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Christian Grimme
Steffen Henzel
Elisabeth Wieland

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## Abstract

Since the seminal speech of Friedman (1977), the causes and consequences of inflation uncertainty are subject to a lively debate. Apparently, inflation uncertainty is an unobserved variable. Hence, various measures have been proposed in the previous literature. However, each measure of inflation uncertainty is derived from different assumptions and it is unclear whether an individual measure delivers a reliable signal. To reduce idiosyncratic measurement error, we propose to use common information contained in different measures. In particular, we show that all series are driven by a common component that constitutes an indicator for inflation uncertainty. Moreover, it appears that systematic measurement error may occur during economic downturns. Finally, we use the indicator to study the Friedman-Ball hypothesis. It turns out that higher inflation is followed by higher uncertainty. However, after an inflationary shock, uncertainty shortly decreases which seems to be traceable to the energy component in CPI inflation.

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Christian Grimme
Ifo Institute – Leibniz Institute for Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1285
grimme@ifo.de

Steffen Henzel
Ifo Institute – Leibniz Institute for Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1652
henzel@ifo.de

Elisabeth Wieland
Ifo Institute – Leibniz Institute for Economic Research
at the University of Munich
and University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/2180-3917
wieland@ifo.de

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# 1 Introduction

In the follow-up of the seminal speech of Friedman (1977), there has originated a still ongoing debate about the link between inflation and inflation uncertainty (Ball, 1992; Cukierman and Meltzer, 1986). However, empirical testing of the causes and consequences of increased inflation uncertainty necessitates a valid measure. Given that inflation uncertainty is an unobserved variable, many different measures have been proposed in the literature. Some studies rely on survey-based measures, others depend on volatility derived from time series models, and some use realized forecast errors. Each measure is derived from different assumptions and it is unclear whether an individual measure delivers the correct signal. That is, any individual measure most likely suffers from idiosyncratic measurement error. Hence, the relationship between uncertainty and macroeconomic variables is subject of a lively debate.[1]

In this study, we propose an approach to mitigate the idiosyncratic measurement error problem. To this end, we derive the most commonly used measures of inflation uncertainty such as, for instance, disagreement, conditional as well as realized forecast error variance. Moreover, we put forward a forecast-based approach which complements the survey-based measures. We use these measures to construct an indicator of inflation uncertainty that condenses the information contained in all measures and, hence, provides a reliable signal. Furthermore, the approach helps us to analyze to which extent individual measure delivers misleading signals. In particular, we discuss whether disagreement of survey expectations is a good proxy for uncertainty.[2]

It turns out that all measures are driven by a common component. Notably, each individual measure contributes to the common component, and the indicator remains largely unaffected if we discard one of the measures. It appears that also disagreement from surveys co-moves with the other measures. However, some caution is warranted because it turns out that respondents tend to cluster their forecasts around the "consensus" forecast in more turbulent times. Moreover, we find that individual measures have the tendency to drift apart if uncertainty rises. That is, the measurement error problem seems to be larger during "uncertain

[1]A number of studies for the U.S. find that inflation causes inflation uncertainty. Davis and Kanago (2000) provide an overview. Others find evidence of the opposite hypothesis. See, for instance, Bhar and Hamori (2004) and Fountas and Karanasos (2007). Mixed results with respect to the direction of causality are obtained *inter alia* by Grier and Perry (1998) and Berument and Dincer (2005).

[2]The relation between disagreement and uncertainty is subject to an ongoing debate. Bomberger and Frazer (1981), Bomberger (1996, 1999) and Giordani and Söderlind (2003) find supportive results, other studies report only a weak relationship or reject disagreement as a proxy (Zarnowitz and Lambros, 1987; Lahiri et al., 1988; Rich and Butler, 1998; Döpke and Fritsche, 2006; Rich and Tracy, 2010). Lahiri and Sheng (2010) find that disagreement is a reliable proxy whenever consensus uncertainty (forecast error variance associated with the mean of individual forecasts) is low.

times". This is unfortunate if we want to analyze the relation between uncertainty and other economic variables. Similar to previous studies, we obtain contradictory results if we use individual measures to test the link between inflation uncertainty and inflation. Overall, these findings further emphasize the benefits of the indicator approach.

In a next step, we make use of the advantages of our approach and study the relationship between inflation and inflation uncertainty. This topic has recently regained relevance because there are claims to increase the inflation target of central bank to mitigate, for instance, the problem of excessive government debt.[3] However, the Friedman-Ball hypothesis suggests that high inflation rates may lead to increased inflation uncertainty which brings about economic cost. The reason is that increased uncertainty would adversely affect investment decisions and bond prices. It turns out that the link is from inflation to higher uncertainty. If we consider an inflationary shock, however, it appears that uncertainty decreases temporarily. Such a behavior seems to be traceable to the energy component in CPI. In particular, we do not obtain a decrease if we consider a shock to core inflation. In either case, uncertainty increases swiftly after a couple of months. Overall, our results are in favor of the Friedman-Ball hypothesis. That is, there appears to be an additional cost of maintaining high inflation rates.

A few studies compare different approaches to measure uncertainty. For instance, Batchelor and Dua (1993, 1996), and Giordani and Söderlind (2003) contrast uncertainty derived from subjective forecast densities contained in the U.S. Survey of Professional Forecasters (SPF) with different types of model-based measures. It appears that both categories do not have much in common. Chua et al. (2011) identify a particular GARCH model that matches the SPF measure closest. These studies consider subjective densities as a benchmark because this measure is theoretically appealing. Such a procedure is valid if the benchmark measure is not severely contaminated by measurement error. However, we may doubt that this is the case. First, quite a few assumptions have to be made to calculate a measure of uncertainty from SPF forecast densities (see, for instance, D'Amico and Orphanides, 2008; Rich and Tracy, 2010). Second, the survey may itself be subject to measurement error, for instance, if participants put little effort in correctly answering the questionnaire. In contrast to our indicator, the SPF measures are rather noisy which suggests that measurement error is present (see Batchelor and Dua, 1993, 1996; Diebold et al., 1999; Giordani and Söderlind,

[3] See, for instance, the IMF Staff Position Note by Olivier Blanchard et al. (SPN/10/03), the address by Charles L. Evans at the Outlook Luncheon on Dec 5, 2011, the NY Times Blog on May 28, 2011 by Paul Krugman, and the comment by Ken Rogoff in the Financial Times on Aug 8, 2011.

2003; Söderlind, 2011). Therefore, we take a different stand and assume that *a priori* each individual measure of uncertainty is equally informative.

The remainder of the paper is organized as follows. In section 2, we introduce the measures of inflation uncertainty. The relation between the different measures is analyzed in section 3. In section 4, we test the Friedman-Ball hypothesis. Section 5 concludes.

# 2 Calculating measures of inflation uncertainty

In the following, we introduce the empirical measures for inflation uncertainty. They are derived from different approaches put forward in previous studies and rely on distinct concepts and assumptions. Hence, they are potentially exposed to different types of measurement error. We introduce survey-based measures, as well as model-based measures. Moreover, we propose a forecast-based approach. Common information contained in these individual measures builds the basis for the indicator in section 3.

## 2.1 Survey-based measures

In a first step, we focus on uncertainty measures which are derived from survey data. Our data source is provided by Consensus Economics Inc. (CE). CE is advantageous because it polls professional forecasters who should be well informed about the current state of the economy. Besides, individual data is provided and the names of the forecasters are given aside the numbers. Hence, there is a strong incentive to make a well-informed prediction in order not to damage the reputation.[4] Against this background, Dovern and Weisser (2011) find that individual forecasts for U.S. inflation are largely unbiased. Moreover, it has the advantage that it runs on a monthly frequency. As uncertainty may move abruptly, many of the effects we want to measure would be washed out in low frequency data. We use data from 1990:M1 to 2009:M12.[5]

Bomberger and Frazer (1981), Cukierman and Wachtel (1982), and Batchelor and Dua (1993, 1996) propose the root mean squared error ($rmse_t^s$) as a measure of uncertainty. It is calcu-

[4] A more detailed description of the data is found in appendix A.1.

[5] Owing to the survey design, studies using probabilistic expectations from SPF are restricted to a yearly frequency. Hence, we cannot use SPF data for the main analysis in this paper. However, as SPF is a common benchmark we compare both approaches in appendix B.4.

lated by averaging the individual squared forecast errors in each period $t$:

$$rmse_t^s = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\Big(\pi_{t+12} - \pi_{i,t}^e\Big)^2}, \tag{1}$$

where $\pi_{t+12}$ denotes realized 12-month ahead CPI inflation and $\pi_{i,t}^e$ denotes the individual point forecast from CE made at time $t$. As far as the timing is concerned, we follow Batchelor and Dua (1993, 1996). That is, an observation for uncertainty at time $t$ is available only when realized inflation is observed at time $t + 12$.

Bomberger and Frazer (1981), Bomberger (1996, 1999), and Giordani and Söderlind (2003) propose the cross-sectional dispersion of point forecasts (disagreement) as a measure of uncertainty. Instead of using the cross-sectional standard deviation of forecasts, we follow Mankiw et al. (2003) and rely on the interquartile range ($iqr^s$) since it is more robust to outliers. $iqr^s$ is defined as the difference between the 25$^{\text{th}}$ and the 75$^{\text{th}}$ percentile.[6]

Mankiw et al. (2003) point out that the distribution of point forecasts may become multimodal if model uncertainty is high, for instance, around structural breaks. Hence, the form of the distribution of individual forecasts may contain information about uncertainty beyond a dispersion measure. Hence, Rich and Tracy (for instance, 2010) suggest using a histogram-based *entropy* ($ent^s$) which is computed as:

$$ent_t^s = -\Big(\sum_{k=1}^{n} p(k)_t[ln(p(k)_t)]\Big), \tag{2}$$

where $p(k)$ denotes the relative frequency of individual forecasts falling in a certain interval $k$. The concept of entropy provides additional information in comparison to the measure of $iqr^s$ in two ways. First, given a certain cross-sectional standard deviation of forecasts, entropy changes with the shape of the histogram of forecasts. In particular, the normal distribution exhibits a higher entropy than any other distribution of the same variance (Vasicek, 1976). Second, given a fixed number of bins and a constant bin width, the histogram-based entropy is maximized if the forecasts are distributed equally among all bins.

[6]We also computed the standard deviation and the quasi-standard deviation of forecasts. The quasi-standard deviation is defined as half the difference between the 16th and 84th percentile. With normally distributed data, this measure coincides with the standard deviation. These alternative measures are highly correlated with $iqr^s$ with correlation coefficient $\rho = 0.86$ and 0.90, respectively.

## 2.2 Forecast-based measures

As a complement to the survey-based measures, we put forward a forecast-based approach that is based on multiple forecast models. We rely on VAR models which are a popular forecast device because of their ability to generate multi-step predictions. To obtain a time-varying uncertainty measure, Giordani and Söderlind (2003) recursively estimate a single VAR model and calculate a standard deviation of the forecast error of inflation for each period. Chua et al. (2011) follow this idea by deriving error bands from the recursive bootstrapped VAR approach proposed by Peng and Yang (2008). However, this approach comes at the cost of being conditional on a specific forecast model which is assumed to provide the correct description of the data. Moreover, the model is assumed to be the same for all forecasters. Hence, model uncertainty is virtually absent and forecaster diversity is neglected. Finally, uncertainty is derived from VAR residuals which are assumed to be homoscedastic. In effect, this is not consistent with the presumption that uncertainty changes systematically over time. To overcome these possible drawbacks, we propose a forecast-based approach which relies on a variety of forecast models.[7] That is, we do not use information contained in residuals but rather resort to the point forecasts of different VAR models.

To obtain multiple forecast models, we first select a number of activity variables proposed by Stock and Watson (1999) to forecast U.S. inflation. Stock and Watson (1999) identify different sub-groups of variables. To keep the analysis tractable, we choose one representative from each of these sub-groups. We end up with 15 variables which are described in table A.1 in the appendix. Note that the estimation period contains the disinflation period during the 1980ies. Hence, inflation enters in first differences (Stock and Watson, 1999, 2007). To derive twelve-months ahead forecasts for inflation, we build a number of different VAR models. Each VAR model is limited in size to avoid over-fitting problems. It comprises the target variable and up to four additional activity variables. Finally, we construct all VAR models that fulfil this criterion, i.e. we consider all possibilities to choose up to four variables out of the 15 activity variables. The lag length of each VAR model is determined by BIC, and we end up with a total number of 1.941 different inflation forecasts for each month. Note that the estimation proceeds recursively. That is, we use data from 1970:M1 up to the period in which the forecast is made. Hence, we calculate forecasts for inflation one year ahead for each month between 1991:M1 and 2010:M12. By design, the forecast-based approach mimics a survey of professional forecasters such as the CE survey. Calculating RMSE as defined in equation (1) yields a forecast-based measure of inflation uncertainty ($rmse^f$). Forecast-based

[7] Hartmann and Herwartz (2009) use an approach similar to ours to derive a measure of uncertainty from five different structural models.

disagreement ($iqr^f$) is given by the dispersion among the point forecasts measured by the interquartile range. As in equation (2), we also calculate an entropy-based measure ($ent^f$).

## 2.3 Model-based measures

### 2.3.1 Conditional forecast error variance

ARCH models of many different shapes have been extensively used to model inflation uncertainty in the U.S.[8] A number of studies highlight that there may be many structural breaks in the inflation process.[9] To account for such events like changes in the monetary regime or the level of steady-state inflation, we follow these studies and opt for a time-varying parameter GARCH (TVP-GARCH) model. This has the advantage of being flexible enough to allow for a non-stationary inflation rate. In terms of Ball and Cecchetti (1990), time variation also adds a second long-term dimension to uncertainty. The TVP-GARCH model provides a coherent framework for the analysis of uncertainty in the sense that it combines conditional error variance as well as model uncertainty into forecast error variance (Evans, 1991). The model is given by a signal equation (3), a state equation (4) and equation (5) describing the evolvement of conditional error variance.

$$\pi_t = [1 \; \pi_{t-1} \; \pi_{t-2}] \, \alpha_t + e_t \qquad e_t \sim N(0, h_t) \tag{3}$$

$$\alpha_{t+1} = \alpha_t + \eta_t \qquad \eta_t \sim N(0, Q) \tag{4}$$

$$h_t = d + \sum_{i=1}^{m} \phi_i e_{t-i}^2 + \sum_{i=1}^{n} \gamma_i h_{t-i} \tag{5}$$

Here, $\alpha_t$ is a vector of time-varying coefficients. We model inflation as an AR(2) process which meets the needs to reproduce the cyclical behavior. $h_t$ describes conditional error variance and $Q$ is a homoscedastic covariance matrix of shocks $\eta_t$. The coefficient vector follows a random walk. Estimations are based on monthly data running from 1990:M1 through 2009:M12.[10] Finally, the Kalman filter provides an estimate for the variance of forecast errors. We use the square root of this variance to measure uncertainty which is labeled *garch*. Note that the measure summarizes model uncertainty emerging from time-variation of the coefficients and

[8] See, for instance, Engle (1983), Cosimano and Jansen (1988), Brunner and Hess (1993), Grier and Perry (1996), Grier and Perry (2000), Elder (2004), Grier et al. (2004) and Chang and He (2010).

[9] See, for instance, Evans (1991), Evans and Wachtel (1993), Berument et al. (2005), Caporale and Kontonikas (2009), and Caporale et al. (2010).

[10] Parameter estimates are given in table A.2 in the appendix. Specification tests do not indicate either autocorrelation or remaining ARCH effects in the model innovations.

uncertainty emerging from the shock process $\eta_t$ (see Evans, 1991; Caporale et al., 2010, for a detailed explanation).

### 2.3.2 Stochastic volatility

Stochastic volatility (SV) models have been used in financial econometrics to model error variance as a latent stochastic process (see, among others, Harvey et al., 1994; Kim et al., 1998). Moreover, they have been proposed as a forecast model for U.S. inflation (Stock and Watson, 2007). In contrast to ARCH models where error variance is fully described by its own past, here, the variance of first moment shocks is assumed to be driven by an exogenous stochastic process. Albeit their ability to model shocks to second moments, so far, stochastic volatility models are rarely used to analyze inflation uncertainty. In the following, we adopt the model proposed by Stock and Watson (2007) whose state-space representation is given by equations (6) to (10).

$$\begin{aligned}
\pi_t &= \mu_t + e_t \qquad e_t \sim N(0, \sigma^2_{e,t}) && (6)\\
\mu_{t+1} &= \mu_t + \eta_t \qquad \eta_t \sim N(0, \sigma^2_{\eta,t}) && (7)\\
\log \sigma^2_{e,t+1} &= \log \sigma^2_{e,t} + \nu_{1,t} && (8)\\
\log \sigma^2_{\eta,t+1} &= \log \sigma^2_{\eta,t} + \nu_{2,t} && (9)\\
\begin{pmatrix} \nu_{1,t} \\ \nu_{2,t} \end{pmatrix} &= N(0, \gamma I_2) && (10)
\end{aligned}$$

Here, $e_t$ is a short-term shock in the measurement equation (6) with variance $\sigma^2_{e,t}$. Moreover, the permanent component of inflation $\mu_t$ follows a random walk which is driven by a permanent (level) shock $\eta_t$ with variance $\sigma^2_{\eta,t}$.[11] We follow the arguments of Ball and Cecchetti (1990) and use the square root of the variance of permanent shocks $\sigma^2_{\eta,t}$ as the measure of inflation uncertainty. In the following, it is denoted by *ucsv*.

[11] The model is estimated with the Gibbs sampler. See also Dovern et al. (2009) for an application of the stochastic volatility model to different macroeconomic variables.

# 3 Characteristics of uncertainty measures

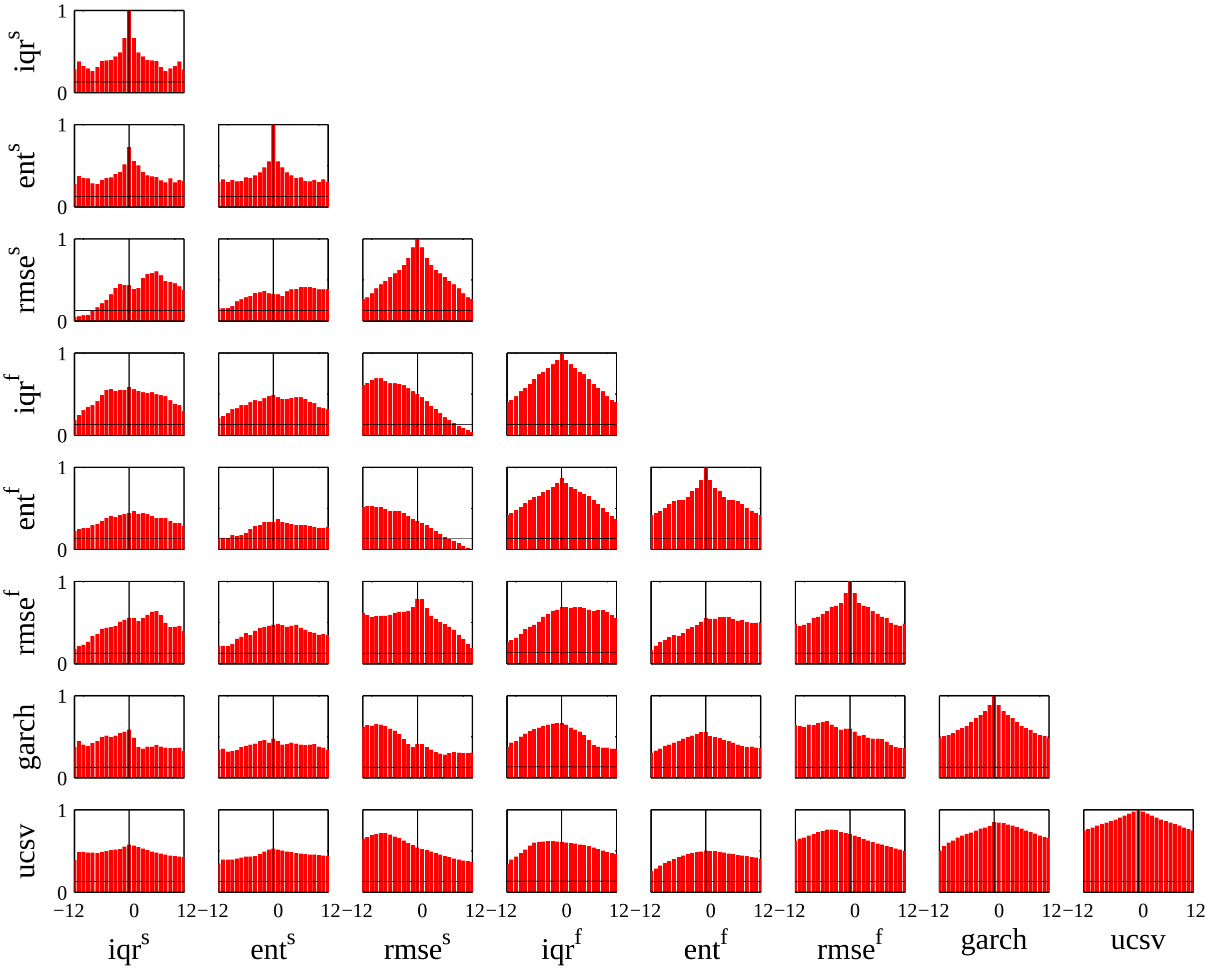
## 3.1 Descriptive analysis

We generate eight individual uncertainty measures: three survey-based measures ($iqr^s$, $ent^s$, $rmse^s$), three forecast-based measures ($iqr^f$, $ent^f$, $rmse^f$), and two model-based measures ($garch$, $ucsv$).[12] All eight measures require a number of assumptions to work as good proxies for uncertainty. In general, deriving valid measures from survey-based approaches assumes that the survey is conducted such that bias and measurement error is small. Moreover, disagreement and entropy are valid proxies only if there is a positive correlation between the dispersion of forecasts of respondents and uncertainty of the participants. However, it might be the case that individual forecasters are highly uncertain and, therefore, are reluctant to deviate from the other forecasters. $rmse$ assumes that high forecast errors in the past increase an individual forecaster's uncertainty about his current point estimate. Measures inferred from the forecast-based approach work as indicators for uncertainty if linear time series models are a good approximation of the model used by individual forecasters. Finally, model-based measures are conditional on a specific forecast model. Moreover, this particular model is assumed to be the same for all forecasters. In addition, $garch$ provides the conditional variance which is dependent on past forecast errors. By contrast, $ucsv$ seems to be more appealing from a theoretical point of view because the approach delivers a forecast error variance which is driven by exogenous second moment shocks. Overall, the respective assumptions are most likely not fulfilled completely. Hence, each measure proposed in the literature is probably contaminated by some sort of measurement error suggesting that it is difficult to identify a benchmark approach from these measures. By contrast, it should be beneficial to base the analysis on information contained in all measures jointly.

In the following, we present some descriptive statistics to characterize the individual measures. Figure 1 displays the autocorrelation of the eight uncertainty measures on the main diagonal. It turns out that the autocorrelation is positive and significant at the 5% level for each measure. The lowest degree of autocorrelation is found for survey disagreement, whereas, by construction, the most sluggish measure is $ucsv$. In general, inflation uncertainty seems to be a persistent phenomenon.

Considering cross-correlations on the off-diagonal elements of figure 1, we find that they are high and significantly positive among all series and throughout all leads and lags. We take

[12] Individual measures are depicted in figure B.1 in the appendix.



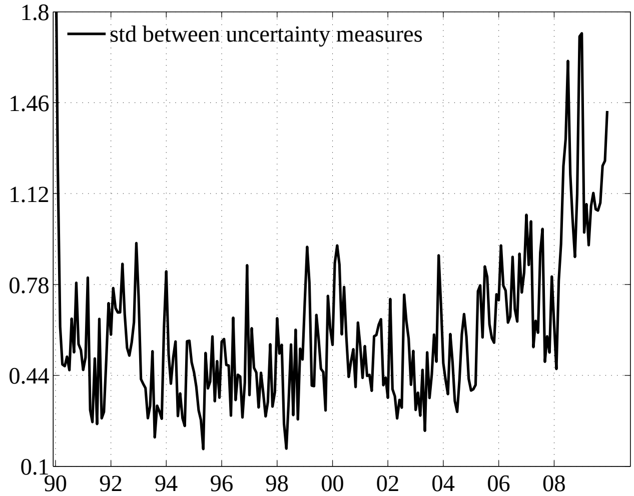

Note: The bars represent cross-correlations corr$(y_{i,t}, y_{j,t+k})$ for each pair of variables where $y_{i,t}$ denotes the row $i$ variable and $y_{j,t+k}$ is given in the column $j$. $k$ varies between $-12$ and $+12$. The 5% significance level is indicated by the horizontal line.

Figure 1: Cross-correlation of uncertainty measures

this as a first indication that all measures contain an important common component. Also note that $rmse^s$ and $rmse^f$ tend to lead the other measures.

We also present contemporaneous correlations of the individual uncertainty measures with other variables in table B.1 in appendix B.1. It turns out that each individual measure has significant correlations with many economic and financial variables. Moreover, the sign of the correlations seems to be unambiguous. For instance, there is a strong positive correlation with indicators of financial market risk. Moreover, the variability of commodity prices and interest rates seem to be positively related. Furthermore, all measures seem to move counter-cyclically, and they are negatively related to house prices, stock returns, and commodity prices. Overall, correlations are roughly in line with what we would expect from a measure of inflation uncertainty, and each measure seems to carry information about underlying inflation uncertainty. However, there appear to be differences with respect to the strength of the correlation. Hence, we may obtain more robust results if we use information from all measures jointly.

The extent of co-movement over time is revealed in figure 2. Here, we depict the evolution of the cross-sectional standard deviation between measures at each point in time. We observe that the standard deviation fluctuates in a rather narrow band during the first half of the sample, whereas the measures start to diverge beginning in 2005. The co-movement between all eight measures further decreases during the recent crisis. It turns out that the cross-sectional mean of all eight measures and the associated standard deviation are strongly correlated ($\rho = 0.66$). Thus, during more turbulent times, individual measures have the tendency to drift apart and measuring uncertainty is more challenging. It appears that a method attenuating the measurement error problem is beneficial particularly in times of high uncertainty.




Note: Individual uncertainty measures have been standardized to have mean zero and standard deviation one before calculating the cross-sectional standard deviation.

Figure 2: Standard deviation of uncertainty measures

## 3.2 Common characteristics

To eliminate the idiosyncratic components (i.e. idiosyncratic measurement error) from the data, we can exploit the commonalities among individual measures documented in the previous section. That is, we use the cross-sectional dimension of the data to alleviate the measurement error problem. For this purpose, we conduct a Principal Component Analysis. As mentioned above, the two variables $rmse^s$ and $rmse^f$ seem to lead the rest of the indicators. We obtain a maximum average cross correlation if we consider 8 and 5 lags, respectively. Note that $rmse$ measures seem to move early because of the timing we impose (compare equation (1)). When estimating the common factors, we follow Stock and Watson (2002) and account for the lead characteristics of these variables. Table 1 shows the loading coefficients of the first three principal components and the individual and cumulative variance proportions of those components.

| | PC 1 | PC 2 | PC 3 |
|---|---|---|---|
| **Eigenvalues** | 5.30 | 0.85 | 0.70 |
| Variance Proportion | 0.66 | 0.11 | 0.09 |
| Cumulative Proportion | 0.66 | 0.77 | 0.86 |
| **Eigenvectors** | | | |
| $iqr^s$ | 0.34 | 0.44 | −0.33 |
| $ent^s$ | 0.31 | 0.58 | −0.36 |
| $rmse^s$ | 0.35 | −0.17 | 0.33 |
| $iqr^f$ | 0.37 | −0.41 | −0.30 |
| $ent^f$ | 0.33 | −0.53 | −0.45 |
| $rmse^f$ | 0.37 | 0.00 | 0.17 |
| $garch$ | 0.38 | 0.05 | 0.35 |
| $ucsv$ | 0.38 | 0.08 | 0.46 |

Table 1: Loadings of first three principal components

The first principal component (PC1) accounts for the major part of the dynamics as it already explains 66% of the total variation of the underlying series. Notably, all eight loading coefficients are clearly positive and lie between 0.31 and 0.38. That is, the loadings are all similar in magnitude and there is no single series driving the component. Moreover, the indicator does not hinge on one of the individual measures as it remains virtually unaffected if we discard one of the measures.[13] In other words, it appears that there is a common driving force that impacts each individual measure in a similar way. PC1 is shown in figure 3.[14] The continuing increase in uncertainty starting in 2006 stands out. This behavior is also apparent in each of

[13]We recalculate the indicator leaving out one of the individual measures in turn. Results are presented in figure B.3 in appendix B.3.

[14]As a robustness check, we compare PC1 to uncertainty measures derived from SPF data in appendix B.4. It appears that PC1 broadly retraces the movements of SPF. However, it turns out that the SPF measure is much more volatile than PC1. Such a finding may occur because, by construction, survey data is probably influenced by some kind of measurement error.

the individual uncertainty measures. A maximum in uncertainty is found in December 2008 and January 2009 which coincides roughly with the peak of the recent economic crisis.[15]

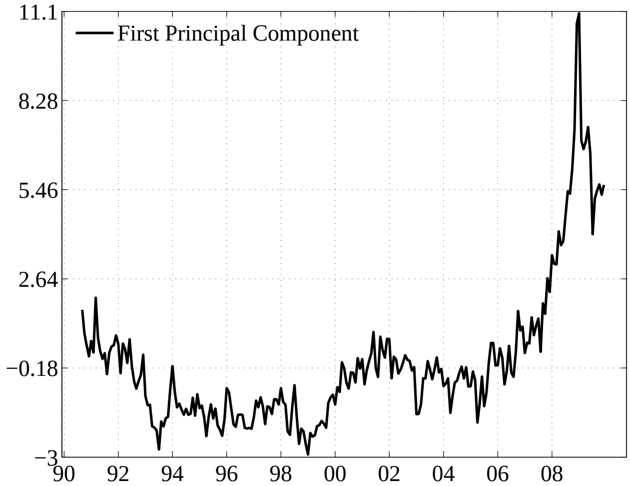



Figure 3: Uncertainty indicator (PC1)

To analyze the information content of PC1, we study the co-movement of PC1 with variables that should be related to inflation uncertainty. Contemporaneous correlations of PC1 and a collection of key variables are presented in table 2. It turns out that PC1 is closely linked to the variability of nominal variables such as commodity prices, interest rates, and money. Similarly, variables representing financial market risk (*vix*, *ted* spreads, corporate bond spreads, and squared returns) seem to rise with PC1. Moreover, PC1 appears to be positively linked to the variability of production growth. Finally, all variables representing the business cycle indicate that inflation uncertainty is associated with economic contraction. We also observe a negative association with short-term interest rates which are, in general, pro-cyclical over the business cycle. Notably, the correlation obtained for long-term rates is somewhat lower compared to short-term rates. This is probably due to the fact that the long-term interest rates is partly driven by the inflation risk premium which tends to increase along with inflation uncertainty.

[15]Generally speaking, uncertainty is a bounded variable. However, the underlying series might be observationally equivalent to a non-stationary process. We analyze this issue in appendix B.2. Common unit-root tests deliver rather mixed results. However, assuming non-stationarity of all series, we apply a parametric approach to extract one common trend from the data. It turns out that such a proceeding produces results that are similar to the results from the non-parametric PCA approach.

| | PC1 | PC2 | PC3 | | PC1 | PC2 | PC3 |
|---|---|---|---|---|---|---|---|
| $(\Delta\pi)^2$ | **0.37** | **0.14** | | $wti$ | | | |
| $(\Delta\pi^{core})^2$ | **0.15** | | | $ppi^{comm}$ | −0.14 | **0.14** | |
| $\Delta M2$ | **0.20** | | | $ppi^{ind}$ | −0.16 | | |
| $(\Delta M2)^2$ | **0.36** | | | $crb$ | −0.28 | **0.23** | |
| $ffr$ | −0.48 | | | $(\Delta wti)^2$ | **0.22** | −0.14 | |
| $r^{3M}$ | −0.53 | | | $(\Delta ppi^{comm})^2$ | **0.47** | | |
| $r^{10Y}$ | −0.28 | −0.17 | −0.18 | $(\Delta ppi^{ind})^2$ | **0.43** | | |
| $\Delta ffr$ | −0.29 | | **0.27** | $(\Delta crb^{return})^2$ | **0.42** | | |
| $\Delta r^{3M}$ | −0.19 | | **0.22** | $ism$ | −0.47 | | **0.15** |
| $\Delta r^{10Y}$ | | | | $ism^{prod}$ | −0.43 | | **0.15** |
| $abs(\Delta ffr)$ | **0.13** | −0.16 | −0.18 | $pmi$ | −0.53 | **0.17** | |
| $abs(\Delta r^{3M})$ | | −0.14 | −0.18 | $pmi^{prod}$ | −0.56 | **0.14** | |
| $abs(\Delta r^{10Y})$ | **0.35** | | | $mhs$ | −0.79 | | **0.14** |
| $vix$ | **0.53** | | | $confidence$ | −0.59 | | **0.21** |
| $ted$ | **0.32** | | | $cu$ | −0.69 | | −0.16 |
| $risk$ | **0.39** | −0.35 | | $cu^{man}$ | −0.72 | | −0.16 |
| $sp500$ | −0.16 | | | $cu^{exIT}$ | −0.76 | | −0.17 |
| $dj$ | −0.16 | | | $\Delta y$ | −0.81 | | |
| $dj5000$ | −0.14 | | | $\Delta y^{man}$ | −0.82 | | |
| $sp500^2$ | **0.27** | | | $(\Delta y)^2$ | **0.53** | −0.19 | |
| $dj^2$ | **0.24** | | | $(\Delta y^{man})^2$ | **0.58** | −0.17 | |
| $dj5000^2$ | **0.27** | | | $\Delta empl$ | −0.77 | | |
| $house$ | −0.61 | | **0.20** | $\Delta jobless$ | **0.67** | −0.20 | |
| $\Delta house$ | | −0.16 | | $\Delta u$ | **0.78** | −0.17 | |
| $(\Delta house)^2$ | **0.46** | | **0.31** | $ur$ | **0.50** | | −0.17 |
| $recession$ | **0.61** | −0.16 | | $\Delta ur$ | **0.79** | −0.15 | |

Note: Positive correlations are printed in bold and negative correlations are in lightface. Correlations that are insignificant at the 5% level do not appear in the table. A detailed description of economic variables is given in table B.2 in appendix B.1.

Table 2: Correlations of principal components with economic and financial variables

## 3.3 Group-specific characteristics

We now shed some light on characteristics that are specific to (groups of) individual measures. That is, we analyze the movements that are not explained by the common component. To this end, we analyze the second principal component (PC2) which accounts for 11% of the total variance of the data. Notably, PC2 provides some insight into the dynamic interrelation of individual uncertainty measures. We obtain high negative loadings for the two forecast-based measures $iqr^f$ and $ent^f$ (−0.41 and −0.53) and, in contrast, high positive loadings are found for the two survey-based variables $iqr^s$ and $ent^s$ (0.44 and 0.58). From the signs of the loadings, we infer that PC2 is driven by factors that separate movements of survey-based and forecast-based measures. The other variables do not contribute to this component in a significant way.

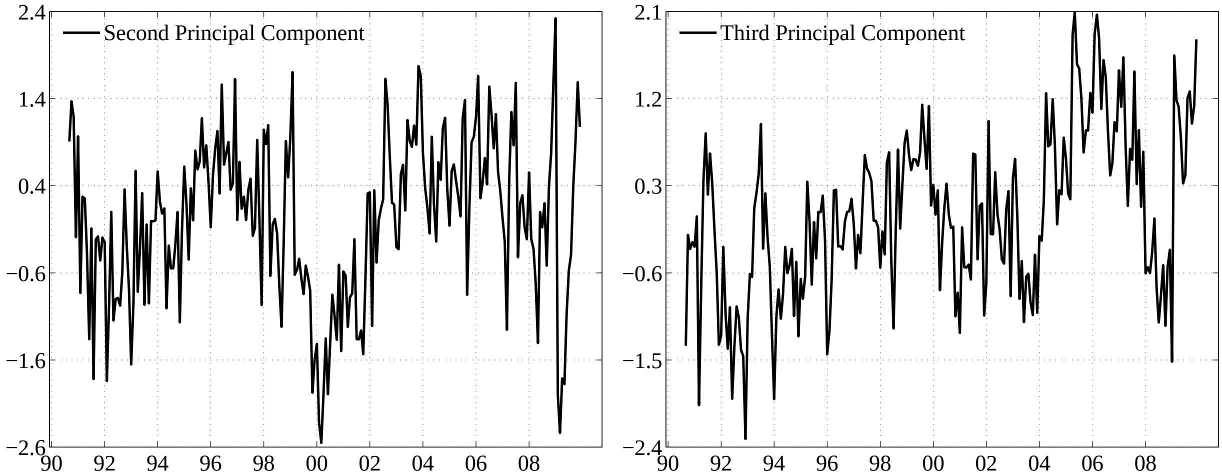



Figure 4: Second and third principal component (PC2, PC3)

The left panel of figure 4 depicts PC2. It appears that PC2 is far from being white noise. That is, deviations between survey-based and forecast-based measures are systematic. To identify situations where both groups of measures move less synchronized, we analyze correlations of PC2 to economic variables in table 2. It turns out that there are fewer significant correlations than for PC1. In opposition to PC1, PC2 co-moves with the business cycle. Hence, the wedge between forecast-based and survey-based measures tends to increase in recessions or during economic downturns. That is, $iqr^s$ and $ent^s$ tend to decrease during recessions while forecast-based measures tend to rise. Similarly, the wedge between both groups of measures increases when the corporate bond risk premium is high or output variability increases. Moreover, a rise in commodity prices is associated with an increase in PC2, probably reflecting the fact that these prices tend to co-move with the business cycle. Hence, disagreement appears to be subject to systematic measurement error in more turbulent times such as economic downturns.

For an economic interpretation, note that, by design, the forecast-based approach mimics a survey of professional forecasters such as the CE survey. However, a conceptual discrepancy to survey-based measures should be highlighted. The forecast-based approach provides a purely mechanistic way to deal with heterogeneous information. As a consequence, VAR model forecasts almost inevitably diverge when indicators provide heterogeneous signals. By contrast, in a survey, the way information is combined into a forecast is to a non-negligible extent governed by subjective elements. For instance, the choice of a particular forecast model, the weights attached to different pieces of information, or judgmental adjustments may influence the forecast reported. Notably, if forecasters are risk-averse, they may choose to stick to the consensus if uncertainty is high, and forecast dispersion may decline. Such a behavior appears to occur here during economically turbulent times such as recessions. Overall, results suggest that using *only* survey disagreement as a measure of inflation uncertainty may deliver misleading results.

The third principal component (PC3) is depicted in the right panel of figure 4. It features highly negative loadings for all disagreement measures ($iqr^s$, $ent^s$, $iqr^f$, $ent^f$), whereas the other measures ($rmse^s$, $rmse^f$, $garch$, $ucsv$) load positively. That is, PC3 appears to capture some of the observed divergence of individual measures (see also figure 2). Note that PC3 is relatively unsystematic and, hence, the correlation to other variables is weak (see table 2). However, there appears to be a positive correlation with the variability of house prices and the first difference of short-term interest rates.

# 4 Test of the Friedman-Ball hypothesis

In the following, we use PC1 to test the relationship between inflation and inflation uncertainty. Friedman (1977) argues that high inflation rates are less predictable than lower rates. Ball (1992) formalizes the idea stating that inflation uncertainty increases in the event of higher inflation because the policy response is harder to predict. In particular, it is harder for economic agents to forecast when there will be a shift to a tougher monetary policy. In contrast, Cukierman and Meltzer (1986) argue that the link is from inflation uncertainty to inflation. In a Barro-Gordon framework, they claim that, with highly uncertain agents, the central bank has an incentive to create surprise inflation to lower unemployment. The inflation - inflation uncertainty link has recently gained relevance with the call for a higher inflation target for central banks.

To test the Friedman-Ball hypothesis, we conduct a Granger causality test. To this end, we estimate bivariate VAR models containing inflation and one uncertainty measure. As we deal with monthly data, the lag length is set to 12. Results are presented in table 3. Although contemporaneous correlations are rather similar across individual measures, results of a Granger causality test are rather mixed (see table B.1). $rmse^s$ and $iqr^f$ seem to be Granger caused by inflation but not vice versa whereas for $iqr^s$ and $garch$ Granger causality appears to hold for both directions. For $ent^s$ and $ent^f$, we find no dynamic relation to inflation. In the case of $rmse^f$ and $ucsv$, it turns out that uncertainty is Granger causal for inflation. When the same test is conducted for the change of inflation, we get almost the same results. Overall, results appear to be inconclusive, and the choice of the measure seems to drive the results. Thus, using individual measures entails the risk that results are driven by idiosyncratic movements that are unrelated to inflation uncertainty.

| | PC1 | $irq^s$ | $ent^s$ | $rmse^s$ | $iqr^f$ | $ent^f$ | $rmse^f$ | $garch$ | $ucsv$ |
|---|---|---|---|---|---|---|---|---|---|
| $H_0$: $\pi$ does not Granger cause IU | **0.00** | **0.00** | 0.08 | **0.02** | **0.01** | 0.79 | 0.08 | **0.00** | 0.16 |
| $H_0$: IU does not Granger cause $\pi$ | 0.27 | **0.01** | 0.31 | 0.27 | 0.48 | 0.82 | **0.03** | **0.03** | **0.00** |
| $H_0$: $\Delta\pi$ does not Granger cause IU | **0.00** | **0.00** | **0.02** | **0.01** | **0.01** | 0.85 | 0.10 | **0.00** | 0.14 |
| $H_0$: IU does not Granger cause $\Delta\pi$ | 0.21 | 0.19 | **0.01** | 0.51 | 0.51 | 0.30 | **0.00** | **0.01** | **0.00** |

Note: Granger causality tests are performed for inflation $\pi$ as well as the monthly change of inflation $\Delta\pi$ and inflation uncertainty (IU). Numbers are p-values for a Granger causality test.

Table 3: Granger causality test for inflation uncertainty and inflation

Using PC1 to measure inflation uncertainty, we find strong support for the Friedman-Ball hypothesis, i.e., inflation Granger causes inflation uncertainty but not vice versa. The same result is obtained if we consider the change in inflation. Most notably, results in table 3 suggest that the indicator provides an insurance against idiosyncratic movements of individual measures.[16] To further substantiate this result, we reestimate each bivariate VAR by three-stage least squares. We employ PC1 as instrument for the individual uncertainty measure and test whether we can recover the result from above. That is, instead of using PC1 directly, we take the variation of each individual measure explained by the common component to identify the effect. We then use the three-stage least squares estimates to perform a Granger causality test. It turns out that we obtain no case where uncertainty seems to Granger cause inflation. Overall, it appears that idiosyncratic movements of individual measures may mask the underlying relationships of interest.

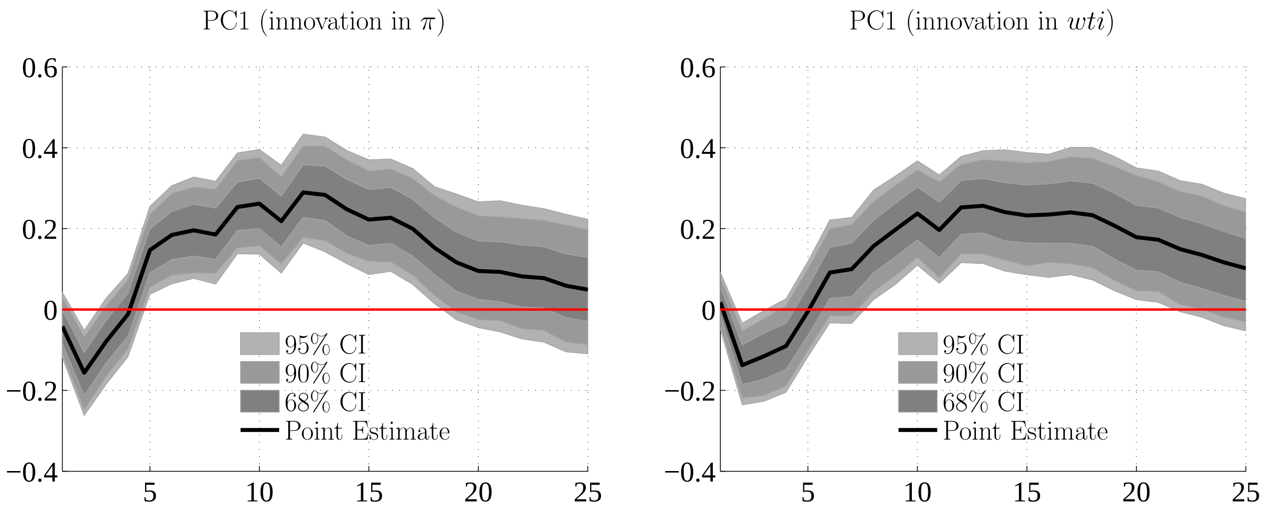
According to the Friedman-Ball hypothesis, there is a positive relationship between inflation and inflation uncertainty. To assess the sign of the effect of an exogenous increase in inflation on uncertainty, we take a dynamic perspective and calculate impulse response functions from the bivariate VAR models introduced above. Orthogonal shocks are identified using a Cholesky ordering such that uncertainty reacts to a shock to inflation instantaneously.[17] This is motivated by the fact that uncertainty may move quickly when agents encounter new macroeconomic information whereas inflation is comparatively slow-moving.[18]

[16] In appendix C.1, we exclude the recent crisis from the sample and end the analysis in 2007:M8 which is roughly when the U.S. sub-prime crisis started to take over to other sectors of the economy. We find that the results derived from the indicator still hold. Also note that the results obtained for individual measures are not robust in the shorter sample.

[17] We also checked the reverse ordering of variables which does not affect the results in a significant way.

[18] Impulse responses of individual measures are presented in appendix C.2. It turns out that responses of individual uncertainty measures to a one standard deviation shock to inflation are rather heterogenous. Again, the link from inflation to inflation uncertainty is not revealed in a conclusive way.

The left panel of figure 5 presents the response of the uncertainty indicator PC1 to a one standard deviation shock to inflation. We observe that uncertainty experiences an initial decline following an inflation shock. In other words, directly after the shock, a forecast for subsequent periods seems to be less uncertain. This may be due to the fact that – given the sluggishness of inflation – a forecast is relatively easy in the period directly following the inflation shock. Let's consider an inflation shock that is the result of a sudden increase in oil prices. Having observed the shock, this very likely decreases uncertainty associated with future inflation. The reason is that forecasters may be relatively sure to observe an instantaneous hike in inflation rates during the first few months after the shock. In the following periods, inflation uncertainty displays a hump-shaped pattern. It quickly increases and becomes positive five months after the shock occurred. Thus, the more time has elapsed since the shock, the more uncertainty is attached to the future course of inflation. Let's consider again a sudden increase in oil prices. In this case, more and more uncertainty develops over time because the long-term effects of such an inflation shock – e.g. via second round effects – are less clear-cut. The response of uncertainty to a shock to the oil price ($wti$) is depicted in the right panel of figure 5. The pattern of the impulse response function very much resembles the response of PC1 to an innovation in inflation. Hence, the plot confirms the hypothesis that the short-term impact of increasing oil prices seems to be relatively clear-cut, whereas longer lasting effects on the inflation rate are uncertain.



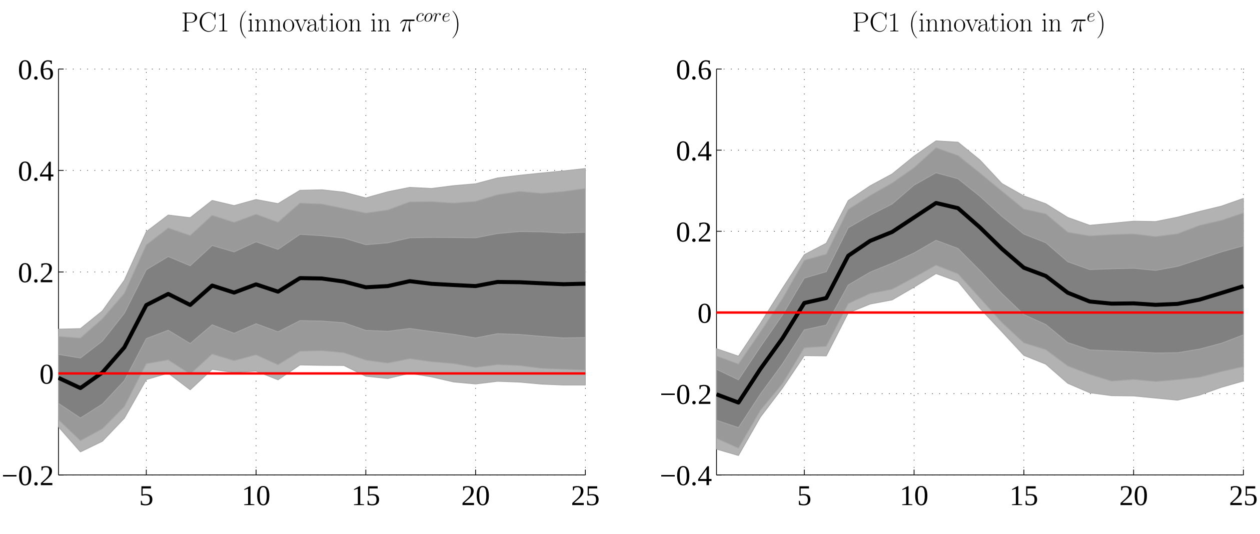

Note: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

Figure 5: Response of inflation uncertainty to different inflation related shocks

In addition to the growing uncertainty about the transmission of a shock, there may be rising uncertainty about the reaction of the central bank. Note that the latter scenario is very much in the spirit of Friedman (1977) who recognizes that, given rising rates of inflation, economic agents become more and more uncertain about the timing and pace at which inflation will return to lower levels again. Overall, the Friedman-Ball hypothesis is confirmed.[19]

Turning to the left panel of figure 6, we observe that a shock to core inflation ($\pi^{core}$) also induces a rise in uncertainty. Here, it takes about four months until uncertainty increases. In contrast to CPI inflation, a shock to core inflation does not induce a fall in uncertainty in the first periods. We take this as further evidence that the initial decrease in uncertainty after a shock to CPI inflation is traceable to the energy component in CPI. That is, once an energy price shock has materialized, the short-run impact of this shock on inflation seems to be well known and, thus, reduces forecast uncertainty. In the long run, however, the rise in uncertainty is even more pronounced after a shock to CPI inflation than after a core inflation shock. Notably, following a one-time increase in core inflation, uncertainty persistently remains on a higher level.

Finally, we consider a shock to inflation expectations ($\pi^e$) as measured by the CE mean forecast (see right panel of figure 6). Here, an increase in inflation expectations is followed by an instantaneous decline in uncertainty. As in the case of inflation and oil price shocks, agents become more and more uncertain about the future path of inflation only in the longer run, given their expectations. Again, this seems to be reasonable if we assume that shifts in inflation expectations are to a considerable extent driven by energy price movements.




Note: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

Figure 6: Response of inflation uncertainty to different inflation related shocks (contd.)

[19] See appendix C.3 for result obtained from standard VARs containing output, inflation, a short-term interest rate, and uncertainty. It turns out that results remain unaffected when a larger VAR is employed. In appendix C.1, we leave out the most recent economic crisis. We find that the response of uncertainty to an inflation shock is largely robust to a change in the sample. However, the reaction is significant only at the 10% level.

In the following, we analyze whether the contribution of inflationary shocks to uncertainty is meaningful in an economic sense. To this end, we present in table 4 the forecast error variance decomposition associated with the bivariate VAR models from the preceding two sections. We find that an inflation shock explains roughly 30% after 15 months. Likewise, core inflation ($\pi^{core}$) shows a peak in the longer run. However, with a value of 14%, it contributes less than headline inflation. It takes 15 months until the oil price ($wti$) contributes substantially. In contrast, shocks to inflation expectations ($\pi^{e}$) explain 10% of the variance of inflation uncertainty on impact, and values increase further with the forecast horizon.

| horizon | **1** | **5** | **10** | **15** | **20** | **25** |
|---|---|---|---|---|---|---|
| $\pi$ | 0.5 | 6.0 | 19.7 | 30.6 | 29.2 | 22.9 |
| $\pi^{core}$ | 0.0 | 1.8 | 7.4 | 11.8 | 13.6 | 14.7 |
| $wti$ | 0.1 | 4.1 | 10.9 | 20.2 | 22.3 | 19.6 |
| $\pi^{e}$ | 10.5 | 13.0 | 15.6 | 19.0 | 15.1 | 12.1 |

Note: Numbers (as % of total variance) give the part of the variance of inflation uncertainty explained by a shock to the respective economic variable. The respective values are derived from bivariate VAR models. Variance decompositions are presented for a horizon of 1, 5, 10, 15, 20, and 25 months.

Table 4: Forecast error variance decomposition

# 5 Conclusion

Analyzing various measures of inflation uncertainty, we find that inflation uncertainty has risen significantly in the aftermath of the recent financial crisis. This highlights the importance of understanding the causes and consequences of inflation uncertainty. However, empirical results derived from different measures are not so clear-cut. One reason may be that the assumptions that need to hold for any individual measure to be a valid proxy for uncertainty differ substantially. Hence, individual measures are likely contaminated with idiosyncratic measurement error.

We use common information contained in different measures to eliminate the measurement error. To this end, we calculate survey-based measures as well as measures derived from time series models, and we put forward a forecast-based approach. We find that each individual measure – including disagreement – contains valuable information about inflation uncertainty. It turns out that all measures are driven by a common component which we interpret as an indicator for inflation uncertainty. Note that the indicator mitigates the measurement error problem and the underlying signal should be revealed with greater precision.

However, the indicator does not completely explain the variation in the data. We find that individual measures tend to differ more during turbulent times, i.e. when uncertainty is high. Moreover, it appears that using only survey disagreement as a measure of uncertainty, a researcher may be confronted with respondents sticking to the consensus during recessions. Hence, using only survey disagreement as a measure of inflation uncertainty may deliver misleading results.

Subsequently, we use the proposed indicator to test the Friedman-Ball hypothesis. It appears that Granger causality tests cannot reject the Friedman-Ball hypothesis. Hence, when the central bank implements a higher inflation rate, it is likely followed by increased uncertainty. Eventually, misallocations arising from increased inflation uncertainty may give rise to additional economic cost.

We also study the dynamic response of uncertainty to an inflation shock. It appears that uncertainty initially tends to decrease. However, uncertainty swiftly increases in subsequent periods. This behavior is traceable to the energy component in CPI inflation. Sudden oil price increases, for instance, are followed by an initial decrease in inflation uncertainty. In the longer run, uncertainty eventually rises because long-term effects of these oil price increases appear to be harder to predict. Overall, we conclude that higher inflation is followed by higher uncertainty. However, it is difficult to establish causal relationships by empirical testing only. Hence, in future research we need to obtain a deeper understanding of the dynamic transmission from inflation to uncertainty. We also need to establish causal economic relationships from theoretical reasoning which would facilitate to find ways to prevent inflation uncertainty.

# Appendix

## A.1 Description of survey data

We use individual forecasts on CPI inflation from professional forecasters polled by Consensus Economics (CE). CE reports average annual growth rates of expected inflation for the current and the next calendar year. However, since the forecast horizon varies for each month, the cross-sectional dispersion of forecasts is strongly seasonal and converges towards zero at the end of each year (Lahiri and Sheng, 2010). To obtain twelve-month-ahead inflation forecasts, we follow Dovern et al. (2009) and calculate a weighted moving average of the annual forecasts. For each month $m$, the fixed horizon forecast is obtained by weighting the two available point estimates according to their respective share in the forecasting horizon, i.e., $\frac{12-m+1}{12}$ for the current year's forecast and $\frac{m-1}{12}$ for the next year's forecast. The average number of fixed horizon forecasts ranges between 16 and 32 per period, with a mean value of 25 observations.

## A.2 Variables used to forecast inflation

| Variable | Transformation |
|---|---|
| Average hourly earnings (nonfarm payroll) | change of growth rate |
| Building permits for new private housing units | growth rate |
| Capacity utilization (manufacturing) | growth rate |
| Crude oil index | change of growth rate |
| Employment (nonagricultural industries) | gap measure |
| Federal funds effective rate | growth rate |
| Interest rate spread | – |
| M3 | change of growth rate |
| New orders (manufacturing) | growth rate |
| Nominal narrow effective exchange rate | growth rate |
| OECD composite leading indicators | growth rate |
| Personal income | growth rate |
| Retail sales | growth rate |
| Total production | gap measure |
| Unemployment rate | gap measure |

Note: "gap measure" denotes series that have been detrended with the HP-filter; "interest rate spread" is defined as the difference between interest rate on government bonds and federal funds rate.

Table A.1: Variables used to forecast inflation

## A.3 TVP-GARCH

| $\sigma^2_{\alpha_0}$ | $\sigma^2_{\alpha_1}$ | $\sigma^2_{\alpha_2}$ | $d$ | $\phi_1$ | $\gamma_1$ |
|---|---|---|---|---|---|
| 0.00 | 0.00 | 0.00 | 0.00 | 0.12 | 0.87 |
| [0.99] | [0.98] | [0.76] | [0.20] | [0.02] | [0.00] |
| $p(Q(1))$ | $p(Q(3))$ | $p(Q(6))$ | $p(Q(9))$ | | |
| 0.15 | 0.15 | 0.45 | 0.64 | | |
| $p(LM(1))$ | $p(LM(3))$ | $p(LM(6))$ | $p(LM(9))$ | | |
| 0.45 | 0.41 | 0.55 | 0.65 | | |

Note: Parameter p-values are given in brackets. p-values for a Q-test as well as an ARCH LM-test are given below.

Table A.2: Parameters and specification tests for the TVP-GARCH model for U.S. inflation

## B.1 Individual uncertainty measures

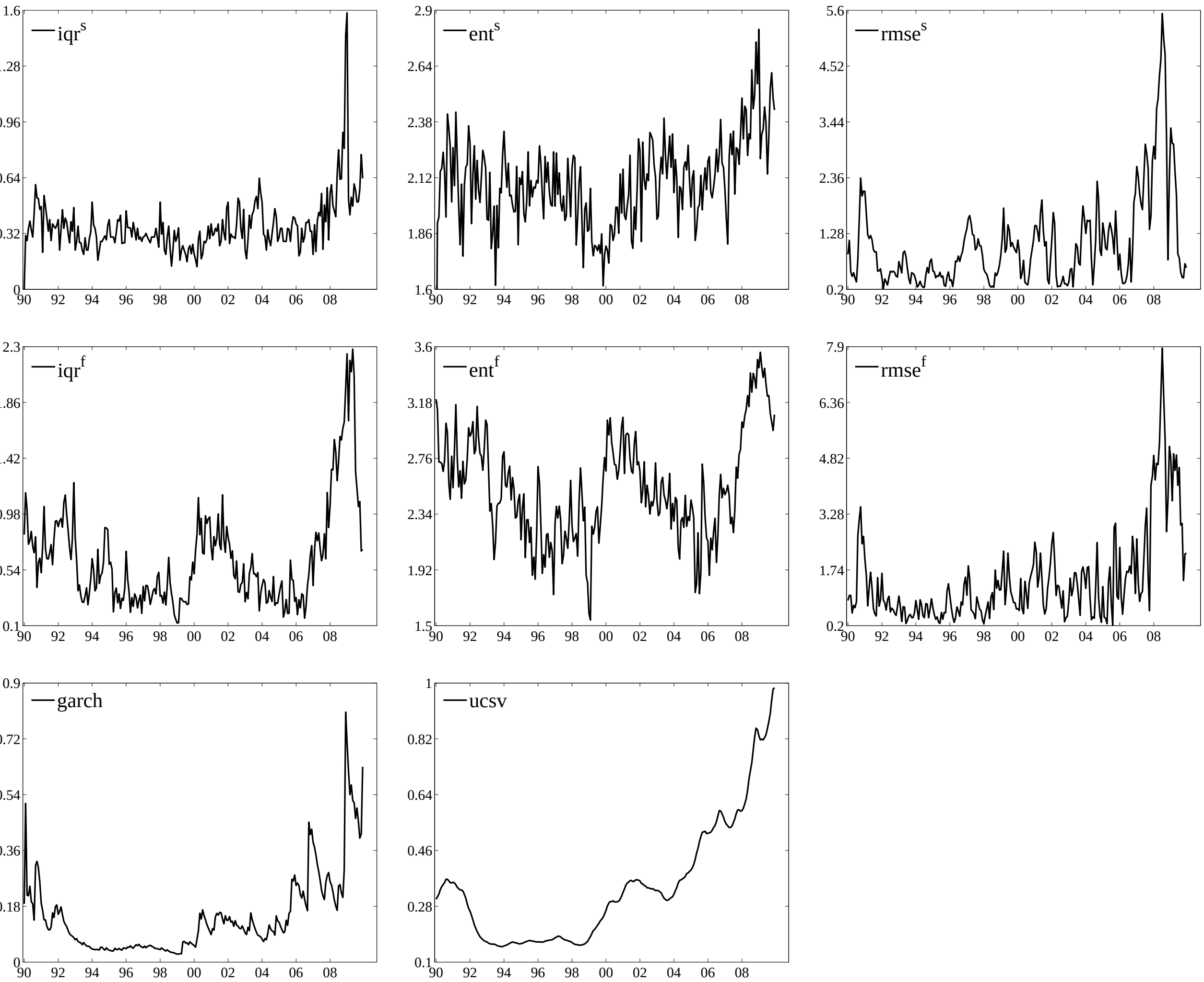



Figure B.1: Survey-based ($iqr^s$, $ent^s$, $rmse^s$), forecast-based ($iqr^f$, $ent^f$, $rmse^f$), and model-based ($garch$, $ucsv$) measures of inflation uncertainty

| | $iqr^s$ | $ent^s$ | $rmse^s$ | $iqr^f$ | $ent^f$ | $rmse^f$ | $garch$ | $ucsv$ |
|---|---|---|---|---|---|---|---|---|
| $(\Delta\pi)^2$ | **0.33** | **0.31** | **0.30** | **0.21** | **0.22** | **0.37** | **0.26** | **0.42** |
| $(\Delta\pi^{core})^2$ | **0.16** | | | **0.18** | **0.18** | **0.14** | | |
| $\Delta M2$ | **0.24** | | **0.18** | **0.15** | | **0.25** | **0.13** | **0.15** |
| $(\Delta M2)^2$ | **0.44** | **0.19** | **0.25** | **0.33** | **0.26** | **0.38** | **0.27** | **0.24** |
| $ffr$ | −0.40 | −0.39 | −0.41 | −0.34 | −0.32 | −0.45 | −0.35 | −0.48 |
| $r^{3M}$ | −0.43 | −0.43 | −0.45 | −0.38 | −0.37 | −0.48 | −0.37 | −0.52 |
| $r^{10Y}$ | −0.23 | −0.24 | −0.19 | | | −0.22 | −0.24 | −0.48 |
| $\Delta ffr$ | −0.26 | −0.25 | −0.15 | −0.32 | −0.36 | −0.24 | −0.14 | −0.16 |
| $\Delta r^{3M}$ | −0.16 | −0.16 | | −0.25 | −0.30 | | | |
| $\Delta r^{10Y}$ | | | | | | | | |
| $abs(\Delta ffr)$ | | | | **0.22** | **0.25** | | | |
| $abs(\Delta r^{3M})$ | | | | **0.19** | **0.23** | | | |
| $abs(\Delta r^{10Y})$ | **0.26** | **0.29** | **0.24** | **0.23** | **0.25** | **0.29** | **0.29** | **0.43** |
| $vix$ | **0.43** | **0.28** | **0.53** | **0.50** | **0.44** | **0.52** | **0.40** | **0.37** |
| $ted$ | **0.26** | **0.16** | **0.36** | **0.35** | **0.22** | **0.31** | **0.16** | **0.24** |
| $risk$ | **0.22** | | **0.38** | **0.46** | **0.43** | **0.40** | **0.27** | **0.31** |
| $sp500$ | −0.15 | | | −0.19 | −0.20 | −0.17 | | −0.15 |
| $dj$ | −0.15 | | −0.14 | −0.18 | −0.19 | −0.16 | | −0.14 |
| $dj5000$ | −0.18 | | | −0.16 | −0.15 | −0.17 | | |
| $sp500^2$ | **0.20** | **0.15** | **0.22** | **0.28** | **0.23** | **0.31** | | **0.22** |
| $dj^2$ | **0.17** | **0.13** | **0.20** | **0.26** | **0.22** | **0.28** | | **0.19** |
| $dj5000^2$ | **0.23** | **0.14** | **0.24** | **0.29** | **0.27** | **0.28** | | **0.19** |
| $house$ | −0.49 | −0.47 | −0.48 | −0.65 | −0.51 | −0.53 | −0.47 | −0.38 |
| $\Delta house$ | | | | | | | | |
| $(\Delta house)^2$ | **0.23** | **0.36** | **0.33** | **0.22** | **0.25** | **0.40** | **0.53** | **0.63** |
| $recession$ | **0.46** | **0.37** | **0.46** | **0.63** | **0.57** | **0.57** | **0.46** | **0.46** |

| | $iqr^s$ | $ent^s$ | $rmse^s$ | $iqr^f$ | $ent^f$ | $rmse^f$ | $garch$ | $ucsv$ |
|---|---|---|---|---|---|---|---|---|
| $wti$ | | −0.14 | | −0.15 | | | | |
| $ppi^{comm}$ | | | −0.21 | −0.20 | | −0.15 | −0.20 | |
| $ppi^{ind}$ | | | −0.20 | −0.21 | | −0.16 | −0.20 | |
| $crb$ | −0.16 | | −0.30 | −0.34 | −0.23 | −0.31 | −0.32 | −0.14 |
| $(\Delta wti)^2$ | | | **0.19** | **0.15** | **0.27** | **0.20** | **0.14** | **0.28** |
| $(\Delta ppi^{comm})^2$ | **0.37** | **0.36** | **0.36** | **0.29** | **0.31** | **0.47** | **0.35** | **0.52** |
| $(\Delta ppi^{ind})^2$ | **0.33** | **0.35** | **0.33** | **0.26** | **0.28** | **0.42** | **0.32** | **0.49** |
| $(\Delta crb^{return})^2$ | **0.34** | **0.33** | **0.32** | **0.29** | **0.29** | **0.41** | **0.27** | **0.47** |
| $ism$ | −0.40 | −0.30 | −0.32 | −0.50 | −0.42 | −0.40 | −0.40 | −0.30 |
| $ism^{prod}$ | −0.39 | −0.29 | −0.31 | −0.45 | −0.38 | −0.37 | −0.36 | −0.27 |
| $pmi$ | −0.40 | −0.28 | −0.39 | −0.55 | −0.50 | −0.46 | −0.46 | −0.38 |
| $pmi^{prod}$ | −0.44 | −0.29 | −0.42 | −0.56 | −0.48 | −0.49 | −0.49 | −0.42 |
| $mhs$ | −0.62 | −0.61 | −0.60 | −0.72 | −0.68 | −0.66 | −0.64 | −0.65 |
| $confidence$ | −0.51 | −0.53 | −0.40 | −0.52 | −0.51 | −0.44 | −0.48 | −0.44 |
| $cu$ | −0.47 | −0.42 | −0.55 | −0.54 | −0.53 | −0.62 | −0.64 | −0.70 |
| $cu^{man}$ | −0.50 | −0.43 | −0.58 | −0.57 | −0.54 | −0.65 | −0.66 | −0.74 |
| $cu^{exIT}$ | −0.51 | −0.44 | −0.62 | −0.62 | −0.59 | −0.69 | −0.70 | −0.77 |
| $\Delta y$ | −0.57 | −0.47 | −0.66 | −0.73 | −0.65 | −0.74 | −0.72 | −0.74 |
| $\Delta y^{man}$ | −0.59 | −0.48 | −0.66 | −0.74 | −0.66 | −0.75 | −0.73 | −0.74 |
| $(\Delta y)^2$ | **0.35** | **0.23** | **0.60** | **0.57** | **0.36** | **0.47** | **0.48** | **0.36** |
| $(\Delta y^{man})^2$ | **0.40** | **0.27** | **0.63** | **0.61** | **0.38** | **0.52** | **0.52** | **0.39** |
| $\Delta empl$ | −0.54 | −0.50 | −0.61 | −0.65 | −0.63 | −0.67 | −0.68 | −0.69 |
| $\Delta jobless$ | **0.49** | **0.36** | **0.54** | **0.70** | **0.59** | **0.60** | **0.56** | **0.51** |
| $\Delta u$ | **0.54** | **0.48** | **0.66** | **0.74** | **0.68** | **0.70** | **0.65** | **0.64** |
| $ur$ | **0.40** | **0.43** | **0.38** | **0.45** | **0.46** | **0.40** | **0.42** | **0.32** |
| $\Delta ur$ | **0.54** | **0.49** | **0.66** | **0.72** | **0.67** | **0.70** | **0.68** | **0.66** |

Note: Numbers represent correlations significant at the 5% level. We do not provide a number for insignificant correlations. Positive correlations are given in bold figures. A detailed description of economic variables is presented in table B.2.

Table B.1: Correlations of uncertainty measures with economic and financial variables

| Variable | Description | Variable | Description |
|---|---|---|---|
| $\pi$ | Consumer Price Inflation | $brent$ | Oil price inflation - Brent spot price for crude oil |
| $\pi^{core}$ | Core Inflation (Consumer Price Index less energy) | $wti$ | Oil price inflation - West Texas Intermediate spot price for crude oil |
| $\Delta\pi$ | MoM change of inflation | $opec$ | Oil price inflation - OPEC reference basket price for crude oil |
| $\Delta\pi^{core}$ | MoM change of core inflation | $ppi^{comm}$ | Producer price inflation - Commodities |
| $(\Delta\pi)^2$ | Squared change of inflation | $ppi^{ind}$ | Producer price inflation - Industrial commodities |
| $(\Delta\pi^{core})^2$ | Squared change of core inflation | $crb$ | Commodity price inflation - Reuters/CRB total return index |
| $\pi^e$ | Expected inflation from Consensus Economics | $(\Delta brent)^2$ | Squared change of brent oil price |
| $\Delta M2$ | MoM change of M2 money supply | $(\Delta wti)^2$ | Squared change of WTI oil price |
| $(\Delta M2)^2$ | Squared change of M2 money supply | $(\Delta opec)^2$ | Squared change of OPEC oil price |
| $ffr$ | Federal funds rate | $(\Delta ppi^{comm})^2$ | Squared change of producer price inflation (commodities) |
| $r^{3M}$ | 3-month treasury bill rate | $(\Delta ppi^{ind})^2$ | Squared change of producer price inflation (industrial commodities) |
| $r^{10Y}$ | 10-year government benchmark, average yield | $(\Delta crb^{return})^2$ | Squared returns Reuters/CRB total return index |
| $\Delta ffr$ | MoM change of federal funds rate | $ism$ | ISM manufacturing total index |
| $\Delta r^{3M}$ | MoM change of 3-month treasury bill rate | $ism^{prod}$ | ISM manufacturing production index |
| $\Delta r^{10Y}$ | MoM Change of 10-year government benchmark rate | $pmi$ | Chicago PMI total index of business activity |
| $abs(\Delta ffr)$ | Absolute change of federal funds rate | $pmi^{prod}$ | Chicago PMI production index of business activity |
| $abs(\Delta r^{3M})$ | Absolute change of 3-month T-Bill | $mhs$ | Consumer survey index - Michigan Household Survey |
| $abs(\Delta r^{10Y})$ | Absolute change of 10-year government benchmark rate | $confidence$ | Consumer confidence index - Conference board |
| $vix$ | CBOE Market volatility index | $cu$ | Capacity utilization rate, total industry |
| $ted$ | Difference between interest rates on interbank loans and treasury bill rate | $cu^{man}$ | Capacity utilization rate, manufacturing |
| $risk$ | Difference between interest rates on corporate bonds and government benchmarks | $cu^{exIT}$ | Capacity utilization rate, manufacturing excluding IT |
| $sp500$ | Standard & Poor's 500 Index returns | $\Delta y$ | Change of monthly index of industrial production |
| $dj$ | Dow Jones Index returns | $\Delta y^{man}$ | Change of monthly index of manufacturing production |
| $dj5000$ | Dow Jones 5000 Index returns | $(\Delta y)^2$ | Squared change of industrial production |
| $sp500^2$ | Squared returns Standard & Poor's 500 Index | $(\Delta y^{man})^2$ | Squared change of manufacturing production |
| $dj^2$ | Squared returns Dow Jones Index | $\Delta empl$ | Change of nonfarm-payroll employment |
| $dj5000^2$ | Squared returns Dow Jones 5000 Index | $\Delta empl^{full}$ | Change of full-time employment |
| $house$ | House price inflation by S&P/Case-Shiller | $\Delta jobless$ | Change of initial jobless claims |
| $\Delta house$ | MoM change of house price inflation | $\Delta u$ | Change of unemployment |
| $(\Delta house)^2$ | Squared change of house price inflation | $ur$ | Unemployment rate |
| $recession$ | NBER recession dummy (recession: 1, no recession: 0) | $\Delta ur$ | Change of unemployment rate |

Table B.2: Description of economic variables

## B.2 Cointegration analysis

In section 3.1, we note that the underlying uncertainty measures are rather persistent. From a theoretical point of view, uncertainty is clearly bounded and cannot rise infinitely. However, from a statistical point of view – depending on the observed time-span – the measures may be observationally equivalent to an integrated process. Consequently, we test each of the variables for stationarity using the DF-GLS test and KPSS test. Test results are presented in table B.3. According to the DF-GLS test, the null of a unit root is rejected for half of the eight uncertainty measures. However, the KPSS test suggests that six uncertainty measures are non-stationary at least at the 5% level. Altogether, we obtain rather mixed results.

| | ERS DF-GLS Test Stat. | KPSS Test Stat. | Lag Order BIC |
|---|---|---|---|
| $iqr^s$ | $-1.51$ | $0.70^{**}$ | 2 |
| $ent^s$ | $-0.30$ | $0.78^{***}$ | 2 |
| $rmse^s$ | $-3.21^{***}$ | $0.74^{***}$ | 2 |
| $iqr^f$ | $-2.57^{**}$ | $0.36^{*}$ | 1 |
| $ent^f$ | $-1.61$ | $0.26$ | 2 |
| $rmse^f$ | $-2.74^{***}$ | $0.90^{***}$ | 2 |
| $garch$ | $-2.35^{**}$ | $0.95^{***}$ | 0 |
| $ucsv$ | $0.80$ | $1.47^{***}$ | 14 |

Note: Intercept, no trend, lag length chosen according to BIC. Null for DF-GLS test: Time series has a unit root. Null for KPSS test: Time series is stationary. Critical values for DF-GLS test statistic: -2.57 (1%), -1.94 (5%), -1.62 (10%). Critical values for KPSS test statistic: 0.74 (1%), 0.46 (5%), 0.35 (10%).

Table B.3: DF-GLS and KPSS test

In table B.4, we also apply panel unit root tests in order to detect an individual or common unit root in the series. Due to their cross-sectional dimension, these tests overcome the drawback of standard unit root tests which have little power to distinguish highly persistent stationary time series from non-stationary processes. It turns out that results are mixed as well. While the respective tests unanimously confirm the presence of a common unit root process in the data, tests for individual unit roots indicate that a fraction of the eight measures is stationary. However, since the null of no common trends among the series can be rejected according to the Nyblom-Harvey test statistic, for the moment we may consider uncertainty being observationally equivalent to an I(1) process. Note that we impose the assumption that there is no mean reversion of individual uncertainty measures.

| Method | Statistic | Prob. |
|---|---|---|
| $H_0$: Unit root (assumes common unit root process) | | |
| Levin, Lin and Chu t* | 2.85 | 0.998 |
| $H_0$: No unit root (assumes common unit root process) | | |
| Hadri Z-stat | 11.88 | 0.000 |
| $H_0$: Unit root (assumes individual unit root process) | | |
| Im, Pesaran and Shin W-stat | $-4.87$ | 0.000 |
| Pesaran's CADF test | $-4.44$ | 0.000 |
| $H_0$: 0 common trends among the 8 series in the panel | | |
| Nyblom-Harvey statistic | $7.88^{***}$ | - |

Note: Individual intercept, no trend. 2 lags used for Pesaran's CADF test. Nyblom-Harvey (NH) test statistic calculated by assuming serially correlated errors with nonparametric adjustment for long-run variance. Critical values for NH test statistic: 2.52 (1%), 2.07 (5%), 1.87 (10%).

Table B.4: Panel unit root tests

We proceed by testing for cointegration among the variables. Table B.5 displays the results from the Johansen cointegration test. Both the Trace and the Maximum Eigenvalue test statistic indicate seven cointegration relations in the data. Hence, we conclude that there is one common trend in the data.

| | $\lambda$-Trace | $\lambda$-Max |
|---|---|---|
| Null | Test Stat. | Test Stat. |
| r = 0 | $457.62^{***}$ | $128.90^{***}$ |
| r $\leq$ 1 | $328.73^{***}$ | $92.00^{***}$ |
| r $\leq$ 2 | $236.73^{***}$ | $68.94^{***}$ |
| r $\leq$ 3 | $167.78^{***}$ | $67.50^{***}$ |
| r $\leq$ 4 | $100.28^{***}$ | $44.78^{***}$ |
| r $\leq$ 5 | $55.49^{***}$ | $37.30^{***}$ |
| r $\leq$ 6 | $18.20^{*}$ | $16.35^{***}$ |
| r $\leq$ 7 | 1.85 | 1.85 |

Note: Intercept, no trend. 2 lags were chosen according to BIC and HQIC.

Table B.5: Johansen cointegration test

We extract the common (permanent) component by means of a multivariate Beveridge-Nelson decomposition. For this purpose, a Vector Error Correction Model (VECM) of the following form is estimated:

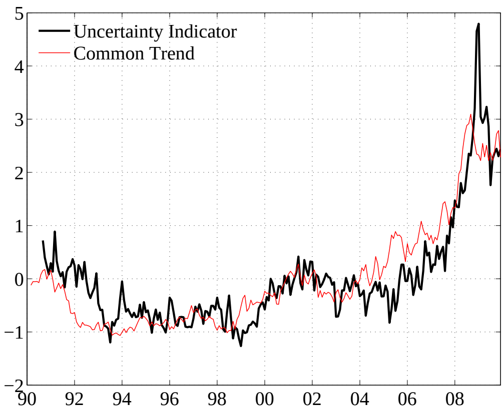
$$\Delta y_t = \alpha(\delta_0 + \beta' y_{t-1}) + \sum_{j=1}^{J} \Gamma_j \Delta y_{t-j} + u_t, \tag{11}$$

where $y_t$ is a $(k \times 1)$ vector of uncertainty measures, $\alpha$ denotes the $(k \times r)$ matrix of loadings, $\beta$ denotes the $(k \times r)$ matrix of parameters in the $r = 7$ cointegration relations and $\Gamma_j$ is the short-run coefficient matrix. 2 lags where chosen according to BIC and HQIC. To obtain the

Beveridge-Nelson decomposition consider the MA representation of the VECM:

$$y_t = \Xi \sum_{i=1}^{t} u_i + \sum_{j=0}^{\infty} \Xi_j^* u_{t-j} + y_0^*, \tag{12}$$

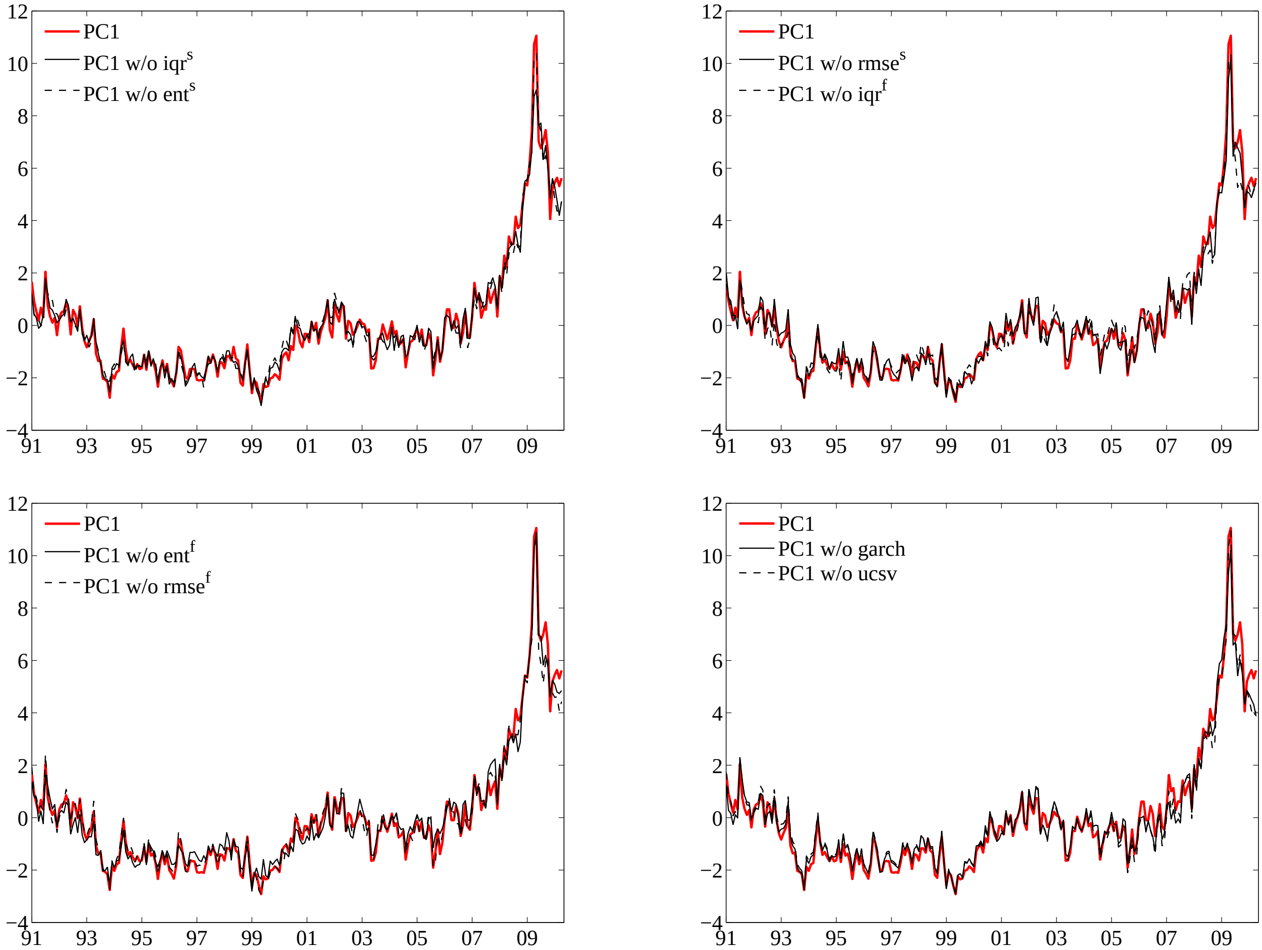
where $\Xi \sum_{i=1}^{t} u_i$ denotes the common trend term and $y_0^*$ represents initial values of the variables. The matrix $\Xi$ has rank 1. The resulting common trend is displayed in figure B.2. It appears that it closely mimics the uncertainty indicator introduced in section 3.2.




Note: The bold black line represents the indicator for inflation uncertainty (PC1), the thin red line depicts the common trend derived from a Beveridge-Nelson decomposition. For comparability, both time series have been normalized to have mean zero and standard deviation one.

Figure B.2: Uncertainty indicator and common trend

## B.3 Robustness of the uncertainty indicator




Note: The bold (red) line represents PC1. The thin line and the dashed line represent an uncertainty measure calculated from a subsample of individual measures discarding one of the measures.

Figure B.3: Different uncertainty indicators constructed from a subsample of individual uncertainty measures

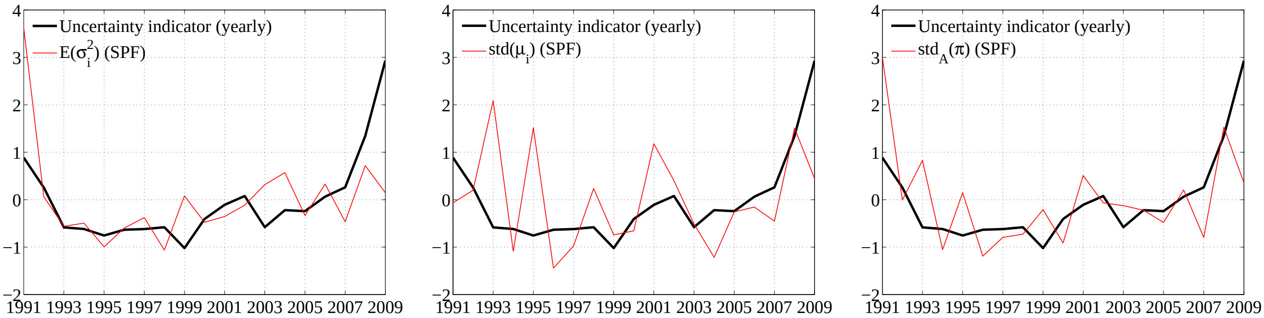
## B.4 Comparison to SPF measures

Some papers propose subjective probability distributions obtained from the Survey of Professional Forecasters (SPF) as a measure of inflation uncertainty (Zarnowitz and Lambros, 1987; Lahiri et al., 1988). These studies distinguish between individual uncertainty, cross-sectional dispersion, and aggregate uncertainty. First, the survey design allows for a deduction of individual uncertainty $E(\sigma_i^2)$ because each respondent provides a histogram of future inflation. Second, it is also possible to calculate disagreement $\mathrm{var}(\mu_i)$ among different forecasters from the mean of individual distributions. Third, a measure of aggregate uncertainty $\mathrm{var}_A(\pi)$ can be calculated if single histograms are aggregated to obtain a finite mixture distribution (Wallis, 2005). As shown by Giordani and Söderlind (2003), these three measures are related by construction:

$$\mathrm{var}_A(\pi) = E(\sigma_i^2) + \mathrm{var}(\mu_i). \tag{13}$$

In the following, we compare the uncertainty indicator from section 3.2 to the measures derived from SPF subjective probability distributions. However, some limitations to such a comparison should be noted. First, SPF forecasts are referring to the GDP deflator since probability forecasts on the CPI inflation rate have only been included in the questionnaire from 2007 onwards. Second, a number of technical assumptions needed to calculate SPF uncertainty measures and changes in the survey design may give rise to measurement error. To calculate SPF uncertainty, we follow D'Amico and Orphanides (2008), and Lahiri and Sheng (2010) by using a non-parametric approach. We obtain $E(\sigma_i^2)$ as the average of individual standard deviations adding a Sheppard correction. To be comparable to most other studies, disagreement, here, is simply the cross-sectional standard deviation of the respective mean of individual probability distributions represented by $\mathrm{std}(\mu_i)$. Aggregate uncertainty is given by calculating the standard deviation of the aggregate distribution $\mathrm{std}_A(\pi)$. We use measures based on a fixed forecast horizon of one year usually published at the end of the first quarter. That is, SPF data is available on a yearly frequency. To compare the monthly uncertainty indicator with SPF measures, we take the value obtained for March of the respective year. In figure B.4, we depict the resulting time series which have both been normalized to have mean zero and standard deviation one.

It turns out that individual uncertainty as well as aggregate uncertainty from SPF are rather volatile with a spike in the year 1991 and an upward movement since 2000. The uncertainty indicator tracks $\mathrm{E}(\sigma_i^2)$ quite well and both series co-move with correlation coefficient 0.42. It appears that our uncertainty indicator (PC1) is less volatile. Moreover, the recent hike in




Note: The bold black line shows the uncertainty indicator transformed into yearly data. The thin red line represents the respective uncertainty measure derived from SPF data.

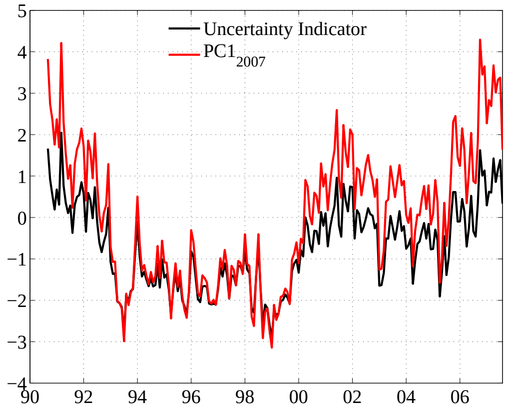
Figure B.4: Yearly uncertainty indicator (PC1) and inflation uncertainty derived from SPF

inflation uncertainty is more pronounced. The movements of SPF disagreement are, however, not so closely tracked by the indicator. This probably reflects the fact that PC1 relies on various measures of uncertainty whereas SPF disagreement covers only a single aspect, i.e. the cross-sectional dispersion. The largest correlation is observed for aggregate uncertainty ($\rho = 0.48$) which covers both, the concept of individual uncertainty and cross-sectional dispersion. Generally speaking, the indicator broadly retraces the movements of uncertainty measures derived from SPF.

## C.1 Excluding the crisis from the sample

Figure C.1 shows the uncertainty indicator PC1 and an indicator derived from a sample that excludes the crisis, $PC1_{2007}$. Differences between the measures are relatively small, in some time periods even non-existent.

Table C.1 presents Granger causalities among different uncertainty measures and inflation $\pi$ and the change in inflation $\Delta\pi$, respectively. It appears that the effects are more pronounced once we include the recent financial crisis into the data set. That is, Granger causality running from inflation to the uncertainty indicator $PC1_{2007}$ is estimated with less precision, though it is significant at the 10% level. Considering the change in inflation, results remain significant at the 5% level. Apart from $ent^s$, the results presented in table 3 are reproduced.




Note: The bold black line represents the indicator for inflation uncertainty (PC1) based on the whole sample. The thin red line labeled $PC1_{2007}$ represents the uncertainty indicator calculated based on a sample ending in 2007 $M8$.

Figure C.1: Uncertainty indicator excluding the crisis

| | $PC1_{2007}$ | $irq^s$ | $ent^s$ | $rmse^s$ | $iqr^f$ | $ent^f$ | $rmse^f$ | $garch$ | $ucsv$ |
|---|---|---|---|---|---|---|---|---|---|
| $H_0$: $\pi$ does not Granger cause IU | 0.07 | **0.00** | **0.01** | 0.44 | 0.56 | 0.82 | 0.95 | **0.02** | 0.11 |
| $H_0$: IU does not Granger cause $\pi$ | 0.93 | 0.71 | 0.90 | 0.07 | 0.90 | 0.68 | 0.37 | 0.19 | 0.96 |
| $H_0$: $\Delta\pi$ does not Granger cause IU | **0.05** | **0.00** | **0.02** | 0.40 | 0.62 | 0.91 | 0.95 | **0.02** | 0.20 |
| $H_0$: IU does not Granger cause $\Delta\pi$ | 0.86 | 0.98 | 0.85 | **0.02** | 0.41 | 0.13 | **0.03** | 0.17 | 0.51 |

Note: Granger causality tests are performed for inflation $\pi$ as well as the change of inflation $\Delta\pi$ and inflation uncertainty (IU). Numbers are p-values for a Granger causality test.

Table C.1: Granger causality test for inflation uncertainty and inflation (1991-2007)

Figure C.2 shows impulse responses of $PC1_{2007}$ to a shock to inflation. When compared to figure 5, the pattern does not change. However, the reaction of uncertainty is significant only at the 10% level. Hence, robustness checks suggest that our results are not driven by the financial crisis only. However, the years 2008 to 2010 seem to be useful to better identify the connection between inflation and uncertainty.

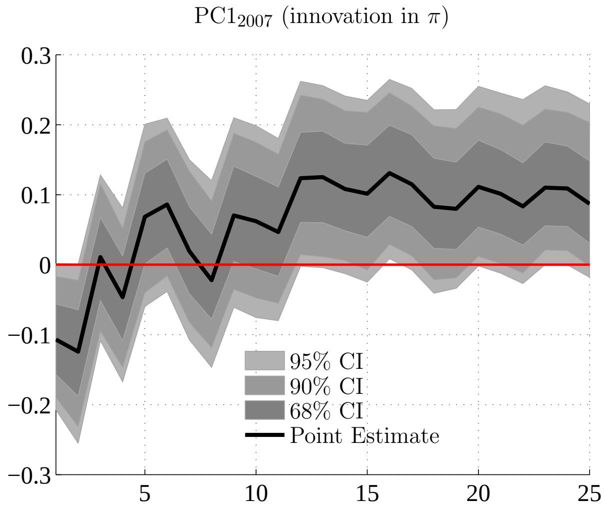
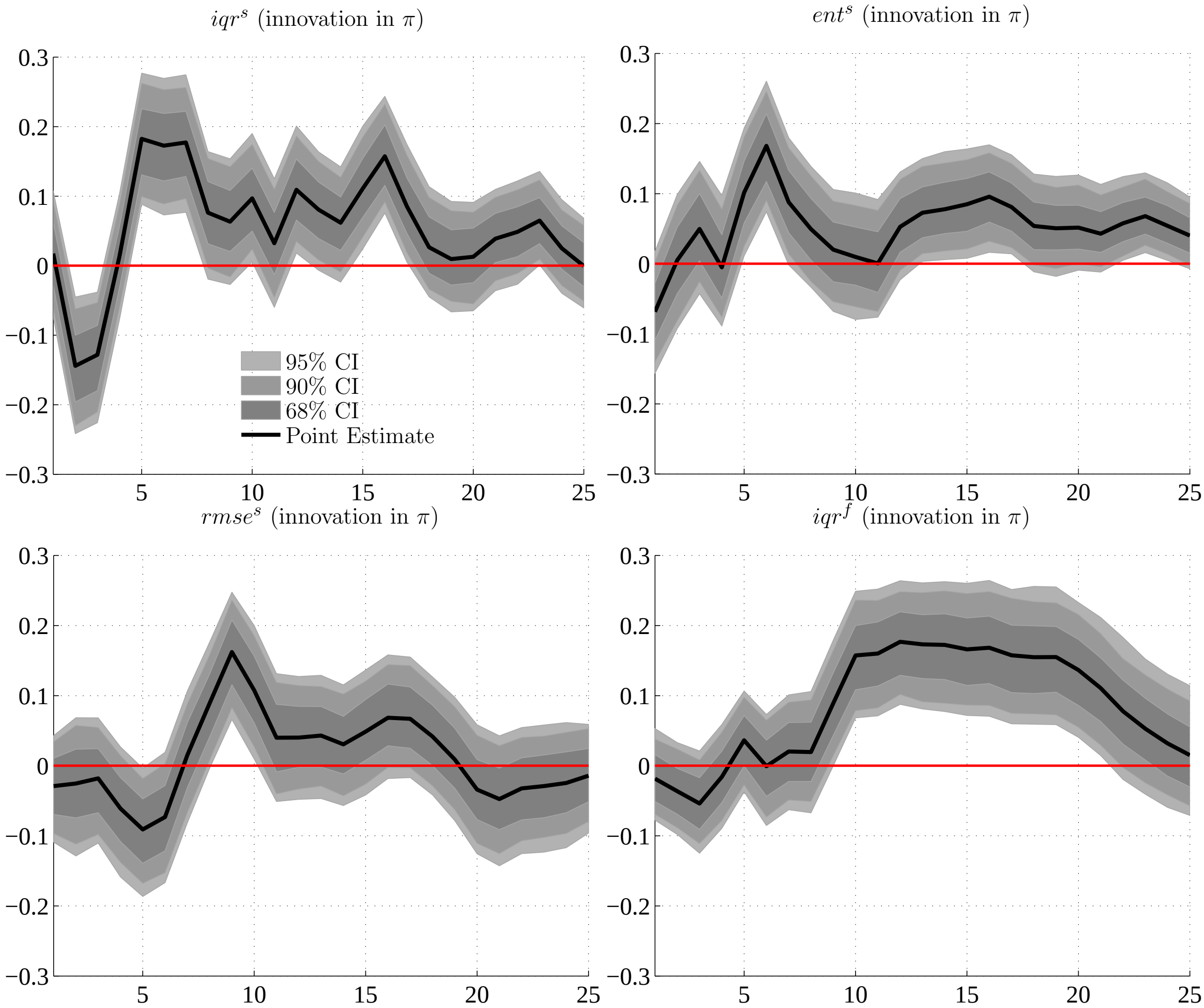


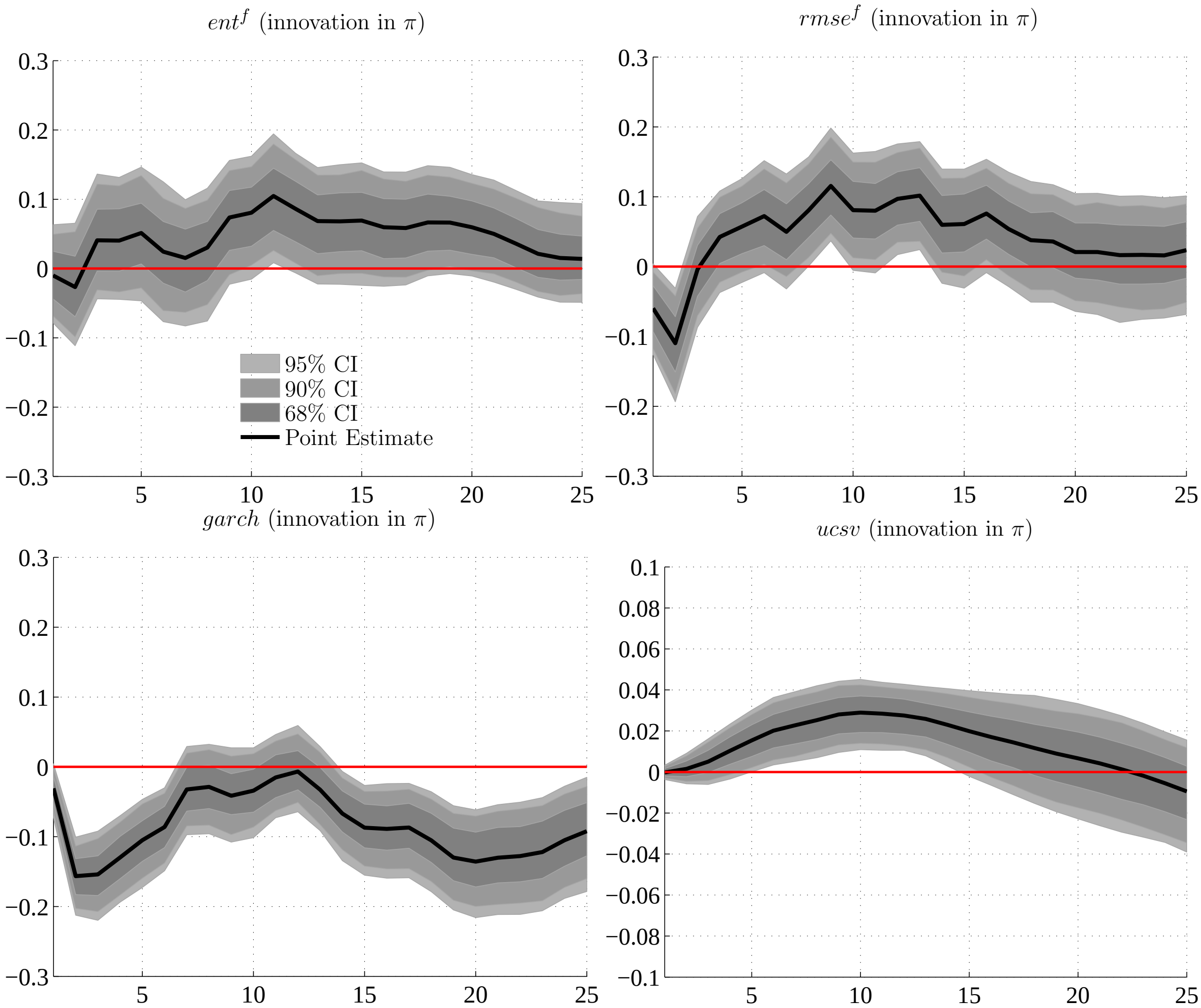

Figure C.2: Response of inflation uncertainty to an inflation shock (1991-2007)

## C.2 Impulse responses of individual uncertainty measures




Note: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

Figure C.3: Response of individual uncertainty measures




Note: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

Figure C.4: Response of individual uncertainty measures (contd.)

## C.3 Robustness of impulse response functions

In the following, we analyze whether the response of uncertainty to an inflation shock is robust to alternative VAR specifications. To this end, we specify a larger VAR which is standard for monetary policy analysis. It includes monthly data on industrial production, consumer prices, the federal funds rate, and inflation uncertainty. Note that inflation uncertainty is ordered last. We consider two alternatives. First, all variables except the interest rate enter in log-levels. Second, we include production growth and inflation instead of production and the price level. The resulting impulse response functions are presented in figure C.5. It turns out that our results remain unaffected by the inclusion of additional variables.

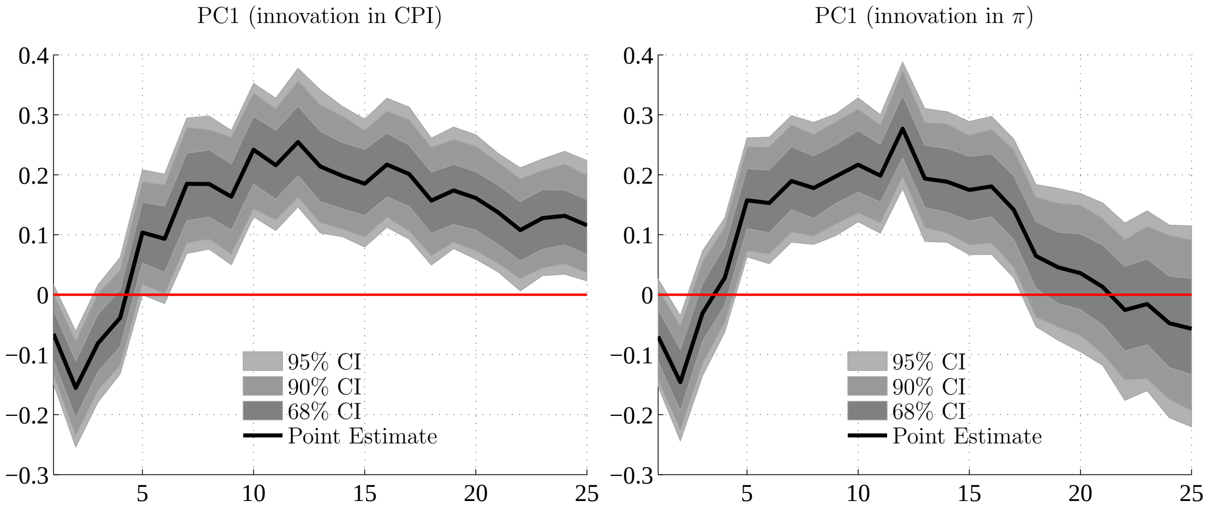



Figure C.5: Response of inflation uncertainty to an inflation shock in a 4-variable VAR

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