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Price Adjustment to News with Uncertain Precision

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Abstract

We analyze how markets adjust to new information when the reliability of news is uncertain and has to be estimated itself. We propose a Bayesian learning model where market participants receive fundamental information along with noisy estimates of news' precision. It is shown that the efficiency of a precision estimate drives the the slope and the shape of price response functions to news. Increasing estimation errors induce stronger nonlinearities in price responses. Analyzing high-frequency reactions of Treasury bond futures prices to employment releases, we find strong empirical support for the model's predictions and show that the consideration of precision uncertainty is statistically and economically important.

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

JEL classification: E44, G14

News on economic fundamentals drives asset prices. A larger amount of news leads to greater and faster price reactions. This is well confirmed by a wide range of empirical studies in asset pricing, market microstructure analysis, corporate finance and financial accounting. Asset-specific news naturally enlarges investors' information set, allowing them to revise their expectations with regard to the underlying fundamental value. We address the issue of precision uncertainty and show that agents underreact to news when there is a chance that the precision of the news could be a lot lower than under regular circumstances.

Investors' updating of expectations in response to the arrival of news and its implications for the underlying asset price process is theoretically best understood in terms of a Bayesian learning model. However, though the mechanism of Bayesian learning is theoretically appealing and tractable, only little empirical evidence of Bayesian updating effects in news-implied asset price reactions is existent. A major reason for this lack of evidence is that Bayesian updating processes ultimately depend on the reliability of the news. Think of announcements on economic fundamentals – typically stemming from surveys – as realizations of a random distribution with a given variance. The reliability of the news is then naturally measured in terms of the random variable's precision (i.e., the inverse of its variance). A major implication of Bayesian learning is that prices react more strongly to more precise news. However, the reliability of a piece of news is generally unknown in reality. If they can at all, market participants can only *estimate* precision of news, leaving them with a noisy estimate.

This paper addresses the missing link between Bayesian learning theory and actually observed news-implied asset price reactions. To confront the theoretical framework with empirical observations, we address the fundamental question of how market participants actually do infer the reliability of news in practice. In this context, we distinguish between two ways in which investors estimate the precision of announcements: first, traders might use additional publicly available information linked to the reliability of news releases. This results in a so-called ”external” precision estimate. For example, natural precision indicators could be sampling statistics on the underlying survey, information on sampling errors, or information on the expected magnitude of revisions to currently released figures as suggested by Hautsch and Hess (2007). Second, in situations where no information on the quality of announcements is readily available, investors are left with inferring the precision of the news from the released information itself, e.g., by looking at the size of a surprise as suggested by Subramanyam (1996). This would result in a non-linear price response. However, such a size-based (or ”internal”) precision signal is rather uninformative and restrictive since it implicitly conjectures that large surprises can only come with low precision.

A major contribution of the paper is to show that the distinction between these two types of precision signals is theoretically important and is empirically supported by the data. In an extended Bayesian learning framework we illustrate that the relative impact of both types of precision proxies ultimately depends on the efficiency of the external estimate. If traders have a highly reliable external precision estimate, the magnitude of a surprise itself provides only little additional information on news' quality. In the limiting case, when the precision of the news is certain, the size of a surprise as a reliability proxy can be completely ignored. In this situation, the resulting price reaction function is linear with its slope positively depending on the indicated precision of releases. In contrast, if the external precision estimate is very noisy, traders are left alone with the size (and sign) of the release. This induces deviations from linearity which increase with surprises' magnitude making the price response curve S-shaped. We empirically show that actually observed news implied price reactions are significantly driven by both underlying effects and that their neglect can induce severe pricing errors.

To date, surprisingly little emphasis has been placed on the role of uncertainty in the reliability of news in financial models. For example, in the informed trade models of Kyle (1985) and Admati and Pfleiderer (1988), information asymmetry is introduced via private signals drawn from a distribution with *known* parameters. Similarly, in the market microstructure models of Blume, Easley, and O'Hara (1994) or Easley, Kiefer, and O'Hara (1997), privately informed agents hold different beliefs but individuals have parameter certainty regarding the distribution (and hence the precision) of their beliefs. Providing another example, models of speculative trade are focusing on the combination of private information and public announcements. Awaiting public releases, heterogeneity among agents is created by differences in prior beliefs (e.g., Holthausen and Verrecchia (1988, 1990), Harris and Raviv (1993) or Kim and Verrecchia (1991a, 1991b)), additional efforts to acquire private information (Kim and Verrecchia 1997) or afterwards simply through individual interpretations (e.g., Harris and Raviv (1993) and Kandel and Pearson (1995)). Again, in these models, the parameters describing the information sets are assumed to be known, at least to individual agents. Likewise, in the Bayesian learning models of David (1997), Veronesi (1999, 2000) and Pástor and Veronesi (2003), where agents face uncertainty about a key valuation parameter, the (im)precision of this parameter is assumed to be known. In a similar way, recent option pricing and trading models consider heterogeneous beliefs but abstract from uncertain precision (e.g., David and Veronesi, 2002, Guidolin and Timmermann, 2003, Buraschi and Jiltsov, 2006, and Buraschi, Trojani, and Vedolin, 2009). Finally, Bayesian learning models assuming differences in information with *given* precision are applied in a wide range of financial markets research dealing with the predictability of asset returns, stock price bubbles, portfolio choice, and mutual fund flows. For a recent survey, see Pástor and Veronesi (2009).

In contrast, empirical research regarding information precision is sparse. Only a few papers stress the importance of accounting for releases' reliability in the analysis of news-induced price reactions. Bayesian learning requires a relative precision measure, i.e., the variance of the announced news has to be weighted against the variance of ex-ante beliefs. Earlier studies have focussed on one of these two components of the (external) precision measure. For example, Buraschi and Jiltsov (2006) and Pasquariello and Vega (2007) use the standard deviation of analyst forecasts surveyed by Money Market Services (MMS) as a measure of the heterogeneity of ex-ante beliefs. On the other hand, Krueger and Fortson (2003) assume that the variance of ex-ante beliefs is constant and suggest to use the sample size as an (external) precision estimate. However, survey size counts are not available in real time, and Krueger and Fortson find only limited evidence for the importance of quality of employment news. Moreover, Pasquariello and Vega (2007) and Gilbert, Scotti, Strasser, and Vega (2010) suggest to use revisions to approximate noise in the announced data assuming that market participants can forecast future revisions, as suggested, for example, by Aruoba (2008) and Gilbert (2010). Hautsch and Hess (2007) combine MMS survey dispersions and revision information to obtain a precision measure in the Bayesian sense. Based on this release-specific precision measure they document a significantly positive relationship between the magnitude of price reactions and the perceived precision of news for the employment report.

Nevertheless, the above mentioned studies do not incorporate the effects of uncertainty in their precision measures. Subramanyam (1996) is the only study relaxing the assumption of known news' precision. However, Subramanyam's setting accounts only for an internal precision signal. By extending this framework to also allow for noisy (external) estimates of the precision of the news, we bridge the gap between the two extreme cases of assuming a perfectly known precision of releases or alternatively assuming precision to be completely unknown with any (external) estimate being absent. As shown in the remainder of the paper this extended framework is flexible enough to capture different scenarios that are realistic in financial practice.

To test the model's implications, we analyze high-frequency price responses in the 10-year U.S. Treasury bond futures market to the U.S. employment report. We focus on the employment report for several reasons. First, numerous studies show that among macroeconomic announcements, employment figures (in particular, the nonfarm payrolls headline) have by far the most pronounced impact on financial markets; see, e.g., Fleming and Remolona (1999c), Balduzzi, Elton, and Green (2001), McQueen and Roley (1993) or Andersen, Bollerslev, Diebold, and Vega (2003). Second, this report provides a unique opportunity to derive an external precision estimate for its most important headline, i.e., the nonfarm payrolls figure. We follow Hautsch and Hess (2007) and exploit predictability in (absolute) sampling errors as revealed by revisions of releases. In principle, we could derive such a measure for other headlines as well. However, there are only a few macroeconomic series for which a sufficiently long history of revision data exists, e.g., for the consumer price report. But unlike the employment report, revision data are not available for the report's most influential headline.[1]

Our estimated price responses reflect that market participants do indeed process *both* types of precision indicators. Differentiating between two benchmark categories associated with high- and low-precision estimates, we observe a steep and nearly linear response curve in the case of precise news and a nonlinear and less steep response function in the case of imprecise news. The fact that price reactions are significantly different in both scenarios suggests that the external precision signal is informative. On the other hand, significant nonlinearities in the price response, particularly for imprecise news, indicates that market participants are well aware of estimation errors influencing the external precision estimate and thus also take into account the size of a surprise as an internal proxy.

The remainder of this paper is organized as follows. The following section presents a theoretical Bayesian learning framework that allows for noise in precision signals. Section II describes the used high-frequency return data as well as employment announcement data and outlines the estimation procedure. The empirical results are presented and discussed in Section III. Section IV concludes.

[1] For example, for consumer prices, producer prices or retail sales revision data are not available for the less volatile components (e.g., CPI excluding food and energy) which have the strongest price impact.

I. A Bayesian Learning Model

A. Standard Bayesian Learning

Bayesian learning models provide a tractable framework to analyze how new information is incorporated into expectations and prices when prior information as well as incoming news may contain errors. Throughout our analysis, we assume that all market participants have the same information just before the release of some public announcement. Each participant is risk-neutral and is equipped with the same utility function as well as 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 (unknown) economic variable X, i.e., $P = \nu \cdot \mathrm{E}[X]$. 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 its precision, defined as the inverse of the variance. This prior information represents the market's assessment of X given all available information and is characterized by a corresponding probability distribution. Empirical research on the impact of scheduled announcements typically assumes that prior beliefs in the market may be approximated by analysts' forecasts. It is thus implicitly assumed that analysts' forecasts are unbiased for X.

Throughout the paper, we assume that μ_F and ρ_F are known. However, this assumption can easily be relaxed to also allow for uncertainty in priors without changing the fundamental implications of the paper.[2] Moreover, as is discussed in more detail in the empirical part, both μ_F and ρ_F can be straightforwardly estimated by the cross-sectional mean and variance of analysts' forecasts. As for most important macroeconomic figures, the cross-section of publicly available analysts' forecasts is quite large, such estimates can be considered to be relatively efficient, making the assumption of known parameters μ_F and ρ_F less restrictive. Accounting for both arguments and aiming to keep the paper possibly simple, we maintain this assumption.

Assume an announcement is released providing a noisy estimate of X including an additive error, i.e., $A = X + \varepsilon$, where ε is a zero-mean normally distributed error term with variance $\mathrm{V}[\varepsilon] = 1/\rho_\varepsilon$ and $\mathrm{E}[X \cdot \varepsilon] = 0$. Consequently, traders receive an unbiased estimate of the underlying variable X whose precision is reflected by ρ_ε. The additive error term implies that the unconditional variance of a news release exceeds the variance of the market's prior information. Accordingly, announcement A is distributed as $A \sim N(\mu_F, 1/\rho_A)$ with $\rho_A^{-1} = \rho_F^{-1} + \rho_\varepsilon^{-1}$. After observing this public announcement, traders adjust their beliefs according to Bayes' rule. Then, it is easily shown that traders' posterior

[2] For example, it can be shown that the main results also hold for the case of ρ_F to be stochastic. For brevity these results are omitted here.

beliefs are normally distributed with

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

and

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

Consequently, the price response is

$$\Delta P = \nu \cdot (\mu_P - \mu_F) = \nu \cdot S \cdot \pi,$$

where $S := A - \mu_F$ denotes the unanticipated information component, i.e., the so-called surprise, and π defines the so-called 'price response coefficient'

$$\pi := \frac{\rho_A}{\rho_F} = \frac{\rho_\varepsilon}{\rho_F + \rho_\varepsilon} < 1.$$

Hence, the main implication of standard Bayesian learning is that price changes are proportional to surprises S, while the proportionality factor π depends on the relative precision of announcements and forecasts. As the precision of the news ρ_ε increases, so does the price response coefficient π. In the limit case of $\rho_\varepsilon \to \infty$, we have $\pi \to 1$.

B. Bayesian Learning with Precision Uncertainty

Contradicting the assumptions of the standard model, announcements such as employment figures are usually released without an associated precision measure. Therefore, market participants regard the precision of the news as uncertain, with ρ_ε and thus ρ_A itself following a random distribution $f(\rho_A)$. Then, the normality of announcements is assumed to hold *conditionally* on ρ_A, i.e., $A|\rho_A \sim N(\mu_F, \rho_A)$. For simplicity and without loss of generality, we assume that the precision of the news may take on only two values with equal probability, i.e., $\rho_A \in \{l, h\}$ with $P(\rho_A = j) = 0.5$ and $j \in \{l, h\}$.[3]

Suppose that market participants have an estimator $\hat{\rho}_\varepsilon$ that is built on information not directly linked to the announced figure itself. For example, $\hat{\rho}_\varepsilon$ might be simply the sample size of a survey (e.g., Krueger and Fortson, 2003) or the cross-sectional standard deviation thereof. Alternatively, for the U.S. employment report, Hautsch and Hess (2007) show that traders may make inferences regarding the precision of announced employment figures by exploiting predictability in the magnitude of revisions. We refer to the resulting estimator $\hat{\rho}_A = \rho_F + \hat{\rho}_\varepsilon$ as an *external* precision signal. Given the discreteness of ρ_A, we assume that $\hat{\rho}_A$ is discrete as well, i.e., $\hat{\rho}_A \in \{L, H\}$. The estimate equals the true precision with probability $1 - p_{err}$, i.e., $P(\hat{\rho}_A = H \mid \rho_A = h) = P(\hat{\rho}_A = L \mid \rho_A = l) = 1 - p_{err}$. Hence, p_{err} reflects the estimation error in the external precision estimate. Finally, we assume that the announcement A and the precision signal $\hat{\rho}_A$ are conditionally independent, given the

[3]This kind of discretization is employed in the empirical implementation and makes the theoretical setting directly applicable. Nevertheless, the setting is readily extended to a continuous framework which, however, does not provide additional insights.

true precision ρ_A.

Bayesian updating of traders' expectations yields

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

with $\mathrm{E}\left[\rho_A \mid A, \hat{\rho}_A\right]$ representing traders' conditional expectation of the precision of the news given the available information. As shown in Appendix A, this conditional expectation is given by a weighted average of the form

$$\mathrm{E}\left[\rho_A \mid A, \hat{\rho}_A\right] = E\left[\rho_A \mid S, \hat{\rho}_A\right] = \frac{h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)},$$

where $\phi_{\rho_A}(x)$ denote $N(0, \rho_A^{-1})$ density functions with $\rho_A \in \{l, h\}$ and $P(\hat{\rho}_A \mid \rho_A)$ being the conditional probability for having the estimate $\hat{\rho}_A \in \{L, H\}$ given $\rho_A \in \{l, h\}$. Hence, the price response coefficient, $\pi(\cdot)$, is no longer constant but depends on both, the external precision signal and the surprise S itself serving as an internal signal on its own precision.

The following proposition shows that traders' conditional expectations of the precision of the news positively depend on the external precision signal $\hat{\rho}_A$. Hence, the central implication of Bayesian learning that prices react more strongly to news that is perceived to be more precise, still holds:

Proposition 1 *: As long as the external signal $\hat{\rho}_A$ is informative, i.e., $p_{err} < 0.5$, the* *price response coefficient* $\pi(S, \hat{\rho}_A)$ *and thus the absolute price change* $|\mu_P - \mu_F|$ *is larger in the case of* $\hat{\rho}_A = H$ *than in the case of* $\hat{\rho}_A = L$*, i.e.,* $\mathrm{E}[\rho_A|A, \hat{\rho}_A = H] > \mathrm{E}[\rho_A|A, \hat{\rho}_A = L]$.

Proof: *See Appendix A.*

Analyzing the impact of surprises S themselves, we show that its (absolute) size $|S|$ is negatively related to the expected precision of releases:

Proposition 2 *: If market participants face uncertainty regarding the precision of the news (i.e.,* $p_{err} > 0$*), the price response coefficient* $\pi(S, \hat{\rho}_A)$ *is strictly decreasing in the absolute value of the surprise:* $\partial\pi(S, \hat{\rho}_A)/\partial|S| < 0$.

Proof: *See Appendix A.*

Intuitively, traders interpret large surprises as being "too large to be true" and consequently associate them with low reliability. Conversely, surprises that are small in magnitude appear not to be very noisy. Consequently, the ultimate change in traders' expectations $(\mu_P - \mu_F)$ and thus the implied price change $\Delta P = \nu(\mu_P - \mu_F)$ are determined by two effects. First, given the price response coefficient $\pi(\cdot)$, a high (low) surprise S strengthens (weakens) the price reaction linearly. Second, it decreases (increases) the expected signal precision and thus decreases (increases) $\pi(\cdot)$. The resulting price response function is thus nonlinear in S.

As one of the major results of the paper, we illustrate that the strength of price adjustments also depends on the precision of the external estimate $\hat{\rho}_A$. The following proposition shows that the uncertainty parameter p_{err} determines how much weight market participants place on both the internal and external precision signals:

Proposition 3 *: A higher error probability p_{err} underlying the external precision signal leads to the weakening (strengthening) of the absolute price reaction if the external precision signal indicates a high (low) precision, i.e., $\partial|\mathrm{E}[X \mid A, \rho_A = h] - \mu_F|/\partial p_{err} < 0$ and $\partial|\mathrm{E}[X \mid A, \rho_A = l] - \mu_F|/\partial p_{err} > 0$.*

Proof: *See Appendix A.*

In the extreme case of $p_{err} = 0$, the precision of the news is completely revealed by the external signal; therefore ρ_A is known with certainty. In this scenario, the size of a surprise, $|S|$, no longer has informational value, and the nonlinearity in price response functions vanishes. Then, the price response curves are linear with the slopes determined by ρ_A. Conversely, when the external precision signal is completely uninformative, i.e., $p_{err} = 0.5$, traders cannot employ external information to discriminate between precise and imprecise news. Then, the curves associated with $\rho_A = l$ and $\rho_A = h$ coincide and converge to an average of both (given that $P(\rho_A = j) = 0.5$ for $j \in \{l, h\}$). The resulting single curve is nonlinear. This scenario corresponds to the setting outlined in Subramanyam (1996), where market participants gather information on the precision of the news by only relying on the released figure itself. As illustrated in the following section, for the case where $0 < p_{err} < 0.5$, price responses are driven by a combination of both extreme effects.

II. Data and Empirical Framework

A. Data

We do not estimate the model in a structural way, as this would require additional structural assumptions in order to estimate $\mathrm{E}[\rho_A | A, \hat{\rho}_A]$. Therefore, we instead test the implications of the model in reduced form by estimating the shape of the price reaction curve in response to S and the perceived precision of news, $\hat{\rho}_A$. We use intraday returns of CBOT 10-year Treasury bond futures, corresponding to one of the most liquid futures markets, as well as monthly releases of the U.S. employment report. This report 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 detailed 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 release of the employment report offers a rare opportunity to analyze Bayesian learning effects in price adjustments to news, as both the amount of unanticipated information *and* a release-specific precision measure can be obtained.

Hautsch and Hess (2007) document the importance of the precision of the news in a framework where traders are assumed to use external information to make inferences about the precision of news. To facilitate a comparison with these results, we employ an almost identical data set based on two-minute log returns of 10-year Treasury bond futures in 90-minute windows around employment announcements. In particular, our dataset covers a sample of 15 years, from January 4th, 1991 to December 2nd, 2005, of high-frequency Treasury bond data obtained from the Chicago Board of Trade (via their Time & Sales records). Log returns are calculated on the basis of the last trading price observed during a two-minute interval. We use the same time window, 8:22-9:52 a.m. EST. Because trading starts at 8:20, we discard the first interval. In order to avoid interference with other announcements, released at 10:00 a.m. EST, only price observations up to 9:52 a.m. EST

[4] See, e.g., Fleming and Remolona (1999c), Hautsch and Hess (2002), Andersen, Bollerslev, Diebold, and Vega (2003) or Boyd, Hu, and Jagannathan (2005).

are used. As in most previous studies, we focus on the front month contract, i.e., the most actively traded contract among the nearby and second nearby contracts. From our sample period, we obtain 161 event windows in which no other major information event occurs aside from the release of the employment report.[5] With this setting, we can be quite sure that information processing during these event windows is primarily driven only by employment figures. In line with 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).[6] The announcement data are extracted from the original, unrevised employment releases from the Bureau of Labor Statistics (BLS).

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

[6]The use of MMS survey forecasts to approximate market participants is standard in the literature. See, for example, McQueen and Roley (1993), Balduzzi, Elton, and Green (2001), Flannery and Protopapadakis (2002) or Andersen, Bollerslev, Diebold, and Vega (2003), to cite only a few. For a recent study on the rationality of these forecasts, see Hess and Orbe (2010).

In line 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}. The surprise in releases of month m is then measured as the difference between the announced figure $A_{.,m}$ and its median forecast $\mu_{F,.,m}$. Note that nonfarm payrolls are revised in the subsequent month. This revision information, $R_{NF,m}$, is included into our analysis as well. In order to facilitate a direct comparison across the information components, all surprise and revision variables are measured in percentage changes.

To measure information precision, we follow the procedure outlined in Hautsch and Hess (2007). First, the precision of prior information, ρ_F, is estimated using the inverse of the cross-sectional standard deviation of analysts' forecasts $\hat{s}_{F,m}$ for a particular month m, i.e., $\hat{\rho}_{F,m} = \hat{s}_{F,m}^{-2}$. This is well 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. See, for example Pasquariello and Vega (2007) for a detailed discussion of the properties of analysts' forecasts dispersion. Second, in order to obtain a measure for the precision of the announced information ρ_ε itself, we exploit information in revisions of releases. A large revision of the previous month's figure (as provided in the *current* report) indicates that the reliability of this release has been poor. Unfortunately, at the time of an announcement, it is unknown to what extent the currently released information will be revised one month later. Nevertheless, we exploit the fact that the *size* of revisions is autocorrelated and thus predictable. Specifically, we compute out-of-sample forecasts using ARMA-GARCH models fitted to the time series of revisions based on rolling 10-year windows. For this exercise we use an extended sample of real-time revisions, i.e., 1980 - 2005, obtained from the Federal Reserve's ALFRED database. Model specification and (re-)estimation are done on a monthly basis. Then, $\hat{\rho}_{\varepsilon,m}$ is computed as the one-step-ahead forecast of the (conditional) variance of revisions, $\hat{\rho}_{\varepsilon,m} = \hat{\mathrm{V}}[R_{NF,m}|R_{NF,m-1}, R_{NF,m-2}, \ldots]^{-1}$.

To reduce the impact of estimation noise on the quantification of the precision of the news and to avoid the need to impose additional assumptions on the functional relationship between the precision measure and the induced price reaction, we distinguish (in line with our theoretical setup) only between precise and imprecise news. It is sensible to assess the magnitude of the precision of the news relative to the (estimated) precision of prior information, $\hat{\rho}_{F,m}$. Therefore, we define two dummy variables $D^{\pi high}$ and $D^{\pi low}$ indicating whether $\hat{\pi}_m = \hat{\rho}_{\varepsilon,m}/(\hat{\rho}_{\varepsilon,m} + \hat{\rho}_{F,m})$ is above (precise news) or below (imprecise news) its sample median.

Summary statistics for the main variables are given in Table I. We distinguish between the entire sample as well as subsamples differentiated by the value of the external precision signal. To control for the possible impact of the general state of the economy on news' quality, we also report summary statistics for observations for which the NBER indicated that the economy had been in a recession (12 out of 161 months). However, there is no systematic link of NBER recessions and the value of the precision measure. Interestingly, we observe a larger range of surprises in states of low information precision. This is well in accordance with our model, since lower precision implies a larger variance of announcements. Table II reports correlations of log returns and the main news variables. As a first piece of evidence supporting our theoretical predictions we can see that price responses are stronger (negatively) correlated with nonfarm payrolls surprises when the information is perceived to more precise.

B. Specification of Price Response Curves

We model the two-minute log return process during the 90-minute-window around news arrival based on ARMA-GARCH specifications augmented by regressors x_t capturing the impact of announced information,

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

with

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

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

To account for conditional heteroskedasticity, the conditional variance equation (2) captures ARCH effects. In addition, z_t consists of regressors controlling for deterministic volatility patterns around news releases. As in Hautsch and Hess (2007), these patterns are modeled using a flexible Fourier form approximation defined over the 90-minute announcement interval. Though it is evident that such a specification captures most of the variation in conditional variances during the analyzed period we cannot exclude the possibility of remaining heteroskedasticity in the error terms. Therefore, we use robust standard errors as proposed by Bollerslev and Wooldridge (1992).

To test for non-linearities, we use different specifications of the vector x_t, covering the cases of linear and nonlinear news response functions as well as the distinction between precise and imprecise news. Possible nonlinearities in news responses are captured by polynomial terms of the surprise, whereas the precision of the news is indicated by interactions with $D^{\pi high}$ and $D^{\pi low}$. To keep the model parsimonious and tractable, we mainly concentrate on the price response induced by announcements in nonfarm payrolls, which is by far the most influential macroeconomic headline figure.

III. Empirical Results

Table III reports estimation results based on five different specifications of equation (1) allowing for different degrees of nonlinearities in the price response function to nonfarm payroll surprises. The lag order of the autoregressive components in both the mean and variance function is chosen according to the Bayes information criterion (BIC) and reveals an AR(2)-ARCH(3) specification as the preferred model. Apart from the variables capturing the price response to nonfarm payroll surprises, the conditional mean function includes variables capturing 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.

Specification (A) provides estimation results for the most restrictive model, which does not account for any release-specific precision and assumes only one single linear price response function. This is equivalent to assuming that precision is constant over time and is known corresponding to a specification used in most previous studies.[7] Estimation results largely confirm previous findings: first, 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

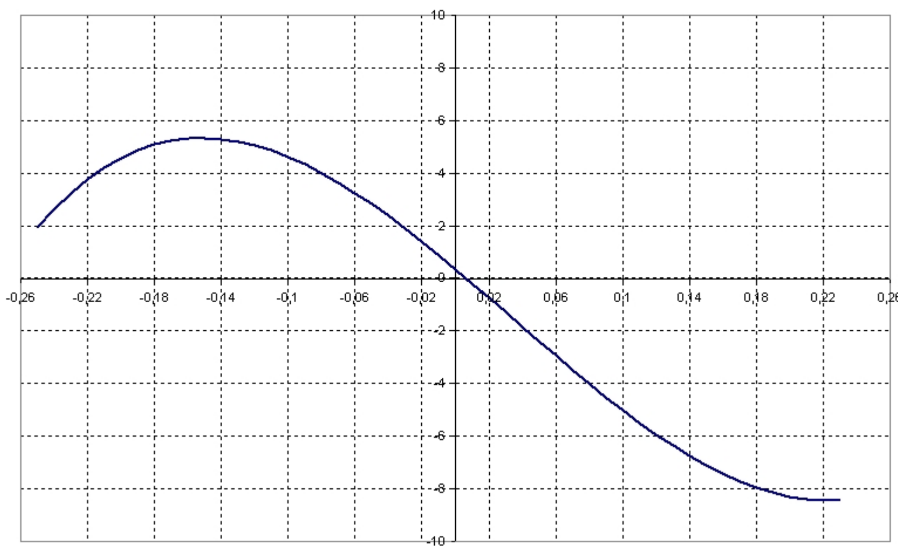
[7]See, for example, Balduzzi, Elton, and Green (2001), Fleming and Remolona (1999a, b, c), or Hautsch and Hess (2002) for bond markets, McQueen and Roley (1993) for stock markets and Almeida, Goodhart, and Payne (1998) or Andersen, Bollerslev, Diebold, and Vega (2003) for foreign exchange markets.

an immediate, strong, and significant impact on intraday returns. The directions of observed price reactions are consistent with standard theory, i.e., 10-year Treasury bond futures prices increase in response to "good" news from the labor factor, i.e., a lower-than-expected increase in nonfarm payrolls and a higher-than-expected unemployment rate. Second, 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 nonlinearities in price responses by including $D_{8:30} \cdot S_{NF}$ as polynomial terms up to order five. Though our theoretical model suggests only symmetric price reactions around zero, the imposed polynomials also capture possible asymmetric effects of "good" and "bad" news in price responses to information releases. This is in line with, e.g., Conrad, Cornell, and Landsman (2002), Andersen, Bollerslev, Diebold, and Vega (2003) or Hautsch and Hess (2007). Specification (B) gives estimation results for a quadratic price response specification, while specifications (C), (D), and (E) include terms up to the orders three, four, and five, respectively. According to likelihood ratio (LR) tests evaluating the individual specifications against each other and the Bayesian information criterion (BIC), we find specification (C) to be mostly supported by the data.

Figure 1 shows the corresponding estimated price response functions according to specification (C). The strong nonlinearities depicted by this function suggest that market participants are aware of a variation in the precision of information across individual releases and that they try to infer this release-specific precision from inspecting the size of surprises. The S-shape pattern clearly indicates that surprises that are "too large to be true" induce lower (marginal) price reactions.

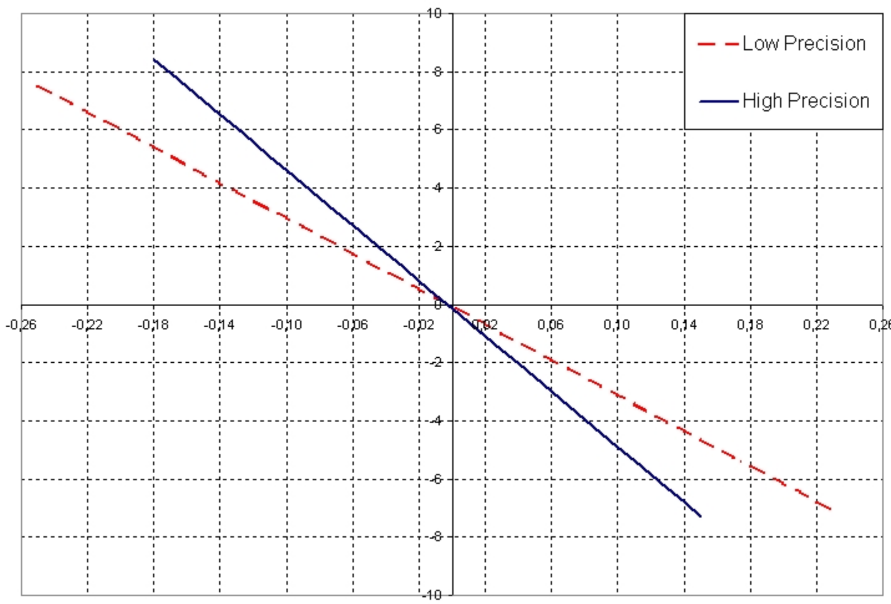
FIGURE 1:
Estimated price response curve allowing only for size-based signals



Estimated price response function according to specification (C) in Table III. 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 $\times 1000$).

To test whether market participants are trying to infer the release-specific precision from external information and hence react differently according to high or low external estimates, we interact the variable $D_{8:30} \cdot S_{NF}$ and corresponding higher-order terms with the dummy variables $D^{\pi high}$ and $D^{\pi low}$. The corresponding estimation results are given in Table IV. The results for specification (F) associated with linear price response functions are largely in line with the findings of Hautsch and Hess (2007), i.e., more precise information leads to significantly stronger (linear) price adjustments. The resulting price response functions for specification (F) are shown in Figure 2. A comparison of the goodness-of-fit of specifications (A) and (F) based on LR tests and likelihood values, the inclusion of precision dummies leads to a significant improvement in the model's goodness-of-fit. This suggests that market participants' reactions to precise vs. imprecise news are better explained by precision estimates on the basis of external information rather than on the basis of the magnitude of surprises solely.

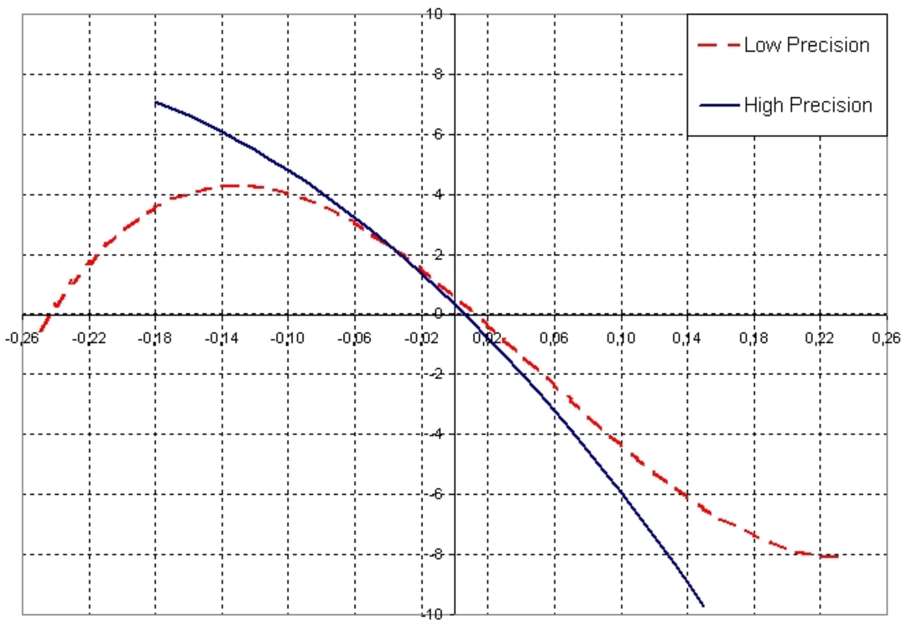
FIGURE 2:
Estimated linear price response curves for high and low external precision signals



Estimated price response function according to specification (F) in Table IV.
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 $\times 1000$).

Finally, successively introducing polynomial terms up to the third order in specifications (G)-(L), we allow for more flexible functional forms and thus, for the case that market participants base their trading decision on both precision proxies. Higher-order polynomials (results not reported) do not significantly improve the model fit. As shown in Table IV, the individual interactions are highly significant. To test for the economic significance of (external) precision effects, we employ a battery of LR tests. It turns out that the most general specification (L) clearly rejects specification (C), providing evidence for the importance of the precision of the news. On the other hand, (L) is rejected against the more parsimonious specification (J), which yields the highest likelihood value and the second-highest BIC.[8]

FIGURE 3:
Estimated price response curves allowing for both size-based and external precision signals



Estimated price response function according to specification (J) in Table IV. 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 $\times 1000$).

We thus find evidence for market participants inferring information precision not only from the magnitude of surprises but also from external information. Finding significantly different price response curves associated with precise and imprecise news suggests that

[8]In terms of the BIC, specifications (C) and (J) yield a comparable fit as induced by the BIC's strong penalization of additional regressors to avoid over-fitting.

the external precision signal is not completely noisy and is obviously taken into account. On the other hand, the strong nonlinearities in the price response functions indicate that traders seem to be well aware of possible errors in the precision estimate, making it necessary to also exploit the size of surprises.

Figure 3 shows that price reactions are particularly nonlinear if the perceived precision using external information is low. In contrast, the nonlinearity is dampened if the external precision signal is high. In this case, we observe a much more linear relationship between price changes and surprises. Consequently, if an announcement is perceived to be of relatively high precision, market participants react to large surprises with almost the same strength as they do to small surprises. In contrast, if the external precision measure indicates that the announced information is of low quality, investors react more moderately to larger surprises. Given the nearly linear shape of the price response curve in a state of high information precision, it seems that market participants almost ignore surprises' size once the precision estimate indicates a high reliability.

Note that instead of capturing nonlinearities based on power functions, we also estimated the model using flexible spline functions defined over the range of surprises receiving. The fact that we get quantitatively the same results indicates the robustness of our findings.[9]

As with any empirical analysis, the question remains whether other potential reasons could explain the observed data. A maintained hypothesis throughout the paper is that the "true" price dependence on the released news is linear. While bond prices are convex

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

in interest rates, at least for the observed small range of intradaily price changes it seems save to assume that price changes are approximately linear in yield changes. Nevertheless, the question remains whether employment news might affect interest rates for some other reason in a non-linear fashion. But it is difficult to imagine factors what could generate an s-shaped response. For example, the news content of employment could be be dependent on the anticipated Federal Reserve response to the implications for both inflation and real growth. The likelihood of a Federal Reserve move could well depend on the size of the announcement. However, if at all, a move would be more (not less) likely when larger changes in (un)employment are reported. Hence, it would be difficult to explain why traders might conjecture that the Federal Reserve will hold tight in face of a large employment drop, if is not that they believe the Federal Reserve also will deem the data to be unreliable. Likewise, other factors might influence the price dependence on employment news, for example, option expiration days or rollover effects. However, it is quite unlikely that these effects are systematically related to a information precision of a macroeconomic release.

IV. Conclusion

Announcements of macroeconomic variables are inherently noisy. From standard Bayesian learning theory, we know that the reliability of news releases has an impact on to what degree investors update their beliefs about the underlying fundamental. However, empirical evidence on these effects is virtually nonexistent. A major reason is that information on the precision of the news is rarely disclosed and thus is itself unknown. In this paper, we theoretically and empirically analyze the role of information precision if the latter is unknown and has to be estimated by market participants. We introduce a framework in which traders can learn about the precision of news from additional (external) information such as, for example, sampling statistics or sampling error estimates from underlying surveys. Moreover, traders can make inferences from the observed surprise itself. In particular, if no other information is available, the size of a surprise is negatively correlated with the reliability of the news, inducing price updates that are nonlinear in terms of the underlying surprise.

We show that the relative importance of both precision signals and thus the shape of the resulting price response functions ultimately depend on the efficiency of the precision estimator. In the extreme case of an error-free precision estimate, the model boils down to a standard Bayesian learning framework with known precision parameters. In this context, the price response function is linear with the slope determined by the precision of the news. In contrast, if the external precision estimate is completely uninformative, traders only can make inferences from the announced information itself. The intuition that a surprise that is "too large to be true" reduces the probability that the news is reliable and induces an S-shaped price response. For intermediate cases between these two extremes, we observe mixtures of both scenarios driven by the error probability of the precision estimate.

Analyzing the impact of U.S. nonfarm payroll announcements on high-frequency data of the U.S. Treasury bond future, we provide evidence for the importance of the precision of the news. By estimating the precision of the news based on information on nonfarm payroll revisions, following the procedure suggested by Hautsch and Hess (2007), we distinguish between the cases of more and less precise news. The estimated price response functions are in line with the theoretical predictions of the proposed extended Bayesian learning model and significantly support the hypothesis that market participants indeed account for both external and size-based precision signals. Observing two significantly different price response functions for the cases of precise and imprecise news implies that market participants obviously employ additional data to obtain information on the precision of the news. Observing also strong nonlinearities in the price response functions indicates that traders are obviously aware of possible estimation errors in the external precision estimate and thus consider also the size of surprises as an indicator for the reliability of releases. In fact, this nonlinearity is clearly stronger when the external signal suggests a low precision. This indicates that the incremental value of a surprise's size depends on whether market participants expect precise or imprecise information to be released.

Overall, our empirical results show that precision effects are important. Ignoring the reliability of the news can lead to significant under- or overestimations of price responses. Given the strong impact of announcements of the leading macroeconomic figures on several markets, a better understanding of the price updating process is crucial for portfolio management, risk management and asset allocation. In this sense, the current paper makes a contribution that should be of interest not only to academics but also to practitioners.

Appendix A

We first derive the posterior beliefs of traders after observing an announcement A and an external signal on its precision $\hat{\rho}_A$ which may take on the values H, L. Recall the assumption that these random variables are conditionally independent given the true precision ρ_A, i.e.,

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

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

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

The expected precision of the announcement is obtained by

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

where the support of $f(\rho_A)$ is given by $S_{\rho_A} \in (0, \rho_F)$. In our setup, we obtain

$$E\left[\rho_A \mid A, \hat{\rho}_A\right] = E\left[\rho_A \mid S, \hat{\rho}_A\right] = \frac{h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)},$$

where $\phi_{rho_A}(x)$ denote $N(0, \rho_A^{-1})$ density functions with precisions $\rho_A \in \{h, l\}$. The fact that $E\left[\rho_A \mid A, \hat{\rho}_A\right] = E\left[\rho_A \mid S, \hat{\rho}_A\right]$ is induced by the assumption that $\mu_F = E[A]$ is assumed to be known. Using these relations we now turn to the proofs of the particular theorems.

Proof of Theorem 1: We need to show that the inequality

$$E[\rho_A \mid A, h] > E[\rho_A \mid A, l]$$

holds. This follows directly from

$$\begin{aligned}
E[\rho_A \mid A, h] &> E[\rho_A \mid A, l] \\
\frac{h \cdot \phi_h(S) \cdot (1 - p_{err}) + l \cdot \phi_l(S) \cdot p_{err}}{\phi_h(S) \cdot (1 - p_{err}) + \phi_l(S) \cdot p_{err}} &> \frac{h \cdot \phi_h(S) \cdot p_{err} + l \cdot \phi_l(S) \cdot (1 - p_{err})}{\phi_h(S) \cdot p_{err} + \phi_l(S) \cdot (1 - p_{err})} \\
(1 - 2 \cdot p_{err})(h - l) \cdot \phi_h(S) \cdot \phi_l(S) &> 0. \ \square
\end{aligned}$$

Proof of Theorem 2: Due to conditional normality, we have $\partial \phi_{\rho_A}(S) \partial S^2 = \left(-\frac{1}{2}\rho_A\right) \phi_{\rho_A}(S)$. We need to show that the partial derivative of the conditional expected precision with respect to the absolute surprise is strictly negative:

$$\begin{aligned}
\frac{\partial E\left[\rho_A \mid A, \hat{\rho}_A\right]}{\partial S^2} &= \frac{\partial}{\partial S^2} \frac{h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)} \\
&= \frac{\frac{\partial}{\partial S^2}[h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)](\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l))}{(\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l))^2} \\
&\quad - \frac{(h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)) \frac{\partial}{\partial S^2}[\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)]}{(\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l))^2} \\
&= \frac{-\frac{1}{2}(h^2 \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l^2 \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l))}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)} \\
&\quad - \frac{(-\frac{1}{2})(h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l))^2}{(\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l))^2} \\
&= -\frac{1}{2}\left[\frac{h^2 \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l^2 \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)} \right. \\
&\quad \left. - \left(\frac{h \cdot \phi_h(S) \cdot P(\hat{\rho}_A \mid h) + l \cdot \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}{\phi_h(S) \cdot P(\hat{\rho}_A \mid h) + \phi_l(S) \cdot P(\hat{\rho}_A \mid l)}\right)^2\right] \\
&= -\frac{1}{2}\left(E[\rho_A^2 \mid A, \hat{\rho}_A] - (E[\rho_A \mid A, \hat{\rho}_A])^2\right) \\
&= -\frac{1}{2} Var[\rho_A \mid A, \hat{\rho}_A] < 0.
\end{aligned}$$

Since $|S|$ and S^2 are positively and monotonically related, the result can be also applied for $|S|$. Then, it is straightforwardly shown that $\partial\pi(S,\hat{\rho}_A)/\partial|S| < 0$. $\square$

Proof of Theorem 3: We need to show that $E[\rho_A|A,h]$ is strictly decreasing in p_{err}.

$$\begin{aligned}
\frac{\partial E[\rho_A|A,h]}{\partial p_{err}} &= \frac{\partial}{\partial p_{err}} \frac{h \cdot \phi_h(S) \cdot (1-p_{err}) + l \cdot \phi_l(S) \cdot p_{err}}{\phi_h(S) \cdot (1-p_{err}) + \phi_l(S) \cdot p_{err}} \\
&= \frac{(l-h)\phi_h(S)\phi_l(S)}{(\phi_h(S) \cdot (1-p_{err}) + \phi_l(S) \cdot p_{err})^2} < 0
\end{aligned}$$

Analogously, it may be shown that $E[\rho_A|A,l]$ is strictly increasing in p_{err}. $\square$

Appendix B

TABLE I

Summary statistics

Panel A: Entire Sample	N	mean	std	min	max
r_t	161	.0129	.6344	-3.4656	2.2060
S_{NF}	161	-.0143	.0856	-.2508	.2233
S_{UN}	161	-.0332	.1473	-.4	.4
R_{NF}	161	.0182	.1187	-.5952	.7440
NBER recession months	12				

Panel B: π high subsample	N	mean	std.	min.	max.
r_t	81	.0156	.6020	-1.6510	2.2060
S_{NF}	81	-.0171	.0788	-.2145	.1508
S_{UN}	81	-.0377	.1305	-.3	.3
R_{NF}	81	.0316	.0996	-.0727	.7440
NBER recession months	10				

Panel C: π low subsample	N	mean	std.	min.	max.
r_t	80	.0101	.6693	-3.4656	1.3629
S_{NF}	80	-.0113	.0924	-.2508	.2233
S_{UN}	80	-.0288	.1632	-.4	.4
R_{NF}	80	.0046	.1346	-.5952	.5067
NBER recession months	2				

The table provides summary statistics for the major variables underlying the study. The sample period covers 15 years (Jan. 1991 - Dec. 2005). r_t denotes log returns, S_{NF} surprises in U.S. nonfarm payrolls, S_{UN} surprises in unemployment rates, and R_{NF} revisions of previous month's nonfarm payrolls figures (all variables are given in percent). Panel A displays the number of observations (N), sample means (mean), sample standard deviations (std), minima (min) and maxima (max) for the entire sample. Panel B and C give the corresponding statistics for the subsamples for which π is high and low, resp. In addition, the number of recession months according to NBER within these samples are given.

TABLE II

Correlations

	(1) Entire sample	(2) π high subsample	(3) π low subsample
$Corr(r_t, S_{NF})$	-0.5665	-0.6844	-0.4756
$Corr(r_t, S_{UN})$	0.2137	0.1652	0.2500
$Corr(r_t, R_{NF})$	-0.2236	-0.3710	-0.1293

The table displays sample correlations of log returns in the 2-min interval following an announcement with the main news variables. r_t denotes log returns, S_{NF} surprises in U.S. nonfarm payrolls, S_{UN} surprises in unemployment rates, and R_{NF} revisions of previous month's nonfarm payrolls figures. Column (1) displays correlations for the entire sample, column (2) for the subsample for which π is high and column (3) for the subsample for which π is low.

TABLE III

Estimation of price response functions with surprises as a size-based 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
$D^{8:30} \cdot S_{NF}^1$	-37,873 ***	-42,415 ***	-53,447 ***	-54,909 ***	-50,344 ***
$D^{8:30} \cdot S_{NF}^2$		-91,220 **	-55,336 *	-119,526	-145,530
$D^{8:30} \cdot S_{NF}^3$			531,752 ***	624,49 ***	80,073
$D^{8:30} \cdot S_{NF}^4$				1658,397	2337,978
$D^{8:30} \cdot S_{NF}^5$					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 III (continued)

QML estimation of AR(2)-ARCH(3) models for two-min log returns during the intraday interval 8:22-9:52 a.m. EST on 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.

The 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 nonlinear 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 IV

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

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 (F)		51,10 ***	54,04 ***	13,08 ***

TABLE IV (continued)

Estimation of price response functions
differentiated by low and high values of the 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 IV (continued)

QML estimation of AR(2)-ARCH(3) models for two-min log returns during the intraday interval 8:22-9:52 a.m. EST on 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 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. ($D^{8:32}$). Surprises are computed based on U.S. employment report figures released by the BLS and consensus forecasts provided by Informa Global Markets (IGM), formerly MMS. The variables S_{NF} are included as polynomials up to order 3 and interact with dummy variables $D^{\pi\ high}$ ($D^{\pi\ low}$) which takes on the value 1 if estimated price response coefficient $\hat{\pi}_m$ at month m is higher (lower) than its sample median, and 0 otherwise. $\hat{\pi}_m$ is given by $\hat{\pi}_m = \hat{\rho}_{A,m} / (\hat{\rho}_{F,m} + \hat{\rho}_{A,m})$, where $\hat{\rho}_{A,m} = 1/\hat{g}_{m+1|m}$, $\hat{g}_{m+1|m}$ is the one-step-ahead prediction of the conditional variance of (percentage) revision of the nonfarm payroll figure in month m, $\dot{R}_{NF,m}$, computed based on rolling sample ARMA-GARCH models for the time series of historical revisions, and $\hat{\rho}_{F,m} = 1/\hat{s}_{F,m}^2$ with $\hat{s}_{F,m}$ denoting the cross-sectional standard deviation of IGM forecasts for the employment release for a particular month m.

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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