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Working Paper

Inflation uncertainty revisited: A proposal for robust measurement

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Inflation uncertainty revisited: A proposal for robust measurement

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Ifo Working Paper No. 111

This version: October 2012

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“Inflation uncertainty revisited: Do different measures disagree?”

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Inflation uncertainty revisited: A proposal for robust measurement*

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Abstract

Any measure of unobserved inflation uncertainty relies on specific assumptions which are most likely not fulfilled completely. This calls into question whether an individual measure delivers a reliable signal. To reduce idiosyncratic measurement error, we propose using common information contained in different measures derived from survey data, a variety of forecast models, and volatility models. We show that all measures are driven by a common component which constitutes an indicator for inflation uncertainty. Moreover, the idiosyncratic component of survey disagreement contains systematic measurement error during economic downturns. Finally, we study the Friedman-Ball hypothesis. Using the indicator, it turns out that higher inflation is followed by higher uncertainty. By contrast, we obtain contradictory results for the individual measures. We also document that, after an inflationary shock, uncertainty decreases in the first two months which is traceable to the energy component in CPI inflation.

JEL Code: C53, E31, E37.

Keywords: Inflation uncertainty, inflation, survey data, stochastic volatility, GARCH, principal component analysis.

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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). 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 which are most likely not fulfilled completely. This calls into question whether an individual measure delivers a reliable signal. That is, any individual measure most likely suffers from idiosyncratic measurement error. Hence, empirical results concerning the relationship between inflation uncertainty and inflation depends crucially on the choice of the uncertainty measure.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. These include survey disagreement derived from a panel of forecasters, realized forecast error variance, and model-based approaches such as GARCH and stochastic volatility. Moreover, we propose an approach which uses a variety of forecast models. We use these measures to construct an indicator of inflation uncertainty that condenses the information contained in all measures and overcomes the idiosyncratic measurement error problem.

We demonstrate that all measures are driven by a common component which we interpret as an indicator for inflation uncertainty. Notably, each individual measure contributes to the indicator with a similar weight. Moreover, the common component remains virtually unaffected when we discard one of the measures in turn. We document that individual measures have the tendency to drift apart when uncertainty rises. That is, the measurement error problem seems to be larger during “uncertain times”. This is unfortunate if we want to analyze the relation between inflation uncertainty and inflation. We obtain contradictory results when we use individual measures. Such a finding may explain the divergent results documented in the previous literature and further emphasizes the benefits of the indicator approach.

¹Mixed results with respect to the direction of causality are obtained *inter alia* by Grier and Perry (1998, 2000), Grier et al. (2004), and Berument and Dincer (2005). See also Davis and Kanago (2000) and Fountas and Karanasos (2007) and the papers cited there.

Furthermore, the approach helps us to analyze to which extent individual measures deliver a misleading signal. In particular, we discuss whether disagreement of survey expectations is a good proxy for uncertainty.² It appears that disagreement from surveys co-moves with the other measures. However, some caution is warranted because we document a systematic measurement error associated with survey disagreement during turbulent times.

In a next step, take advantage of our approach and study the relationship between inflation and inflation uncertainty. This topic has recently regained relevance because several economists call for a temporary increase of central banks' inflation target to mitigate problem of debt overhang and to fight unemployment.³ Against this background the Friedman-Ball hypothesis suggests that high inflation rates may lead to increased inflation uncertainty which brings about economic cost (see, for instance, Bernanke and Mishkin, 1997). Our results are in favor of the Friedman-Ball hypothesis. HWe also document that, after an inflationary shock, uncertainty decreases in the first two months. Such a behavior appears to be traceable to the energy component in the CPI as we do not observe a decrease following a shock to core inflation. After a few months, uncertainty increases swiftly for all inflation related shocks.

A few studies compare different approaches to measure inflation uncertainty. For instance, Batchelor and Dua (1993, 1996) contrast inflation uncertainty obtained from subjective probability distributions from the NBER-ASA survey (later: U.S. Survey of Professional Forecasters, SPF) with different model-based measures. They find no significant correlation between both categories. Taking uncertainty measures derived from the SPF as a benchmark, Giordani and Söderlind (2003) document that model-based measures in general have problems in timely capturing regime changes. However, the standard deviation of a VAR estimated on a rolling window tracks the time profile of SPF uncertainty quite well. Recently, Chua et al. (2011) identify a particular GARCH model that matches the SPF measure closest.

We contribute to this debate by comparing measures derived from various approaches. Moreover, our measures are based on monthly data to account for the fact that uncertainty may emerge rather quickly. Furthermore, we highlight that it may be risky to rely on an individual measure. All of the above studies take subjective densities as the observa-

²The relation between disagreement and uncertainty is subject of 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 (2010b) argue that disagreement is a reliable proxy for overall uncertainty if the forecast environment is stable.

³See, for instance, the IMF Staff Position Note by Olivier Blanchard et al. (SPN/10/03), the comment by Ken Rogoff in the Financial Times on Aug 8, 2011, the address by Charles L. Evans at the Outlook Luncheon on Dec 5, 2011, and the comment by Paul Krugman in the NY Times on April 6, 2012.

tional equivalent of inflation uncertainty. Although SPF uncertainty is theoretically appealing, it is very likely subject to measurement error itself (Batchelor and Dua, 1993, 1996; D’Amico and Orphanides, 2008). Therefore, in our analysis, we consider SPF uncertainty as an alternative rather than a benchmark measure of inflation uncertainty.

The remainder of the paper is organized as follows. In section 2, we introduce survey-based measures, as well as model-based measures. Moreover, we present a “forecast-based” approach which relies on multiple forecast models. The relation between the different measures is analyzed in section 3. In section 4, we analyze the link between inflation and inflation uncertainty. Section 5 concludes.

2 Individual measures of inflation uncertainty

2.1 Survey-based measures

In a first step, we derive uncertainty measures from survey data. We use individual forecasts for CPI inflation from professional forecasters conducted 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, 2010a). 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 forecast 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 sample period covers the period 1990:M1 to 2009:M12. The average number of fixed horizon forecasts ranges between 16 and 32 per period, with a mean value of 25 observations.

The CE survey 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-founded prediction in order not to damage the reputation. Against this background, Dovern and Weisser (2011) find that individual forecasts of U.S. inflation are largely unbiased. Moreover, CE data 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 harder to identify in low frequency data.

Among others, Bomberger and Frazer (1981), Cukierman and Wachtel (1982), and Batchelor and Dua (1993, 1996) propose the root mean squared error ($rmse^s$) as a measure of uncertainty. It is calculated by averaging the individual squared forecast errors in each period t :

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

where π_{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). This implies that $rmse^s$ is an ex-post measure. 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 25th and the 75th percentile.⁴

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. As dispersion neglects the form of the distribution Rich and Tracy (2010), among others, suggest using a histogram-based entropy (ent^s) which is computed as:

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

where $p(k)$ denotes the relative frequency of individual forecasts falling in a certain interval k . The entropy provides additional information beyond iqr^s in two ways. First, given the cross-sectional standard deviation of forecasts, the 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.

⁴We 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 propose a forecast-based approach which relies on multiple forecast models. To simplify the analysis, we use VAR models which are a popular forecast device because of their ability to generate multi-step predictions. A VAR model is also employed by Giordani and Söderlind (2003). To obtain a time-varying uncertainty measure, they 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 do not use VAR residuals but point forecasts of a variety of VAR models.⁵

To obtain multiple forecast models, we select a number of activity variables proposed by Stock and Watson (1999) to forecast U.S. inflation. The authors 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 1980s. 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 fulfill 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 is based on a rolling window covering 20 years of data.⁶ That is, the first sample comprises observations beginning in 1970:M1 and ending in 1990:M1. Subsequently, we derive one-year-ahead forecasts for inflation. We iterate through time until 2009:M12. Calculating RMSE as defined in equation (1) yields a forecast-based measure of inflation uncertainty

⁵Compare also Hartmann and Herwartz (2009) who derive a measure of uncertainty from five different structural models.

⁶Giordani and Söderlind (2003) advocate the use of a “windowed” VAR – in opposition to a recursive VAR – where changes to the inflation process are quickly reflected in the parameter estimates.

($rmse^f$). Forecast-based 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.⁷ A number of studies highlight the presence of structural breaks in the inflation process.⁸ 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 GARCH model with time-varying parameters. This has the advantage of being flexible enough to allow for a non-stationary inflation rate. The model is given by a signal equation (3), a state equation (4) and equation (5) describing how conditional error variance evolves.

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

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

$$h_t = d + \phi e_{t-1}^2 + \gamma h_{t-1} \quad (5)$$

Here, α_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. The coefficient vector follows a random walk. h_t describes conditional error variance which emerges from a GARCH(1,1) process. Q is a homoscedastic covariance matrix of shocks η_t . The estimations are based on rolling windows covering 20 years of monthly data to replicate a forecast situation. In accordance with the forecast-based measures introduced in the previous section, the first estimation window starts in 1970:M1 and ends in 1990:M1. The Kalman filter provides an estimate for the variance of the forecast error in the last period. Note that this variance combines model uncertainty emerging from time-variation of the coefficients and uncertainty emerging from the shock process η_t (see Evans, 1991; Caporale et al., 2012, for a detailed explanation). We successively iterate through time until 2009:M12 and obtain an estimate for the variance of the forecast error at each point in time which obtains the label *garch*.

⁷See, 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).

⁸See, for instance, Evans (1991), Evans and Wachtel (1993), Bhar and Hamori (2004), Berument et al. (2005), Caporale and Kontonikas (2009), and Caporale et al. (2012).

2.3.2 Stochastic volatility

Stochastic volatility models are used in financial econometrics to model error variance as a latent stochastic process (see, among others, Harvey et al., 1994; Kim et al., 1998). The variance of first moment shocks is assumed to be driven by an exogenous stochastic process. This is in contrast to ARCH models where error variance is fully described by its own past. Moreover, a stochastic volatility model is proposed as a forecast model for U.S. inflation by Stock and Watson (2007). We follow Doornik et al. (2009) and employ the model to measure inflation uncertainty. The state-space representation is given by equations (6) to (10).

$$\pi_t = \mu_t + e_t \quad e_t \sim N(0, \sigma_{e,t}^2) \quad (6)$$

$$\mu_{t+1} = \mu_t + \eta_t \quad \eta_t \sim N(0, \sigma_{\eta,t}^2) \quad (7)$$

$$\log \sigma_{e,t+1}^2 = \log \sigma_{e,t}^2 + \nu_{1,t} \quad (8)$$

$$\log \sigma_{\eta,t+1}^2 = \log \sigma_{\eta,t}^2 + \nu_{2,t} \quad (9)$$

$$\begin{pmatrix} \nu_{1,t} \\ \nu_{2,t} \end{pmatrix} = N(0, \gamma I_2) \quad (10)$$

Here, e_t is a short-term shock in the measurement equation (6) with variance $\sigma_{e,t}^2$. Moreover, the permanent component of inflation μ_t follows a random walk which is driven by a (level) shock η_t with variance $\sigma_{\eta,t}^2$. The model is estimated with the Gibbs sampler. As in the case of *garch*, we use a rolling window covering 20 years of data. Hence, we only use information known to the researcher at the time the estimate is provided. Finally, we follow the arguments of Ball and Cecchetti (1990) and use the square root of the variance of permanent shocks $\sigma_{\eta,t}^2$ as the measure of inflation uncertainty. In the following, it is denoted by *ucsv*.

3 Characteristics of uncertainty measures

3.1 Descriptive analysis

All measures presented in section 2 require a number of assumptions to work as good proxies for uncertainty. Most likely, these assumptions are not fulfilled completely. For instance, 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. $rmse$ is an ex-post measure that captures realized forecast error variance, and we assume that this differs from the subjective uncertainty of the forecaster only by a random error. 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, that is, there is no disagreement.⁹ In addition, $garch$ provides the conditional variance which is dependent on past forecast errors. Hence, each measure proposed in the literature is probably contaminated by some sort of measurement error. Thus, it should be beneficial to base the analysis on information contained in all measures jointly.

We generate the eight individual uncertainty measures introduced in section 2: 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 ($garch$, $ucsv$). The individual measures are depicted in figure 1. All eight measures exhibit a similar pattern, particularly during the recent economic crisis. However, there are also periods when some of the measures diverge.

In the following, we present some descriptive statistics to characterize the individual measures. Figure 2 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 the most sluggish measure is $ucsv$. In general, inflation uncertainty seems to be a persistent phenomenon. Cross-correlations are given on the off-diagonal elements of figure 2. We find that cross-correlations are high and significantly positive among all series and throughout all leads and lags. We take this as a first indication that all measures contain a common component. Also note that $rmse^s$ and $rmse^f$ tend to lead the other measures.

⁹According to Lahiri and Sheng (2010b), overall forecast uncertainty is the sum of the variance of future aggregate shocks and the variance of idiosyncratic shocks. The model-based measures capture only the uncertainty common to all forecasters and neglect forecaster-specific shocks which are responsible for the disagreement among different forecasters.

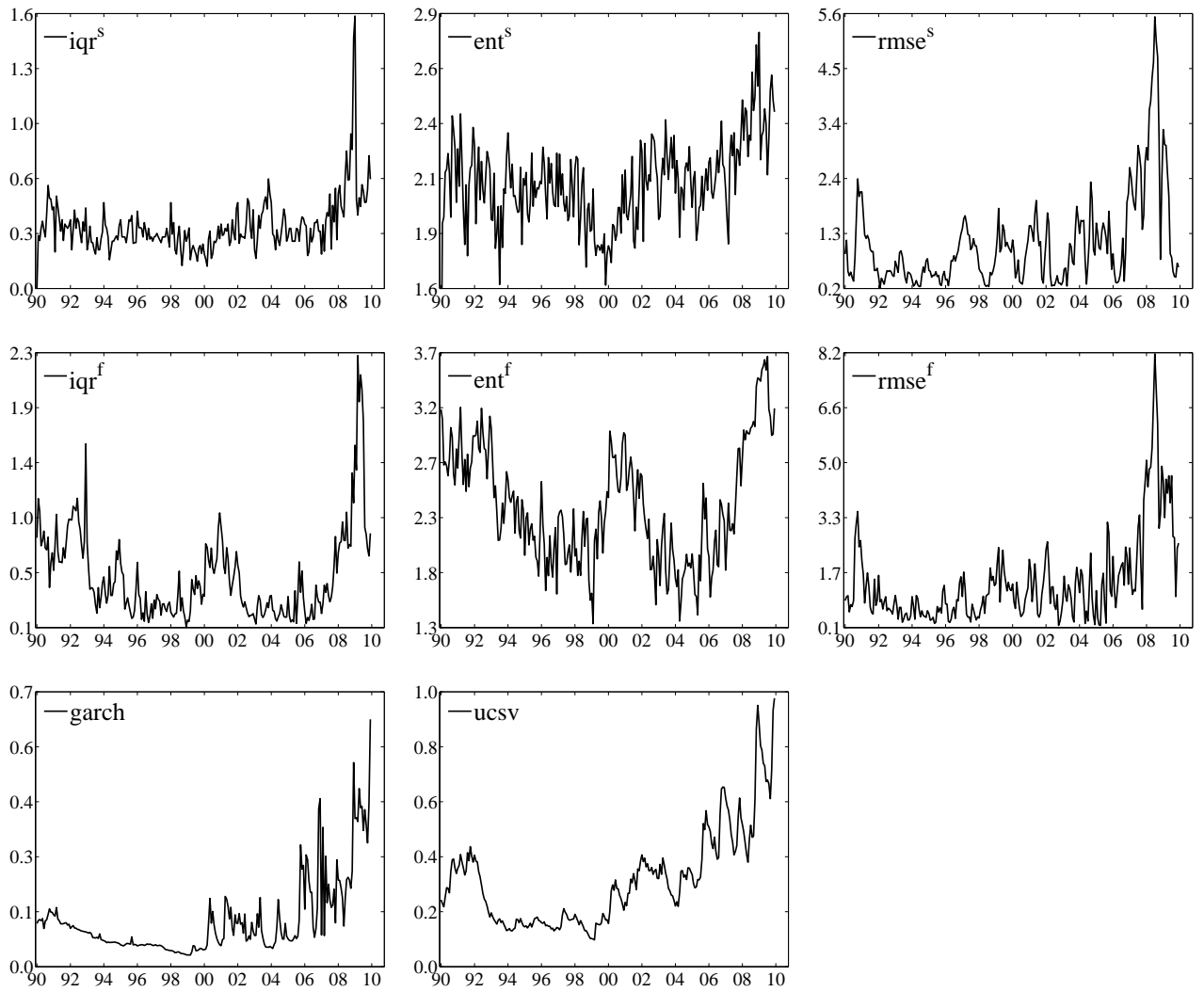
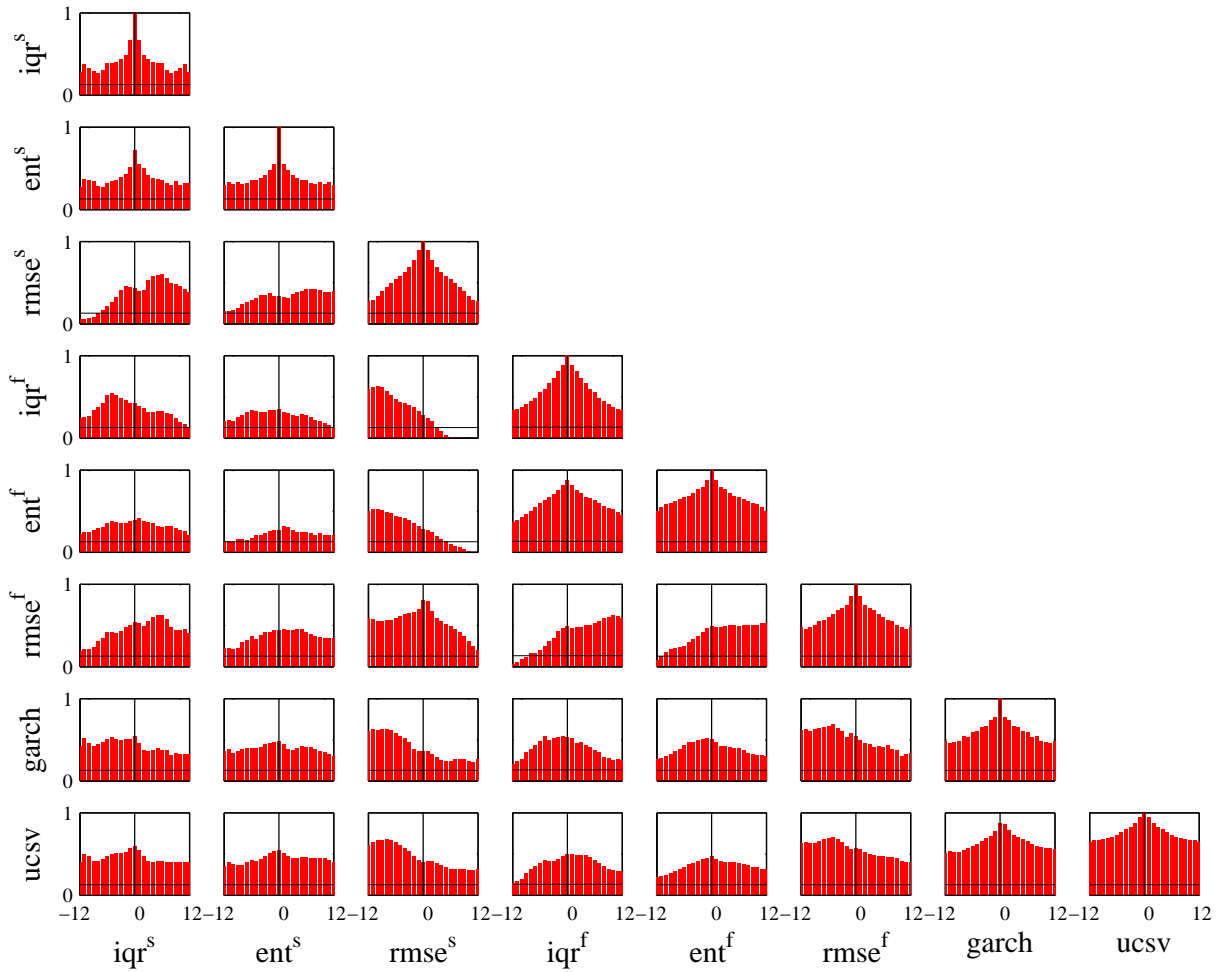


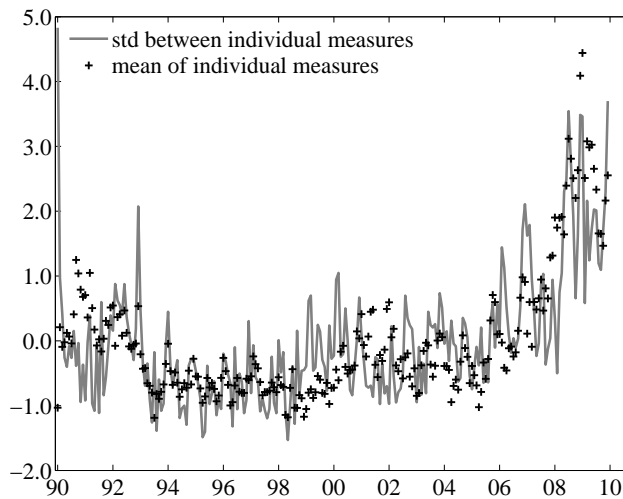
Figure 1: Survey-based (iqr^s , ent^s , $rmse^s$), forecast-based (iqr^f , ent^f , $rmse^f$), and model-based ($garch$, $ucsv$) measures of inflation uncertainty



Note: The bars represent cross-correlations $\text{corr}(y_{i,t}, y_{j,t+k})$ 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 2: Cross-correlation of uncertainty measures

The extent of co-movement over time is revealed in figure 3. Here, we depict the evolution of the cross-sectional standard deviation between all measures at each point in time (solid line). We observe that the standard deviation fluctuates around a constant value during the first part of the sample, whereas the measures start to diverge towards the end of the sample. The co-movement between all eight measures further decreases during the recent crisis. Figure 3 also depicts the cross-sectional mean of all eight measures which is strongly correlated with the associated standard deviation ($\rho = 0.68$). 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 before calculating the cross-sectional standard deviation.

Figure 3: Dispersion of uncertainty measures

3.2 Common characteristics

To eliminate the idiosyncratic components 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 at 8 and 5 lags, respectively. 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	4.98	1.07	0.72	
Variance Proportion	0.62	0.13	0.09	
Cumulative Proportion	0.62	0.76	0.85	
	Loadings			R^2
iqr^s	0.34	0.34	-0.44	0.59
ent^s	0.31	0.44	-0.51	0.48
$rmse^s$	0.36	-0.04	0.31	0.63
iqr^f	0.33	-0.56	-0.23	0.56
ent^f	0.33	-0.57	-0.26	0.54
$rmse^f$	0.37	0.10	0.20	0.70
$garch$	0.38	0.09	0.40	0.72
$ucsv$	0.39	0.17	0.35	0.76

Note: R^2 calculated from a regression of the respective individual uncertainty measure on PC1.

Table 1: Principal component analysis

The first principal component (PC1) accounts for the major part of the dynamics of the data as it explains 62% of the total variation of the underlying series. The second principal component (PC2) carries much less information as it explains only 13% of the variation. Table 1 also shows that the contribution of the third principal component is minor. We conclude that the dataset can be explained by two common components which explain the bulk of the variation.¹⁰ Therefore, in the following, we will focus on the first two principal components.

From table 1, we infer that all eight loading coefficients of PC1 are positive and lie between 0.31 and 0.39. That is, the loadings are all similar in magnitude and, hence, each of the proposed measures carries information we can use to estimate the unobserved inflation uncertainty. This is also reflected by the fact that PC1 has noticeable explanatory power for each of the individual measures. As indicated by the R^2 in table 1, the variance share explained by PC1 varies between 48% and 76%. Also note that the loadings suggest that, in applied research, the idiosyncratic component can be successfully removed from the data by taking a simple average of the individual measures.¹¹

¹⁰Such a result is backed up by standard testing procedures such as the scree test.

¹¹Due to the CE survey, the main analysis is limited to a sample beginning in 1990. Hence, our sample covers a rather tranquil period as far as inflation is concerned. To see whether the results also hold for periods of high and volatile inflation, we conduct the analysis for the years 1970 to 1995 considering only the forecast-based and the model-based approaches. It turns out that our results hold for the earlier time-span as well. First, there appears to be a common component which explains the majority of the variation in the data (58%). Second, all individual measures contribute with a non-negligible weight. Third, the loadings appear to be quite similar. Detailed results are available upon request.

The first principal component is shown in figure 4. Following a rather tranquil period with moderate movements, PC1 starts to rise beginning roughly in 2007 followed by a surge towards the end of 2008 which coincides roughly with the peak of the recent economic crisis. This is in line with, for instance, Clark (2009) who documents that macroeconomic variability has been recently increasing due to larger oil price and financial shocks. Also note that a large part of the surge in uncertainty is only temporary as PC1 quickly drops to about half the value of 2008 in the subsequent months.

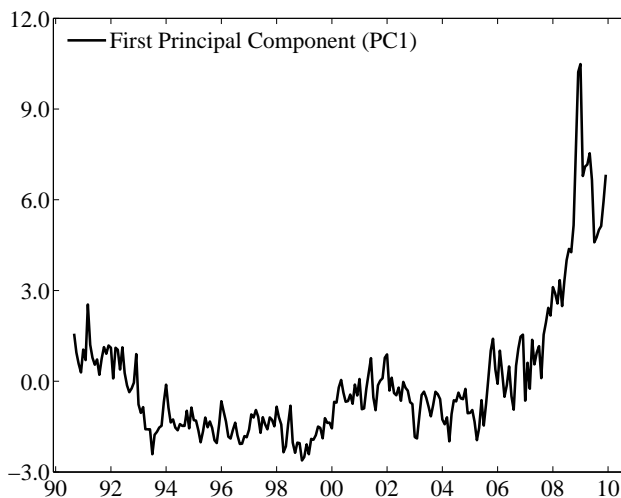
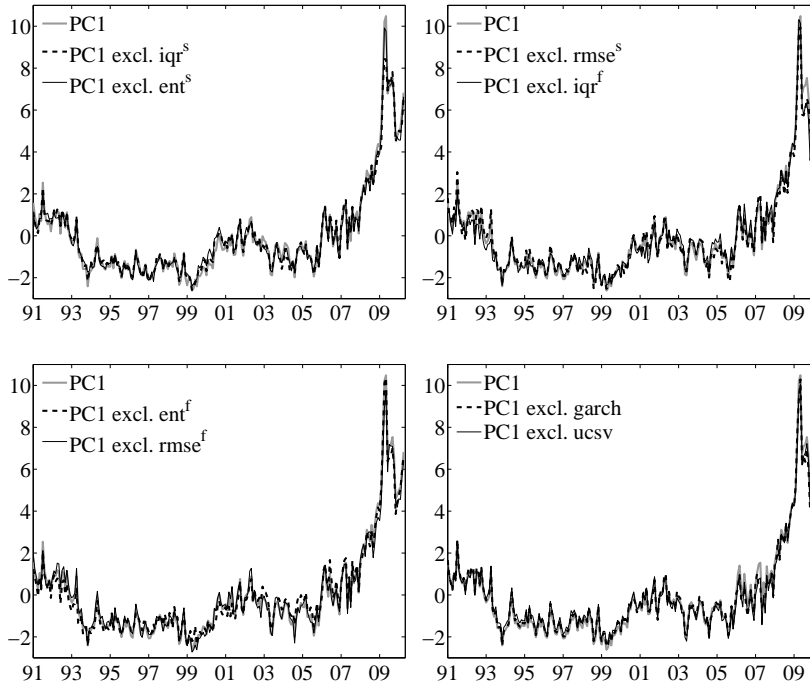


Figure 4: Uncertainty indicator (PC1)

As a robustness exercise, we analyze whether any of the individual measures is responsible for the dynamics of PC1. To this end, we recalculate the indicator leaving out one of the individual measures in turn. Results are presented in figure 5. Excluding one measure does not affect the uncertainty indicator in a significant way. This documents that PC1 is robust and, consequently, our results do not hinge on one of the individual measures.

To analyze the information content of PC1, we study the co-movement of PC1 with economic variables that one would expect to 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, long-term interest rates, and money. Similarly, variables representing financial market risk (*viz.*, *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



Note: The bold grey line represents PC1. The thin line and the dashed line represent the first principal component calculated from a sub-sample of individual measures.

Figure 5: Different uncertainty indicators constructed from a sub-sample of individual uncertainty measures

for long-term rates is somewhat lower compared to short-term rates. This is probably due to the fact that the long-term interest rate is partly driven by the inflation risk premium which tends to increase along with inflation uncertainty.

		PC1	PC2			PC1	PC2	
Consumer prices	$(\Delta\pi)^2$	0.40	0.14	Commodity prices	<i>wti</i>	-0.13		
	$(\Delta\pi^{core})^2$	0.18	-0.14		<i>ppi^{comm}</i>	-0.19	0.23	
Money aggregate	$\Delta M2$	0.16	0.21		<i>ppi^{ind}</i>	-0.19	0.20	
	$(\Delta M2)^2$	0.33	0.15		<i>crb^{return}</i>	-0.32	0.28	
Interest rates	<i>ffr</i>	-0.45	-0.24		$(\Delta wti)^2$	0.21		
	r^{3M}	-0.48	-0.24		$(\Delta ppi^{comm})^2$	0.47	0.16	
	r^{10Y}	-0.23	-0.33		$(\Delta ppi^{ind})^2$	0.43	0.15	
	Δffr	-0.27			$(\Delta crb^{return})^2$	0.39	0.18	
	Δr^{3M}	-0.18			Business activity	<i>ism</i>	-0.47	
	Δr^{10Y}					<i>ism^{prod}</i>	-0.42	
	$abs(\Delta ffr)$		-0.17	<i>pmi</i>		-0.53	0.20	
		$abs(\Delta r^{3M})$		-0.13	<i>pmi^{prod}</i>	-0.56	0.15	
	$abs(\Delta r^{10Y})$	0.37		Consumer climate	<i>mhs</i>	-0.81		
Financial market risk	<i>vix</i>	0.51		<i>confidence</i>	-0.61			
	<i>ted</i>	0.30		Capacity utilization	<i>cu</i>	-0.67		
	<i>risk</i>	0.35	-0.20	rate	<i>cu^{man}</i>	-0.69		
Stock prices	<i>sp500</i>				<i>cu^{exIT}</i>	-0.74		
	<i>dj</i>			Production and employment	Δy	-0.81		
	<i>dj5000</i>				Δy^{man}	-0.82		
	$sp500^2$	0.24			$(\Delta y)^2$	0.55	-0.22	
	dj^2	0.21			$(\Delta y^{man})^2$	0.59	-0.20	
$dj5000^2$	0.24		$\Delta empl$		-0.77			
House prices	<i>house</i>	-0.64	0.18	$\Delta jobless$	0.66	-0.17		
	$\Delta house$		-0.17	Δu	0.79	-0.16		
	$(\Delta house)^2$	0.47	0.14	<i>ur</i>	0.55	-0.14		
NBER dates	<i>recession</i>	0.58		Δur	0.80	-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 A.2 in appendix A.2.

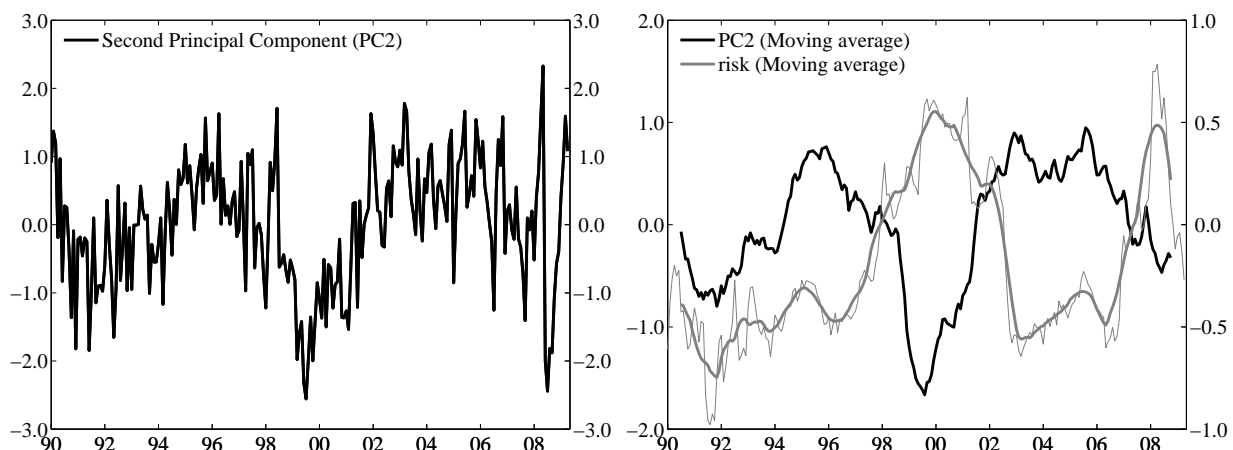
Table 2: Correlations of principal components with economic and financial variables

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 PC1. To this end, we focus on the second principal component which accounts for 13% of the total variance of the data. Notably, PC2 provides some insight into the dynamic interrelation of individual uncertainty measures. We obtain positive loadings for survey disagreement iqr^s and ent^s (0.34 and 0.44). That is, survey disagreement is governed by noticeable idiosyncratic movements. By contrast, PC2 loads negatively on the two forecast-based measures iqr^f and ent^f (-0.56 and -0.57). From the opposite signs of the loadings, we infer that PC2 represents

a factor that makes survey-based and forecast-based measures move into opposite directions; the other measures do not contribute to PC2 significantly.

The left panel of figure 6 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 contemporaneous correlations of PC2 to economic variables in table 2. It turns out that there are fewer significant correlations than for PC1 which is probably due to the fact that PC2 carries more noise. In opposition to PC1, PC2 tends to co-move with the business cycle as we obtain a positive correlation with pmi and negative correlations with all unemployment variables. Hence, the idiosyncratic part of iqr^s and ent^s decreases during a downswing while the idiosyncratic part of iqr^f and ent^f tends to rise. Similarly, 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. Overall, survey disagreement appears to be subject to systematic measurement error during economic downturns.



Note: In the right panel, the bold lines show a twelve month moving average of the second principal component (black) and the (log of) the corporate bond risk premium (grey). The thin lines represent the unfiltered data.

Figure 6: Second principal component (PC2)

Moreover, PC2 decreases when the corporate bond risk premium ($risk$) or the output variability increase. Note that both variables are indicators for overall economic risk (see, for instance, Bachmann et al., 2012). As contemporaneous correlations neglect dynamic relations, we plot PC2 along with the corporate risk premium in the right panel of figure 6. For illustration purpose, we smooth both series by taking a twelve-month centered moving average. We observe that the risk premium moves whenever PC2 experiences large swings. Especially the pronounced drop around the year 2000 coincides with a distinct increase of overall economic risk. Once the risk premium starts to come down, PC2 escalates and remains at a high

level while economic risk appears to remain low until 2007. That is, both series move into opposite directions. Hence, there appears to be systematic measurement error such that the idiosyncratic part of survey disagreement decreases in economically turbulent times.

For an interpretation of PC2 we may draw the attention to the conceptual differences between the measures that contribute to the component. However, note that forecast-based and survey-based disagreement also share some important characteristics because the multitude of VAR models can be interpreted as a panel of forecasters where each forecaster uses a different forecast model. A conceptual discrepancy arises from the fact that the forecast-based approach provides a purely mechanistic way to deal with heterogeneous information. As a consequence, forecasts from different VAR models 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. Note that this cannot happen to the forecast-based measures. Hence, one explanation for the decline of the idiosyncratic part of survey disagreement is that forecasters tend to cluster their forecasts around the consensus during turbulent times. Note that our results are also consistent with the theoretical considerations by Lahiri and Sheng (2010b) who assume that individual forecast errors are driven by common and idiosyncratic shocks. Under these assumptions, they show that disagreement is a reliable proxy for overall uncertainty only during stable periods, that is, whenever the shocks common to all forecasters are small. Overall, our results suggest that using *only* survey disagreement as a measure of inflation uncertainty may be misleading.

3.4 Comparison to SPF inflation uncertainty

Many studies use uncertainty measures based on the U.S. Survey of Professional Forecasters (SPF) which is conducted quarterly by the Federal Reserve Bank of Philadelphia (Zarnowitz and Lambros, 1987; Lahiri et al., 1988; Batchelor and Dua, 1993, 1996; Giordani and Söderlind, 2003; Chua et al., 2011). The reason is that the SPF provides individual histograms of expected inflation. This specific survey design allows to derive for each forecaster the individual standard deviation σ_i of the inflation forecast. The average over individual standard deviations provides an obvious measure of overall inflation uncertainty (Giordani and Söderlind, 2003).

Ideally, our uncertainty indicator presented in section 3.2 should incorporate information from SPF uncertainty as well. However, this is not feasible since the SPF is conducted quarterly. Furthermore, SPF predictive densities relate to fixed-event forecasts. Hence, a one-year horizon is polled only in the first quarter of a year. As the forecast horizon shrinks in the subsequent quarters of the year, the uncertainty surrounding the respective forecast declines as well. Nevertheless, we compare PC1 to SPF uncertainty but have to restrict our comparison to yearly observations. As SPF forecasts are usually published at the end of the first quarter, we compare the value of SPF uncertainty with the value of PC1 in March of a respective year. To calculate forecaster-specific uncertainty σ_i , we follow D'Amico and Orphanides (2008), and Lahiri and Sheng (2010b) and use a non-parametric procedure. We obtain SPF uncertainty as the average of individual standard deviations adding a Sheppard correction. Figure 7 depicts the resulting time series which are both normalized to have mean zero and standard deviation one.

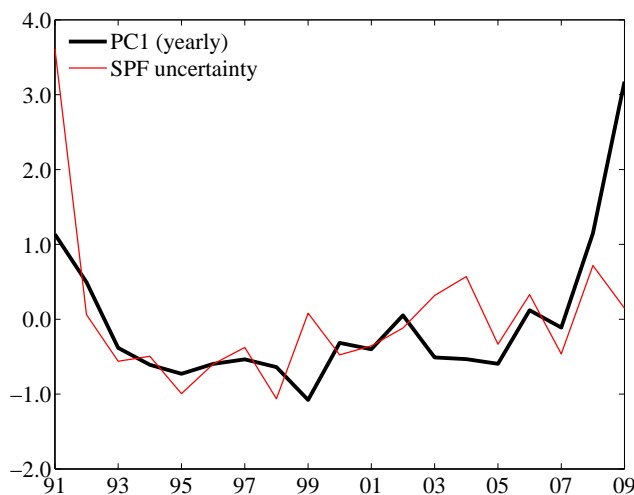


Figure 7: Yearly uncertainty indicator (PC1) and SPF uncertainty

SPF uncertainty moves rather abruptly with a spike in the year 1991 followed by a decline and an upward movement in the last decade. In contrast, PC1 appears to be more persistent whereas the recent hike in inflation uncertainty is more pronounced. The first-order autocorrelation coefficient amounts to 0.41 for yearly data of PC1 whereas it is practically zero (0.09) for SPF uncertainty. Nevertheless, our uncertainty indicator and SPF uncertainty co-move at large, and the correlation coefficient is 0.45.

Some limitations of such a comparison have to be noted. First, SPF uncertainty refers to the GDP deflator as opposed to CPI inflation as probability forecasts for the CPI inflation rate are not available before 2007. Moreover, a number of assumptions have to be made to

derive an uncertainty measure from SPF forecast histograms, and it is unclear whether these assumptions are justified (see, for instance, D’Amico and Orphanides, 2008; Rich and Tracy, 2010). Furthermore, changes in the survey design concerning, for example, the number and width of histogram bins may distort the signal. Overall, SPF uncertainty is very likely subject to measurement error – as any other measure – which may explain a temporary divergence of SPF uncertainty and PC1 (also compare Batchelor and Dua, 1993, 1996).

4 The link between inflation and inflation uncertainty

The link between inflation and inflation uncertainty has recently gained renewed relevance with the call for temporary higher inflation rates to mitigate the problem of debt overhang. From a theoretical point of view, 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 (Friedman-Ball hypothesis). 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.

We use both, PC1 and the individual measures to investigate the link between inflation and inflation uncertainty. This helps to assess whether PC1 has value added to the individual series from which it is derived. If we are able to remove the idiosyncratic component from the individual measures we should obtain a more precise estimate of the relation between inflation and inflation uncertainty. In that sense, the test result derived from PC1 would be more robust because it is not influenced by idiosyncratic movements.

To further examine whether PC1 is a valid measure of uncertainty, we analyze the sign of the relation between inflation and inflation uncertainty. Note that both theories, Friedman-Ball and Cukierman-Meltzer, suggest that both variables co-move over time. Although it is impossible to directly show that PC1 retraces the movements of the unobserved “true” inflation uncertainty, we should be able to establish a positive link if PC1 is a valid measure of inflation uncertainty.

In a first step, we test the Friedman-Ball hypothesis by means of 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 of a Granger causality test are presented in table 3. The p-values reveal a strikingly inconclusive picture. *rmse*^s

and iqr^f seem to be Granger caused by inflation but not vice versa whereas for iqr^s Granger causality appears to hold for both directions. For ent^s , ent^f , and $garch$, we find no dynamic relation to inflation. In the case of $rmse^f$ and $ucsv$, it turns out that uncertainty is followed by inflation. When the same test is conducted for the change of inflation, we obtain similar results. Overall, it appears that the choice of the measure is crucial. Thus, using individual measures entails the risk that results are driven by idiosyncratic movements that are unrelated to inflation uncertainty.

	PC1	iqr^s	ent^s	$rmse^s$	iqr^f	ent^f	$rmse^f$	$garch$	$ucsv$
H_0 : π does not Granger cause IU	0.00	0.00	0.08	0.02	0.02	0.58	0.07	0.07	0.91
H_0 : IU does not Granger cause π	0.39	0.01	0.31	0.27	0.17	0.29	0.01	0.50	0.03
H_0 : $\Delta\pi$ does not Granger cause IU	0.00	0.00	0.30	0.02	0.01	0.64	0.07	0.01	0.90
H_0 : IU does not Granger cause $\Delta\pi$	0.29	0.19	0.14	0.01	0.00	0.01	0.00	0.19	0.02

Note: Granger causality tests are performed for inflation π as well as the monthly change of inflation $\Delta\pi$ and inflation uncertainty (IU). Numbers are p-values for a Granger causality test performed by means of a joint F-Test. The lag length of each VAR model is set to 12. Sample ranges from 1990M09 to 2009M12.

Table 3: Granger causality test for inflation uncertainty and inflation

Using PC1 to measure inflation uncertainty, we find that inflation Granger causes inflation uncertainty but not vice versa. Although Granger causality is only a prerequisite for economic causality, such a result is in favor of the Friedman-Ball hypothesis. The same result is obtained if we consider the change in inflation.¹² Most notably, results in table 3 suggest that the indicator provides an insurance against idiosyncratic movements of individual measures.

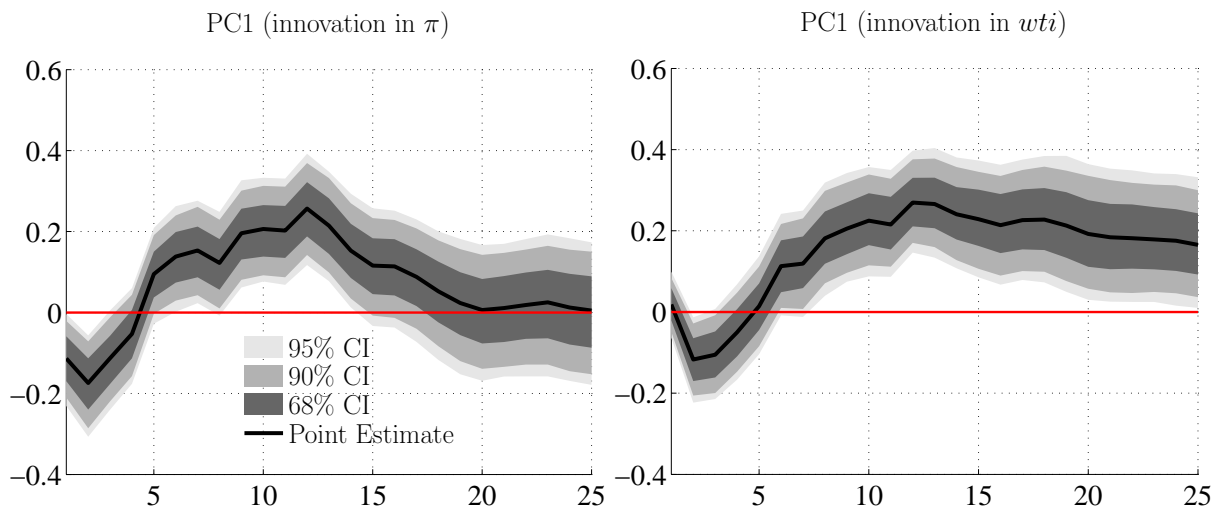
In a second step, we assess the sign of the effect of an exogenous increase in inflation on inflation uncertainty. We take a dynamic perspective and calculate impulse response functions from the bivariate VAR models introduced above. Orthogonal shocks are identified using a Cholesky ordering such that uncertainty reacts to a shock to inflation instantaneously.¹³ This is motivated by the fact that uncertainty may move quickly when agents encounter new macroeconomic information whereas inflation is comparatively slow-moving.

The left panel of figure 8 presents the response of the uncertainty indicator PC1 to a one standard deviation shock to inflation. Following an inflation shock, we observe that uncertainty experiences an initial significant decline for about two months. 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

¹²The result is robust to the choice of the lag length of the VAR according to BIC which suggests two lags. Furthermore, it is robust if we exclude the recent crisis and end the sample in 2007:M8 which is roughly when the U.S. sub-prime crisis started to spill over into other sectors of the economy.

¹³We also checked the reverse ordering of variables which does not affect the results in a significant way.

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 increase 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 significantly positive about 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, uncertainty accumulates 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 oil price inflation (*wti*) is depicted in the right panel of figure 8. 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.¹⁴



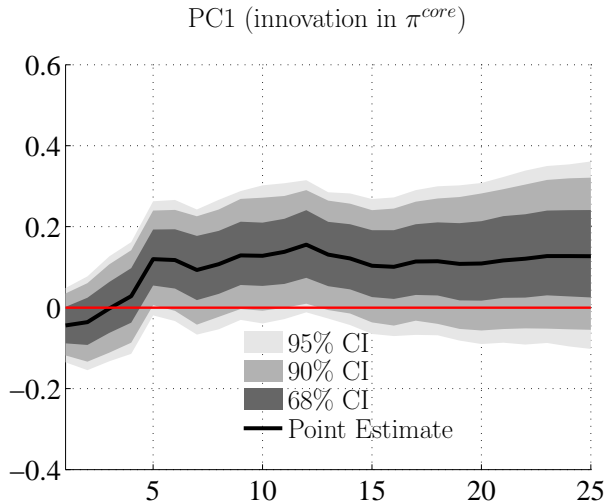
Note: Confidence intervals are obtained from a bias adjusted bootstrap procedure (Kilian, 1998).

Figure 8: Response of inflation uncertainty to inflation and *wti*

Turning to figure 9, we observe that a shock to core inflation (π^{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,

¹⁴See appendix A.4 for results obtained from monetary VARs containing output, inflation, a short-term interest rate, and uncertainty. It turns out that results remain unaffected when a larger VAR is employed. Furthermore, the impulse responses are qualitatively the same when we estimate the bivariate VARs on a sample ending in 2007:M8.

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.



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

Figure 9: Response of inflation uncertainty to core inflation

We document a significant increase of inflation uncertainty following an inflation shock. That is, PC1 co-moves with inflation. We highlight that the increase is probably due to growing uncertainty about the transmission of a shock. In addition, increased inflation uncertainty may also be the result of rising uncertainty about the reaction of the central bank. 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, PC1 delivers results consistent with standard theory on the link between inflation and inflation uncertainty. In contrast, when we repeat the exercise for each individual uncertainty measure, we find that the response of uncertainty is rather heterogenous.¹⁵ Hence, the link from inflation to inflation uncertainty is not revealed in a conclusive way if we rely on a single measure.

Finally, we analyze whether the contribution of inflationary shocks to PC1 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 presented in figures 8 and 9. We find that an inflation shock explains roughly 21% of the forecast error variance of inflation uncertainty after 15 months. With a value of only 7.7% after 15 months, core inflation (π^{core}) explains less than headline inflation suggesting that the energy component in the CPI is a major

¹⁵The individual impulse responses are presented in figure A.1 in appendix A.3.

determinant of inflation uncertainty. Likewise, the contribution of oil price inflation (*wti*) peaks in the longer run at about 22% which confirms the importance of oil price movements for uncertainty.

horizon	1	5	10	15	20	25
π	3.2	6.8	14.0	20.6	15.2	10.7
<i>wti</i>	0.1	2.8	11.8	22.2	21.6	19.8
π^{core}	0.4	1.5	4.7	7.7	7.4	7.6

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 Concluding remarks

Analyzing various measures of inflation uncertainty, we document that inflation uncertainty has risen significantly in the aftermath of the recent financial crisis. This finding together with the recent calls for higher inflation to mitigate the problem of debt overhang highlights the importance of understanding the relationship between inflation and inflation uncertainty. However, empirical results derived from different measures are ambiguous. An explanation is that each individual measure is derived from different assumptions which are very likely not fulfilled completely. Hence, individual measures may be contaminated by idiosyncratic measurement error.

We use common information in different uncertainty 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 propose a forecast-based approach. We find that all measures – including disagreement – are driven by a common component which we interpret as an indicator for inflation uncertainty. Notably, the indicator helps to overcome the measurement error problem, and the underlying signal should be revealed with greater precision. Moreover, we find that the common component loads about equally on each individual measure. Hence, taking a simple average over the individual measures is a viable alternative which delivers a robust indicator of inflation uncertainty.

However, the indicator does not completely explain the variation in the data. We find that, in general, individual measures tend to differ more during turbulent times. Moreover, a researcher may be confronted with survey respondents sticking to the consensus when macroe-

conomic risk is high which induces a downward bias in survey disagreement. Hence, using only survey disagreement as a measure of inflation uncertainty is a risky strategy.

Subsequently, we use the proposed uncertainty indicator to analyze the inflation - inflation uncertainty link. It appears that Granger causality tests are in favor of the Friedman-Ball hypothesis. We also study the dynamic response of uncertainty to an inflation shock. We document that uncertainty initially decreases and shows a swift increase in subsequent periods. This behavior is traceable to the energy component in CPI inflation. A sudden rise of the oil price, for instance, is 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 demonstrate that higher inflation is followed by higher uncertainty. However, we are aware of the difficulty to infer causality by empirical testing only. Hence, future research should integrate inflation uncertainty into a structural macroeconomic model to establish a causal economic relationship.

Appendix

A.1 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

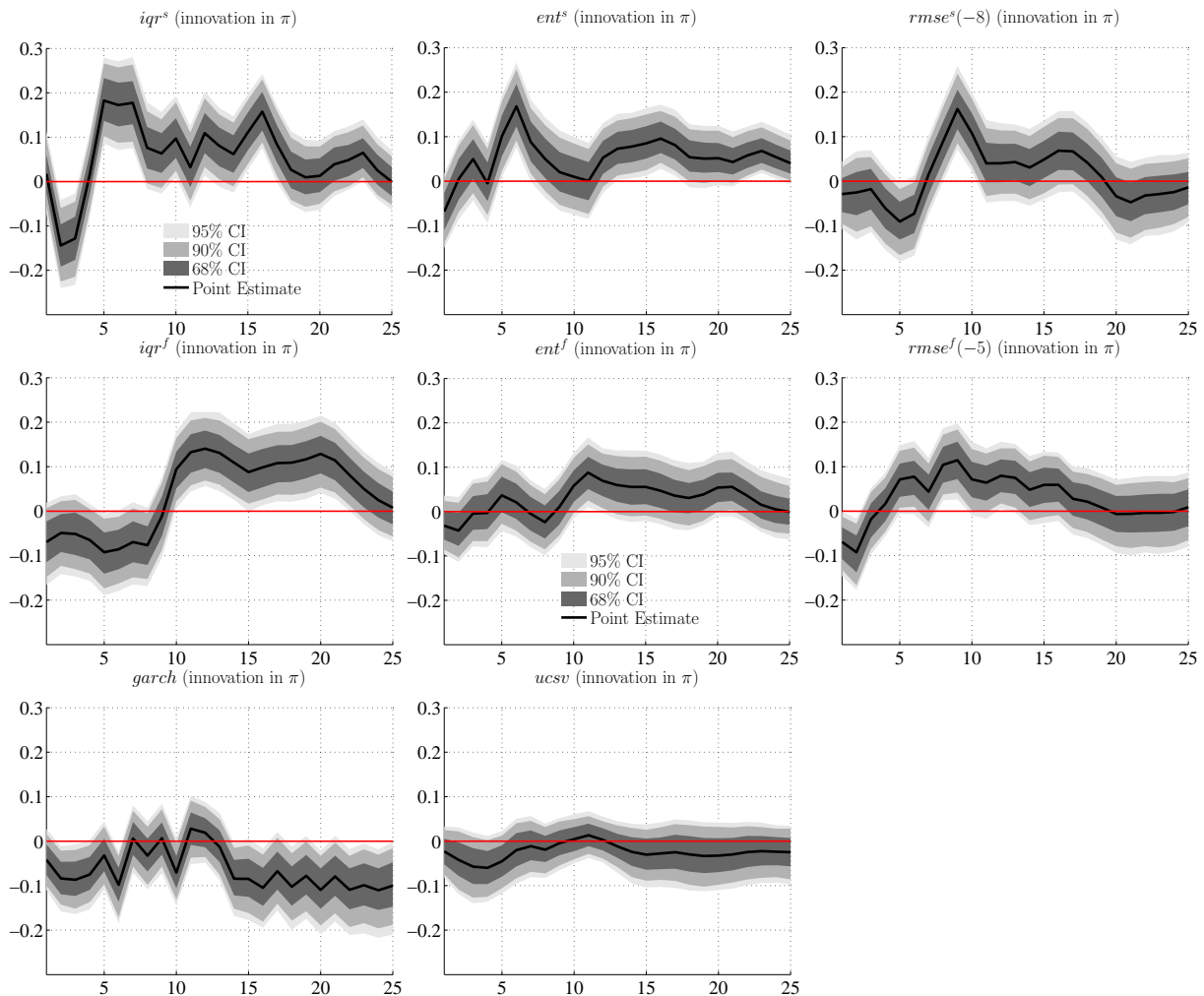
Note: “gap measure” denotes series that have been detrended with the HP-filter; “interest rate spread” is defined as the difference between interest rate on government bonds and federal funds rate.

Table A.1: Variables used to forecast inflation

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

Table A.2: Description of economic variables

A.3 Impulse responses of individual uncertainty measures



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

Figure A.1: Response of individual uncertainty measures

A.4 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 model 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 A.2. It turns out that our results remain unaffected by the inclusion of additional variables.

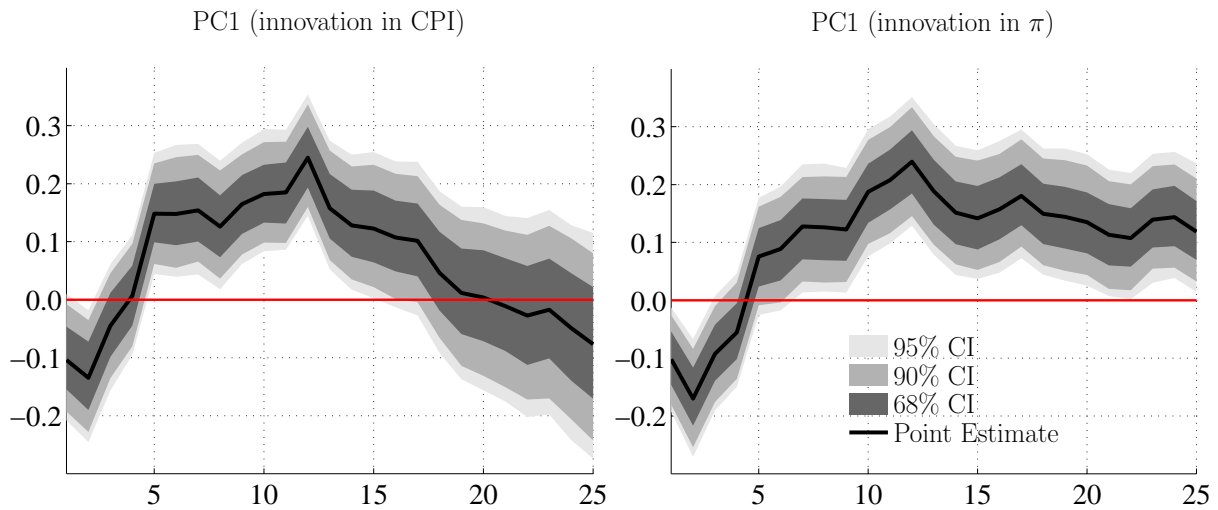


Figure A.2: Response of inflation uncertainty to a CPI shock (left) and to an inflation shock (right) in a 4-variable VAR

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