. In addition, by interacting these terms with the dummy variables indicating a low or high value of the external precision signal, we can analyze whether the shapes of the price response functions differ and thus can gain insights regarding the relative weight, market participants place on internal and external precision signals.

In order to keep the model parsimonious and tractable we mainly concentrate in the following on the price response induced by announcements in nonfarm payrolls which is by far the most influential macroeconomic headline figure.

4 Empirical Results

Our empirical analysis proceeds in two steps. Firstly, we will analyze whether we find significant evidence for S-shaped price response functions in accordance with Section 2.2. Secondly, we will investigate the impact of external precision signals on the strength and the shape of the price response in line with Section 2.3.

4.1 Non-linearities in the Price Response due to Internal Precision Signals

Table 1 reports estimation results based on five different specifications of equation (9). The lag order of the autoregressive components is chosen according to the Bayes information criterion (BIC) and reveals an AR(2)-ARCH(3) specification as the preferred model. Besides the variables discussed in the previous section, the conditional mean function includes additional variables consisting of surprises in the unemployment rate, S_{UN}, as well as revisions in the nonfarm payrolls figure, R_{NF}. Moreover, we allow for potential information leakage effects in the interval 8:28-8:30 as well as lagged price responses in the interval 8:32-8:34.

As a starting point, specification (A) provides estimation results for a basic model that does not account for any release-specific precision of unanticipated information. The results confirm several major findings of previous studies:[11] Firstly, the large values of the highly significant coefficients of $D_{8:30} \cdot S_{NF}$ and $D_{8:30} \cdot S_{UN}$ show that surprising headline information has a strong and significant impact on intraday returns. The directions of observed price reactions are consistent with standard theory, i.e., T-bond futures prices rise in response to 'good' news from the factor labor, i.e. a lower than expected increase in nonfarm payrolls and a higher than expected unemployment rate. Secondly, markets process unanticipated headline information very rapidly. As indicated by the insignificant coefficient of $D_{8:32} \cdot S_{UN}$ and the relatively small coefficient of $D_{8:32} \cdot S_{NF}$ (as compared to $D_{8:30} \cdot S_{NF}$), the price reaction is completed within two to four minutes.

Specifications (B) - (E) allow for non-linearities in price responses. Specifically, the variables capturing the immediate price impact of unanticipated information in the nonfarm payrolls figure, $D_{8:30} \cdot S_{NF}$, are included as polynomial terms up to order three. Note that the theoretical Bayesian learning model with uncertain news' precision suggests that price reactions are symmetric around zero. Nevertheless, the imposed polynomials also allow for non-symmetric price responses. In particular, previous empirical studies suggest asymmetric effects of 'good' and 'bad' news to information releases.[12]

Specification (B) shows estimation results for a quadratic specification of the price

[11]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 (2003) for foreign exchange markets.

[12]See, e.g. Conrad, Cornell, and Landsman (2002), Andersen, Bollerslev, Diebold, and Vega (2003) and Hautsch and Hess (2007).

response, while specification (C) includes terms up to the third order. Corresponding likelihood ratio (LR) tests clearly reject the linear specification (A) in favor of the nonlinear models. Hence, higher order terms provide additional explanatory power for price responses to unanticipated information in the nonfarm payroll figure. On a 1%-level, the more parsimonious specification (C) with terms up to the third order may not be rejected versus (D) and (E). Overall, in line with the LR tests, the Bayesian information criterion (BIC) suggests that specification (C) explains price responses best.

The results imply that the standard Bayesian learning model with a constant price response to unanticipated information may be clearly rejected. As an illustration, Figure 2 shows the estimated price-response curve to releases of the nonfarm payroll figure under specification (C). We find clear evidence for an S-shaped price response where price reactions to 'large' surprises are relatively weaker than reactions to 'small' surprises. This suggests that market participants evaluate the amount of unanticipated information contained in an announcement as an internal signal on information precision confirming the model by Subramanyam (1996).

4.2 External Precision Signals and the Strength of the Price Response

In order to investigate the impact of the external precision measure $\hat{\rho}_A$, we split up the variable $D_{8:30} \cdot S_{NF}$ (including higher order terms) into interactions with the dummy variables $D^{\pi high}$ and $D^{\pi low}$ accounting for high vs. low values of π_m.

The estimation results based on alternative specifications of the immediate price response function are given in Table 2. The results for specification (F) confirm the findings in Hautsch and Hess (2007) that more precise information leads to significantly stronger price adjustments. Note that this base case does not account for nonlinear price adjustments but implies a linear price reaction as graphically illustrated in Figure

3. A comparison of the goodness-of-fit of specification (A) and (F) based on the BIC suggests that the inclusion of precision dummies leads to a significant improvement of the model's goodness-of-fit. This impression is confirmed on the basis of a LR test which clearly rejects specification (A) in favor of (F).

In specifications (G)-(L) the precision dummies are interacted with different power functions of S_{NF} of order up to three. It turns out that higher orders than three are not required and do not significantly improve the model fit. In order to gain sufficient insights into the underlying nonlinear effects, we consider alternative specifications based on different polynomial functions. Specification (H) includes third order terms for low values of the external precision signal, i.e. for $D^{\pi low} = 1$, and first order terms for high values of the external precision signal (specification (I) vice versa). Model (J) includes third order terms for $D^{\pi low} = 1$, and captures quadratic impacts for $D^{\pi high} = 1$ (for model (K) vice versa). The most comprehensive model (L) includes third order terms for both low and high values of the external precision signal. However, the LR tests as well as the BIC values prefer specification (J). Figure 4 provides a graphical illustration of the estimated price response curves for the best performing specification (J) over the range of observed surprise values.

Finally, a comparison of the models underlying Sections 2.3 and 2.2 is obtained on the basis of a LR test of specification (L) against (C). Here, specification (C) is clearly rejected.[13] Note that specifications (C) and (J) yield nearly the same BIC values which indicates that precision effects do not significantly improve the model's goodness-of-fit over the whole 90 minutes period. However, this is due to the fact that price adjustments are mainly only observed over 2-4 minutes after the announcement corresponding to 2-4% of the sample. In this sense, the BIC is not very informative on the statistical (and particularly the economic) importance of precision effects. Therefore, we rather rely on

[13] Note that model (C) is not nested in (J) and thus a LR test is not applicable.

the significance of estimates and the employed LR tests which reflect that short-term price adjustments are significantly affected by precision effects.

Thus, we can summarize that both the internal and the external precision signal contribute to the explanation of differences in the strength of the price reaction. This suggests that traders try to infer the information precision from different sources, not only by looking at the magnitude of the surprise as suggested by Subramanyam (1996), but also by inspecting additional detail information related to the headline figures as suggested by Hautsch and Hess (2007).

As shown in Figure 4, prices react in a quite non-linear way if the perceived precision is low. We find strong evidence for an S-shaped price response curve as predicted by the model by Subramanyam (1996). In particular, the price response coefficient is decreasing in absolute surprises, in the positive as well as in the negative surprise range. For large negative surprises we even obtain some evidence of a negative marginal price reaction.

Moreover, we find evidence that the S-shape of the price response curve is dampened if the external precision signal is high. Then, the curvature of the price response function significantly declines and we observe a nearly linear relationship between price changes and surprises. I.e., if an announcement figure is perceived to be of high precision, market participants react to large surprises with a similar relative strength as to small surprises. In contrast, if the external precision measure indicates a low quality of the announced information, investors react more moderately to larger surprises. Given the nearly linear shape of the price response curve in a state of high information precision, we might be tempted to argue that market participants completely ignore the internal precision signal if the perceived precision is high.

However, the model derived in 2.3 suggests that the opposite is true. In fact, non-linearities in the price response should be only more pronounced for a high value of the external precision signal (recall Figure 1 for an illustration). Within our sample period, we do not have sufficiently large enough surprise values in order to observe a situation as depicted by Figure 1 (a). Presumably we rather face a situation as illustrated by Figure 1 (b), where in a relatively narrow region around zero the curvature is dampened and the price response curves becomes almost linear when the precision is high. Consequently, we should be careful in interpreting the reduced non-linearities in the price-response curve in periods of high precision.

Note that our results are robust regarding the imposed functional from of the price response relationship. Instead of capturing potential nonlinearities based on power functions we also estimated the model based on flexible Fourier forms defined over the range of surprises. The fact that we get quantitatively the same results indicates the robustness of our findings.[14]

As it can be seen from the following example, our results are also significant from an economic perspective. Assume that market participants observe a median sized piece of 'good' nonfarm payrolls news (i.e. a nonfarm payrolls figure which is 0.06% lower than the median forecast) in connection with a 'low' external precision. According to the best performing specification (J) accounting for both the internal and external precision, prices increase by about 0.31% in response to this release. If, instead, market participants ignore both precision signals (in accordance with the standard Bayesian learning model in specification (A)), prices would only increase by about 0.22%. Hence, ignoring both precision signals would lead to a severe underestimation of the price response by about one third. In contrast, suppose that an extreme surprise of $S_{NF} = -0,18\%$ is observed, corresponding to the 90% quantile for 'good news', again in connection with a 'low' external precision signal. Since the internal signal suggests a very low precision,

[14]For sake of brevity the latter results are not included in the paper but are available upon request from the authors.

according to specification (J) prices react only slightly stronger, i.e. we would observe a return of $0,36\%$. However, ignoring both precision signals would strongly overestimate price responses by 89% expecting a return of $0,67\%$.

Overall, these results provide strong evidence in favor of the claim of Bayesian learning that the *perceived* quality of information plays an important role in determining its price impact. The results suggest that market participants actually use both – internal as well as external signals – to determine the precision of released news. Ignoring the available precision information on news precision may result in strong over- or underestimations of the price reaction.

5 Conclusion

If agents in financial markets are confronted with new information they process the latter by adjusting their expectations on asset values. Bayesian learning provides a concept of how to process this information consistently. Since the precision of information is rarely available to market participants, we derive different settings of Bayesian learning models which allow for uncertainty in the precision of news. Within these models, one common principle remains true: Market participants' perception of information quality plays a major role for the strength of price adjustments. However, this perception of precision may be based on different precision signals.

The theoretical models show that the amount of unanticipated information in an announcement may provide traders with an 'internal' signal on its precision, i.e. the price response coefficient is decreasing in the magnitude of surprises. In addition, price responses to news may be influenced by 'external' signals on news precision such as the reputation of an auditing company, the reliability of a newspaper or the data coverage of an agency. If we observe a high value for such an external precision measure the price response to a given surprise is relatively stronger than in a situation of low perceived precision.

To test these implications, we focus on the most influential macroeconomic report, i.e., the U.S. employment release. For its headline figures, this report does not contain any release-specific precision measures. However, market participants may extract precision measures of the released headline figures by analyzing related detail information. As suggested by Hautsch and Hess (2007), revisions of previously announced figures in connection with the cross-sectional standard deviations of analysts' forecasts may be used to derive such an external precision measure.

We investigate the price reaction of CBOT T-bond futures to these employment announcements using high-frequency data. The price response curves extracted from the data illustrate a non-linear price impact of information depending on its surprise component. As predicted by theory, our empirical results suggest that market participants seem to interpret the magnitude of the surprise contained in a signal as an internal indication of its precision. Consequently, if traders observe an announcement that deviates much from their expectations, they tend to conclude that this announcement is less precise.

Using the precision measures proposed by Hautsch and Hess (2007) as an additional external signal on the precision of the released data, we confirm the strong link between the *perceived* precision of news and the price response. If the precision signal derived from past revision data indicates a high relative precision level of news, market prices react stronger to the unanticipated part of the data. If the external precision signal indicates a poor quality of the released figures, market prices react only weakly.

Overall, our empirical analysis provides evidence in favor of Bayesian learning under the presence of uncertain precision of news. The results show that the quality of news significantly determine their implied price impact. The results suggest that if exact quality measures for a release are missing, traders try to infer news' precision by drawing on different sources. When observing a piece of news, they assess themselves how precise it is. While doing that, market participants seem to include information on the reliability of the source of the message.

To our knowledge, the present analysis is the first that describes the impact of these two simultaneous – internal and external – precision signals in a unified framework. Such Bayesian learning models accounting for uncertain news precision provide further insights into price formation mechanisms and help to assess risky positions. For example, to infer how the release of an unexpectedly high unemployment figure will affect the value of a bond portfolio, traders and portfolio managers need to use an adequate model for the price impact of employment data. We show that ignoring the available information on announcements' precision may result in strong over- or underestimations of the price impact of news.

Appendix A

We first derive the posterior beliefs of traders after observing an announcement and a proxy for the precision of the signal. Recall the assumption that the random variables A and $\hat{\rho}_A$ are conditionally independent given the precision ρ_A, i.e.

$$f_{A,\hat{\rho}_A|\rho_A}(A, \hat{\rho}_A \mid \rho_A) = f_{A|\rho_A}(A \mid \rho_A) f_{\hat{\rho}_A|\rho_A}(\hat{\rho}_A \mid \rho_A). \tag{11}$$

Then, the conditional expectation of X given A and $\hat{\rho}_A$ is given by

$$\begin{aligned}
\mu_P &= E[X \mid A, \hat{\rho}_A] \\
&= E[E[X \mid A, \hat{\rho}_A, \rho_A] \mid A, \hat{\rho}_A] \\
&= E[\mu_F + (A - \mu_F)\rho_A/\rho_F \mid A, \hat{\rho}_A] \\
&= \mu_F + E[(A - \mu_F)\rho_A/\rho_F \mid A, \hat{\rho}_A] \\
&= \mu_F + (A - \mu_F) E[\rho_A \mid A, \hat{\rho}_A]/\rho_F \\
&\equiv \mu_F + S \cdot \pi(S, \hat{\rho}_A).
\end{aligned}$$

The expected precision of the announcement is given as

$$\begin{aligned}
E[\rho_A \mid A, \hat{\rho}_A] &= \int_{S_A} \rho_A f(\rho_A \mid A, \hat{\rho}_A) d\rho_A \\
&= \int_{S_A} \rho_A \frac{f(A, \hat{\rho}_A \mid \rho_A) f(\rho_A)}{f(A, \hat{\rho}_A)} d\rho_A \\
&= \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{f(A, \hat{\rho}_A)} \\
&= \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A, \hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A} \\
&= \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A},
\end{aligned}$$

where the support of $f(\rho_A)$ is given by $S_A \in (\rho_F, \infty)$.

Using these relations we now turn to the proofs of the particular theorems.

Proof of Theorem 1: Note that $\partial f(A \mid \rho_A)\partial S^2 = \left(-\frac{1}{2}\rho_A\right) f(A \mid \rho_A)$, since we assumed that A is conditionally normally distributed given ρ_A. We need to show that the partial derivative of the conditional expected precision with respect to the absolute surprise is strictly negative.

$$
\begin{aligned}
\frac{\partial E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\partial S^2} &= \frac{\partial}{\partial S^2} \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A} \\
&= \frac{\left(\frac{\partial}{\partial S^2} \int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right) \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
&\quad - \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \left(\frac{\partial}{\partial S^2} \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
&= \frac{-\frac{1}{2} \int_{S_A} \rho_A^2 f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
&\quad - \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \left(-\frac{1}{2}\right) \int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
&= -\frac{\int_{S_A} \rho_A^2 f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{2 \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A} \\
&\quad + \frac{\left(\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2}{2\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
&= -\frac{1}{2} \left[\frac{\int_{S_A} \rho_A^2 f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A} \right. \\
&\quad \left. - \left(\frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A} \right)^2 \right] \\
&= -\frac{1}{2} \left(E[\rho_A^2 \mid A, \hat{\rho}_A] - (E[\rho_A \mid A, \hat{\rho}_A])^2 \right) \\
&= -\frac{1}{2} Var[\rho_A \mid A, \hat{\rho}_A] < 0,
\end{aligned}
$$

for any non-degenerate distribution of the precision ρ_A. Since $|S|$ and S^2 are positively and monotonically related, the result can be applied for $|S|$. Then, it is straightforwardly shown that $\partial \pi(S, \hat{\rho}_A)/\partial |S| < 0$.

□

Proof of Theorem 2: Note that $\partial f(A \mid \rho_A) \partial S = -\rho_A S f(A \mid \rho_A)$, since we assumed that A is conditionally normally distributed given ρ_A. Then,

$$\frac{\partial E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\partial S} = 2S \cdot \frac{\partial E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\partial S^2}.$$

Hence, using Theorem 1 we get

$$\frac{\partial E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\partial S} = -S \cdot Var[\rho_A \mid A, \hat{\rho}_A]$$

and thus

$$\frac{\partial(\mu_P - \mu_F)}{\partial S} = \pi(S, \hat{\rho}_A) + \frac{S}{\rho_F} \frac{\partial E[\rho_A | A, \hat{\rho}_A]}{\partial S} = \pi(S, \hat{\rho}_A) - \frac{S^2}{\rho_F} Var[\rho_A \mid A, \hat{\rho}_A].$$

□

Proof of Theorem 3: Note that $\partial f(\hat{\rho}_A \mid \rho_A)\partial\hat{\rho}_A = \left(-\frac{\hat{\rho}_A-\rho_A}{2\sigma^2_{\hat{\rho}_A}}\right) f(\hat{\rho}_A \mid \rho_A)$, since we assumed a normal distribution for $\hat{\rho}_A$. We need to show that the partial derivative of the conditional expected precision with respect to the precision signal is strictly positive,

$$
\begin{aligned}
& \frac{\partial E[\rho_A \mid A, \hat{\rho}_A]}{\partial \hat{\rho}_A} \\
= \quad & \frac{\int_{S_A} \rho_A f(A \mid \rho_A) \frac{\partial f(\hat{\rho}_A \mid \rho_A)}{\partial \hat{\rho}_A} f(\rho_A) d\rho_A \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
- \quad & \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \int_{S_A} f(A \mid \rho_A) \frac{\partial f(\hat{\rho}_A \mid \rho_A)}{\partial \hat{\rho}_A} f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
= \quad & \frac{\int_{S_A} \rho_A f(A \mid \rho_A) \left(-\frac{\hat{\rho}_A-\rho_A}{2\sigma^2_{\hat{\rho}_A}}\right) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
- \quad & \frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A \int_{S_A} f(A \mid \rho_A) \left(-\frac{\hat{\rho}_A-\rho_A}{2\sigma^2_{\hat{\rho}_A}}\right) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\left(\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A\right)^2} \\
= \quad & \frac{1}{2\sigma^2_{\hat{\rho}_A}} \left[\frac{\int_{S_A} \rho_A^2 f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}\right. \\
- \quad & \left.\left(\frac{\int_{S_A} \rho_A f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}{\int_{S_A} f(A \mid \rho_A) f(\hat{\rho}_A \mid \rho_A) f(\rho_A) d\rho_A}\right)^2\right] \\
= \quad & \frac{1}{2\sigma^2_{\hat{\rho}_A}} \left(E[\rho_A^2 \mid A, \hat{\rho}_A] - (E[\rho_A \mid A, \hat{\rho}_A])^2\right) \\
= \quad & \frac{1}{2\sigma^2_{\hat{\rho}_A}} Var[\rho_A \mid A, \hat{\rho}_A] > 0,
\end{aligned}
$$

for any non-degenerate distribution of the precision ρ_A. Then, it is straightforwardly shown that $\partial\pi(S, \hat{\rho}_A)/\partial\hat{\rho}_A > 0$ and $\partial|\mu_P - \mu_F|/\partial\hat{\rho}_A > 0$.

□

Proof of Theorem 4: The posterior mean of X is written as

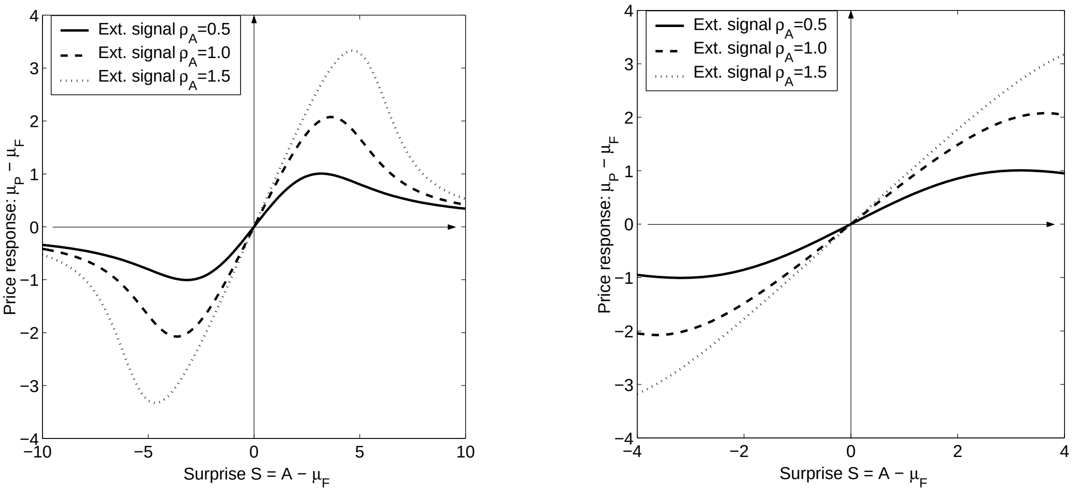
$$
\begin{aligned}
\mu_P &= E\left[X \mid A, \hat{\rho}_A\right] \\
&= E\left[E\left[X \mid A, \rho_F, \rho_A, \hat{\rho}_A\right] \mid A, \hat{\rho}_A\right] \\
&= E\left[(A-\mu_F)\rho_A/\rho_F + \mu_F \mid A, \hat{\rho}_A\right] \\
&= \mu_F + (A-\mu_F)\cdot E\left[\rho_A/\rho_F \mid A, \hat{\rho}_A\right] \\
&= \mu_F + (A-\mu_F)\cdot \int_{S_F}\int_{S_A} \rho_A/\rho_F f(A,\hat{\rho}_A \mid \rho_A,\rho_F) f(\rho_A,\rho_F) d\rho_A d\rho_F \\
&= \mu_F + (A-\mu_F)\cdot \int_{S_F} 1/\rho_F \underbrace{\int_{S_A} \rho_A f(A,\hat{\rho}_A \mid \rho_A,\rho_F) f(\rho_A \mid \rho_F) d\rho_A}_{E[\rho_A|A,\rho_F,\hat{\rho}_A]} f(\rho_F) d\rho_F \\
&\equiv \mu_F + (A-\mu_F)\cdot \pi(S,\hat{\rho}_A).
\end{aligned}
$$

Using the result established in Theoreom 1, we can show

$$
\begin{aligned}
\partial\pi(S)/\partial S^2 &= \frac{\partial}{\partial S^2}\int_{S_F} 1/\rho_F \int_{S_A} \rho_A f(A,\hat{\rho}_A \mid \rho_A,\rho_F) f(\rho_A \mid \rho_F) d\rho_A f(\rho_F) d\rho_F \\
&= \int_{S_F} 1/\rho_F \frac{\partial \int_{S_A} \rho_A f(A,\hat{\rho}_A \mid \rho_A,\rho_F) f(\rho_A \mid \rho_F) d\rho_A}{\partial S^2} f(\rho_F) d\rho_F \\
&= \int_{S_F} 1/\rho_F \underbrace{\frac{\partial E\left[\rho_A \mid A, \rho_F, \hat{\rho}_A\right]}{\partial (S^2)}}_{<0} f(\rho_F) d\rho_F < 0.
\end{aligned}
$$

Here, the price response coefficient $\pi(S,\hat{\rho}_A)$ is just a weighted average of the price response coefficients in the case of a known variance of the prior information weighted by the corresponding probability. Hence, the results established by Theorems 1 and 3 still hold analogously.□

Appendix B



(a) Large range of surprises (b) Small range of surprises

Figure 1: **Price response curves resulting from the Bayesian learning model,** x-axis: surprises in the announcement $S = (A - \mu_A)$, i.e. deviations of the announced figure from its mean, y-axis: price responses, i.e. changes in expectations $\mu_P - \mu_F$. The graphs show a numerical example of price response curves given the model specification in section 2.3. Prior beliefs are normally distributed with $\mu_F = 0$ and $\rho_F = 1$, while news' precision ρ_A follows a truncated gamma distribution with scale parameter $\lambda = 1$ and shape parameter $r = 1$. Additionally, an external estimate of news' precision $\hat{\rho}_A$ is observed which is normally distributed as $\hat{\rho}_A \sim N(\rho_A, \sigma_{\hat{\rho}_A})$. Price response curves are increasing in the observed value of the precision proxy, the graphs correspond to external precision signals of $\hat{\rho}_A = 0.5, 1, 1.5$ while we choose $\sigma_{\hat{\rho}_A} = 0.25$.

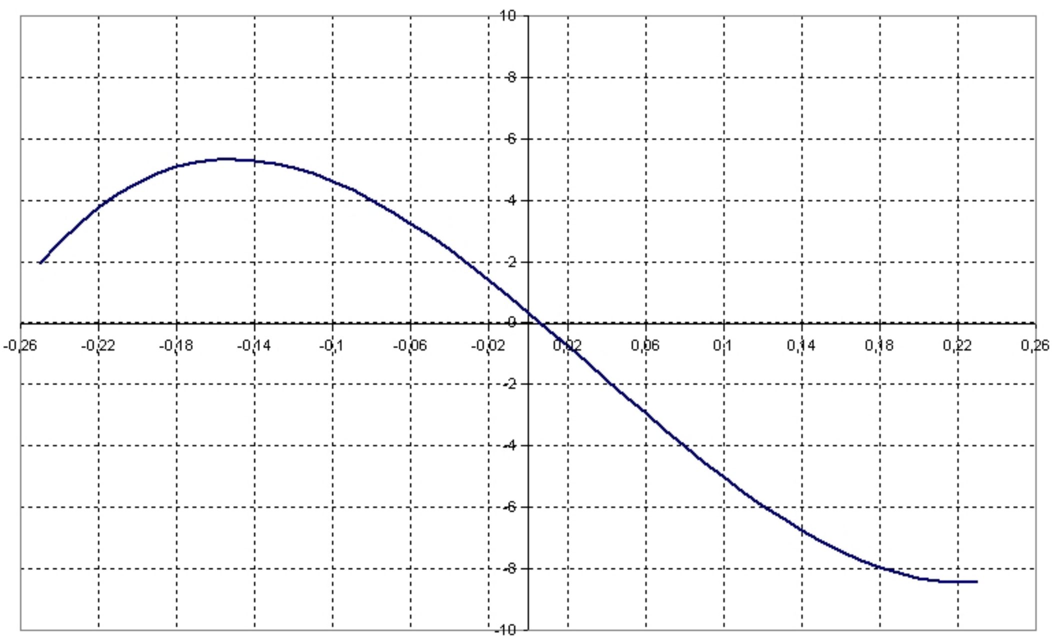


Figure 2: **Estimated price-response curve allowing for internal precision signals,** x-axis: surprises in the U.S. nonfarm payrolls figure S_{NF} (in percentage points), y-axis: estimated price response $\hat{r_t}$ (log-returns $\times 1000$). This figure provides an illustration of the price response curve to surprises in announcements of nonfarm payrolls figures corresponding to specification (C) in table 1. The results are based on a 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. 2005, resulting in 7245 observations (i.e. 161 days with no overlapping announcements $\times$ 45 2-min intervals). According to the Bayes information criterion (BIC), the model that includes polynomial terms in nonfarm payrolls surprises up to the third order provides the best specification. So as predicted by the theoretical model, the resulting price response curves are non-linear since large surprises serve as a signal for low news' precision. Therefore, high surprises in the announced figure lead to relatively weaker price reactions than small surprises.

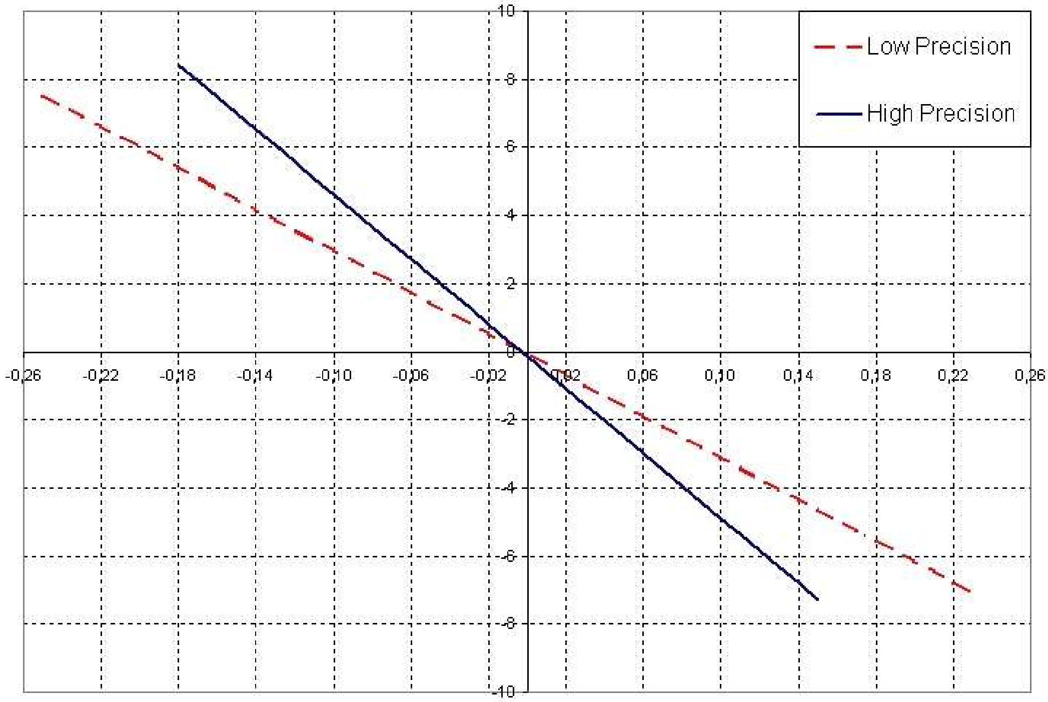


Figure 3: **Estimated linear price-response curves for high and low external precision signals,** x-axis: surprises in the U.S. nonfarm payrolls figure S_{NF} (in percentage points), y-axis: estimated price response $\hat{r_t}$ (log-returns $\times 1000$). A graphical illustration of the price response curve to nonfarm payrolls figures as described by specification (F) in table 2. The results are based on a 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. 2005, resulting in 7245 observations (i.e. 161 days with no overlapping announcements $\times$ 45 2-min intervals). The curve corresponding to high precision signals has a significantly larger slope. A higher external precision signal leads to stronger price reactions given the same amount of unexpected information in a news release.

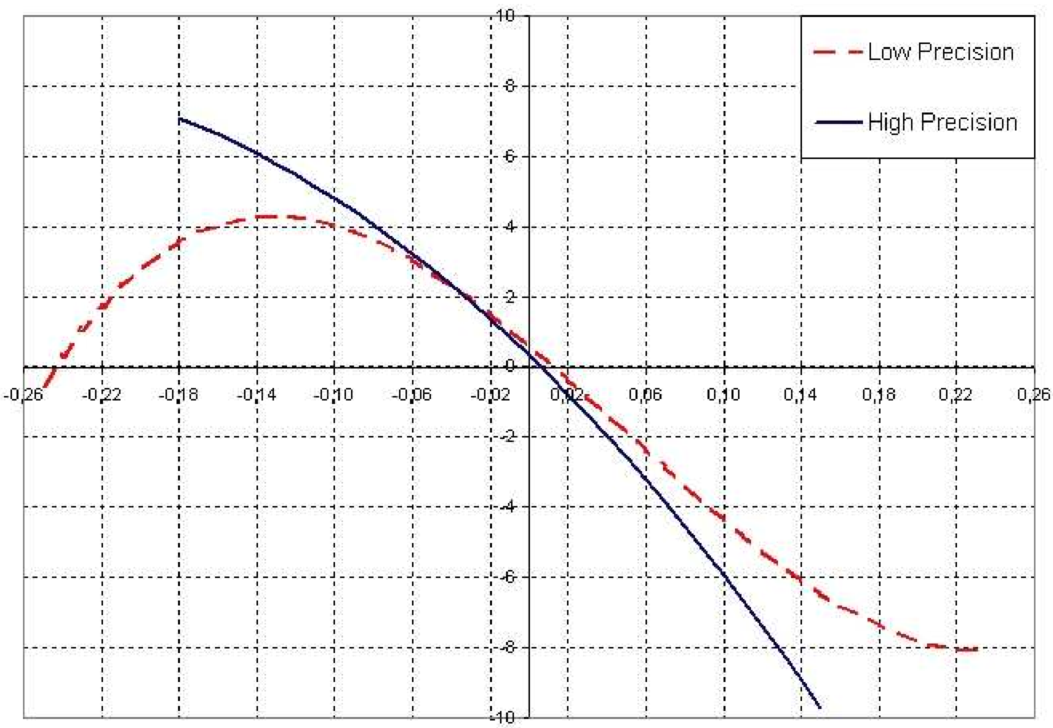


Figure 4: **Estimated price-response curves allowing for internal and external precision signals,** x-axis: surprises in the U.S. nonfarm payrolls figure S_{NF} (in percentage points), y-axis: estimated price response $\hat{r}_t$ (log-returns $\times 1000$). A graphical illustration of the price response curve to nonfarm payrolls figures as described by specification (J) in table 2. The results are based on a 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. 2005, resulting in 7245 observations (i.e. 161 days with no overlapping announcements $\times$ 45 2-min intervals). Prices tend to react stronger to news with a high precision signal. For high precision signals polynomial terms in nonfarm payroll surprises only up to second order are captured, while for low precision signals terms up to third order are included.

TABLE 1

Estimation of price response functions with surprises as an internal precision signal

Model	**(A)**	**(B)**	**(C)**	**(D)**	**(E)**
Mean equation					
cons	-0,002	-0,002	-0,002	-0,002	-0,002
$D^{8:28} \cdot S_{NF}$	4,406	3,619	3,927	4,078	3,829
$D^{8:30}$	-0,080	0,530	0,355	0,558	0,637
$D^{8:30} \cdot S^1_{NF}$	-37,873 ***	-42,415 ***	-53,447 ***	-54,909 ***	-50,344 ***
$D^{8:30} \cdot S^2_{NF}$		-91,220 **	-55,336 *	-119,526	-145,530
$D^{8:30} \cdot S^3_{NF}$			531,752 ***	624,49 ***	80,073
$D^{8:30} \cdot S^4_{NF}$				1658,397	2337,978
$D^{8:30} \cdot S^5_{NF}$					9945,756
$D^{8:32} \cdot S_{NF}$	-4,000 **	-4,322 **	-4,274 **	-4,181 **	-4,277 **
$D^{8:28} \cdot S_{UN}$	1,636	1,278	1,320	1,314	1,175
$D^{8:30} \cdot S_{UN}$	5,003 **	5,617 **	5,746 ***	6,212 ***	6,367 ***
$D^{8:32} \cdot S_{UN}$	1,448 *	1,325	1,356	1,332	1,286
$D^{8:28} \cdot R_{NF}$	2,206	1,841	2,010	1,999	1,839
$D^{8:30} \cdot R_{NF}$	-6,872 ***	-6,390 ***	-6,215 **	-5,889 **	-5,808 **
$D^{8:32} \cdot R_{NF}$	0,083	-0,428	-0,071	-0,106	-0,258
r_{t-1}	-0,091 ***	-0,091 ***	-0,090 ***	-0,090 ***	-0,091 ***
r_{t-2}	-0,001	0,000	0,000	0,000	0,000
Variance equation					
cons	0,439 ***	0,439 ***	0,436 ***	0,436 ***	0,437 ***
$ARCH(1)$	0,148 **	0,141 ***	0,146 ***	0,145 ***	0,144 ***
$ARCH(2)$	0,057 ***	0,059 ***	0,058 ***	0,058 ***	0,058 ***
$ARCH(3)$	0,031 ***	0,033 ***	0,034 ***	0,034 ***	0,034 ***
LL	-8020,69	-7999,57	-7987,29	-7985,32	-7984,12
BIC	2,2485	2,2439	2,2417	2,2424	2,2433
LR-Test against model (A)		42,24 ***	66,80 ***	70,73 ***	73,13 ***
LR-Test against model (B)			24,56 ***	28,49 ***	30,89 ***
LR-Test against model (C)				3,93 **	6,33 **
LR-Test against model (D)					2,40

TABLE 1 (continued)

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. 2005, resulting in 7245 observations (i.e. 161 days with no overlapping announcements $\times$ 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 a.m., x_t denotes a vector of explanatory variables and β 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 $s_t = \delta^s \cdot \bar{t} + \sum_{j=1}^{5} \left(\delta_{c,j}^s \cos(j \cdot \bar{t} \cdot 2\pi) + \delta_{s,j}^s \sin(j \cdot \bar{t} \cdot 2\pi) \right)$ denotes the seasonality function based on the parameters δ^s, $\delta_{c,j}^s$, $\delta_{s,j}^s$ and a normalized time trend $\bar{t} \in [0, 1]$ given by the elapsed time (in minutes) in the interval 8:22 to 9:52 a.m. 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 a.m. ($D^{8:28}$), 8:30-8:32 a.m. ($D^{8:30}$) and 8:32-8:34 a.m. ($D^{8:32}$). To capture non-linear immediate price responses in the interval 8:30-8:32, surprises in nonfarm payrolls S_{NF} are included as polynomials up to the order 5. Surprises are computed based on U.S. employment report figures released by the BLS and consensus forecasts provided by Informa Global Markets, formerly MMS.

The table reports the log likelihood (LL), the Bayes information criterion (BIC) and χ^2 statistics of LR tests on the inequality of individual parameters. 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.

TABLE 2

Estimation of price response functions
differentiated by low and high values of the additional external precision proxy

Model	**(F)**	**(G)**	**(H)**	**(I)**
Mean equation				
cons	-0,002	-0,002	-0,002	-0,002
$D^{8:28} \cdot S_{NF}$	4,365	3,411	3,862	4,147
$D^{8:30} \cdot D^{\pi low}$	-0,074	0,782	0,611	-0,069
$D^{8:30} \cdot D^{\pi high}$	-0,141	0,315	-0,131	0,203
$D^{8:30} \cdot S^1_{NF} \cdot D^{\pi low}$	-30,439 ***	-34,498 ***	-46,901 ***	-30,356 ***
$D^{8:30} \cdot S^1_{NF} \cdot D^{\pi high}$	-47,601 ***	-53,413 ***	-47,713 ***	-56,190 ***
$D^{8:30} \cdot S^2_{NF} \cdot D^{\pi low}$		-106,693 **	-77,937 **	
$D^{8:30} \cdot S^2_{NF} \cdot D^{\pi high}$		-87,544 *		-61,651
$D^{8:30} \cdot S^3_{NF} \cdot D^{\pi low}$			503,544 **	
$D^{8:30} \cdot S^3_{NF} \cdot D^{\pi high}$				217,349
$D^{8:32} \cdot S_{NF}$	-4,020 **	-4,694 **	-4,422 **	-4,305 **
$D^{8:28} \cdot S_{UN}$	1,623	1,197	1,327	1,499
$D^{8:30} \cdot S_{UN}$	5,553 **	6,275 ***	6,286 ***	5,723 **
$D^{8:32} \cdot S_{UN}$	1,484 *	1,286	1,414	1,349
$D^{8:28} \cdot R_{NF}$	2,051	1,701	1,989	1,885
$D^{8:30} \cdot R_{NF}$	-5,901 **	-5,220 **	-5,424 **	-5,585 **
$D^{8:32} \cdot R_{NF}$	-0,080	-0,664	0,010	-0,460
r_{t-1}	-0,091 ***	-0,091 ***	-0,091 ***	-0,090 ***
r_{t-2}	0,000	0,000	0,000	0,000
Variance equation				
cons	0,437 ***	0,437 ***	0,437 ***	0,437 ***
$ARCH(1)$	0,151 **	0,143 **	0,148 **	0,148 **
$ARCH(2)$	0,057 ***	0,059 ***	0,057 ***	0,058 ***
$ARCH(3)$	0,032 ***	0,035 ***	0,033 ***	0,034 ***
LL	-8008,54	-7982,99	-7981,52	-8002,00
BIC	2,2476	2,2430	2,2426	2,2482
LR-Test against model (A)	24,30 ***	75,40 ***	78,34 ***	37,38 ***
LR-Test against model (C)				
LR-Test against model (F)		51,10 ***	54,04 ***	13,08 ***

TABLE 2 (continued)

Estimation of price response functions
differentiated by low and high values of the additional external precision proxy

Model	**(J)**	**(K)**	**(L)**
Mean equation			
$cons$	-0,002	-0,002	-0,002
$D^{8:28} \cdot S_{NF}$	3,660	3,400	3,651
$D^{8:30} \cdot D^{\pi low}$	0,630	0,774	0,624
$D^{8:30} \cdot D^{\pi high}$	0,323	0,236	0,264
$D^{8:30} \cdot S^1_{NF} \cdot D^{\pi low}$	-46,957 ***	-34,580 ***	-46,950 ***
$D^{8:30} \cdot S^1_{NF} \cdot D^{\pi high}$	-53,605 ***	-55,948 ***	-55,534 ***
$D^{8:30} \cdot S^2_{NF} \cdot D^{\pi low}$	-78,320 **	-106,453 **	-78,297 **
$D^{8:30} \cdot S^2_{NF} \cdot D^{\pi high}$	-89,156 *	-66,847	-73,585
$D^{8:30} \cdot S^3_{NF} \cdot D^{\pi low}$	512,233 **		509,326 **
$D^{8:30} \cdot S^3_{NF} \cdot D^{\pi high}$		186,343	141,106
$D^{8:32} \cdot S_{NF}$	-4,692 **	-4,693 **	-4,692 **
$D^{8:28} \cdot S_{UN}$	1,169	1,207	1,176
$D^{8:30} \cdot S_{UN}$	6,694 ***	6,097 ***	6,556 ***
$D^{8:32} \cdot S_{UN}$	1,230	1,338	1,267
$D^{8:28} \cdot R_{NF}$	1,707	1,745	1,744
$D^{8:30} \cdot R_{NF}$	-4,736 **	-5,464 **	-4,932 **
$D^{8:32} \cdot R_{NF}$	-0,549	-0,510	-0,435
r_{t-1}	-0,091 ***	-0,091 ***	-0,091 ***
r_{t-2}	0,000	0,000	0,000
Variance equation			
$cons$	0,436 ***	0,437 ***	0,436 ***
ε^2_{t-1}	0,146 **	0,143 **	0,146 **
ε^2_{t-2}	0,059 ***	0,059 ***	0,058 ***
ε^2_{t-3}	0,035 ***	0,035 ***	0,035 ***
LL	-7974,53	-7982,74	-7974,38
BIC	2,2419	2,2441	2,2431
LR-Test against model (A)	92,32 ***	75,90 ***	92,62 ***
LR-Test against model (C)			25,82 ***
LR-Test against model (F)	68,02 ***	51,59 ***	68,31 ***
LR-Test against model (G)	16,92 ***	0,50	17,21 ***
LR-Test against model (H)	13,98 ***		14,27 ***
LR-Test against model (I)		38,51 ***	55,22 ***
LR-Test against model (J)			0,29
LR-Test against model (K)			16,71 ***

TABLE 2 (continued)

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. 2005, resulting in 7245 observations (i.e. 161 days with no overlapping announcements $\times$ 45 2-min intervals).

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The table reports the log likelihood (LL), the Bayes information criterion (BIC) and χ^2 statistics of LR tests on the inequality of individual parameters. 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.

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