Essays on Inflation Uncertainty and Inflation Expectations

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To my parents,
Margarete & Reinhold Wieland.

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Preface

Inflation targeting has become an important policy of central banks during the most recent two decades. An increasing number of monetary institutions in high-income countries have adopted an inflation targeting framework or central elements of inflation targeting policies (Roger, 2009). At the same time, the period from the early-nineties onwards has generally been marked by low and stable inflation rates. Since price stability is the main focus of policy makers, it is important to know how people form their expectations about future inflation and how uncertainty surrounding inflation evolves. The present thesis addresses both topics. Whereas the first two chapters are devoted to the measurement and the international linkages of inflation uncertainty, the third chapter of this thesis analyzes the process of inflation expectations formation by means of international survey data.

Increased inflation uncertainty is related to economic cost that goes beyond the cost of inflation. For example, uncertainty about future inflation distorts the allocation of long-term savings and investment. Likewise, nominal contracts involving, for instance, wages and financial assets become riskier (Bernanke and Mishkin, 1997). Moreover, higher inflation uncertainty is associated with higher inflation (Friedman, 1977; Ball, 1992; Cukierman and Meltzer, 1986). This link has recently gained renewed relevance in light of the Great Recession of 2008-2009, which has caused debt-to-GDP ratios to rise drastically in high-income countries. Central bankers are now confronted with the call for a temporary increase of their inflation target to mitigate the debt burden (Aizenman and Marion, 2011). They might also encounter difficulties in achieving the inflation target since increasing fiscal pressure entails the risk of higher inflation expectations (Davig et al., 2011). Overall, the positive link between inflation uncertainty and inflation increases the cost of high inflation and complicates the anchoring of low inflation expectations. Understanding the evolution and international linkages of inflation uncertainty is therefore crucial if we want to maintain the benefits of low and stable inflation rates.

Chapter 1 deals with the measurement problem of unobserved inflation uncertainty.[1] It is motivated by the fact that any individual measure of inflation uncertainty relies on specific assumptions which are most likely not fulfilled completely. In order to reduce idiosyncratic measurement error, we propose using joint information of different measures. To this end, we rely on the most commonly used measures of inflation uncertainty. These include survey disagreement and realized forecast error variance derived from a panel of professional forecasters as well as model-based approaches such as conditional forecast error variance and stochastic volatility. In addition, we present an approach which relies on a large cross-section of forecast models.

Based on a principal components analysis, we combine the different measures to obtain an indicator of inflation uncertainty. We show that the first principal component provides an adequate indicator since it condenses the essential information in all measures and overcomes the idiosyncratic measurement error problem. Notably, each individual measure contributes to the indicator with a similar weight. The common component thus remains virtually unaffected if one of the measures is excluded. Furthermore, analyzing the part which is not captured by the first common component sheds light on to which extent individual measures may deliver a divergent signal. In particular, we find that some caution is warranted with disagreement measures, that is, the cross-sectional dispersion of point forecasts derived from survey data or from a variety of forecast models. Although disagreement measures co-move with the other uncertainty measures and are to a large extent reflected in the common component, our results also suggest that using only one individual disagreement measure may be misleading particularly during turbulent times.

The construction of an indicator of inflation uncertainty finally allows for the testing of its link with inflation without relying on assumptions specific to individual measures. We find support for the Friedman-Ball hypothesis that higher inflation is followed by higher uncertainty. By contrast, using the individual measures provides contradictory results with respect to the direction of Granger causality. We also document that, after an inflationary shock, uncer-

[1]This chapter is based on Grimme et al. (2011), which is available as Ifo Working Paper No. 111.

tainty decreases in the first two months. This effect seems to stem from the energy component in CPI inflation. Eventually, uncertainty rises because the long-term effects of these energy price increases appear to be harder to predict; this dynamic response is also in line with the Friedman-Ball claim.

Chapter 2 investigates the international linkages of inflation uncertainty in the G7.[2] A large amount of empirical literature analyzes the international connectedness of first moment variables such as GDP growth and inflation.[3] However, little is known about the extent to which inflation uncertainty is synchronized across countries. Against that background, the contribution of this chapter is twofold. First, it analyzes the degree and sources of synchronization of international inflation uncertainty. Thereby, common shocks and spillover effects from one country to another are considered as possible explanations for synchronization. Second, we investigate the origins of changes in the dynamics of national inflation uncertainty. Both questions are tackled by means of a Factor-Structural Vector Autoregression (FSVAR) model which decomposes the total volatility of inflation uncertainty of one country into the contributions of international shocks, spillover effects, and own shocks.

Covering a long time span from 1960 to 2012, we document a high degree of co-movement of G7 inflation uncertainty at business cycle frequencies. Moreover, the degree of synchronization has increased during the most recent two decades. Estimation of an FSVAR model provides evidence of one common international shock that drives national inflation uncertainty into the same direction within the G7 countries. This common shock is in turn found to be related to international commodity price uncertainty. By contrast, shocks originating in the US have an impact on a subset of countries only.

Time-varying estimations suggest that the volatility of inflation uncertainty has decreased over time, paralleling the process of "Inflation Stabilization". In order to shed light on the sources of this increased stability, we analyze whether the size of shocks impinging on inflation uncertainty has declined ("good luck") or whether structural changes in the economy and improved (monetary) policy have altered the propagation of these shocks ("good policy"). The main channel for lower volatility of inflation uncertainty seems to be domestic shocks that

[2]This chapter is based on Henzel and Wieland (2013), which is available as CESifo Working Paper No. 4194.

[3]See, for instance, Stock and Watson (2005), Kose et al. (2008), Ciccarelli and Mojon (2010), Mumtaz and Surico (2012), and Bataa et al. (2013a).

translate less extensively into the individual economies. This finding supports the hypothesis of "good policy". Finally, we document that the relative importance of international shocks has increased, which explains a higher connectedness of inflation uncertainty among the G7. Overall, considerable changes in the conduct of monetary policy are likely an important source of the reduction in inflation uncertainty and its associated volatility. Since our results in Chapter 2 attribute an important role to policy changes, they also suggest that the trend of generally low and stable inflation uncertainty during the most recent two decades might be reversed if central bankers are less credibly committed to price stability.

The final part of this thesis focuses on the process of inflation expectations formation by addressing the question of whether forecasters have imperfect information. The resulting informational rigidities provide an explanation for the real effects of monetary policy via a short-run Phillips curve (Mankiw and Reis, 2010). Imperfect information can arise either due to delayed ("sticky") information (Mankiw and Reis, 2002) or partial ("noisy") information (Sims, 2003). In macroeconomic theory, agents with imperfect information challenge implications derived from a world of full-information rational expectations. In the context of inflation targeting, for instance, Ball et al. (2005) show that it is optimal to target the price level rather than the inflation rate under sticky information.

In *Chapter 3*, we assess the degree of information rigidity in inflation forecasts for high-income countries provided by the CESifo World Economic Survey (WES). Thereby, we follow an approach by Coibion and Gorodnichenko (2010), which is directly related to models of imperfect information. In contrast to previous tests of forecast rationality, it not only allows testing for the presence of informational rigidities but also provides the chance to determine the economic significance and mechanisms behind departures from full-information rational expectations. In addition, we address the more recent question of whether information updating is state-dependent. An important merit of our cross-country panel dataset is that it explicitly allows us to test for state-dependence in inflation expectations. Since WES forecasters evaluate the importance of a given choice of potential economic problems, we are able to investigate whether different "states" concerning the importance assigned to the economic problem "inflation" influence the formation of inflation expectations.

Applying the approach by Coibion and Gorodnichenko (2010), we find evidence of informational rigidities in inflation forecasts. On average, WES experts update their information set every three to four months. However, the degree of information rigidity crucially depends on the forecast horizon. We also document state-dependence in the process of forecasting inflation. When the majority of WES experts assesses the economic problem "inflation" as being highly important, information updating speeds up. That is, forecasters are more attentive when inflation concerns are prevailing. This conclusion is robust when considering the level of expected and past inflation. Whenever the value of expected trend inflation or past quarterly inflation is above a critical threshold, forecasters are on average more attentive.

For economic modeling, two implications arise from the empirical findings in Chapter 3. A degree of information rigidity which varies across forecast horizons is consistent with noisy-information models (Lucas, 1972; Woodford, 2001; Sims, 2003) in contrast to the constant updating frequency implied by sticky-information models. Moreover, we provide evidence that the degree of information rigidity varies with the importance attached to the forecasting variable inflation. This finding suggests a state-dependent rule of information updating, as recently advocated by Gorodnichenko (2008) and Woodford (2009).

Chapter 1

Inflation uncertainty revisited: A proposal for robust measurement

1.1 Introduction

In the follow-up of the seminal speech of Friedman (1977), a still ongoing debate has originated concerning 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 literature. While some studies rely on survey-based measures, others depend on volatility derived from time series models, or 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 at any time. That is, any individual measure most likely suffers from idiosyncratic measurement error. Hence, empirical results concerning the relationship between inflation uncertainty and inflation depend 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 rely on 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

[1]Mixed 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 therein.

as GARCH and stochastic volatility. Moreover, we present an approach which is based on 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. The common component thus remains virtually unaffected when we discard one of the measures. Moreover, 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". Such a finding emphasizes the benefits of the indicator approach.

Furthermore, the indicator approach helps examining to which extent individual measures may deliver a misleading signal since it enables us to analyze the part of the dynamics which is not captured by the common component. In particular, we discuss whether disagreement is a good proxy for uncertainty.[2] For this purpose, we analyze disagreement in survey forecasts and disagreement derived from a variety of forecast models. It appears that both disagreement measures co-move with the other uncertainty measures and are to a large extent reflected in the common component. However, some caution is warranted because our results also suggest that using only one individual disagreement measure may be misleading particularly during turbulent times.

In a further step, we 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 the 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

[2]The relation between disagreement and uncertainty is the subject of an ongoing debate. Bomberger and Frazer (1981), Bomberger (1996, 1999) and Giordani and Söderlind (2003) find supportive results, yet 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.

[3]See, 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.

about economic cost (see, for instance, Bernanke and Mishkin, 1997). Our results are in favor of the Friedman-Ball hypothesis. We also document that, after an inflationary shock, uncertainty decreases during the first two months. Such a behavior appears to be traceable to the energy component in the CPI since 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 US 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. Nonetheless, the standard deviation of a VAR estimated on a rolling window tracks the time profile of SPF uncertainty quite well. Chua et al. (2011) have recently identified a particular GARCH model that matches the SPF measure closest.

All of the above studies take subjective densities of the SPF as the observational equivalent of inflation uncertainty. Although SPF is conducted on a quarterly frequency, a time path for subjective uncertainty relating to forecasts with a constant forecast horizon is available only on an annual basis. However, uncertainty may emerge rather quickly. Against this background, recent studies analyze the effects of uncertainty at a monthly frequency (Bloom, 2009; Knotek and Khan, 2011; Bachmann et al., 2013). To address this issue, our measure of inflation uncertainty is derived on a monthly basis, yet we document that our uncertainty indicator produces a time profile which is similar to yearly SPF uncertainty.

The remainder of the paper is organized as follows. In section 1.2, 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 1.3. In section 1.4, we investigate the link between inflation and inflation uncertainty. Section 1.5 concludes.

1.2 Individual measures of inflation uncertainty

1.2.1 Survey-based measures

First, we derive uncertainty measures from survey data. We use individual forecasts for CPI inflation from professional forecasters conducted by Consensus Economics (CE). CE reports expected consumer-price inflation for the current and 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-months-ahead inflation forecasts, we follow Dovern et al. (2012) 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. Moreover, individual data is provided and the names of the forecasters are given alongside the numbers. Hence, there is a strong incentive to make a well-founded prediction in order not to damage the forecaster's reputation. Against this background, Dovern and Weisser (2011) find that individual forecasts of US inflation are largely unbiased. In addition, 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) suggest using 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:

$$rmse_t^s = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\pi_{t+12} - \pi_{i,t}^e\right)^2}, \tag{1.1}$$

where π_{t+12} denotes realized twelve-months-ahead CPI inflation and $\pi_{i,t}^e$ is the individual point forecast from CE made at time t. As far as the timing is concerned, we follow Batchelor and Dua (1993, 1996) such that a forecast error realized at time $t + 12$ represents uncertainty at time t. This implies that $rmse^s$ is an ex-post measure (see also Hartmann and Herwartz, 2013).

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. (2004) and rely on the interquartile range (iqr^s) since it is more robust to outliers. iqr^s is defined as the difference between the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentiles.[4]

Mankiw et al. (2004) point out that the distribution of forecasts may become multimodal if model uncertainty is high. This is the case, 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:

$$ent_t^s = -\Big(\sum_{k=1}^{n} p(k)_t[ln(p(k)_t)]\Big), \tag{1.2}$$

where $p(k)$ denotes the relative frequency of individual forecasts falling in a certain interval k. For a given number of bins and a constant bin width, the histogram-based entropy is maximized if the forecasts are distributed equally among all bins. The entropy provides additional information beyond iqr^s. 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).

1.2.2 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

[4]We also computed the standard deviation and the quasi-standard deviation of forecasts (Giordani and Söderlind, 2003). The quasi-standard deviation is defined as half the difference between the 84$^{\text{th}}$ and 16$^{\text{th}}$ percentiles. With normally distributed data, this measure equals the standard deviation. The correlation coefficient of these alternative dispersion measures and iqr^s amounts to 0.86 and 0.90, respectively.

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 homoskedastic. In effect, this is not consistent with the notion 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.

To obtain multiple forecast models, we select a number of activity variables proposed by Stock and Watson (1999) to forecast US 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 1.A.1 in the appendix. 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. The estimation is based on a rolling window covering 20 years of data.[5] 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. Note that the estimation period contains the disinflation period during the 1980s. Hence, inflation enters the VAR model in first differences (Stock and Watson, 1999, 2007). Calculating RMSE as defined in equation (1.1) yields a forecast-based measure of inflation uncertainty ($rmse^f$). Forecast-based disagreement (iqr^f) is given by the dispersion among the point forecasts measured

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

by the interquartile range. According to equation (1.2), we also calculate an entropy-based measure (ent^f).[6]

1.2.3 Model-based measures

1.2.3.1 Conditional forecast error variance

ARCH models of many different shapes have been extensively used to model inflation uncertainty in the US.[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. The model is given by a signal equation (1.3), a state equation (1.4) and equation (1.5) describing how conditional error variance evolves.

$$\begin{aligned} \pi_t &= [1\ \pi_{t-1}\ \pi_{t-2}]\ \alpha_t + e_t \qquad e_t \sim N(0, h_t) && (1.3)\\ \alpha_{t+1} &= \alpha_t + \eta_t \qquad \eta_t \sim N(0, Q) && (1.4)\\ h_t &= d + \phi e_{t-1}^2 + \gamma h_{t-1} && (1.5) \end{aligned}$$

Here, α_t is a vector of time-varying coefficients which follow a random walk. We model inflation as an AR(2) process which meets the needs to reproduce the cyclical behavior. h_t describes conditional error variance which emerges from a GARCH(1,1) process. Q is a homoskedastic covariance matrix of shocks η_t. The estimation is based on a rolling window 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

[6] To see whether our results are affected by data revisions, we recalculate the three forecast-based measures using real-time data. For the purpose of our analysis, we find that revisions of the target variable CPI inflation are negligible (see appendix 1.A.2).

[7] 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).

[8] See, 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).

until 2009:M12 and obtain an estimate for the variance of the forecast error at each point in time which obtains the label *garch*.

1.2.3.2 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). Moreover, a stochastic volatility model is proposed as a forecast model for US inflation by Stock and Watson (2007). 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. We follow Dovern et al. (2012) and employ the model to measure inflation uncertainty. The state-space representation is given by equations (1.6) to (1.10).

$$\pi_t = \mu_t + \eta_t \qquad \eta_t \sim N(0, \sigma^2_{\eta,t}) \tag{1.6}$$

$$\mu_{t+1} = \mu_t + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma^2_{\epsilon,t}) \tag{1.7}$$

$$\log \sigma^2_{\eta,t+1} = \log \sigma^2_{\eta,t} + \nu_{1,t} \tag{1.8}$$

$$\log \sigma^2_{\epsilon,t+1} = \log \sigma^2_{\epsilon,t} + \nu_{2,t} \tag{1.9}$$

$$\begin{pmatrix} \nu_{1,t} \\ \nu_{2,t} \end{pmatrix} \sim N(0, \gamma I_2) \tag{1.10}$$

In the measurement equation (1.6), η_t is a short-term shock with variance $\sigma^2_{\eta,t}$. Moreover, the permanent component of inflation μ_t follows a random walk which is driven by a (level) shock ϵ_t with variance $\sigma^2_{\epsilon,t}$. 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 $\sigma^2_{\epsilon,t}$ as the measure of inflation uncertainty. Subsequently, it is denoted by *ucsv*.

1.3 Characteristics of uncertainty measures

1.3.1 Descriptive analysis

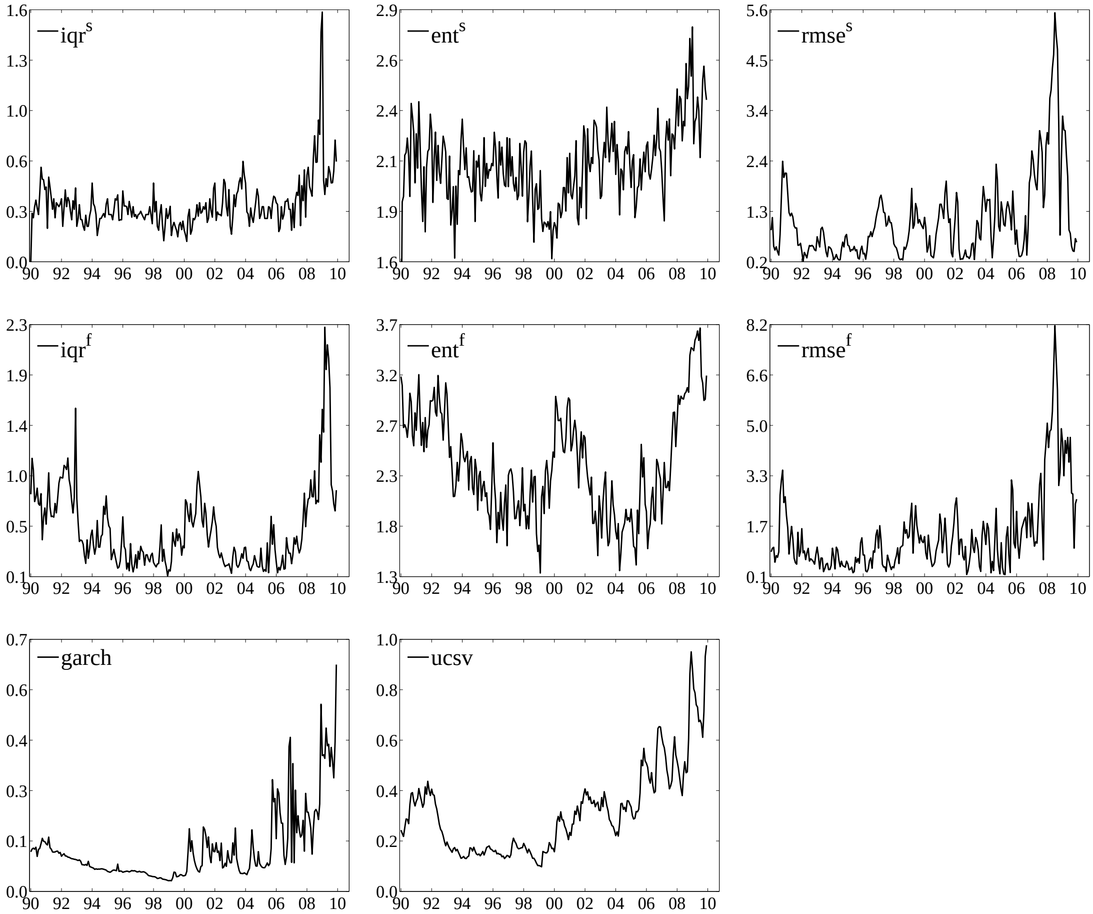
All measures presented in section 1.2 require a number of assumptions to work as good proxies for uncertainty. Most likely, these assumptions are not fulfilled completely. For instance, deriving valid measures from survey-based approaches assumes that the survey is conducted such that bias and measurement 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, 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 driven by forecast errors from previous periods. Hence, each measure proposed in the literature is probably subject to idiosyncratic 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 1.2: 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 1.1. All eight measures exhibit a similar pattern, particularly during the recent economic crisis. Nevertheless, there are also periods when some of the measures diverge.

In the following, we present some descriptive statistics to characterize the individual measures. Figure 1.2 displays the autocorrelation of the eight uncertainty measures on the main diagonal. It shows 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 1.2. We find that cross-correlations are high and significantly positive among all series and

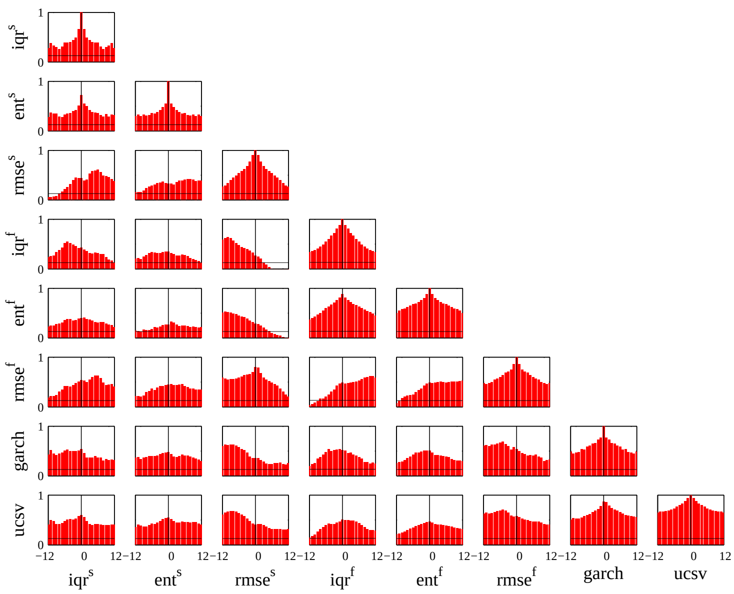
[9] According to Lahiri and Sheng (2010b), overall forecast uncertainty is the sum of the variance of future aggregate shocks and the variance of idiosyncratic shocks. Model-based measures capture only the uncertainty common to all forecasters and neglect forecaster-specific shocks which are responsible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

Figure 1.1: 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



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.

Figure 1.2: Cross-correlations of uncertainty measures

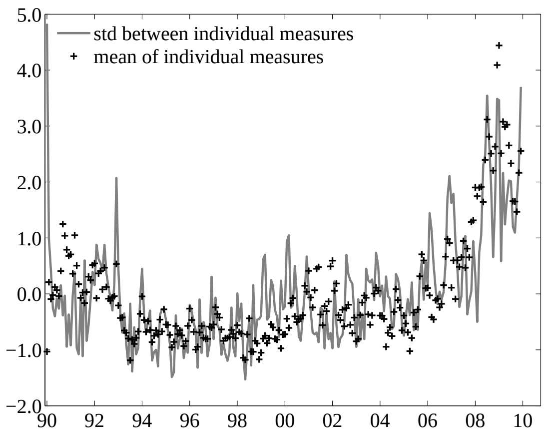


Note: The bars represent cross-correlations $\text{corr}(y_{i,t}, y_{j,t+k})$ for each pair of variables, where $y_{i,t}$ denotes the row i variable and $y_{j,t+k}$ is given in the column j. k varies between -12 and $+12$. The 5% significance level is indicated by the horizontal line.

The extent of co-movement over time is revealed in figure 1.3. 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, yet the measures start to diverge towards the end of the sample. The co-movement between all eight measures further decreases during the recent crisis.[10] Figure 1.3 also depicts the cross-sectional mean of all eight measures, which is strongly correlated with the cross-sectional standard deviation; the correlation coefficient amounts to 0.68. Thus, during more turbulent times, individual measures have the tendency to drift apart and measuring uncertainty becomes more challenging. It appears that a method attenuating the idiosyncratic measurement error problem is particularly beneficial in times of high uncertainty.

[10]In appendix 1.A.3, we validate that the increase of this cross-sectional standard deviation is not traceable to an individual measure only.

Figure 1.3: Dispersion of uncertainty measures



Note: Individual uncertainty measures have been standardized before calculating the cross-sectional standard deviation.

1.3.2 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 idiosyncratic 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 1.1 shows the loading coefficients of the first three principal components and the individual and cumulative variance proportions of those components.

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 less information since it explains only 13% of the variation. A scree test indicates that there are two informative principal components in the dataset (the first two eigenvalues are larger than one). Table 1.1 also shows that the contribution of the third principal component is relatively small. We conclude that the bulk of the variation is explained by two principal components and the following analysis thus focuses on these two components.

Table 1.1: Principal component analysis

	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.

From table 1.1, 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 each of the proposed measures therefore carries information we can use to estimate unobserved inflation uncertainty.[11] 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 1.1, the variance share explained by PC1 varies between 48% and 76%. Also note that the loadings suggest that, in applied research, the idiosyncratic components can be successfully removed from the data by taking a simple average of the individual measures.[12]

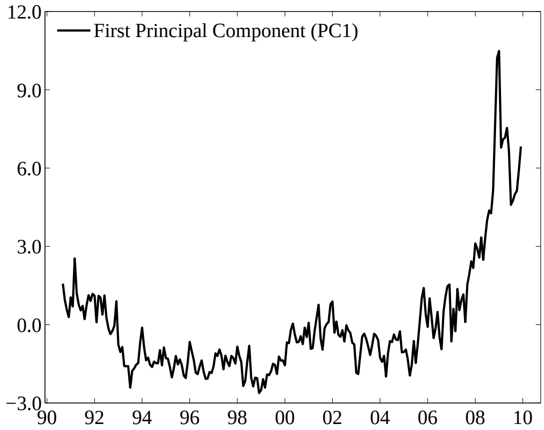
The first principal component is shown in figure 1.4. Following a rather tranquil period with moderate movements, PC1 starts to rise beginning roughly in 2007 followed by a surge towards the end of 2008, which coincides roughly with the peak of the recent economic crisis. This is in line with, for instance, Clark (2009) who documents that macroeconomic variability has recently been increasing due to larger financial and oil price-related shocks. Also note that a large part of the surge in uncertainty is only temporary as PC1 quickly drops to about

[11] Note that given the very similar factor loadings, PC1 remains virtually unaffected when we exclude one measure from the analysis. Our results thus do not hinge on one individual measure.

[12] Due 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 model-based approaches. Our main findings are also confirmed for the earlier time-span (see appendix 1.A.4).

half the value of the 2008-peak in the subsequent months.

Figure 1.4: Uncertainty indicator (PC1)



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 1.2. Results show 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 and stock prices (*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 interest rates is somewhat lower in absolute terms 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.

1.3.3 Group-specific characteristics

We now shed some light on the idiosyncratic movements; i.e., the dynamics which are specific to (some of) the individual measures. The informative part of the idiosyncratic dynamics is reflected in the second principal component (PC2) and we thus use it to analyze the group-specific characteristics. The loadings associated

Table 1.2: Correlations of principal components with economic and financial variables

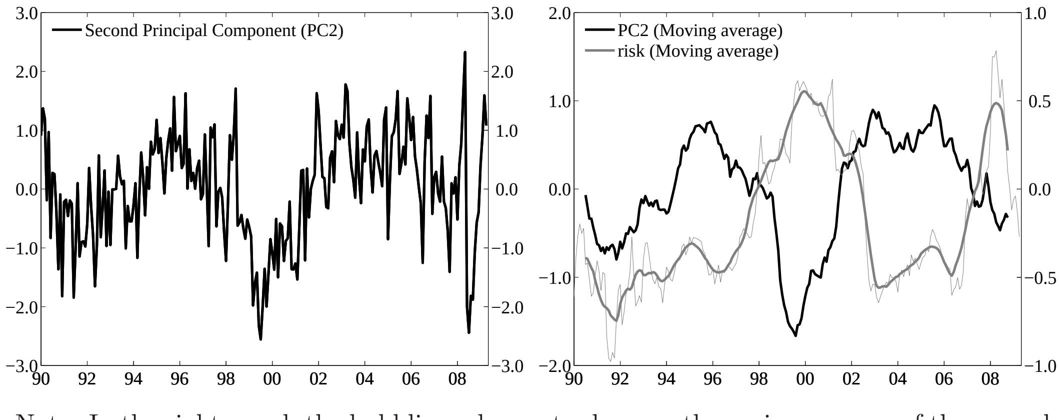
		PC1	PC2			PC1	PC2
Consumer prices	$(\Delta\pi)^2$	**0.40**	**0.14**	Commodity prices	wti	−0.13	
	$(\Delta\pi^{core})^2$	**0.18**	−0.14		ppi^{comm}	−0.19	**0.23**
Money aggregate	$\Delta M2$	**0.16**	**0.21**		ppi^{ind}	−0.19	**0.20**
	$(\Delta M2)^2$	**0.33**	**0.15**		crb^{return}	−0.32	**0.28**
Interest rates	ffr	−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	ism	−0.47	
	Δr^{10Y}				ism^{prod}	−0.42	
	$abs(\Delta ffr)$		−0.17		pmi	−0.53	**0.20**
	$abs(\Delta r^{3M})$		−0.13		pmi^{prod}	−0.56	**0.15**
	$abs(\Delta r^{10Y})$	**0.37**		Consumer climate	mhs	−0.81	
Financial market risk	vix	**0.51**			$confidence$	−0.61	
	ted	**0.30**		Capacity utilization rate	cu	−0.67	
	$risk$	**0.35**	−0.20		cu^{man}	−0.69	
Stock prices	$sp500$				cu^{exIT}	−0.74	
	dj			Production and employment	Δy	−0.81	
	$dj5000$				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	$house$	−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**		ur	**0.55**	−0.14
NBER dates	$recession$	**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 1.A.3 in appendix 1.A.5.

with PC2 provide insight into the interrelation of the 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 disagreement 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 drives survey-based and forecast-based measures into opposite directions; the other measures do not contribute to PC2 significantly.

The left panel of figure 1.5 depicts PC2, which is far from being white noise. To identify situations where survey-based and forecast-based disagreement measures move less synchronized, we analyze the contemporaneous correlations of PC2 to economic variables in table 1.2. In opposition to PC1, PC2 tends to co-move with the business cycle as we obtain a positive correlation with the Purchasing Manager Index (pmi) and negative correlations with all unemployment-related 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 and the forecast-based disagreement measures tend to drift apart during economic downturns.

Figure 1.5: Second principal component (PC2)



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

Moreover, PC2 decreases when the corporate bond risk premium ($risk$) or the output variability increases. Note that both variables are indicators for overall economic risk (see, for instance, Bachmann et al., 2013). As contemporaneous correlations neglect dynamic relations, we plot PC2 along with the corporate risk premium in the right panel of figure 1.5. For illustration purposes, we smooth both series by taking a twelve-month centered moving average. We observe that the risk premium and PC2 move in opposite directions. The pronounced drop of PC2 around the year 2000 especially 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 stays low until 2007. Thus, survey-based and forecast-based disagreement measures tend to drift apart during economically turbulent times such that the idiosyncratic part of iqr^s and ent^s decreases while the idiosyncratic part of iqr^f and ent^f mounts.

For an interpretation of the above findings, we draw attention to the conceptual ideas behind these measures. First, note that forecast-based and survey-based disagreement measures are conceptually similar because both rely on a number of different forecasts. In particular, we may interpret the multitude of VAR models as a panel of forecasters where each forecaster uses a different VAR 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. If forecasters are risk-averse, they may choose to stick to the consensus if uncertainty is high, and forecast dispersion may decline. Thus, an explanation for the divergence of survey-based disagreement and forecast-based disagreement is that forecasters may cluster their forecasts around the consensus during turbulent times. This typically does not happen to the forecast-based measures. Being a mechanistic approach, forecast-based disagreement, in fact, appears to overstate "true" inflation uncertainty. Overall, our results suggest that using only one individual disagreement measure may be misleading during turbulent times. Note that this finding is also consistent with 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; i.e., whenever the shocks common to all forecasters are small.

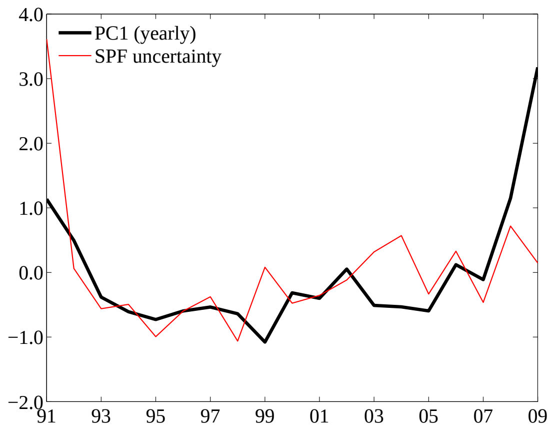
1.3.4 Comparison to SPF inflation uncertainty

Many studies use uncertainty measures based on SPF data (see, for instance, 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. Due to this specific survey design, we can derive for each forecaster i 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 1.3.2 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 also declines. Nevertheless, we compare PC1 to SPF uncertainty but have to restrict our comparison to yearly observations. Since one-year-ahead 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 1.6 depicts the resulting time series, which are both normalized to have mean zero and standard deviation one.

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 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. We also compare SPF uncertainty to the individual measures,

Figure 1.6: Yearly uncertainty indicator (PC1) and SPF uncertainty



and we obtain a positive correlation for all measures. Moreover, PC1 appears to have a higher correlation with SPF uncertainty than most of the individual measures.[13]

Some limitations of such a comparison have to be noted. First, SPF uncertainty refers to the GDP deflator as opposed to CPI inflation since 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 (see, for instance, D'Amico and Orphanides, 2008; Rich and Tracy, 2010). Furthermore, changes in the survey design concerning, for example, the number and the width of histogram bins may distort the signal. Overall, SPF uncertainty is very likely subject to idiosyncratic measurement error – as any other measure – which may explain a temporary divergence of SPF uncertainty and PC1 (see also Batchelor and Dua, 1993, 1996).

1.4 The link between inflation and inflation uncertainty

The relationship 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

[13]For detailed results and a graphical representation, see figure 1.A.4 in appendix 1.A.6.

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. If we are able to remove the idiosyncratic component from the individual measures, PC1 should yield a more precise and robust estimate of the relation between inflation and inflation uncertainty since it summarizes the information in the individual measures. 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.

First, we test the inflation-inflation uncertainty link 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 1.3. The p-values reveal a strikingly inconclusive picture. $rmse^s$ and iqr^f seem to be Granger caused by inflation, yet 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 is understood that uncertainty is followed by inflation. When the same test is conducted for the change of inflation, we also obtain divergent results across measures. Overall, it appears that the choice of the measure is crucial. Using individual measures therefore entails the risk that results are driven by idiosyncratic movements that are unrelated to inflation uncertainty.

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.[14] Most notably, results in table 1.3 suggest that PC1 provides an

[14]The result is robust to the choice of the lag length of the VAR according to BIC, which

Table 1.3: Granger causality test for inflation uncertainty and inflation

	PC1	irq^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 conducted 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 1990:M9 to 2009:M12.

insurance against idiosyncratic measurement error attached to the individual measures.

Second, 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 instantaneously reacts to a shock to inflation.[15] This is motivated by the fact that uncertainty may move quickly when agents encounter new macroeconomic information whereas inflation is comparatively slow-moving.

The upper-left panel of figure 1.7 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 us 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 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

suggests two lags (see appendix 1.A.7). Furthermore, it is robust if we exclude the recent crisis and end the sample in 2007:M8, which is roughly when the US sub-prime crisis started to spill over into other sectors of the economy (see appendix 1.A.8).

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

time that has elapsed since the shock, the more uncertainty is attached to the future course of inflation. Again, let us consider 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 upper-right panel of figure 1.7. 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.[16]

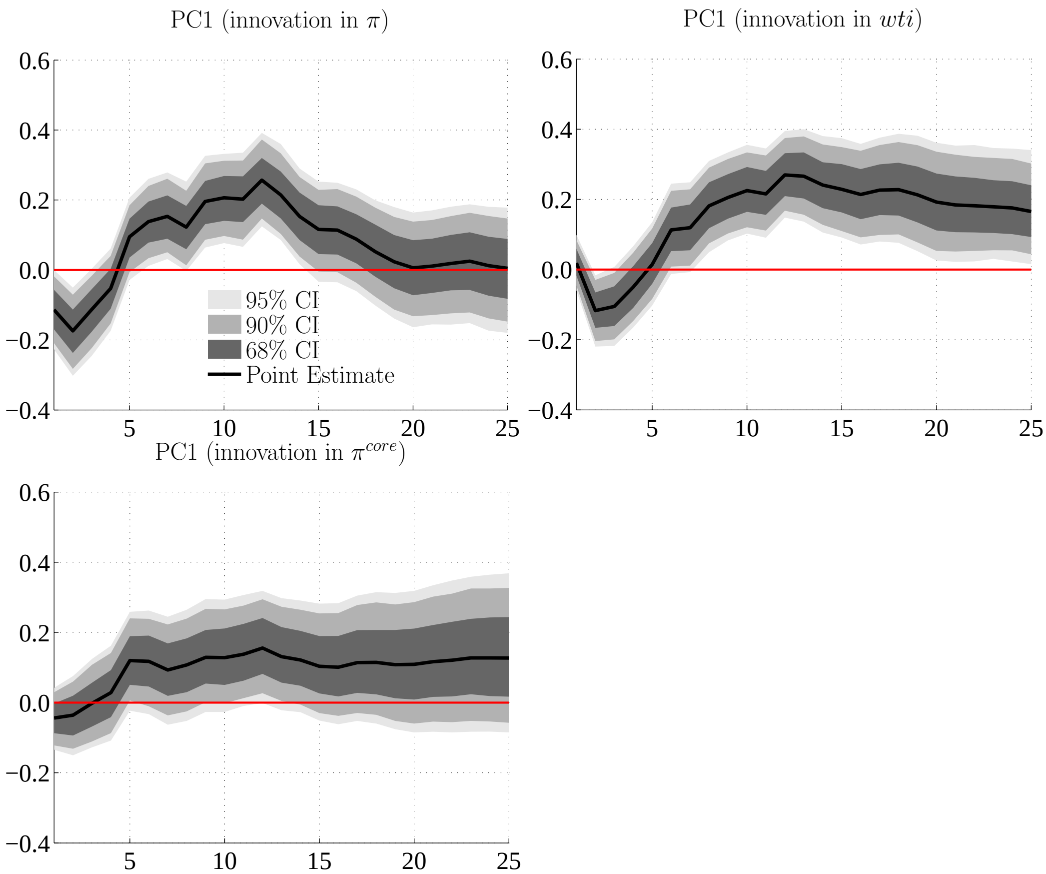
Turning to the lower panel of figure 1.7, we observe that a shock to core inflation (π^{core}) also induces a rise in uncertainty. Here, it takes about four months until uncertainty increases. In contrast to CPI inflation, a shock to core inflation does not induce a fall in uncertainty in the first periods. 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 consequently 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.

Taken together, 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 inflation-inflation uncertainty link. Such a finding provides evidence to support the claim that PC1 is a valid measure. In contrast, when we repeat the exercise for each individual uncertainty measure,

[16] See appendix 1.A.9 for results obtained from monetary VARs containing output, inflation, a short-term interest rate, and inflation uncertainty. Our results remain unaffected when a larger VAR is employed. Furthermore, the impulse response is qualitatively the same when we estimate the bivariate VAR on a sample ending in 2007:M8 (see appendix 1.A.8).

we find that the response of uncertainty is rather heterogeneous.[17] Hence, the link from inflation to inflation uncertainty is not revealed in a conclusive way if we rely on a single measure.

Figure 1.7: Response of inflation uncertainty to inflation, wti, and core inflation



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

Finally, we analyze whether the contribution of inflationary shocks to PC1 is meaningful in an economic sense. To this end, table 1.4 presents the forecast error variance decomposition associated with the bivariate VAR models shown in figure 1.7. 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 determinant of

[17]The individual impulse responses are illustrated in figure 1.A.8 in appendix 1.A.10.

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.

Table 1.4: Forecast error variance decomposition

horizon	**1**	**5**	**10**	**15**	**20**	**25**
π	3.2	6.8	14.0	20.6	15.2	10.7
wti	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.

1.5 Concluding remarks

After 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 relies on different assumptions which are very likely not fulfilled completely. Hence, individual measures may be subject to idiosyncratic measurement error.

We use common information in different uncertainty measures to eliminate the idiosyncratic 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 idiosyncratic measurement error problem, and the underlying signal should be revealed with greater precision. Moreover, we find that the loadings of the individual measures on the common component are approximately equal. Therefore, taking a simple average over the individual measures is a viable alternative which delivers a robust indicator of inflation uncertainty.

Our indicator of inflation uncertainty does not completely explain the variation in the data. In general, individual measures tend to differ more during turbulent times. From the idiosyncratic dynamics not captured by the common component, we infer that a researcher may be confronted with survey respondents sticking to the consensus when macroeconomic risk is high, which induces a downward bias in survey disagreement. In contrast, forecast-based disagreement might overstate “true” inflation uncertainty. Hence, using only one individual disagreement measure is a risky strategy.

Subsequently, we use the proposed uncertainty indicator to analyze the link between inflation and inflation uncertainty. Our results based on 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 in 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 of inferring causality by empirical testing only. In future research, it would certainly be fruitful to increase the effort to integrate inflation uncertainty into a structural macroeconomic model in order to establish a causal economic relationship.

Acknowledgments

I am indebted to Christian Grimme and Steffen Henzel, who are co-authors of Chapter 1.

Appendix

1.A.1 Dataset to estimate forecast-based measures

Table 1.A.1: Variables used to forecast inflation

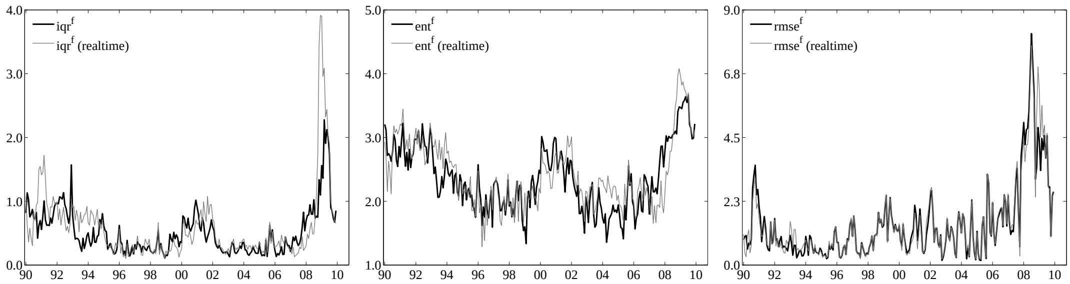
Variable	**Transformation**
Average hourly earnings (nonfarm payroll)	change of growth rate
Building permits for new private housing units	growth rate
Capacity utilization (manufacturing)	growth rate
Crude oil index	change of growth rate
Employment (non-agricultural industries)	gap measure
Federal funds 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 Hodrick-Prescott filter; "interest rate spread" is defined as the difference between interest rate on government bonds and federal funds rate.

1.A.2 Using real-time data

To see whether our results are affected by data revisions, we recalculate the forecast-based measures using real-time data whenever consistently available since 1970. This is the case for the CPI, employment, the unemployment rate, and industrial production which are taken from the FRED database. We use the four real-time series with the remaining 12 variables (e.g., new orders, interest spread, and M3) to build the rolling VAR models. As in the main body of the paper, we proceed as follows: For each vintage, we use the Hodrick-Prescott filter to obtain detrended values of employment, the unemployment rate, and industrial production. From the forecasts of the VAR models, we calculate the three uncertainty measures. The resulting series are depicted in figure 1.A.1 along with the original forecast-based measures from the main part of the paper. The measures iqr^f, ent^f and $rmse^f$ co-move closely with their real-time equivalent (the correlation coefficient is 0.75, 0.84 and 0.97, respectively). Moreover, we calculate the Mean Absolute Revision of CPI inflation between the first vintage and the value reported half a year later between 1972 (first year with CPI vintage data) and 2009. On average, CPI inflation was revised only by 0.019 percentage points during this time span. Hence, in our framework, revisions of the target variable CPI inflation are – in opposition to the GDP deflator – rather negligible.

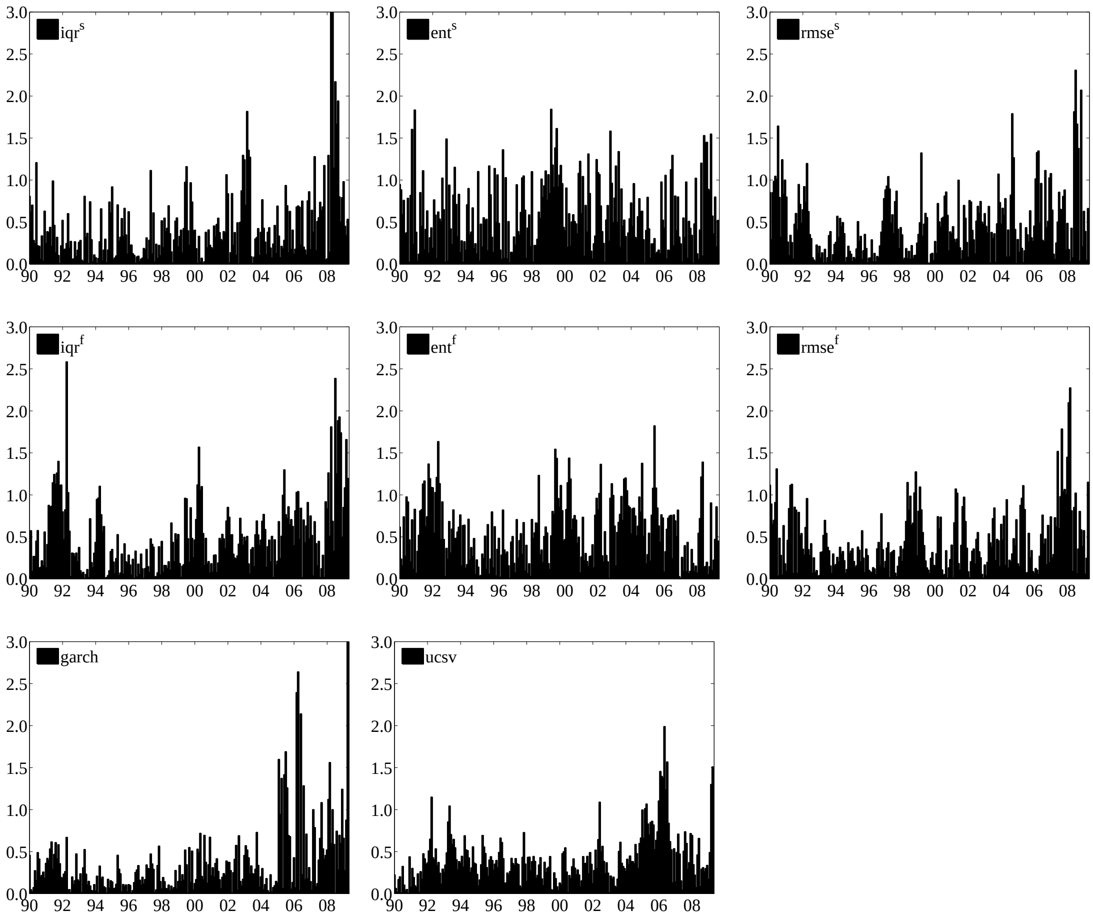
Figure 1.A.1: Forecast-based measures estimated from revised and from real-time data



1.A.3 How strongly do individual measures "disagree"?

In section 1.3.1, we document that individual measures have the tendency to drift apart during more turbulent times, as reflected by their cross-sectional standard deviation. In the following, we examine whether the increase of the standard deviation in figure 1.3 in the paper is traceable to a particular measure. For this purpose, figure 1.A.2 displays the absolute deviation of each measure from the cross-sectional mean at each point in time. We find that the deviation from the mean varies over time for all measures. Overall, we cannot identify a single measure that drives the standard deviation shown in figure 1.3 in the main text.

Figure 1.A.2: Absolute deviation of individual uncertainty measures from mean



Note: The bars represent the absolute deviation of each measure from the mean, which is calculated as the average over all individual measures for each point in time.

1.A.4 Uncertainty indicator for the period 1970-1995

Due to the CE survey data, our main analysis is limited to a sample starting in 1990, which covers a rather tranquil period as far as inflation is concerned. To see whether our results also hold for periods of high and volatile inflation, we conduct the analysis for the years 1970 to 1995 and, consequently, consider only the forecast-based and model-based approaches. For this purpose, we first calculate the three forecast-based measures (iqr^f, ent^f, $rmse^f$) for the longer time-span. To be consistent with the analysis in the paper, we rely on a rolling window covering 20 years of data. Hence, we estimate the VAR models starting with a data window 1950:M1-1969:M12 and iterate further until the last period (1975:M1-1995:M12). Second, we estimate the GARCH and the UC-SV model over a rolling data window for the same sequence of time periods. Following this, we perform the principal component analysis for the sample ranging from 1970 to 1995. Results of the principal component analysis are presented in table 1.A.2, and the first principal component is plotted in figure 1.A.3.

Table 1.A.2: Principal component analysis (1970-1995)

	PC 1	PC 2	PC 3	
Eigenvalues	2.89	1.02	0.53	
Variance Proportion	0.58	0.20	0.11	
Cumulative Proportion	0.58	0.78	0.89	
	Loadings			R^2
iqr^f	0.41	0.58	−0.31	0.49
ent^f	0.42	0.55	0.37	0.51
$rmse^f$	0.43	−0.40	0.66	0.54
$garch$	0.46	−0.36	−0.56	0.61
$ucsv$	0.50	−0.27	−0.12	0.73

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

Evidently, our main results can also be replicated for the earlier time-span. First, we document a common component which explains with 58% the majority of variation in the data. Second, all individual measures contribute to this common component with a non-negligible weight and similar loadings. As depicted in figure 1.A.3, the combined measure indicates high inflation uncertainty during the pre-Volcker period of accommodating monetary policy and rising inflation rates. Inflation uncertainty starts to decline with the set-in of disinflationary policy at the beginning of the 1980s and bottoms out in the early 1990s with temporary increases around 1987 ("Black Monday") and 1991 (recession date according to the National Bureau of Economic Research).

Figure 1.A.3: PC1 for the period 1970-1995

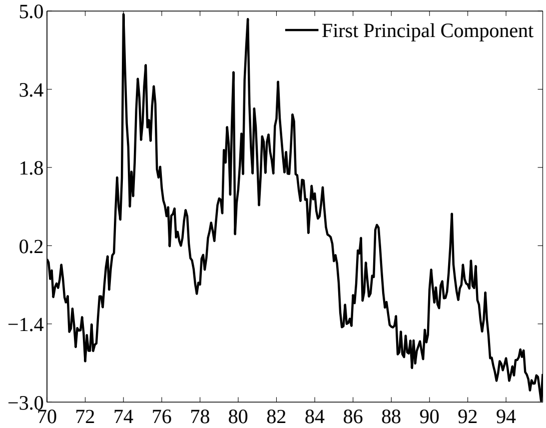
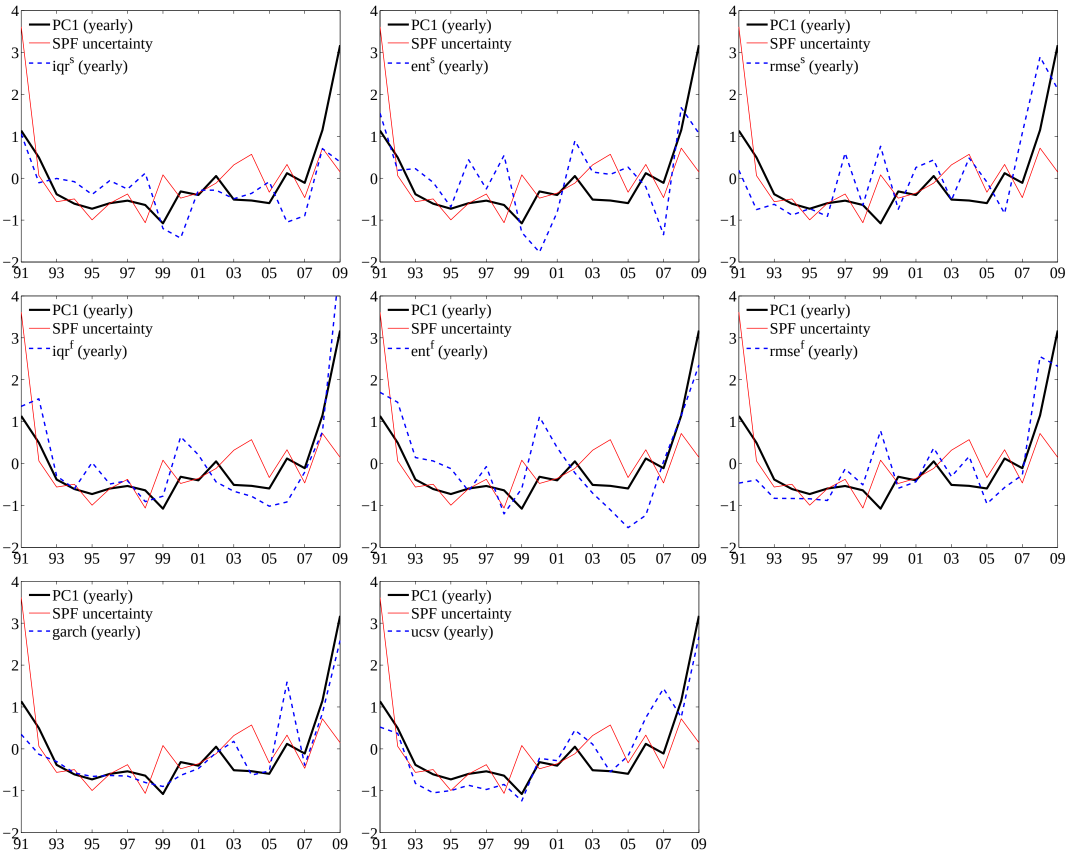


Table 1.A.3: Description of economic variables

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

1.A.6 Comparison of individual uncertainty measures to SPF inflation uncertainty

Figure 1.A.4: Yearly individual uncertainty measures and SPF uncertainty



Note: Correlation coefficients of the yearly individual uncertainty measures and SPF uncertainty are, respectively, 0.48 (iqr^s), 0.50 (ent^s), 0.27 ($rmse^s$), 0.29 (iqr^f), 0.39 (ent^f), 0.22 ($rmse^f$), 0.36 ($garch$), and 0.33 ($ucsv$).

1.A.7 Sensitivity of Granger causality tests

In the following, we check the sensitivity of the Granger causality tests presented in section 1.4 of the paper. As a first robustness exercise, we show that our results are robust with respect to the choice of the lag length. For each of the bivariate VAR models, we selected the number of lags according to BIC and subsequently performed the Granger causality test. Table 1.A.4 displays the results of this test and the corresponding lag length. For the VAR models comprising the level of inflation π, the BIC selects lags between 2 and 3. In contrast, a lag length of 12 is broadly supported for the change in inflation $\Delta\pi$. Note that we also obtain a lag length of 12 lags in the majority of cases according to AIC. Evidently, a different choice of the lag length does not change our main conclusions. We still obtain mixed results concerning the direction of Granger causality with respect to the individual measures. Moreover, the lag length does not influence the results of the Granger causality test for PC1. In contrast, results for some of the individual measures hinge on the lag length chosen (cp. table 1.3 in the main text).

Table 1.A.4: Sensitivity of Granger causality test w.r.t. selected lag length

	PC1	irq^s	ent^s	$rmse^s$	iqr^f	ent^f	$rmse^f$	$garch$	$ucsv$
H_0: π does not Granger cause IU	**0.04**	**0.00**	0.87	0.43	0.48	0.46	0.22	0.72	0.91
H_0: IU does not Granger cause π	0.21	**0.01**	0.71	0.07	0.15	0.14	**0.01**	0.41	0.58
Lag length (BIC)	2	3	2	3	2	2	3	2	2
Lag length (AIC)	12	11	12	12	11	3	12	12	11
H_0: $\Delta\pi$ does not Granger cause IU	**0.00**	**0.00**	0.82	**0.02**	0.82	0.53	0.07	**0.01**	0.90
H_0: IU does not Granger cause $\Delta\pi$	0.29	0.19	0.90	**0.01**	0.55	0.85	**0.00**	0.19	**0.02**
Lag length (BIC)	12	12	2	12	2	1	12	12	12
Lag length (AIC)	12	12	12	12	12	12	12	12	12

Note: Granger causality tests are conducted 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 selected according to BIC. Sample ranges from 1990:M9 to 2009:M12.

As a second robustness exercise, we ignore the forward-looking information in the individual *rmse* measures. That is, we use contemporaneous values of $rmse^s$ and $rmse^f$ instead of lagged values to estimate PC1 (cp. section 1.3.2) and subsequently conduct the Granger causality test presented in table 1.A.5. It is obvious that timing matters for the two individual *rmse* measures as the results of the Granger causality test become partly insignificant. In contrast, the results for PC1 are not affected.

Table 1.A.5: Sensitivity of Granger causality test w.r.t. timing of $rmse^s$ and $rmse^f$

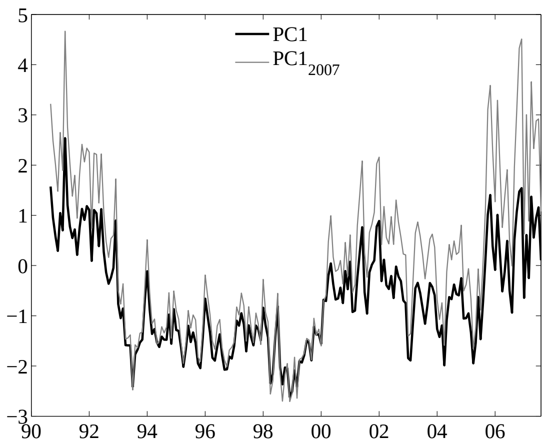
	PC1	irq^s	ent^s	$rmse^s$	iqr^f	ent^f	$rmse^f$	$garch$	$ucsv$
H_0: π does not Granger cause IU	**0.01**	**0.00**	0.08	0.24	**0.02**	0.58	0.13	0.07	0.91
H_0: IU does not Granger cause π	0.55	**0.01**	0.31	0.37	0.17	0.29	0.21	0.50	**0.03**
H_0: $\Delta\pi$ does not Granger cause IU	**0.01**	**0.00**	0.30	0.23	**0.01**	0.64	0.17	**0.01**	0.90
H_0: IU does not Granger cause $\Delta\pi$	0.22	0.19	0.14	0.07	**0.00**	**0.01**	**0.00**	0.19	**0.02**

Note: Granger causality tests are conducted 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 1990:M9 to 2009:M12.

1.A.8 Excluding the recent crisis from the sample

Figure 1.A.5 shows the uncertainty indicator PC1 and an indicator derived from a sample that excludes the recent financial and economic crisis, $PC1_{2007}$. The differences between both measures are relatively small and in some time periods even non-existent, with a correlation coefficient of 0.98.

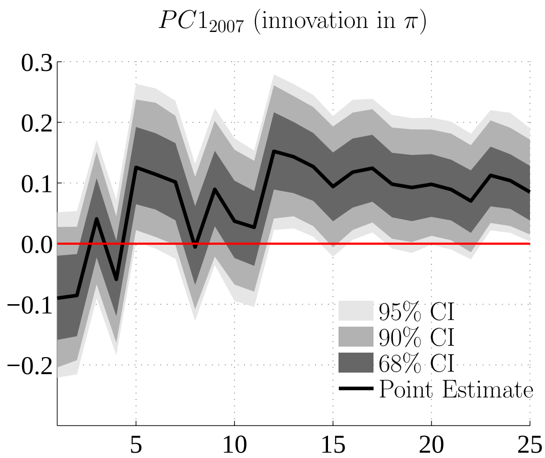
Figure 1.A.5: Uncertainty indicator excluding the recent crisis



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 2007M8.

Testing the Granger causality with $PC1_{2007}$ clearly supports the Friedman-Ball hypothesis. The null that inflation or the change in inflation does not Granger cause the uncertainty indicator can be rejected with a p-value of 0.01 and 0.02, respectively. In contrast, the reverse Granger causality cannot be confirmed (the corresponding p-value is 0.90 and 0.99). The Friedman-Ball hypothesis is also supported by the impulse response of $PC1_{2007}$ to a shock to inflation as illustrated in figure 1.A.6. When compared to figure 1.7 in the paper, the overall pattern does not change; a one-standard deviation shock to inflation triggers a significant increase in inflation uncertainty in the longer run. These robustness checks suggest that our results are not solely driven by the recent financial crisis.

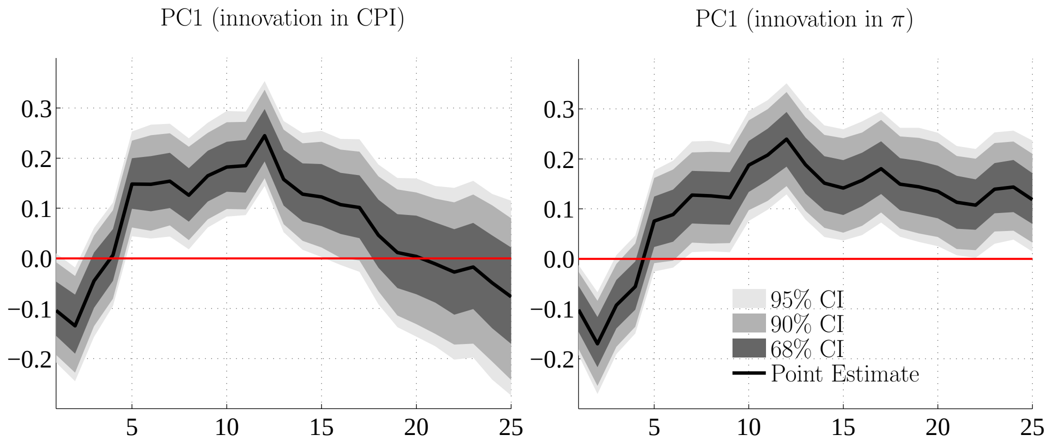
Figure 1.A.6: Response of inflation uncertainty to an inflation shock (1990:M9-2007:M8)



1.A.9 Alternative VAR specifications

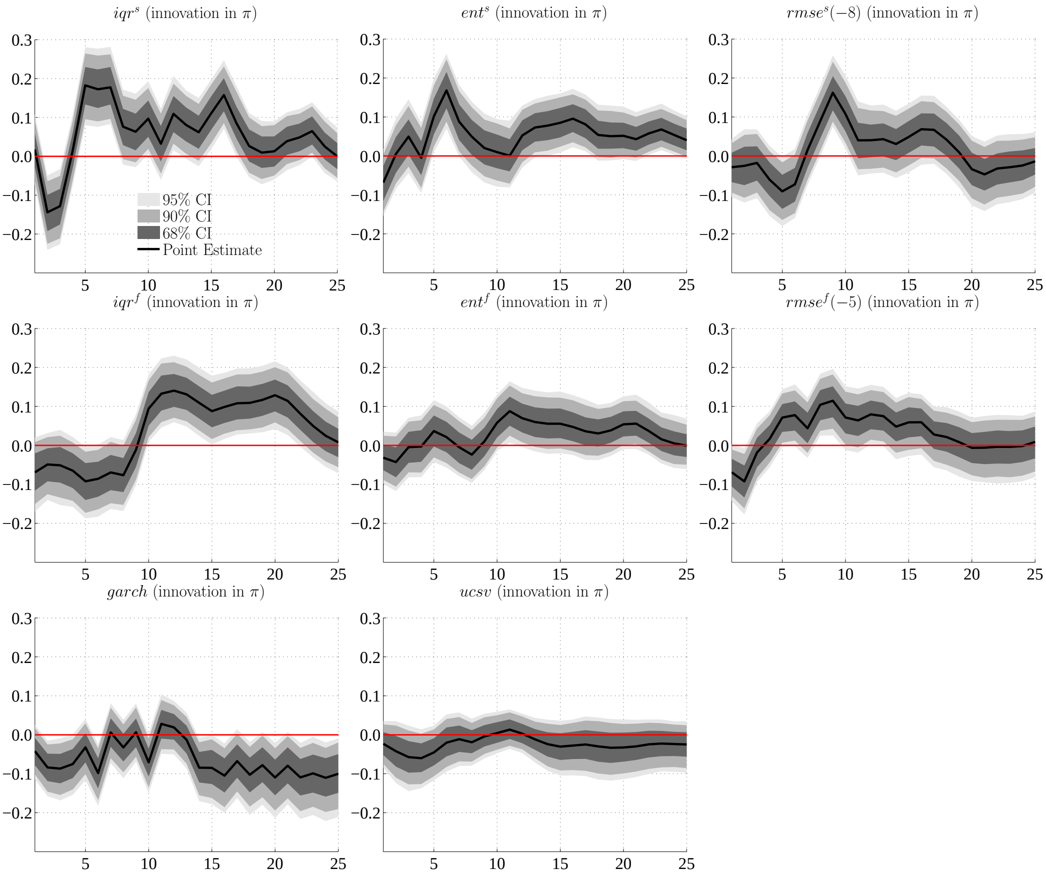
In the following, we analyze whether the response of uncertainty to an inflation shock is robust to alternative VAR specifications. To this end, we specify a larger VAR model which is standard for monetary policy analysis. It includes monthly data on industrial production, consumer prices, the federal 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 1.A.7. It is understood that our results remain unaffected by the inclusion of additional variables.

Figure 1.A.7: Response of inflation uncertainty to a CPI shock and to an inflation shock in a 4-variable VAR



1.A.10 Impulse responses of individual uncertainty measures

Figure 1.A.8: Response of individual uncertainty measures



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

Chapter 2

Synchronization and changes in international inflation uncertainty

2.1 Introduction

It is well known that increased inflation uncertainty may lead to economic cost. For instance, higher uncertainty about future inflation might trigger a disproportionate reallocation from nominal to real assets and makes nominal contracts involving wages and financial assets riskier (Fischer and Modigliani, 1978; Bernanke and Mishkin, 1997).[1] Moreover, a strand of literature stresses that higher inflation uncertainty is typically associated with higher inflation (Friedman, 1977; Ball, 1992; Cukierman and Meltzer, 1986). As a consequence, inflation uncertainty increases the cost of high inflation and hampers the anchoring of low inflation expectations. Hence, understanding the evolution of inflation uncertainty is crucial if we want to maintain the benefits of low and stable inflation rates.[2]

Our study aims to provide additional insight into the international linkages of

[1]Recently, uncertainty shocks have also gained attention as drivers of business cycle fluctuations. A growing amount of literature documents their potential effects on the real economy. See, for example, Bloom (2009); Alexopoulos and Cohen (2009); Fernandez-Villaverde et al. (2011); Bachmann et al. (2013); Baker et al. (2013).

[2]Consequently, a large number of empirical studies analyze the effects of increased inflation uncertainty. Previous studies typically discuss its relation to inflation and output at the national level. See, for instance, Baillie et al. (1996), Grier and Perry (1998), Bhar and Hamori (2004), Fountas and Karanasos (2007), Fountas (2010), and Caporale et al. (2012).

inflation uncertainty. The contribution of the present paper is twofold. First, we document the extent of co-movement of inflation uncertainty among the G7 and analyze the sources of international synchronization. Second, we investigate the origins of changes in the dynamics of national inflation uncertainty by accounting for international factors and spillover effects from one country to another. We tackle both questions with the help of a Factor-Structural Vector Autoregression (FSVAR) model which allows for a decomposition of the total variation of inflation uncertainty in one country into the contributions of international shocks, own shocks, and spillover effects.

A number of studies focus on common factors as a reason for business cycle synchronization (see, for instance, Stock and Watson, 2005; Kose et al., 2008). Likewise, incomplete exchange rate adjustment and exposure to global shocks, such as, oil-supply or commodity price shocks, provide a basis for a common component in national inflation rates (see, for instance, Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012). Bataa et al. (2013a) analyze international linkages of inflation between major industrialized countries. They provide evidence of increased co-movement among the Euro area countries as well as a rising correlation between the US, Canada and the Euro area aggregate. We extend this literature by analyzing the degree and sources of synchronization of international inflation uncertainty. We consider common shocks and spillover effects as possible explanations for synchronization of inflation uncertainty in the G7 and quantify the importance of each of these components for national inflation uncertainty.

Another strand of literature documents a decline in the volatility of inflation in the US since the mid-eighties (Stock and Watson, 2007, 2010; Cogley et al., 2010; Canova and Ferroni, 2012, see). Cecchetti et al. (2007) demonstrate that the volatility of trend inflation has also decreased over time in the other G7 countries which constitutes an "Inflation Stabilization" process. Bataa et al. (2013a,b) analyze the nature and timing of the changes in international inflation uncertainty by means of a statistical break test. In particular, for most G7 countries, they document a structural break in the volatility of inflation in the mid-eighties which is followed by a decline in inflation uncertainty.[3] In this

[3] As documented by Bataa et al. (2013b), in Canada, the US, and (to a lesser extent) in the Euro area, the decline appears to be only temporary as the volatility of inflation shocks began to rise in the late nineties again.

paper, we investigate how the inflation uncertainty process has changed over time and place emphasis on changes in the stability of inflation uncertainty. In order to shed light on the sources of these changes, we quantify the role of the size of shocks impinging on inflation uncertainty ("good or bad luck"). In addition, we assess to what extent changes in the structure of the economy and (monetary) policy stance have altered the propagation of these shocks ("good or bad policy").[4]

Our results can be summarized as follows. First, we find evidence of synchronization among inflation uncertainty in the G7 notably at business cycle frequencies. We show that the degree of synchronization has increased during the recent two decades. Second, we reveal a common shock that moves domestic inflation uncertainty in all G7 countries into the same direction. We find that this common shock is closely related to oil and commodity price uncertainty. By contrast, shocks originating in the US have an impact on a subset of countries only. Third, based on recursive estimations, we document that there has been a marked increase in the stability of inflation uncertainty, paralleling the "Inflation Stabilization" process. To the best of our knowledge this has not been documented elsewhere. Fourth, we document that the propagation mechanism of shocks to inflation uncertainty in the G7 has changed considerably over time. It appears that domestic shocks translate less extensively into the individual economies. We interpret this finding in favor of the "good policy" hypothesis. Finally, the relative importance of international shocks has increased over time, which provides an explanation for the higher degree of synchronization among the G7.

The paper is organized as follows. We introduce our measure of inflation uncertainty in section 2.2. In section 2.3, we examine the degree of synchronization of G7 inflation uncertainty and test for structural breaks in the inflation uncertainty process. The set-up of the FSVAR model is explained in section 2.4. The empirical results of the FSVAR estimation are presented in section 2.5. Section 2.6 summarizes and provides conclusions.

[4] A similar approach has been used, for instance, by Ahmed et al. (2004), Stock and Watson (2005), Giannone et al. (2008), Justiniano and Primiceri (2008), and Galí and Gambetti (2009) to analyze the sources of the "Great Moderation" in the US.

2.2 Measuring inflation uncertainty

Before turning to the main analysis we require a measure of unobserved inflation uncertainty. Ideally, uncertainty is derived from subjective probability density functions of decision makers. Such a measure relies on information about the subjective probability that future inflation will fall in a certain range. For the US, a number of studies use these types of uncertainty measures (see, for example, Zarnowitz and Lambros, 1987; Giordani and Söderlind, 2003; Rich and Tracy, 2010). However, consistent data for a longer time span including all G7 countries are not available at this present time.[5] This is why we opt for a model-based measure which has the advantage of being consistently available for a long history to analyze the international linkages among the G7.

In this study we use a stochastic volatility model which has recently been proposed to model uncertainty (see, for instance, Fernandez-Villaverde et al., 2011; Dovern et al., 2012). The stochastic volatility model – in contrast to a GARCH model – allows for a separate innovation impinging on volatility (see, for instance, Fernandez-Villaverde and Rubio-Ramirez, 2010). Moreover, Grimme et al. (2011) show that a measure based on stochastic volatility compares well with other (survey-based) measures of inflation uncertainty. We derive the measure from an unobserved component model with stochastic volatility (UC-SV). Notably, Stock and Watson (2007) show that the UC-SV model captures the salient features of inflation and that it is very well suited as a forecast device. One reason for the comparatively good forecast performance is that it decomposes inflation into a stochastic trend and a transitory component. The UC-SV model is given by equations (2.1) to (2.5).

$$\pi_t = \bar{\pi}_t + \eta_t \qquad \eta_t \sim N(0, \sigma^2_{\eta,t}) \tag{2.1}$$

$$\bar{\pi}_{t+1} = \bar{\pi}_t + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma^2_{\epsilon,t}) \tag{2.2}$$

$$\log \sigma^2_{\eta,t+1} = \log \sigma^2_{\eta,t} + \nu_{1,t} \tag{2.3}$$

$$\log \sigma^2_{\epsilon,t+1} = \log \sigma^2_{\epsilon,t} + \nu_{2,t} \tag{2.4}$$

$$\begin{pmatrix} \nu_{1,t} & \nu_{2,t} \end{pmatrix}' \sim N(0, \gamma I_2) \tag{2.5}$$

[5]Subjective probability densities are provided for the US by the Survey of Professional Forecasters (SPF) maintained by the Federal Reserve Bank of Philadelphia, the ECB's Survey of Professional Forecasters which polls expectations about aggregate Euro area data, and the Survey of External Forecasters conducted by the Bank of England.

In this state-space model the trend $\bar{\pi}_t$ is modeled as a random walk with a level shock ϵ_t. The innovation process η_t captures the transitory part. The setting incorporates second moment shocks $\nu_{1,t}$ and $\nu_{2,t}$ which inflate the volatility of the process. The model is estimated with the Gibbs sampler.[6] An increase in the standard deviation of the permanent shock reflects that trend inflation is subject to larger changes which translate into larger forecast errors. Hence, $\sigma_{\epsilon,t}$ may be interpreted as long-term inflation uncertainty. Since it is reasonable to assume that policy makers are more concerned with uncertainty about long-term inflation, we follow Cecchetti et al. (2007) and focus on $\sigma_{\epsilon,t}$.

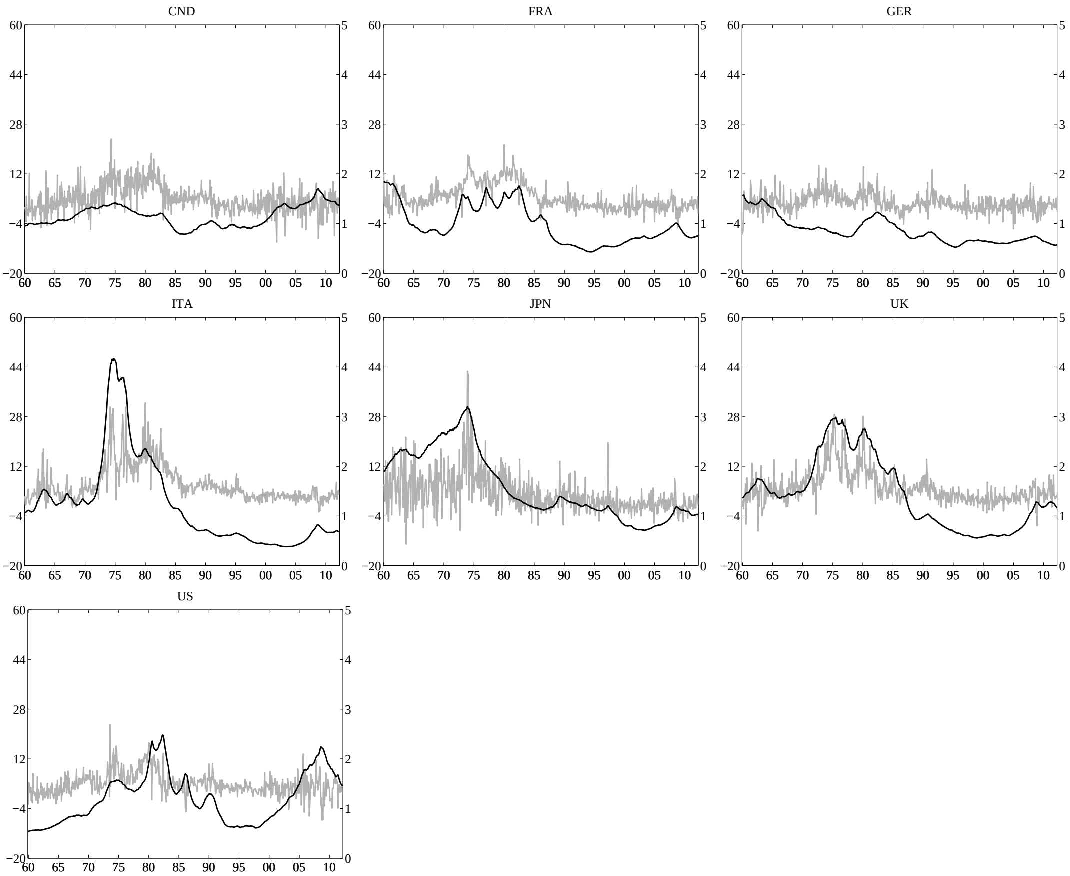
Our sample comprises the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom, and the US) over the period 1960:M1-2012:M4. We measure inflation as the annualized monthly percent change in the Consumer Price Index (CPI) given by $1200 \times \log(CPI_t/CPI_{t-1})$. The inflation series are obtained from the OECD database and are seasonally adjusted. Finally, outliers in the data have been removed, most of which are attributable to announced changes in the value-added tax rate.[7]

Figure 2.1 shows the uncertainty measures together with actual inflation. A similar pattern emerges for the G7. In light of the high inflation rates observed in the seventies, we measure a steady increase in inflation uncertainty. This upswing is followed by a marked reduction in volatility of inflation rates in the mid-eighties which constitutes the process of "Inflation Stabilization" (Cecchetti et al., 2007). During the end of the last decade, uncertainty has slightly risen in the majority of the G7 economies. In particular, most uncertainty measures peaked again during the Global Financial Crisis (see also Clark, 2009, and Dovern et al., 2012, concerning this point).

[6]Estimation is based on the replication files of Stock and Watson (2007) which are available from Mark W. Watson's website: http://www.princeton.edu/~mwatson/publi.html. The model has only one scalar parameter γ which determines the smoothness of the stochastic volatility. Stock and Watson (2007) calibrate this parameter to $\gamma = 0.20$ for quarterly inflation rates. Since we have monthly data which usually carries more noise, we set $\gamma = 0.2/3$.

[7]See appendix 2.A.1 for a detailed description of outlier adjustment.

Figure 2.1: Inflation and long-term inflation uncertainty



Note: The gray line represents actual inflation (left axis), the dark line represents the long-term stochastic volatility measure of inflation uncertainty (right axis).

2.3 Synchronization of inflation uncertainty in the G7

The first contribution of our study is to assess the degree of synchronization of inflation uncertainty among the G7. As proposed by Croux et al. (2001), we calculate the *dynamic correlation* between each country pair which shows the degree of synchronization at a given frequency. In the bivariate case, dynamic correlation between two variables x and y is defined as

$$\rho_{xy}(\lambda) = \frac{C_{xy}(\lambda)}{\sqrt{S_x(\lambda) S_x(\lambda)}}, \tag{2.6}$$

where $S_x(\lambda)$ and $S_y(\lambda)$ are the spectral density functions of x and y, $-\pi \leq \lambda < \pi$ is the frequency, and $C_{xy}(\lambda)$ is the cospectrum. The frequency λ is inversely related to the number of periods per cycle, $p = \frac{2\pi}{\lambda}$. Given our monthly data, a frequency of $\frac{\pi}{4}$, for example, corresponds to a cycle of 8 months.[8]

For a group of countries, co-movement can be summarized by the measure of cohesion which is defined as the (weighted) average of dynamic correlations among all possible country pairs:

$$coh_x(\lambda) = \frac{\sum_{i \neq j} w_i w_j \rho_{x_i x_j}(\lambda)}{\sum_{i \neq j} w_i w_j}, \tag{2.7}$$

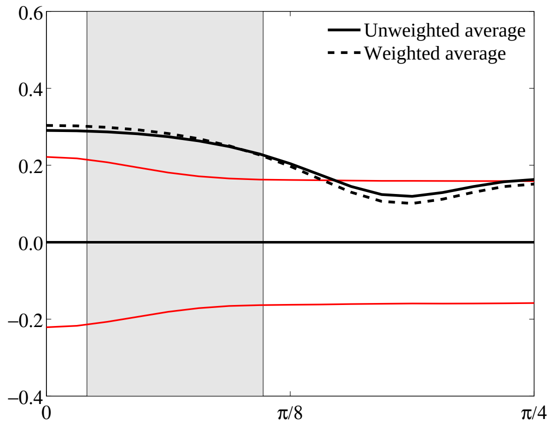
where x denotes a vector of variables, and w_i denotes the respective weight of country i. We consider two approaches. First, dynamic correlations are weighted equally with $w_i = 1$. Second, we use weights according to the country's share in the aggregate GDP of the G7.

Confidence bands for both dynamic correlations and cohesion are obtained from a bootstrapping procedure (see also Martin and Guarda, 2011). For each country pair, we calculate the dynamic correlation of two random normally distributed series of the same sample size and standard deviation as the original series. Based on $5,000$ replications, we construct a confidence band at every frequency related to the null hypothesis that the two series are uncorrelated. Confidence bands for cohesion are given by the (weighted) average of the individual confidence bands.

[8] We depict the pairwise dynamic correlations in figure 2.A.1 in appendix 2.A.2. Results show that dynamic correlations at business cycle frequencies are positive and significant for most country pairs.

The degree of synchronization as measured by cohesion is shown in figure 2.2. Cohesion is depicted at frequencies on the interval $[0, \pi/4]$, that is, from long-term cycles on the left-hand side up to the shortest cycle of 8 months on the right-hand side. The shaded area indicates the business cycle frequencies, which typically cover 1.5 to 8 years. Generally, unweighted cohesion is significantly positive at business cycle frequencies since it remains above the confidence bands related to the null of no correlation. This finding suggests that business cycle frequencies contribute extensively to the co-movement of uncertainty measures across G7 countries. This result is also confirmed when we measure cohesion as a weighted average of G7 countries (dashed line in figure 2.2).

Figure 2.2: Cohesion of inflation uncertainty among the G7



Note: The shaded area represents business cycle frequencies (8 to 1.5 years). Thin lines report 95% bootstrap confidence intervals. The weighted average is calculated according to the country shares in aggregate GDP of the G7 (based on values in US Dollars, constant prices and constant PPPs, OECD base year). The uncertainty measures were differenced beforehand. The Bartlett window size is set to 12.

Given that our sample comprises more than fifty years of data, we may wonder whether there have been any major changes in the synchronization of inflation uncertainty. Moreover, one possible reason for the synchronization in the last fifty years may be that the countries experienced a common structural break. In the following, we assess whether there have been mean and/or variance breaks in the inflation uncertainty process. To this end, we conduct a standard sup-Wald test (Andrews, 1993), which also helps us to infer when a change occurs because it relies on the assumption of an unknown break date. For each country in our sample, we compute the Wald form of the Quandt likelihood ratio (QLR) statistic, maximized over the central 70% of the sample. The test for a mean break relies on an autoregressive model with 12 lags and the null hypothesis of constant autoregressive lag coefficients. To ensure non-negative values, we take the variables in logs. The test statistic for a break in the conditional variance is based on the null of a constant variance of the error term of the autoregressive model (see also Stock and Watson, 2003b). The test allows for the possibility of two different break dates for the conditional mean and the conditional variance. The p-values corresponding to the QLR test statistics and the estimated break dates are reported in table 2.1.

Table 2.1: Break tests for inflation uncertainty

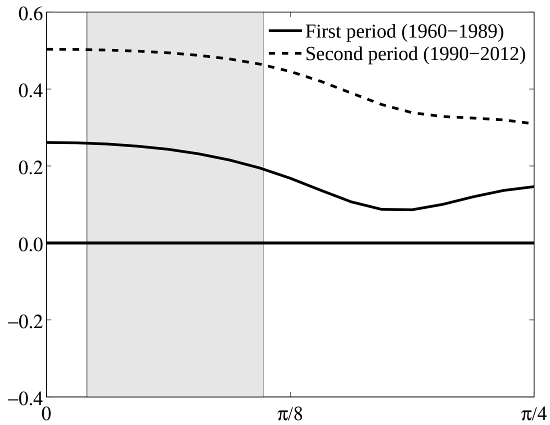
	Conditional mean			Conditional variance		
	p-value	Break date	67% confidence interval	p-value	Break date	67% confidence interval
CND	0.05			0.41		
FRA	0.00	1993:M12	1993:M10 - 1994:M02	0.00	1987:M04	1986:M12 - 1988:M08
GER	0.00	1990:M11	1990:M09 - 1991:M01	0.01	1987:M05	1985:M07 - 1990:M10
ITA	0.01	1984:M12	1984:M10 - 1985:M02	0.00	1977:M03	1976:M03 - 1979:M12
JPN	0.00	1973:M12	1973:M10 - 1974:M02	0.02	1996:M03	1990:M02 - 1998:M06
UK	0.02	1984:M11	1984:M09 - 1985:M01	0.04	1987:M01	1983:M12 - 1991:M07
US	0.00	1973:M03	1973:M01 - 1973:M05	0.04	1979:M06	1969:M11 - 1981:M10

Note: Estimation based on AR(12) models for $\log \sigma_{\epsilon}$. The QLR test statistic on the conditional mean refers to the null of no break in the AR lag coefficients. The test statistic on the conditional variance refers to the null of no break in the variance of the AR error term. The break date and its confidence interval are estimated by OLS according to Stock and Watson (2005). Results are displayed only if the QLR test statistic is significant at least at the 5% level.

We find evidence of breaks in the conditional mean as well as in the conditional variance for all countries. One exception is Canada where the null of no change in the mean and the null of no change in the AR innovations cannot be rejected at the 5% level. Concerning the conditional mean, the estimated break date is quite dispersed. Some countries experience a break during the first half of the seventies (Japan and the US), others in the mid-eighties (Italy and UK), and some in the beginning of the nineties (France and Germany). Hence, we cannot uniquely identify a (common) break date in the mean of inflation uncertainty. Notably, with the exception of France, the break occurs before the early nineties. Turning to breaks in the conditional variance, there seems to be some clustering for subgroups of countries. While variance shifts are detected in the late seventies in Italy and the US, the break in France, Germany, and the UK appears to occur in the late eighties. Again, most of the countries experience a break in the variance before the early nineties. Japan is somewhat of an exception. Here, a break in the conditional variance is indicated during the mid-nineties. Taken together, there have been marked changes in the dynamics of inflation uncertainty. However, it is difficult to identify a common break taking place in all countries synchronously. That is, the sources of the discrete breaks in the inflation uncertainty process appear to be country-specific and, hence, are not well suited as an explanation for the observed synchronization.

While we find evidence that inflation uncertainty in the G7 is intertwined in the full sample, an open question is whether synchronization of inflation uncertainty has changed over time. Given the above break dates, it appears reasonable to split the sample in 1990, which is roughly in the middle of the period. Since most countries have experienced a break before 1990, we compare synchronization, again measured by cohesion, before and after the change in the dynamics of inflation uncertainty. Figure 2.3 depicts cohesion calculated for the period 1960-1989 and 1990-2012, respectively. It becomes evident that cohesion increases considerably, that is, inflation uncertainty co-moves more strongly during the second sub-sample.[9]

Figure 2.3: Cohesion of inflation uncertainty, 1960-1989 and 1990-2012



Note: The shaded area represents business cycle frequencies (8 to 1.5 years).

[9]To test if the difference between the two sub-samples is statistically significant, we consider changes in the bivariate correlations obtained for the bandpass-filtered version of inflation uncertainty. Table 2.A.2 in appendix 2.A.3 reports the difference in pairwise correlations between the sub-samples 1960-1989 and 1990-2012. Results show that the majority of pairwise correlations has increased significantly.

2.4 The Factor-Structural VAR model

The results presented in the previous section raise the question of why uncertainty is synchronized in the G7 economies. In general, there might be two possible causes: common (global) shocks to inflation uncertainty and spillover effects from one country to another. To disentangle both channels, we rely on a Factor-Structural VAR (FSVAR) model of the following form (see Stock and Watson, 2005):[10]

$$
\begin{aligned}
Y_t &= A(L)Y_{t-1} + v_t && (2.8)\\
v_t &= \Lambda f_t + \xi_t && (2.9)\\
E(v_t v_t') &= \Sigma_v && (2.10)\\
E(f_t f_t') &= diag(\sigma_{f_1}, ..., \sigma_{f_k}) && (2.11)\\
E(\xi_t \xi_t') &= diag(\sigma_{\xi_1}, ..., \sigma_{\xi_7}) && (2.12)
\end{aligned}
$$

Here, Y_t is a 7×1 vector stacking the demeaned uncertainty measures of the G7. The common factors are captured by f_t, Λ is the $7 \times k$ matrix of factor loadings, and ξ_t denotes the idiosyncratic shocks. By assumption, the idiosyncratic shocks are uncorrelated with the common factors. The FSVAR model is estimated with Maximum Likelihood.[11] We set the lag length to 12, which should be enough to capture the dynamics of the monthly data. In order to ensure non-negative values of uncertainty, we take the log of $\sigma_{\epsilon,t}$.

According to equation (2.9), the error term of the FSVAR model is decomposed into country-specific idiosyncratic shocks and common shocks. Hence, a country-specific shock originating, for instance, in the US may be distinguished from a global shock. The global shock is identified by the assumption that it impacts all countries immediately whereas idiosyncratic shocks have an impact on other countries only via the autoregressive dynamics of the FSVAR model. We emphasize that, by using monthly data, we are less restrictive than previous studies dealing with business cycle synchronization based on quarterly data (see,

[10] The FSVAR set-up is also used by Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), and Clark and Shin (2000) to model regional spillovers. For an application to international spillovers, see also Carare and Mody (2010) and Lahiri and Isiklar (2010).

[11] Estimations are based on the replication files of Stock and Watson (2005) which are available at Mark W. Watson's website.

for instance, Stock and Watson, 2005; Carare and Mody, 2010). In our case, spillovers are assumed to occur after one month already, which implies that we attribute less explanatory power to the global shock(s) than studies based on quarterly data. However, if there are several global factors, these need to be identified separately. A common approach is to impose zero restrictions on the entries of Λ, the matrix of factor loadings (see, for instance, Stock and Watson, 2005; Gorodnichenko, 2006). We define Λ as an upper triangle where the first factor loads onto all G7 countries, the second factor has a zero restriction on the country ordered last (US), and the third factor has zero impact on both last-ordered countries (UK and US).

In the next step, we have to pin down the number of common factors k which is achieved by testing the overidentifying restrictions of the model. The null hypothesis states that the FSVAR model has k common factors and 7 idiosyncratic shocks whereas the alternative states that there are no restrictions imposed on the covariance matrix of the reduced-form errors v_t. The results of the corresponding Likelihood Ratio (LR) test are presented in table 2.2. For the sample 1960-2012, the test supports one common factor as the null of $k = 1$ cannot be rejected at the 5% level, although this is a borderline case since one factor can still be rejected at the 10% level. We discuss the results of a specification with two common factors in section 2.5.1 later in the text and in appendix 2.A.4.

Table 2.2: Testing for the number of common factors in the FSVAR model

k	logL (10^4)	d.f.	LR Stat.	p-value
0	20.5003	–	–	–
1	20.4897	14	21.30	0.09
2	20.4966	8	7.38	0.50
3	20.4991	3	2.48	0.48

Note: H_0: The reduced-form error covariance matrix has a k-factor structure. H_1: Unrestricted reduced-form error covariance. The number of overidentifying restrictions (d.f.) is given by $n(n+1)/2 - (nk - \sum_{j=0}^{k-1} j + n)$ where n is the number of equations in the FSVAR model.

2.5 Empirical results

This section presents the empirical findings of the FSVAR estimation. We first analyze the importance of the three different types of shocks in each country.

Second, we investigate the impulse responses of the individual countries to the common shock as well as to a US shock. Third, we provide an economic interpretation of the common shock. Finally, we assess to what extent changes in the shock size or in the structure of the economy have altered the propagation of these shocks ("good luck" or "good policy").

2.5.1 How important are international shocks to inflation uncertainty?

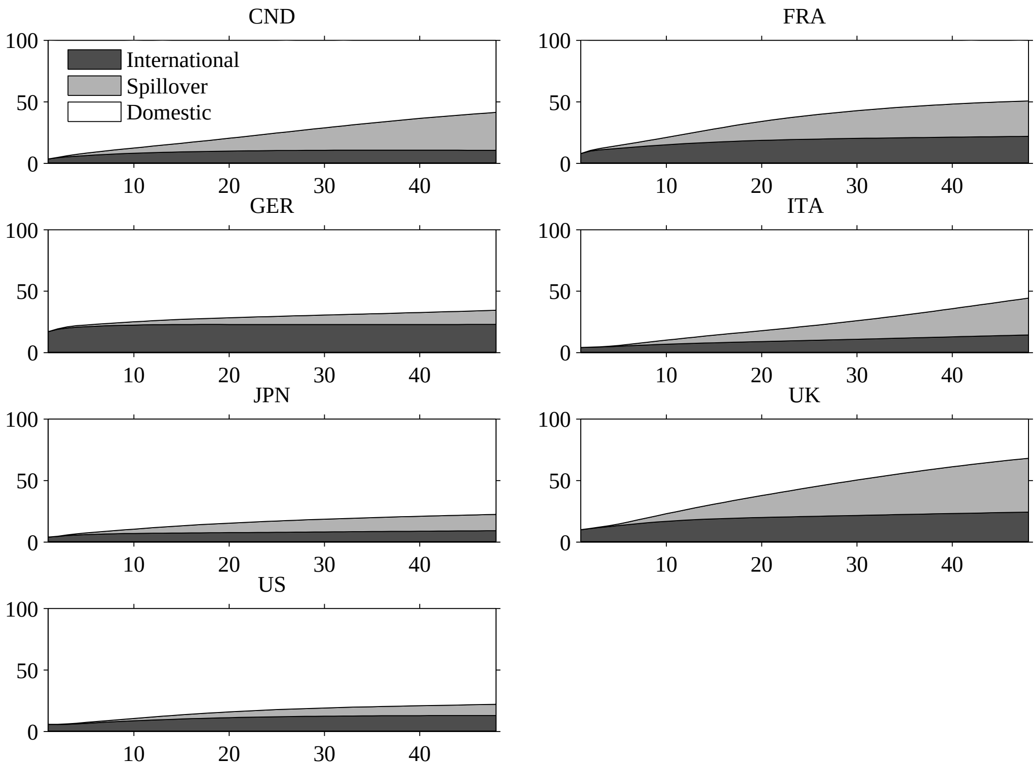
In the following, we assess the importance of the respective shocks impinging on inflation uncertainty with a particular focus on the international dimension. Since ξ_t and f_t in the FSVAR model are uncorrelated by assumption, the forecast error variance for each country can be decomposed into international shocks, own shocks and spillovers received from other countries. Based on the FSVAR estimation, figure 2.4 displays the contribution of the three different types of shocks to the forecast error variance of inflation uncertainty at forecast horizons up to 48 months.

The lower areas of figure 2.4 display the proportion of the international shock. The common factor has a noticeable impact on the Euro area countries and the UK. Table 2.A.3 in the appendix provides results for selected forecast horizons. At the two-year horizon, the international factor captures up to 23% of the variance in the countries mentioned before. In contrast, for the North American countries and Japan, the common factor remains at about 10% across all horizons. For Japan, the contribution of the international factor is the smallest of all countries.

The middle areas of figure 2.4 represent the proportion of spillovers. As noted before, spillovers do not contribute to the forecast error variance at the one-month horizon by assumption. Generally, the proportion of spillovers increases with the forecast horizon. At the one-year horizon, the contribution of spillovers ranges between 3% and 8%.[12] In contrast, at the longest horizon, spillover-related shocks explain a comparably large part of the variance of inflation uncertainty, notably in Canada, France, Italy, and UK where the contribution ranges between 29% and 44%. In the US and Japan, the proportion of spillovers is somewhat smaller

[12] Note that this compares roughly with the contribution of monetary policy shocks to inflation documented in the literature (see, for instance, Christiano et al., 2005; Bernanke et al., 2005).

Figure 2.4: Variance decomposition



Note: The above areas refer to the variance share of international shocks, spillovers, and domestic shocks, respectively. The forecast horizon in months is plotted on the abscissae. The results are based on an FSVAR model with one common factor and 12 lags.

than in the other countries but comparable to the proportion of the international shock. The turbulent economic situation of Japan during the nineties and early 2000s associated with the asset price bubble seems to be reflected by a higher importance of domestic shocks. Likewise, Germany receives little spillover from abroad. This result is in line with the fact that the German Bundesbank has given very high priority to price stability during the entire sample period.

For most countries, the largest variance share is captured by domestic shocks, as reflected by the upper areas in figure 2.4. Generally, the proportion of domestic shocks declines with the forecast horizon in favor of the international component (that is, in favor of common shocks or spillovers). At longer forecast horizons, the largest proportion of domestic shocks can be found in Japan and the US. Overall, the results of the decomposition suggest that domestic shocks play a major role in the forecast error variance of inflation uncertainty.

Given that one common factor may be rejected in favor of two common factors at the 10% level, we examine whether our results change when we introduce a second international shock. In table 2.A.3 in the appendix, we provide the results of the forecast error variance decomposition of an FSVAR model with two common factors. For the majority of countries, the fraction of variance explained by the international component is practically unaffected if a second international shock is added to the model. Moreover, the fraction of own shocks hardly declines. Finally, the proportion explained by spillovers falls only marginally. A difference occurs, however, in the case of the US. Here, we observe an increase in the explained variance share; that is, the second shock adds explanatory power mainly for US inflation uncertainty.[13] Therefore, we believe that it is reasonable to proceed the analysis with one international shock.

2.5.2 Impulse response analysis

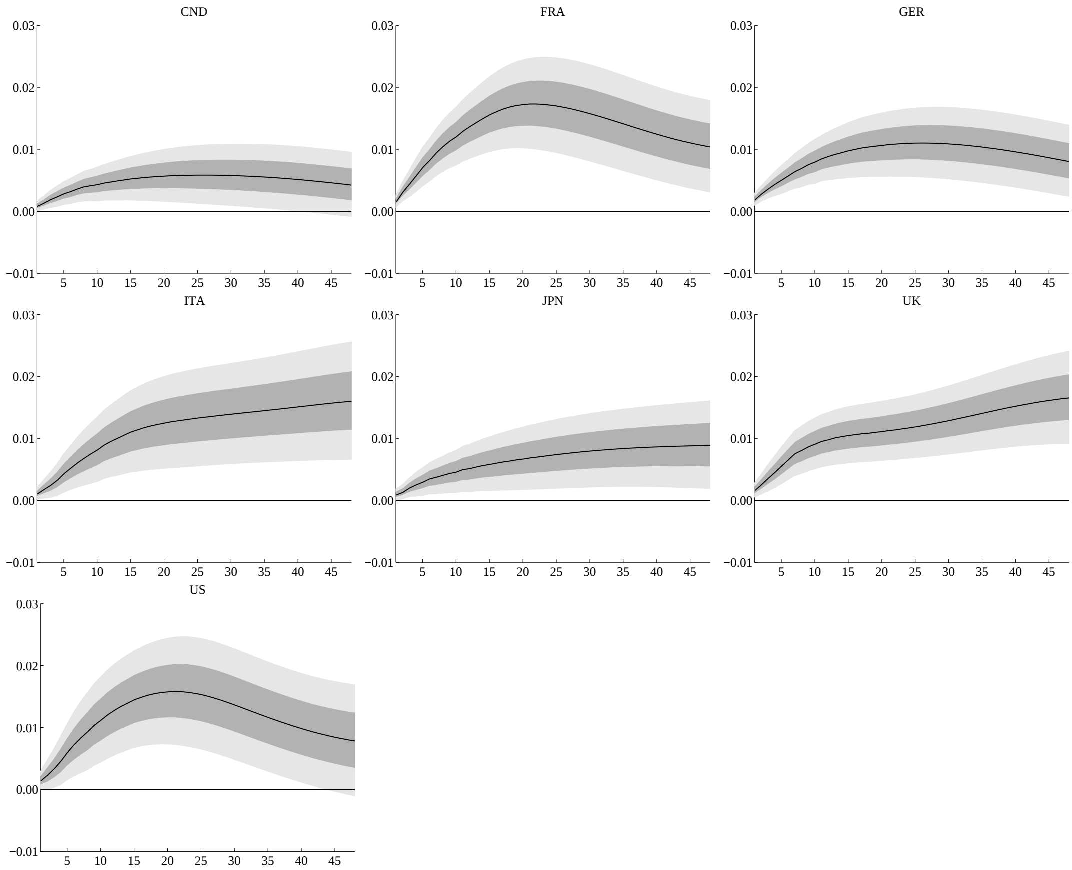
To see whether the common factor f_t qualifies for an international driver of inflation uncertainty, we calculate the response to a surprise increase in f_t. Figure 2.5 displays the impulse response functions of the individual countries following

[13]The contribution of the two international shocks is also given separately in table 2.A.3. The first international shock appears to be a shock that impinges on the US, and to a lesser extent, on Canada whereas the second international shock mainly affects the remaining countries. Note that this distinction is the result of the identification strategy concerning the factor loadings. The assumption of a recursive structure entails that the second common shock does not affect the US contemporaneously.

a one-standard deviation shock to the common factor. We find that a surprise innovation in the international factor shifts inflation uncertainty upwards in all countries. The impulse response follows a hump-shaped pattern, with a strong reaction in France, Italy, the UK and the US and a less pronounced increase in Canada, Germany and Japan. As the common shock uniformly drives uncertainty in the G7 economies into the same direction, f_t may be interpreted as an international shock to inflation uncertainty. Even more important, it provides a possible explanation for the synchronization which we document for these countries in section 2.3.

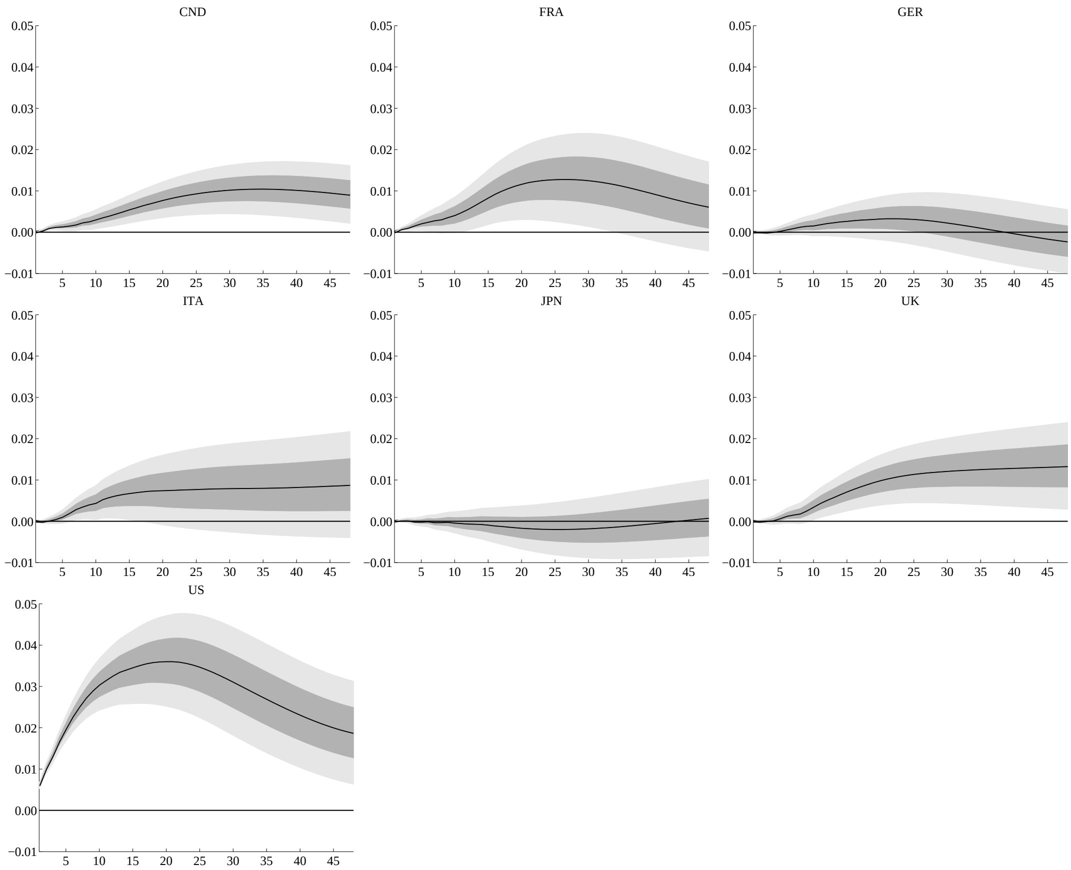
Also of interest is whether the international shock may be distinguished from a shock originating in the US. A sizeable impact of US shocks on the other G7 countries is, for example, documented by Bataa et al. (2013a). In the following, we analyze the effect of a surprise innovation in US inflation uncertainty. The impulse responses to a US shock are shown in figure 2.6. Note again that spillovers have no impact at the one-month horizon by assumption. Consequently, the contemporaneous effect of a shock to US inflation uncertainty is zero. In contrast to the common factor, the response to a US shock is mixed. In Canada, France, and the UK, a surprise innovation in US inflation uncertainty generates a significant rise which tends to be however smaller and less persistent than the response to the international shock. For Germany and Japan, the reaction to the US innovation is insignificant. Hence, there seem to be country-specific differences, probably pertaining to the monetary regime, that determine how much inflation uncertainty spillover is received from the US. Given the countries' rather mixed reactions following a US shock, we conclude that the international factor can be distinguished from a shock to US inflation uncertainty. Moreover, the US innovation is only partly able to explain the synchronization among the G7.

Figure 2.5: Response of inflation uncertainty to a shock to the common factor



Note: The bold black line represents the response of inflation uncertainty in the respective country to a one-standard deviation shock in the common factor. The shaded areas represent ± (2 times) the standard error.

Figure 2.6: Response of inflation uncertainty to a US shock



Note: The bold black line represents the response of inflation uncertainty in the respective country to a one-standard deviation US shock. The shaded areas represent ± (2 times) the standard error.

2.5.3 Interpretation of the international shock

The following section aims to provide an economic interpretation of the international shock to inflation uncertainty. However, the FSVAR method does not allow for a direct interpretation of the common shock, and we are thus dependent on indirect evidence. A possible driver of international inflation uncertainty is the uncertainty associated with prices of goods which are traded all over the world at a common price, and which have a non-negligible share in the overall price index. Candidates are oil and commodity prices. Consequently, we would expect that the uncertainty related with those variables is foreshadowed by positive common shocks. We can infer whether f_t and any other measure of uncertainty are related by estimating the following regression:

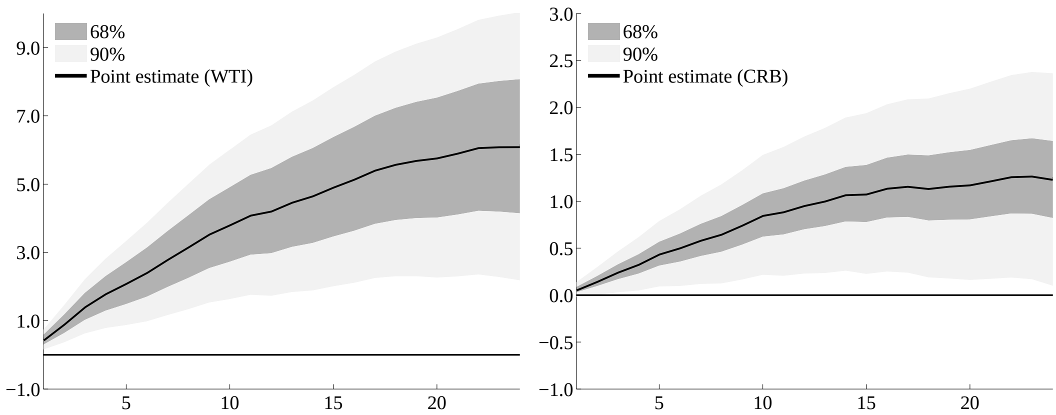
$$unc_t^i = c_0 + \sum_{j=0}^{J} \phi_j^i f_{t-j} + \nu_t^i, \tag{2.13}$$

where unc_t^i represents a measure of uncertainty, and ν_t^i is the respective regression residual. Since f_t is an orthogonal white noise process by assumption, the coefficients ϕ_j^i are a measure of connectedness between unc_t^i and the common shock. Moreover, owed to the simplicity of the regression model, the cumulative coefficients can be interpreted as the impulse response of unc_t^i following a one-percent increase in f_t (see, for instance, Kilian, 2009; Romer and Romer, 2010). We estimate the model with $J = 24$ lags.

To obtain a measure of oil price uncertainty, we use the UC-SV model introduced in section 2.2 and apply it to the monthly growth rate of the spot price for crude oil (WTI). The estimation sample runs from 1979:M6 until 2012:M4 since there is practically no monthly variation in WTI oil prices before that period. In addition, we also use the CRB/Reuters commodity price index and derive a measure of overall commodity price uncertainty in the same way. The CRB is more comprehensive than the WTI oil price since it measures the price of a basket of different commodities. Moreover, the CRB is available for the entire sample period (1960:M1 until 2012:M4). In order not to run into stationarity problems, unc_t^i is the log-change of the respective standard deviation associated with the long-term component of oil or commodity price inflation.

Figure 2.7 illustrates the dynamics of unc_t^i following an increase in the common shock f_t. It appears that both oil and commodity price uncertainty are con-

Figure 2.7: Response of oil and commodity price uncertainty to f_t



Note: The solid line represents the response of unc_t^i to a one-percent increase in f_t. The 68% and 90% error bands are obtained by a block bootstrap using a block size of 12 and $20,000$ replications. The left panel depicts the response of WTI oil price uncertainty while the right panel depicts the response of CRB commodity price uncertainty.

nected with the international shock to inflation uncertainty. Notably, increases in the international shock seem to foreshadow increases in oil and commodity price uncertainty.[14] Taken together, our results provide evidence that f_t may be interpreted as a shock to international commodity price uncertainty which shows up as a common shock to inflation uncertainty in the G7.

2.5.4 Changes in the dynamics of international inflation uncertainty

Up to now, we have based the analysis on the full sample period. However, the break test in section 2.3 already indicated that there have been changes to the inflation uncertainty process during the last fifty years. In what follows, we investigate whether and how the dynamics of inflation uncertainty in the G7 have changed over time. To this end, we perform a recursive estimation of the FSVAR model with one common factor. A time-varying specification based on the whole sample is obtained by two-sided exponential weighting (Stock and Watson, 2005; Bataa et al., 2013a), that is, the regression at time t is calculated using weighted observations. The observation at time s receives an exponentially decreasing weight $\delta^{|t-s|}$ with a discount factor $\delta = 0.97$. Running $t = 1 \ldots T$

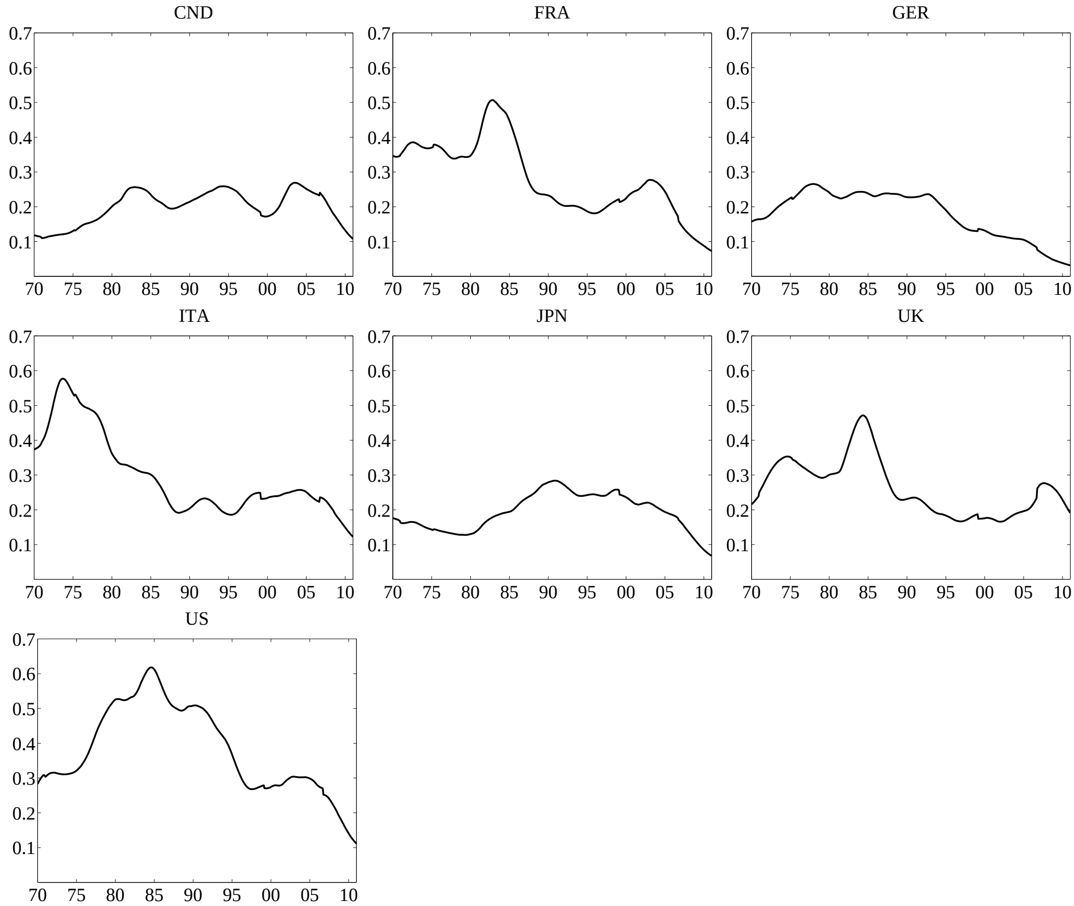
[14] In appendix 2.A.5, we also run the regression in equation (2.13) for a measure of financial market uncertainty used in Bloom (2009). We find no significant relation between the international factor and financial market uncertainty.

over the whole sample, we obtain a time-varying estimate for the volatility of inflation uncertainty measured by the total forecast error variance. Note that the weighted estimation implies a smooth transition of the coefficients over time. It is therefore not possible to retrace sudden breaks in the data. Nevertheless, the method provides us with an intuition of whether there have been changes over the full sample period.

The time-varying forecast error variance of inflation uncertainty is depicted in figure 2.8 from 1970:M1 onwards. In most countries, we observe a decline in volatility taking place in the mid-eighties to the early nineties. Except for Germany and Japan, a temporary increase in volatility can be observed in the beginning of the new millennium. Towards the end of the sample, the variance has decreased to historically low levels in all countries. The timing of the observed changes suggests that the decline of the fluctuations of uncertainty has paralleled the process of world-wide "Inflation Stabilization" (see, for instance, Cecchetti et al., 2007; Mumtaz and Surico, 2012). Indeed, inflation uncertainty has not only come down to lower levels but is now also much more stable and, consequently, easier to predict.

In general, two possible explanations are at hand for the documented increase in the stability of inflation uncertainty: either the size of the shocks has decreased ("good luck") or structural changes in the economy have dampened the transmission of the shocks ("good policy"). In the following, we decompose the decline of the total forecast error variance into the effect of the shock size and the propagation of the different types of shocks. Given the break dates obtained in section 2.3, we split the sample roughly in half and consider the periods 1960-1989 and 1990-2012. This allows us to compare the forecast error variance decompositions for the two different sub-samples. Moreover, we are able to distinguish between changes in the shock size and changes in the impulse response. Let V_p denote the variance of the forecast error, where $p = 1; 2$ refers to the first and second sub-sample, respectively. For notational simplicity, we suppress the dependence on the forecast horizon and the country. Since the FSVAR model incorporates eight sources of variation (one international shock, one domestic shock, and six different spillover terms emerging from the idiosyncratic shocks), the total variance can be written as $V_p = V_{p,1} + ... + V_{p,8}$ with $V_{p,j}$ denoting the contribution of the jth shock in sub-sample p. Consequently, the difference between the first- and the second-period variance can be expressed as

Figure 2.8: Time-varying volatility of inflation uncertainty



Note: The bold line refers to the twelve-months-ahead total forecast error variance of inflation uncertainty. Results are derived from a recursively weighted estimation of an FSVAR model with one common factor and 12 lags.

$V_2 - V_1 = (V_{2,1} - V_{1,1}) + ... + (V_{2,8} - V_{1,8})$. The variance of the forecast error consists of two parts: $V_{p,j} = a_{pj}\sigma^2_{pj}$, where a_{pj} is given by the cumulated squared impulse responses to a standardized (unit) shock j. σ^2_{pj} denotes the variance of shock j in sub-sample p. For each shock j, the change in the contribution to the total variance can be expressed as

$$V_{2j} - V_{1j} = \left(\frac{a_{1j} + a_{2j}}{2}\right)(\sigma^2_{2j} - \sigma^2_{1j}) + \left(\frac{\sigma^2_{1j} + \sigma^2_{2j}}{2}\right)(a_{2j} - a_{1j}). \tag{2.14}$$

The first term on the right-hand side in equation (2.14) refers to the contribution from the change in the shock size whereas the second term refers to the contribution from the change in the impulse response function. Table 2.3 reports the decomposition of changes in the twelve-months-ahead forecast error variance of inflation uncertainty. Focusing on the first panel, the total variance has decreased significantly in most countries during the second period, as shown in column (3). That is, inflation uncertainty has become more stable and its predictability has increased. In Canada and Japan, the forecast error variance has slightly increased; however, this increase is statistically insignificant. Overall, the decline in volatility inferred from visual inspection of the recursive FSVAR estimation above can be recovered when we split the sample.

The second panel of table 2.3 reports the contribution to the change in the forecast variance by *changes in the shock size*. The decline in the forecast variance is partly due to smaller shocks, as shown in column (7). This negative change in the shock size is statistically significant for France, Italy, and the US. The presence of smaller shocks suggests that “good luck” has contributed to the decline of the volatility of inflation uncertainty in these countries. Concerning the different shock types, mainly domestic shocks account for a decline in the shock size. In the majority of countries, smaller spillovers also contributed to this downward trend in a significant way. By contrast, international shocks are larger in the second period, although this change is not statistically significant.

The third panel of table 2.3 displays the contribution of *changes in the impulse responses*, that is, changes in the way shocks translate into the domestic economy. As reported in column (11), the sensitivity towards shocks has generally decreased. In all countries except Canada and Japan, changes in the impulse responses significantly contributed to the overall decline in variance. It appears that “good policy” is responsible for most of the decline in the volatility of in-

Table 2.3: Decomposition of changes in the forecast error variance

	Total variances			**Contribution of change in shock size**				**Contribution of change in impulse responses**			
	1960-1989 (1)	1990-2012 (2)	Change (3)	Common (4)	Spillover (5)	Domestic (6)	Total (7)	Common (8)	Spillover (9)	Domestic (10)	Total (11)
CND	2.74***	3.26***	0.53	0.05	−0.14*	0.33	0.24	0.08	0.05	0.16	0.29
	(0.37)	(0.45)	(0.58)	(0.13)	(0.08)	(0.30)	(0.35)	(0.42)	(0.22)	(0.39)	(0.66)
FRA	24.75***	4.36***	−20.39***	0.40	−0.41*	−7.72***	−7.73***	−5.20***	−0.37	−7.09***	−12.66***
	(3.25)	(0.61)	(3.30)	(0.61)	(0.21)	(1.39)	(1.47)	(1.58)	(0.68)	(1.70)	(2.63)
GER	7.16***	1.92***	−5.24***	0.15	−0.14*	−0.77	−0.76	−2.06***	−0.09	−2.33***	−4.48***
	(0.96)	(0.25)	(0.99)	(0.24)	(0.08)	(0.48)	(0.48)	(0.73)	(0.23)	(0.62)	(0.97)
ITA	18.98***	5.80***	−13.19***	0.09	−0.05	−5.84***	−5.80***	−1.19	−0.79	−5.40***	−7.39***
	(2.56)	(0.78)	(2.67)	(0.29)	(0.15)	(1.23)	(1.31)	(1.07)	(0.56)	(1.76)	(2.29)
JPN	2.88***	3.47***	0.59	0.02	−0.26**	0.58**	0.34	−0.21	0.52*	−0.06	0.25
	(0.38)	(0.47)	(0.60)	(0.07)	(0.11)	(0.27)	(0.31)	(0.26)	(0.31)	(0.45)	(0.63)
UK	8.72***	3.89***	−4.83***	0.13	−0.29*	−0.56	−0.72	−1.41	−0.90*	−1.81**	−4.11***
	(1.11)	(0.58)	(1.26)	(0.30)	(0.18)	(0.74)	(0.71)	(0.92)	(0.53)	(0.78)	(1.37)
US	18.52***	5.87***	−12.66***	0.31	−0.17	−8.53***	−8.38***	2.87**	−0.91	−6.23***	−4.27*
	(2.52)	(0.82)	(2.66)	(0.42)	(0.18)	(1.85)	(1.71)	(1.15)	(0.61)	(1.72)	(2.49)

Note: The left panel shows the twelve-months-ahead forecast error variance of inflation uncertainty for two sub-samples and the difference between the two sub-samples based on an FSVAR estimation with one common factor and 12 lags. The middle panel shows the contribution of the shock size to the changes in column (3). The right panel shows the contribution of changes in the impulse responses to the changes in column (3). Columns (7) and (11) add up to the total change shown in column (3). The values are multiplied by 100 and bootstrap standard errors are reported in parentheses.

flation uncertainty. The total contribution of the propagation mechanism can be further decomposed into the contribution of the transmission of the international shock, spillovers from other countries, and own shocks. Results regarding the international shock are rather mixed. In France and Germany, the effect of the international shock becomes weaker whereas the effect becomes significantly stronger in the US. The propagation mechanism of spillovers remains largely unchanged as the estimated difference is insignificant in most countries. Finally, the majority of G7 countries became less sensitive to own shocks. Notably, the change in the propagation of own shocks accounts for the largest part of the decline reported in column (11).

The main message from table 2.3 is twofold. First, changes in the propagation mechanism of shocks to inflation uncertainty have primarily contributed to a "moderation" in inflation uncertainty. Second, the size of domestic shocks to inflation uncertainty has decreased in many countries while international shocks have become slightly larger. Taken together, the international shock has gained relative importance. Hence, increased synchronization is the result of own shocks losing importance relative to the international factor.

The above results raise the question of what is so different in the second period that led to a stabilization of inflation uncertainty? One policy area that underwent major changes in the last two decades is the field of monetary policy. Researchers seem to agree that, in the developed countries, there is now a better understanding of how to implement monetary policy (see, for instance, Summers, 2005; Cecchetti et al., 2006). Particularly in the US, monetary policy moved from an accommodative stance to an inflation-stabilizing policy (see, for example, Clarida et al., 2000). In a related empirical exercise, Ahmed et al. (2004) document that most of the decline in inflation volatility in the US may be explained by better monetary policy. Similarly for the G7, Cecchetti et al. (2007) argue that the world-wide "Inflation Stabilization" is strongly linked to central banks acting more responsive to inflationary shocks. Accompanying this policy shift, there have been a number of institutional changes in monetary policy in the G7. Major legislative reforms that enhanced central bank independence were adopted in France, Italy, Japan, and the UK during the nineties. Measured by different indices of political and economic autonomy, central bank independence has generally risen in G7 countries from the first half of our sample to the second half since 1990 (see Acemoglu et al., 2008; Arnone et al., 2009). Institutional changes during the last two decades also comprise the announcement of an inflation target. Among the G7, Canada and the UK introduced an official inflation target in the early nineties whereas the EMU countries adopted the ECB's quantitative target of price stability "below, but close to, 2% over the medium term".[15] Among others, Mishkin and Schmidt-Hebbel (2007) document that countries following an inflation targeting strategy successfully improve their macroeconomic performance by providing a strong nominal anchor. They also stress that inflation targeting countries are less sensitive to international shocks by strengthening domestic monetary policy independence. Our results suggest that the above policy changes not only reduced inflation uncertainty in the last two decades but also contributed to a stabilization of inflation uncertainty.

2.6 Concluding remarks

Our study provides additional insight into the international linkages of inflation uncertainty. For this purpose, we use monthly CPI inflation rates in the G7 from 1960 onwards. Our results can be summarized as follows: First, we find evidence of synchronization among inflation uncertainty in the G7. We show that the degree of synchronization has increased during the most recent two decades. Second, in an FSVAR framework, we reveal a common shock that moves national inflation uncertainty in all countries into the same direction. We find that this common shock is closely related to oil and commodity price uncertainty. By contrast, a pure US shock induces mixed responses in the G7. Third, based on recursive estimations, we show that the volatility of inflation uncertainty has decreased over time, paralleling the process of "Inflation Stabilization". Fourth, we document that the propagation mechanism of shocks to inflation uncertainty in the G7 has changed considerably since 1990. The main channel for the decline of the volatility of inflation uncertainty seems to be domestic shocks that translate less extensively into the individual economies. This finding supports the hypothesis of "good policy". Finally, there appears to be a higher connectedness of inflation uncertainty among the G7 which is traceable to an increase in the relative importance of international shocks.

As stressed by Cecchetti et al. (2007), the main candidate for the "Inflation

[15] Since the beginning of 2012, that is, towards the end of our sample, the US and Japan also communicate an inflation target.

Stabilization" in the G7 are changes in the monetary regime. This also provides a possible explanation for the observed "moderation" in inflation uncertainty. Although inflation uncertainty is currently rather stable, we should bear in mind that this appears to be the result of central banks credibly committed to price stability. Moreover, accepting higher inflation – as recently called for to deal with the problem of excessive debt – may bring about the additional cost of higher worldwide inflation uncertainty via spillover effects.

Acknowledgments

I am indebted to Steffen Henzel, who is co-author of Chapter 2.

Appendix

2.A.1 Outlier adjustment

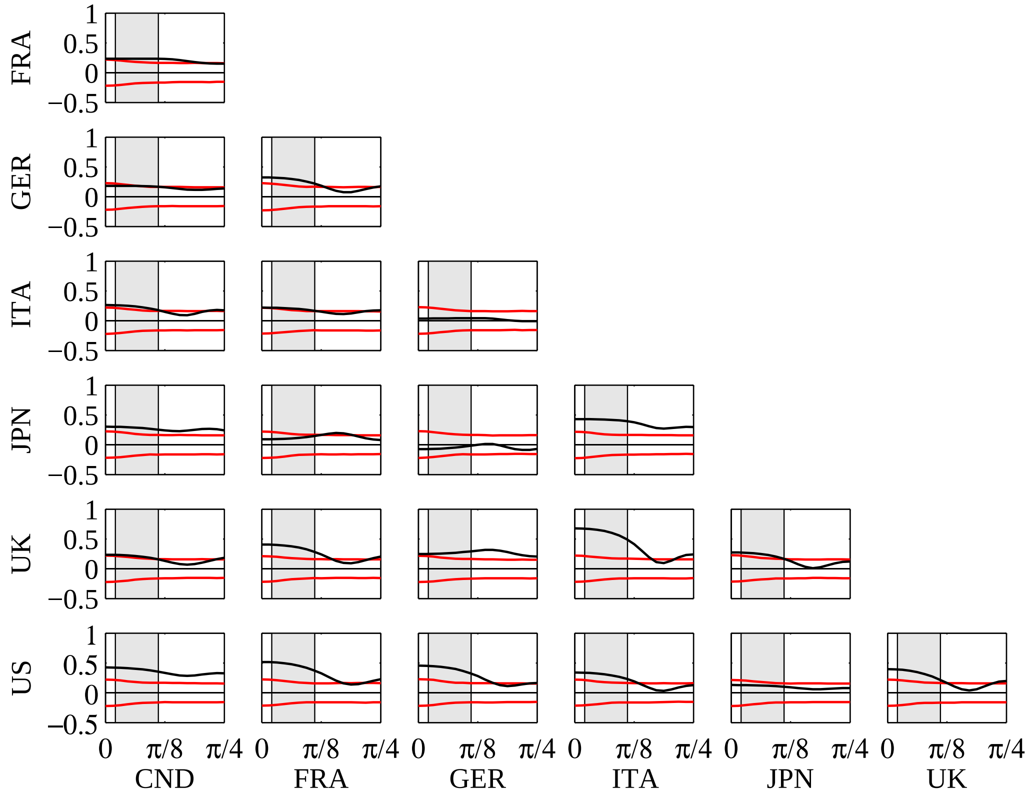
Before the analysis is conducted, we remove a number of outliers in the seasonally adjusted monthly inflation rates. Table 2.A.1 summarizes the adjustment of outliers. First, we identified outliers which are traceable to changes in the tax system; in most cases, we identify an increase in the value-added tax rate. The outliers in France in 1965:M6 and 1965:M7 are due to one exceptional observation in the level series of the CPI. Second, following Stock and Watson (2003a), we refer to an outlier in the data if an observation deviates more than six times the interquartile range from the local mean. These outliers are marked with an asterisk in table 2.A.1. All outliers are replaced with the mean of the six adjacent observations.

Table 2.A.1: Adjustment of outliers in inflation

Canada		France		Germany	
1991:M1	goods and services tax	1965:M6	–	1991:M10	German reunification
1994:M1	arctic outbreak	1965:M7	–	1993:M1	VAT rate from 14% to 15%
1994:M2	severe spending cuts				
UK		US			
1975:M5*	–	2008:M11*	–		
1979:M7	VAT rate from 8% to 15%				
1991:M4	VAT rate from 15% to 17.5%				

2.A.2 Dynamic correlations among country pairs

Figure 2.A.1: Dynamic correlation of inflation uncertainty in the G7 countries



Note: The shaded area represents business cycle frequencies (8 to 1.5 years). Red lines report 95% bootstrap confidence intervals. The uncertainty measures were differenced beforehand. The Bartlett window size is set to 12.

2.A.3 Testing for changes in correlations among country pairs

Table 2.A.2: Differences in pairwise correlations of inflation uncertainty

	Difference between 1990-2012 and 1960-1989					
	CND	**FRA**	**GER**	**ITA**	**JPN**	**UK**
FRA	0.41^{**}					
	(0.19)					
GER	0.36^{**}	0.32^{**}				
	(0.17)	(0.14)				
ITA	0.44^{*}	0.53^{**}	0.13			
	(0.24)	(0.22)	(0.23)			
JPN	0.11	0.16	0.29^{*}	0.01		
	(0.29)	(0.24)	(0.16)	(0.31)		
UK	0.62^{***}	0.39^{*}	-0.03	0.31^{**}	0.21	
	(0.15)	(0.22)	(0.13)	(0.16)	(0.21)	
US	0.48^{***}	0.35^{**}	0.05	0.47^{***}	0.25	0.63^{***}
	(0.15)	(0.17)	(0.20)	(0.17)	(0.19)	(0.19)

Note: The entries indicate the difference in correlation between the two sub-samples. Newey-West standard errors robust to heteroskedasticity and autocorrelation up to 12 lags are reported in parentheses. Uncertainty measures were detrended by means of a bandpass filter which extracts business cycle frequencies (1.5 to 8 years).

2.A.4 Number of common factors in the FSVAR model

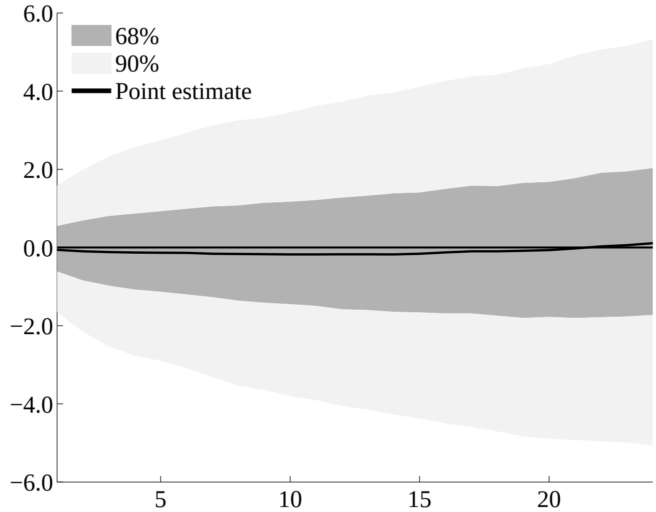
Table 2.A.3: Variance decomposition into international shocks, spillovers, and domestic shocks

		One common factor				Two common factors					
		FE	Fraction of FEV due to:			FE	Fraction of FEV due to:				
	Horizon	STD	Int.	Spillovers	Own	STD	Int.	Int. 1	Int. 2	Spillovers	Own
CND	1	0.00	0.04	0.00	0.96	0.00	0.04	0.03	0.01	0.00	0.96
	12	0.25	0.09	0.05	0.86	0.25	0.12	0.09	0.03	0.04	0.84
	24	0.86	0.10	0.13	0.76	0.87	0.16	0.13	0.03	0.10	0.74
	48	2.87	0.11	0.31	0.59	2.91	0.21	0.19	0.03	0.22	0.56
FRA	1	0.01	0.08	0.00	0.92	0.01	0.07	0.03	0.04	0.00	0.93
	12	0.45	0.16	0.08	0.76	0.46	0.16	0.07	0.09	0.07	0.77
	24	1.73	0.19	0.19	0.62	1.73	0.21	0.09	0.11	0.17	0.62
	48	5.44	0.22	0.29	0.49	5.44	0.25	0.13	0.13	0.25	0.50
GER	1	0.00	0.17	0.00	0.83	0.00	0.15	0.03	0.13	0.00	0.85
	12	0.28	0.23	0.03	0.74	0.28	0.21	0.05	0.17	0.03	0.75
	24	1.06	0.23	0.06	0.71	1.06	0.22	0.05	0.17	0.06	0.72
	48	3.59	0.23	0.11	0.66	3.59	0.22	0.05	0.17	0.11	0.67
ITA	1	0.01	0.04	0.00	0.96	0.01	0.05	0.00	0.05	0.00	0.95
	12	0.43	0.07	0.05	0.88	0.43	0.09	0.01	0.08	0.04	0.87
	24	1.68	0.10	0.11	0.79	1.68	0.12	0.02	0.10	0.10	0.78
	48	5.39	0.14	0.30	0.56	5.39	0.18	0.04	0.14	0.28	0.55
JPN	1	0.00	0.04	0.00	0.96	0.00	0.09	0.00	0.09	0.00	0.91
	12	0.28	0.07	0.04	0.88	0.28	0.12	0.00	0.12	0.05	0.84
	24	1.08	0.08	0.09	0.83	1.08	0.12	0.00	0.12	0.09	0.79
	48	3.84	0.09	0.13	0.78	3.84	0.13	0.00	0.13	0.13	0.74
UK	1	0.01	0.10	0.00	0.90	0.01	0.13	0.00	0.13	0.00	0.87
	12	0.34	0.18	0.08	0.74	0.34	0.21	0.02	0.19	0.08	0.71
	24	1.21	0.21	0.22	0.57	1.21	0.25	0.05	0.20	0.20	0.55
	48	4.08	0.24	0.44	0.32	4.05	0.30	0.10	0.20	0.38	0.31
US	1	0.01	0.06	0.00	0.94	0.01	0.44	0.44	0.00	0.00	0.56
	12	0.52	0.09	0.03	0.88	0.52	0.44	0.44	0.01	0.02	0.53
	24	2.01	0.12	0.06	0.83	1.99	0.44	0.42	0.02	0.06	0.50
	48	6.28	0.13	0.09	0.78	6.18	0.43	0.40	0.03	0.09	0.48

Note: The table reports the standard deviation (STD) and the variance decomposition of inflation uncertainty forecast errors at the 1-, 12-, 24-, and 48-months horizon. Fractions are given as percentage of total forecast error variance (FEV). The estimation is based on an FSVAR model with 12 lags.

2.A.5 Financial market uncertainty and the common shock

Figure 2.A.2: Response of financial market uncertainty to the common shock



Note: The solid line represents the response of financial market uncertainty to a one-percent increase in the common shock f_t. Financial market uncertainty is the log of the uncertainty measure in Bloom (2009), who uses the VXO and the VIX from the Chicago Board Options Exchange to construct a long time series of financial market uncertainty beginning in 1962:M8. For the estimations in the present paper, we have updated Bloom's series until 2012:M4. The 68% and 90% error bands are obtained by a block bootstrap using a block size of 12 and $20,000$ replications.

Chapter 3

The process of expectations formation and the economic problem "inflation": Evidence from the World Economic Survey

3.1 Introduction

In forecast evaluation, a major theme is whether forecasters are rational. Information rigidities provide an explanation for often observed departures from forecast rationality in survey data.[1] Consequently, recent macroeconomic theory has started to account for informational rigidities based on models of imperfect information. Two key approaches are related to informational constraints either due to delayed ("sticky") information (Mankiw and Reis, 2002; Reis, 2006) or partial ("noisy") information (Woodford, 2001; Sims, 2003; Maćkowiak and Wiederholt, 2009).[2]

This study examines the process of inflation expectations formation in high-income countries. In particular, we assess the degree of information rigidity in inflation forecasts following an approach by Coibion and Gorodnichenko (2010), which is directly related to models of imperfect information. In contrast to previous tests of forecast rationality, their approach not only allows testing for the

[1] See Pesaran and Weale (2006) for an overview of studies testing the rationality of survey expectations.

[2] Mankiw and Reis (2010) provide a thorough survey of literature since the last decade.

presence of informational rigidities but also provides the chance to determine the economic significance and mechanisms behind departures from forecast rationality.

We use a unique dataset of inflation forecasts for 16 high-income countries provided by the CESifo World Economic Survey (WES). The WES is conducted quarterly by the Ifo Institute in Munich in co-operation with the International Chamber of Commerce (ICC) in Paris. To this date, about 1,200 national experts assess the general economic situation and indicate their expectations on macroeconomic indicators of their country, including the annual average rate of inflation. Two advantages arise with WES data. First, they provide fixed-event inflation forecasts, i.e., a sequence of forecasts related to the same event such as reported by Consensus Economics and the Survey of Professional Forecasters (SPF). This kind of forecast is well suited to evaluating the incorporation of new information. Second, the WES polls the experts' opinion on problems their economy is facing at present. Thereby, respondents are asked to assess the importance of a given variety of economic problems such as unemployment, insufficient demand, public deficits, and inflation. Focusing on the question related to inflation, we are able to identify periods where this problem is deemed highly important. This allows us to analyze how changes in the importance of the problem "inflation" affect the process of forecasting inflation.

Our study is closely linked to literature that relates survey expectations to models of imperfect information, that is, to both sticky and noisy information, and that tests for informational rigidities. Andrade and Le Bihan (2010) analyze individual forecasts provided by the European Survey of Professional Forecasters. They find evidence of inattentive forecasters with characteristics implied by these two classes of models. However, their proposed model comprising both characteristics fails to describe the underlying expectations formation process well. Coibion and Gorodnichenko (2010) report informational rigidities in SPF and Consensus Economics forecasts that point to noisy-information models rather than models based on sticky information. Also focusing on professional forecasters, Dovern et al. (2013) document a higher degree of information rigidity for the consensus forecast than for individual forecasts. They infer from the individual updating frequencies that results are more in accordance with noisy-information models. Dräger and Lamla (2013) also find support for models of imperfect information based on consumers' inflation expectations.

We contribute to this literature by testing whether inflation expectations can be characterized by sticky or noisy information. In addition, we address the more recent question of whether information updating is state-dependent. In that sense, Coibion and Gorodnichenko (2010) document that professional forecasters exhibit a state-dependent updating behavior in response to changes in macroeconomic volatility and large visible shocks such as recessions and the 9/11 attacks. Using a panel of advanced and emerging economies, Loungani et al. (2011) show that the degree of information rigidity declines during recessions and banking crises. Recent contributions by Lamla and Sarferaz (2012) and Dräger and Lamla (2013) provide evidence on inflation-related news effects that drive the updating behavior of consumers' inflation expectations. An important feature of the present study is that it relies on a cross-country panel dataset which explicitly allows testing for state-dependence in inflation expectations. Since WES experts indicate the importance of a given set of economic problems, we are able to investigate whether different "states" concerning the importance assigned to the economic problem "inflation" influence the formation of inflation expectations.

Our findings can be summarized in the following way. First, we find evidence of informational rigidities in inflation forecasts with WES experts updating their information set every three to four months. However, the degree of information rigidity crucially depends on the forecast horizon. Second, we document state-dependence in the process of forecasting inflation. When the majority of WES experts assess the economic problem "inflation" as being of high importance, the implied degree of information rigidity is smaller. That is, forecasters are more attentive when inflation concerns are prevailing. The same implication is obtained when expected trend inflation or past inflation is above a certain threshold. These empirical findings are supportive of models with noisy information (Woodford, 2001; Sims, 2003; Maćkowiak and Wiederholt, 2009) and state-dependent updating of information (Gorodnichenko, 2008; Woodford, 2009).

The remainder of this study is as follows. Section 3.2 illustrates models of imperfect information and the related test for informational rigidities. Section 3.3 describes the WES dataset and presents descriptive statistics on the inflation forecasting process. Our findings concerning the test for informational rigidities using WES inflation forecasts are reported in section 3.4. Consequently, we discuss the results of testing for state-dependence in the forecasting process in section 3.5. Section 3.6 provides conclusions.

3.2 Models of imperfect information

There is a large amount of empirical evidence that full-information rational expectations are not always given in practice.[3] Recent macroeconomic theory incorporates imperfect information in the modeling of the expectations formation process. Two key models are based on either sticky information (Mankiw and Reis, 2002) or noisy information (Sims, 2003).[4] Coibion and Gorodnichenko (2010) show that these two approaches have common implications concerning the implied degree of information rigidity and propose a test for the presence of informational rigidities. In the following, we present a short description of their test and the underlying models of imperfect information.[5]

In the sticky-information model, forecasters have rational expectations, yet they are inattentive and do not update their information set every period (Mankiw and Reis, 2002; Reis, 2006). Assuming that in each period only a fraction $(1-\lambda)$ of forecasters acquire new information, the average forecast F_t can therefore be expressed as a weighted average of the contemporaneous rational expectations forecast and the previous period's average forecast:

$$F_t\pi_{t+h} = (1-\lambda)(\pi_{t+h} + u_{t+h,t}) + \lambda F_{t-1}\pi_{t+h}, \tag{3.1}$$

where h denotes the forecast horizon and $u_{t+h,t}$ is a combination of shocks that take place from t to $t+h$ representing the rational expectations error. Based on equation (3.1), the average ex-post forecast error is a function of the average forecast revision:

$$\pi_{t+h} - F_t\pi_{t+h} = \frac{\lambda}{(1-\lambda)}\left(F_t\pi_{t+h} - F_{t-1}\pi_{t+h}\right) + u_{t+h,t}, \tag{3.2}$$

where the effect of the forecast revision on the forecast error is directly related to

[3]Concerning fixed-event forecasts, see, for example, evidence by Nordhaus (1987), Clements (1997), Isiklar et al. (2006), Clements et al. (2007), Ager et al. (2009), and Dovern and Weisser (2011).

[4]Mankiw and Reis (2010) also refer to these two types of models as the delayed and partial information model, respectively.

[5]See Coibion and Gorodnichenko (2010, 2012) for details and extensions of more general or specific cases.

the underlying degree of information rigidity λ. Subsequently, one can infer the average number of periods between information updates by the formula $1/(1-\lambda)$. Two implications arise from the sticky-information model. First, with $\lambda = 0$, forecasters have perfect information. Second, λ is a constant value which should hold irrespective of the forecast horizon.

A counterpart to the sticky-information model is based on the assumption of noisy information (Woodford, 2001; Sims, 2003). Within this framework, forecasters permanently observe inflation, but only obtain a noisy signal rather than full information about the true state of inflation. Let each forecaster i receive an individual signal of inflation:

$$s_{i,t} = \pi_t + \omega_{i,t}, \tag{3.3}$$

where $\omega_{i,t} \sim i.i.d.\ N(0, \Sigma_\omega)$ is the individual noise of the signal. The forecasters solve this signal extraction problem by means of the Kalman filter:

$$F_{i,t}\pi_t = G\left(\pi_t + \omega_{i,t}\right) + (1-G)F_{i,t-1}\pi_t, \tag{3.4}$$

where $G \in (0,1)$ is the Kalman gain reflecting the relative weight on new information. Averaging over forecasters and iterating the expectations forward, the average ex-post forecast error can be expressed as:

$$\pi_{t+h} - F_t\pi_{t+h} = \frac{1-G}{G}(F_t\pi_{t+h} - F_{t-1}\pi_{t+h}) + u_{t+h,t}, \tag{3.5}$$

where the degree of information rigidity is now given by $(1-G)$. In contrast to the sticky-information model, the extent to which new information is incorporated in the noisy-information model depends on the precision of the forecaster's underlying signal $s_{i,t}$. As pointed out by Coibion and Gorodnichenko (2010), the degree of information rigidity might differ with the strength of the signal and, thus, across forecast horizons.[6]

Although equation (3.2) of the sticky-information model and equation (3.5) of the noisy-information model are based on a different microfoundation, both have the same implication: in the presence of informational rigidities, the average

[6] Similarly, the Kalman gain in the noisy-information model is also determined by the persistence of the underlying times series and might consequently differ across macroeconomic variables.

ex-post forecast error is predictable by means of the average ex-ante forecast revision. Note that this implication is obtained by averaging over forecasters and might not hold at the individual level. Within a regression framework, Coibion and Gorodnichenko (2010) propose to test for informational rigidities in survey expectations by regressing the average forecast error on the preceding average forecast revision. The null of the test states that forecasters have full-information rational expectations.

3.3 The WES data

We analyze inflation forecasts provided by the CESifo World Economic Survey (WES). This survey is conducted jointly by the Ifo Institute in Munich and the International Chamber of Commerce (ICC) in Paris. National experts assess the general economic situation and indicate their expectations with respect to macroeconomic indicators of their country. Currently, the WES polls about 1,200 experts in 125 countries. Experts are from different institutions such as international corporations, economic research institutes, chambers of commerce, embassies, and international organizations. All respondents have a leading position in common or are professionally affiliated with economic research.[7]

The survey is carried out on a quarterly basis during January, April, July, and October of each year. Previous studies using WES data mainly deal with *qualitative* information about experts' expectations. Henzel and Wollmershäuser (2005, 2008), for instance, focus on qualitative WES inflation expectations, that is, whether most experts expect future inflation to go up, down or remain unchanged. In the present study, we analyze inflation forecasts based on the single *quantitative* question provided by the WES on a quarterly basis. Since 1996:Q1, participants are asked each quarter of a year:[8]

Question 4b: The rate of inflation on average
of this year will be _________% (p.a.)

[7] See Stangl (2007) for a detailed description of the WES data.

[8] Before that time, the WES included a question on six-months-ahead inflation since 1990:Q3. However, the wording of this question changed a few times before 1996. See table 3.A.1 in the appendix for a detailed description of the survey question on the inflation rate.

This question reflects short-term inflation expectations related to a fixed event where the forecast horizon h declines subsequently with each quarter from $h = 4$ in January to $h = 1$ in October of a given year.

Our sample comprises high-income countries classified according to the World Bank's annual World Development Report. We restrict our sample to countries with inflation forecasts consistently available for the period 1996:Q1-2012:Q4 and with at least four inflation forecasts per period, although the number of forecasts per country has generally risen towards the end of the sample. Our final dataset consists of inflation forecasts for 16 high-income economies. Throughout our analysis, we consider the median inflation forecast as this measure is more robust to outliers than the mean.

Table 3.1 presents summary statistics of the WES inflation forecasts and realized inflation. Annual CPI inflation was obtained from the OECD database. For the UK, the inflation rate of the Retail Price Index provided by the UK Office for National Statistics was taken as the realized target variable until 2004:Q4 since this data is more closely related to the forecast series (see figure 3.A.1 in the appendix).[9] Note that all countries in our panel are (de facto) inflation targeters.[10] On average, there are 19 inflation forecasts per country and per period available. The number of forecasts varies between 10 (Australia and New Zealand) and 51 forecasts (Germany). The cross-country average of actual inflation is less than 2% and reflects the low inflation rates of these high-income countries during the most recent two decades. The average forecast error is defined as realized inflation minus the median forecast and is negative in most countries. This suggests that forecasters have generally overestimated inflation. Yet, the magnitude of the average forecast error is below 0.2 percentage points in the majority of countries and is subsequently rather small. The average Root Mean Squared Error (RMSE) is reported in the last two columns of table 3.1. At the 4-quarter horizon, the smallest RMSE is found in the Netherlands (0.42) whereas the highest value is present for Sweden (1.17). Unsurprisingly, the RMSE declines with a reduction in the forecast horizon when more and more information about the target variable is revealed.

[9] In the present study, we do not use real-time data on CPI inflation. However, the CPI is generally subject to fewer and smaller revisions than real variables such as GDP growth (see, for instance, Giannone et al., 2012, for evidence on the euro area, Japan, and the US).

[10] Since early 2012, the US and Japan have also been communicating an official inflation target.

Table 3.1: Summary statistics of WES inflation forecasts and actual inflation

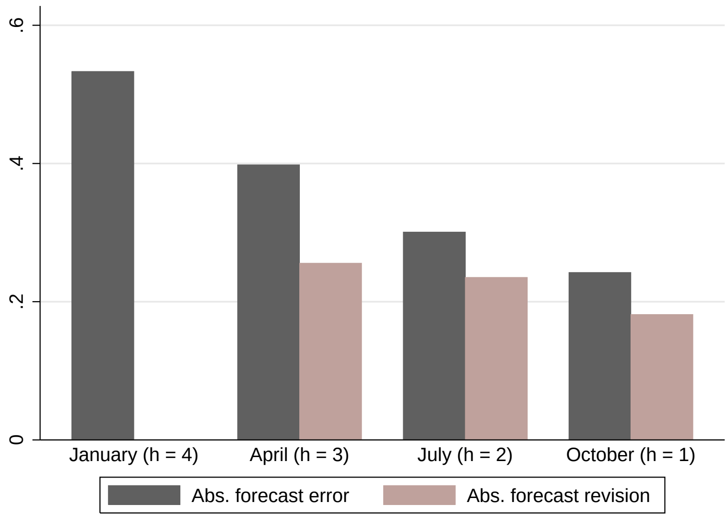
Country	Avg. # fore-casters	Avg. forecast (median)	Avg. actual inflation	Avg. forecast error	Avg. RMSE ($h = 4$)	Avg. RMSE ($h = 1$)
Australia	10	2.9	2.6	−0.24	0.91	0.55
Austria	12	1.8	1.9	0.06	0.73	0.17
Belgium	14	2.0	2.1	0.07	0.75	0.22
Canada	11	2.0	2.0	−0.08	0.48	0.28
Finland	17	1.8	1.7	−0.13	0.82	0.28
France	16	1.7	1.6	−0.12	0.57	0.24
Germany	51	1.7	1.5	−0.16	0.45	0.28
Italy	21	2.3	2.3	−0.01	0.61	0.17
Japan	30	0.1	-0.1	−0.16	0.54	0.30
Netherlands	15	2.2	2.1	−0.05	0.42	0.22
New Zealand	10	2.5	2.3	−0.17	0.69	0.58
Spain	23	2.7	2.7	0.02	0.76	0.24
Sweden	14	1.7	1.2	−0.44	1.17	0.55
Switzerland	14	1.0	0.7	−0.26	0.66	0.20
United Kingdom	17	2.6	2.7	0.13	0.63	0.37
United States	25	2.5	2.4	−0.05	0.69	0.57
Average	19	2.0	1.9	−0.10	0.68	0.33

Note: Sample averages refer to the period 1996:Q1-2012:Q4.

Figure 3.1 shows the size of forecast errors and revisions by different forecast horizons. On average, the absolute forecast error is the highest in the January survey of a target year and declines with the forecast horizon. With $h = 1$, the size of the forecast error has more than halved. As the calculation of forecast revisions requires one preceding forecast, the first revision is available in April of a target year. The size of forecast revisions exhibits a similar downward trend across horizons, although the difference between subsequent quarters is smaller.

The WES also polls the experts' opinion on prevailing economic problems in their country. The wording of the question is:

Figure 3.1: Size of forecast errors and revisions by forecast horizons



Question 9: Please try to assess the **importance** of the following **problems** the economy of your country is facing **at present:**

	most important	important	not so important
- Lack of confidence in the government's economic policy	☐	☐	☐
- Insufficient demand	☐	☐	☐
- Unemployment	☐	☐	☐
- Inflation	☐	☐	☐
- Lack of international competitiveness	☐	☐	☐
- Trade barriers to exports	☐	☐	☐
- Lack of skilled labour	☐	☐	☐
- Public deficits	☐	☐	☐
- Foreign debts	☐	☐	☐
- Capital shortage	☐	☐	☐

To this date, the question concerning current economic problems is posed bi-annually in the WES questionnaire (April and October of a given year). It provides three qualitative answers: "most important", "important", and "not so important". At the country level, the qualitative answers can be summarized by a balance statistic where the answers "most important" receive a value of 1, "important" a value of 0 and "not so important" a value of -1. Hence, a balance statistic within the range of 0 to 1 indicates that the majority of experts evaluate the problem as being highly important. In contrast, a balance statistic within the range of -1 to 0 suggests that the problem is predominantly assessed as being not so important. Overall, the qualitative question on economic problems allows for the identification of periods where inflation concerns are prevailing. The average number of assessments per country ranges between 10 to 54. On average, each economic problem was evaluated by 20 respondents, which is similar to the average number of inflation forecasts.[11]

3.4 Testing the inflation expectations process of WES forecasters

We examine the process of WES inflation expectations by applying the framework by Coibion and Gorodnichenko (2010). To test for the presence of informational rigidities, we estimate the following equation:

$$\pi_{i,t+h} - F_t\pi_{i,t+h} = \beta_0 + \beta_1 \Delta F_t \pi_{i,t+h} + \nu_{i,h,t}, \tag{3.6}$$

where i denotes the country index, h is the forecast horizon, and $\nu_{i,h,t}$ represents the rational expectations error. The forecast revision $\Delta F_t \pi_{i,t+h}$ is the difference between two subsequent forecasts of current-year inflation ($F_t\pi_{i,t+h} - F_{t-1}\pi_{i,t+h}$). In the presence of informational rigidities, β_1 is expected to be significantly positive. In the case of professional forecasters, the revision process might be governed by strategic behavior due to reputational objectives or forecasting competition (Marinovic et al., 2013). However, as WES experts are anonymous, the estimate of β_1 should fully reflect the underlying degree of information rigidity.

An alternative test advocated by Coibion and Gorodnichenko (2010) consists of regressing the forecast revision on the present and lagged forecast:

$$\pi_{i,t+h} - F_t\pi_{i,t+h} = \beta_0 + \gamma_1 F_t\pi_{i,t+h} + \gamma_2 F_{t-1}\pi_{i,t+h} + \nu_{i,h,t}. \tag{3.7}$$

If the coefficient on the forecast revision in equation (3.6) is positive, this implies that $\gamma_1 > 0$, $\gamma_2 < 0$, and $\gamma_1 + \gamma_2 = 0$.

[11] See appendix 3.A.1 for a detailed description of the WES question on economic problems. Summary statistics of the number of respondents are reported in table 3.A.3 in the appendix.

For the period 1996-2012, we have a total of 17 forecast events available per country. Thus, we apply a fixed-effects panel estimator. Given that CPI inflation is to a large extent driven by energy and commodity prices and therefore includes a global component, it is reasonable to assume that forecast errors and revisions are possibly correlated across countries. This might, in turn, violate the central assumption of the fixed-effects model that innovations are cross-sectionally independent. Table 3.2 shows the Pesaran (2004) Cross-section Dependence (CD) test statistic. The hypothesis that residuals of the fixed-effects model are uncorrelated across countries can be rejected at all conventional significance levels. The average absolute correlation between the innovations amounts to 0.30 at the longest forecast horizon $h = 3$. Therefore, we estimate the fixed-effects model with Driscoll and Kraay (1998) standard errors which are robust to cross-sectional correlation across countries as well as to heteroskedasticity and autocorrelation.[12]

Table 3.2: Testing for cross-sectional independence

	$h = 1, 2, 3$	$h = 1$	$h = 2$	$h = 3$
Pesaran's CD test statistic	15.10***	4.73***	5.32***	9.10***
Average abs. correlation of residuals	0.25	0.25	0.23	0.30

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Based on a fixed effects (within) estimation of the following model: $\pi_{i,t+h} - F_t\pi_{i,t+h} = \beta_0 + \beta_1 \Delta F_t \pi_{i,t+h} + \nu_{i,h,t}$.

The regression results of the two tests for informational rigidities are reported in table 3.3. Concerning equation (3.6), the coefficient on the forecast revision is $\hat{\beta}_1 = 0.12$ when pooling across forecast horizons. According to the sticky-information model, the degree of information rigidity is $\lambda = \frac{\beta_1}{1+\beta_1} = 0.11$. Hence, the average number of periods between information updates is $\frac{1}{(1-\lambda)} = 1.12$, implying that forecasters acquire new information approximately every quarter. In the context of the noisy-information model, this signifies a weight $G = \frac{1}{1+\beta_1} = 0.89$ on new information relative to the previous forecast. Turning to the separate

[12]Estimation is based on the Stata modules `xtcsd` by De Hoyos and Sarafidis (2006) and `xtscc` by Hoechle (2006). For all pooled specifications in the present study, outliers were identified and removed according to Cook's distance to obtain more precise estimates. Including the outliers does not change the results in a qualitative way.

forecast horizons, results differ considerably. At horizons 1 and 2, we do not find evidence of information rigidity as the coefficient on the forecast revision is insignificant. That is, the null of full-information rational expectation cannot be rejected at very short forecast horizons. In contrast, at $h = 3$, the estimated coefficient is 0.40 and statistically different from zero at the 1% significance level. This suggests information updating every four months (1.4 quarters) or a weight of 0.71 on new information relative to the previous period's forecast.

The results of regression model (3.7) are displayed in the lower part of table 3.3 and confirm that the forecast horizon does indeed seem to matter. If forecast errors are pooled across horizons, evidence of the predictions implied by models of informational rigidities is found neither by the sign of the coefficients nor by statistical significance. At the shortest horizon $h = 1$, the signs of the coefficients on the current and past forecast would be inconsistent with predictions from the sticky- or noisy-information model. Only at $h = 3$ do both coefficients have the expected sign and are statistically significant. Additionally, the null that both coefficients add up to zero cannot be rejected at the 10% level. Overall, we only find support for models of imperfect information at a longer forecast horizon.

Taken together, the message from table 3.3 is twofold. First, we find evidence of a moderate degree of information rigidity in inflation forecasts of three to four months. This updating frequency is higher than found by Coibion and Gorodnichenko (2010) for the US (six to seven months). However, the authors report a smaller degree of information rigidity when using cross-country data and notably when results are solely based on Consensus Economics inflation forecasts. Moreover, evidence on micro price changes also suggests an average updating frequency of about one quarter (Klenow and Malin, 2010).

Second, we find that the degree of information rigidity in WES inflation forecasts differs across forecast horizons. As laid out in section 3.2, this is in contrast to the prediction of the sticky-information model where λ should hold irrespective of the time distance to the forecasting variable. Divergent results across forecast horizons are rather supportive of noisy-information models (Coibion and Gorodnichenko, 2010). Given that WES experts forecast the annual average rate of inflation, they have little information available at the January survey of a given year. With the end of the target year approaching, they obtain increasingly more information to predict annual average inflation. In the context of the noisy-information model, this implies that the forecasters' signal about the true state of annual average inflation is revealed more precisely with each subsequent quarter of a target year. Conversely, the degree of information rigidity increases with the forecast horizon of a target year. This feature of noisy-information models is reflected by WES forecasts. A higher degree of information rigidity at longer forecast horizons is also documented for Consensus Economics survey data which consists in year-on-year growth rates or annual average growth rates (Coibion and Gorodnichenko, 2010; Loungani et al., 2011).

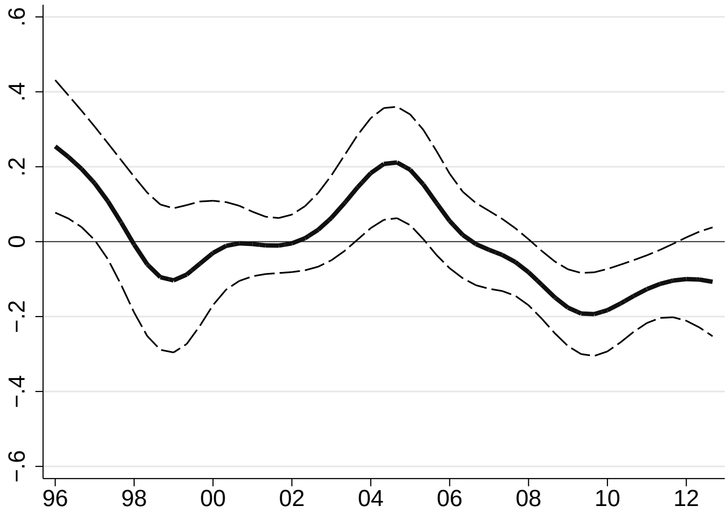
Table 3.3: Testing for the presence of informational rigidities

Dependent variable: $\pi_{t+h} - F_t\pi_{t+h}$	$h = 1, 2, 3$ (1)	$h = 1$ (2)	$h = 2$ (3)	$h = 3$ (4)
$\Delta F_t\pi_{t+h}$	0.12^{**}	-0.10	0.05	0.40^{***}
	(0.06)	(0.06)	(0.07)	(0.11)
R-squared	0.18	0.30	0.19	0.20
# observations	768	260	260	256
$F_t\pi_{t+h}$	0.08	-0.14^{**}	0.01	0.40^{***}
	(0.06)	(0.06)	(0.08)	(0.11)
$F_{t-1}\pi_{t+h}$	0.00	0.22^{***}	0.09	-0.28^{***}
	(0.06)	(0.07)	(0.10)	(0.09)
p-value ($\gamma_1 + \gamma_2 = 0$)	0.00	0.02	0.01	0.10
R-squared	0.20	0.37	0.21	0.21
# observations	766	260	261	257

Driscoll-Kraay standard errors in parentheses. Each specification includes country-fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In general, our sample period is characterized by lower macroeconomic volatility in light of the "Great Moderation" and by the introduction of (de facto) inflation targeting in most countries. Therefore, it is also of interest to see whether the degree of information rigidity was rather stable or changing during the period 1996-2012. Recent contributions emphasize that the degree of inattention in inflation expectations is time-varying (Coibion and Gorodnichenko, 2010; Lamla and Sarferaz, 2012; Dräger and Lamla, 2012). We follow the former and estimate equation (3.6) for each point in time by Pooled Ordinary Least Squares. The smoothed coefficient $\beta_{1,t}$ is shown in figure 3.2. Evidently, the underlying degree of information rigidity is not constant over time. The coefficient on the forecast revision is on average higher during the first half of the sample with a significant increase during the mid-2000s. It exhibits a sharp significant drop during the recent Global Financial Crisis. Note that our estimation is based on a rather small sample resulting in a higher parameter uncertainty. Nevertheless, figure 3.2 suggests that there are changes in the underlying degree of information rigidity. Notably, the extent to which forecasters are inattentive might change with the economic stance.

Figure 3.2: Time-varying estimate of information rigidity



Note: The figure shows the coefficient on the forecast revision based on a Gaussian kernel smoother with a bandwidth of three quarters (solid line) together with ±1 standard error (dashed lines).

3.5 Testing for state-dependence in inflation expectations

The previous section showed that the degree of information rigidity in WES inflation forecasts varies over time. Consequently, we address the question of whether the degree of inattention is subject to changes over the course of the economy. State-dependence in the expectations formation process has also been emphasized by recent empirical studies (Coibion and Gorodnichenko, 2010; Loungani et al., 2011; Lamla and Sarferaz, 2012). In the context of imperfect information models, it can be optimal for agents to be inattentive given lower macroeconomic volatility or to focus more on idiosyncratic rather than aggregate conditions

(Sims, 2003; Branch et al., 2009; Maćkowiak and Wiederholt, 2009). Likewise, recent contributions combine state-dependent characteristics of updating or pricing behavior with informational rigidities (Gorodnichenko, 2008; Knotek, 2010; Woodford, 2009).[13] In this section, we analyze whether the degree of information rigidity in inflation forecasts is subject to economic conditions. We consider two approaches. First, we investigate whether the degree of information rigidity varies when the economic problem "inflation" is assessed as being highly important by WES experts. Second, we analyze in this vein whether forecasters are more attentive when realized inflation is above a certain threshold. In our application, both approaches suggest that the degree of information rigidity is state-dependent.

3.5.1 Subjective assessment of the economic problem "inflation"

The WES asks participants to evaluate the importance of a given choice of economic problems. Consequently, we are able to investigate whether different "states" of the importance assigned to the problem "inflation" influence the expectations formation process. Figure 3.3 shows the balance statistic of the problem "inflation" (left axis) together with annual average inflation (right axis). The balance statistic ranges between −1 and 1 whereas actual inflation is centered roughly around its mean value. The latter is not known before January of the following year whereas the last forecast is made in October of a given year. Although the balance statistic has predominantly remained negative, there are periods where the economic problem "inflation" is more prevailing. In these periods, the respective balance statistic is close to zero ("important") or even positive ("most important"). This increase in the balance statistic is generally accompanied by an increase in inflation. Both variables are strongly linked with a correlation coefficient of 0.66. That is, the balance statistic is a good predictor of whether annual average inflation will be (subjectively) high. An increase in the balance statistic can be observed in most countries during the early 2000s, the oil price hike in 2008 and in the aftermath of the Great Recession with a pickup of inflation rates in 2011. The lowest maximum balance statistic over time is found in Japan (−0.32), which reflects the prolonged deflation era of this

[13] See Mankiw and Reis (2010), chapter 7.1, for an overview of this strand of literature.

country. In Spain, experts generally assigned a high importance to the problem of inflation from the end of the 1990s onwards until 2008. During this period, Spain also experienced on average the highest inflation rate of all countries in our sample.

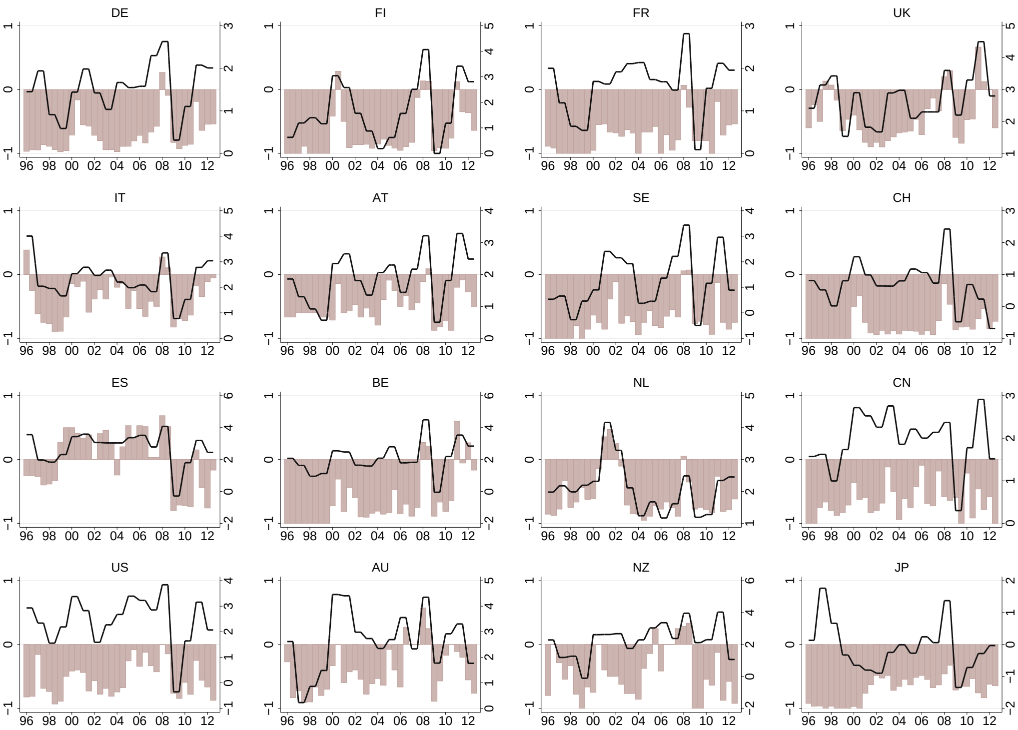
Alternatively, we can assess to which extent WES experts perceive the problem "inflation" as being important in comparison to other economic problems mentioned in the questionnaire. To obtain a ranking of economic problems, the balance statistics of the ten given economic problems are sorted from the highest to lowest value for each country and period. Accordingly, a rank of 1 indicates the highest rank possible, and 10 the lowest. Figure 3.4 displays the rank of the economic problem "inflation" over time. The co-movement with actual inflation is inverse to the previous figure. Peaks of annual average inflation generally coincide with a high ranking of the economic problem "inflation" and thus a low value of the rank. The ranking exhibits a strong negative correlation with actual inflation and the balance statistic shown in figure 3.3; the correlation coefficient is -0.55 and -0.82, respectively. Overall, the rank of the problem "inflation" is on average not ranked highest of the ten economic problems. This is similar to findings by Ehrmann and Tzamourani (2012). Using data from the World Values Survey for 23 industrialized countries, the authors document that respondents do not assign the highest importance to "fighting rising prices" from a given choice of policy priorities. Nevertheless, the ranking of the economic problem "inflation" presented here is far from being time-invariant, as it indicates periods with higher inflation concerns. Given that the WES survey provides a direct measures of the (subjective) importance of inflation, one would expect that forecasters are more attentive during these periods.

In the following, we test for state-dependence in WES inflation expectations by augmenting the test for informational rigidities in section 3.4 with interaction variables referring to states when inflation is deemed highly important. A similar approach is conducted by Coibion and Gorodnichenko (2010) and Loungani et al. (2011). Since our regression results in section 3.4 revealed that informational rigidities are mainly prevailing at the longest forecast horizon, we perform the subsequent analysis at $h = 3$ only and estimate the following equation:[14]

$$\pi_{t+3} - F_t\pi_{t+3} = \beta_0 + \beta_1 \Delta F_t \pi_{t+3} + \beta_2 D_t^{Pr.\pi} + \beta_3 \Delta F_t \pi_{t+3} \times D_t^{Pr.\pi} + \nu_t, \quad (3.8)$$

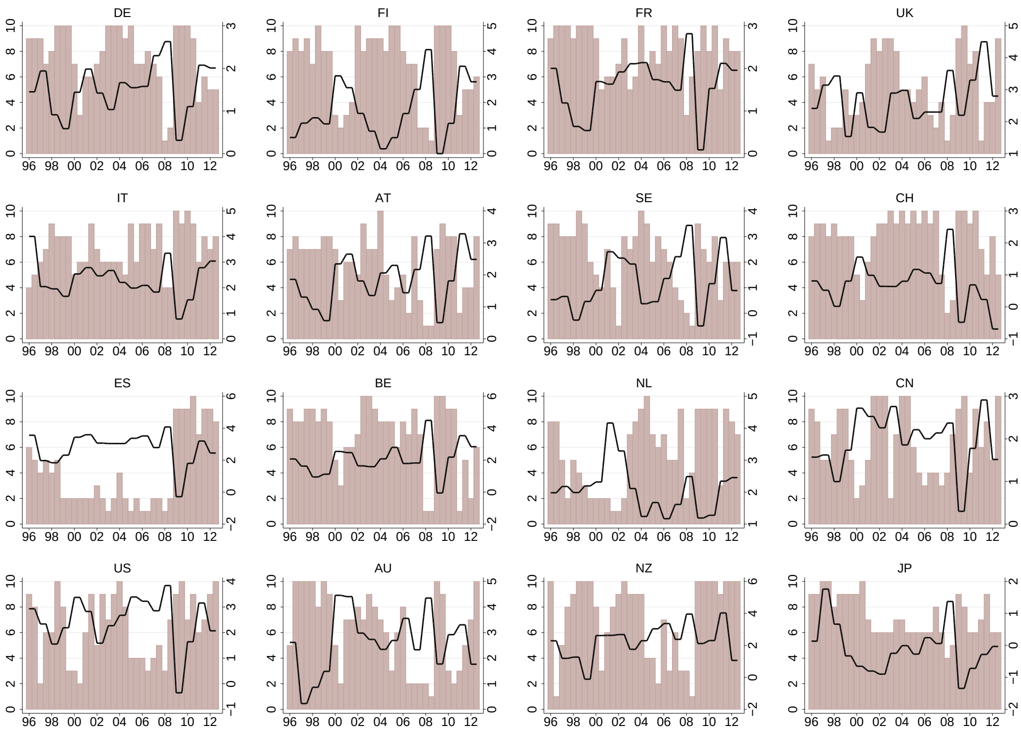
[14]To simplify the notation, we drop the country subscript from the subsequent equations.

Figure 3.3: Importance of the economic problem "inflation" and actual inflation



Note: This figure shows the WES balance statistic of the economic problem "inflation" (bar chart, left axis) together with annual average inflation (black line, right axis) of a respective year. In calculating the balance statistic, answers indicating "most important" receive a value of 1, "important" a value of 0 and "not so important" a value of −1.

Figure 3.4: Rank of the economic problem "inflation" and actual inflation



Note: This figure shows the WES ranking of the economic problem "inflation" (bar chart, left axis) together with annual average inflation (solid line, right axis) of a respective year. The rank is ranging from 1 (highest value of the balance statistic out of 10 given economic problems) to 10 (lowest value).

where $D_t^{Pr.\pi}$ is an indicator variable for periods when the economic problem "inflation" is predominantly assessed as being highly important. We consider three alternative indicators. First, the indicator $D_t^{Pr.\pi}$ equals one when the balance statistic of the problem "inflation" is positive; otherwise, the indicator equals zero. Second, we consider an alternative balance statistic where both the answers "most important" and "important" receive a value of 1 and "not so important" a value of 0. Based on this alternative balance statistic, we then define a continuous indicator $D_t^{Pr.\pi}$ which varies between 0 and 1. Third, we focus on the rank of inflation among the ten possible economic problems. In particular, $D_t^{Pr.\pi}$ equals one when inflation is among the three most important economic problems during this period, and zero otherwise. In all cases, β_3 reflects the difference in the effect of the forecast revision (that is, the underlying degree of information rigidity) in periods of a subjective higher importance of inflation in contrast to periods where this problem is not as prevailing. In case of full-information rational expectations, the sum of the coefficient on the forecast revision and the interaction with the indicator variable should equal zero.

Regression results are summarized in table 3.4. The first regression model is based on the indicator equal to one when the majority of experts evaluate the problem "inflation" as highly important. The coefficient on the interaction term between the indicator variable and the forecast revision is significantly negative. Thus, the degree of information rigidity is lower when inflation concerns are prevailing. Regression (2) displays the specification based on the alternative balance statistic. We also find a significantly negative interaction term between the indicator variable and the forecast revision. When the fraction of experts indicating "most important" or "important" increases, the associated degree of information rigidity in inflation forecasts is lower. A similar result is obtained with regression (3). When inflation is among the top 3 economic problems as given in the WES questionnaire, the degree of inattention declines. The Wald test on whether both coefficients related to the forecast revision add up to zero is displayed in the lower part of table 3.4. In regressions (2) and (3), we cannot reject the null hypothesis that forecasters have full-information rational expectations. In the case of regression (1), the null that β_1 and β_3 are equal in magnitude can be rejected at all conventional significance levels. Given that the estimated coefficient on the interaction term is absolutely larger than the coefficient on the forecast revision, this finding does not suggest a departure from full-information rational expectations but rather overshooting expectations concerning future inflation (Coibion and Gorodnichenko, 2010). Note that the coefficient on all indicator variables is positive and significant at the 1% level. This implies that the forecast error is significantly different in periods of a higher importance of inflation than in periods when this economic problem is not as prevailing. However, a constant term of a specific event is not informative about departures from full-information rational expectations. Rather, it indicates whether all forecasts made within this event have the same bias (Bakhshi et al., 2005). Here, in times of a higher importance of the problem inflation, forecast errors generally have an upward bias. Taken together, the above findings point to state-dependence in the forecasting process with information being acquired and processed more quickly when the economic problem "inflation" is highly important.

Table 3.4: Testing for state-dependence in inflation expectations given the importance of the economic problem "inflation"

Dependent variable: $\pi_{t+3} - F_t\pi_{t+3}$	Balance statistic of problem "inflation" > 0 (1)	Alt. balance statistic of problem "inflation" $\in [0, 1]$ (2)	Rank of problem "inflation" ≤ 3 (out of 10) (3)
$\Delta F_t\pi_{t+3}$	0.47***	0.44***	0.44***
	(0.09)	(0.08)	(0.08)
$D_t^{Pr.\pi}$	0.38***	0.57***	0.42***
	(0.12)	(0.16)	(0.10)
$\Delta F_t\pi_{t+3} \times D_t^{Pr.\pi}$	−0.67***	−0.55***	−0.56***
	(0.14)	(0.17)	(0.15)
p-value ($\beta_1 + \beta_3 = 0$)	0.00	0.39	0.32
R-squared	0.26	0.28	0.31
# observations	257	258	258

Driscoll-Kraay standard errors in parentheses. Each specification includes country-fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Likewise, large changes in the subjective importance of inflation might have an effect on the degree of information rigidity. To this end, we estimate the following model:

$$\pi_{t+3} - F_t\pi_{t+3} = \beta_0 + \beta_1\Delta F_t\pi_{t+3} + \beta_2 D_t^{\Delta Pr.\pi} + \beta_3\Delta F_t\pi_{t+3} \times D_t^{\Delta Pr.\pi} + \nu_t, \quad (3.9)$$

where $D_t^{\Delta Pr.\pi}$ equals one in case of large changes in the balance statistic of the economic problem "inflation" and zero otherwise. Large changes are defined as being in the upper 90th percentile of the non-negative distribution of changes. Thereby, we consider both the balance statistic (ranging between -1 and 1) and the alternative balance statistic (ranging between 0 and 1). Estimation results are reported in table 3.5. Regression (1) comprises the indicator based on changes in the balance statistic. The related interaction term with the forecast revision is significantly negative and larger in magnitude than the coefficient on the forecast revision. Once more, forecasters seem to have overshooting expectations; the null that both coefficients add up to zero is rejected at the 1% level. A significantly lower degree of information rigidity is also found when the analysis is based on the alternative balance statistic. Here, we cannot reject the null that the coefficients are equal in absolute value. In both specifications, the intercept of the indicator variable is again significantly different from periods with no large changes in the importance of inflation. Our findings suggest that information updating speeds up when the economic problem "inflation" has gained importance. This confirms state-dependent behavior in inflation forecasting.

Table 3.5: Testing for state-dependence in inflation expectations given changes in the importance of the economic problem "inflation"

Dependent variable: $\pi_{t+3} - F_t\pi_{t+3}$	Change in balance stat. of problem "inflation" (1)	Change in alt. balance stat. of problem "inflation" (2)
$\Delta F_t\pi_{t+3}$	0.37***	0.38***
	(0.11)	(0.11)
$D_t^{\Delta Pr.\pi}$	0.55***	0.42*
	(0.12)	(0.21)
$\Delta F_t\pi_{t+3} \times D_t^{\Delta Pr.\pi}$	−0.85***	−0.72**
	(0.13)	(0.27)
p-value ($\beta_1 + \beta_3 = 0$)	0.00	0.22
R-squared	0.22	0.20
# observations	242	243

Driscoll-Kraay standard errors in parentheses. Each specification includes country-fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2 Level of expected trend inflation and past inflation

As documented in the previous section, forecasters are on average more attentive during periods of a higher importance of the economic problem "inflation". In a similar vein, we would expect a lower degree of information rigidity when the level of inflation is high. Most countries in our sample can be seen as (de facto) inflation targeters with generally an announced band of inflation within the range 1-3% (Roger, 2010). This raises the question of whether the degree of inattention changes when inflation is higher than the announced target. For this purpose, we define high-inflation states by means of two alternative measures. First, we derive a measure of trend inflation from an Unobserved Components-Stochastic Volatility (UC-SV) model. The estimation is performed recursively with data from 1991:Q1 onwards through each forecast quarter t. This yields a one-sided estimate of the trend component of inflation, which can be seen as a measure of long-term inflation expectations (Stock and Watson, 2010). Second, we also compare past levels of the annualized quarterly rate of inflation.[15] Since the WES is queried within January, April, July, and October of a given year, we assume that the previous quarter's (trend) inflation is in the information set of WES experts.

As before, we test for state-dependence by augmenting equation (3.6) with indicator variables for high-inflation states:

$$\pi_{t+3} - F_t\pi_{t+3} = \beta_0 + \beta_1 \Delta F_t \pi_{t+3} + \beta_2 D_t^{HI} + \beta_3 \Delta F_t \pi_{t+3} \times D_t^{HI} + \nu_t, \qquad (3.10)$$

where D_t^{HI} equals one during periods when (trend) inflation is above a certain threshold value and zero otherwise.

Table 3.6 reports the regression results concerning the different threshold values of inflation. Regressions (1) to (3) are based on trend inflation. Whenever this measure is above a threshold of 2.5 percentage points, the implied degree of information rigidity is significantly smaller. This effect is amplified when the threshold value is set to 3 percentage points or to the 90$^{\text{th}}$ percentile of the distribution of inflation rates, as indicated by the increasing magnitude of the coefficient on the interaction term. In all cases, we cannot reject the null that the sum of coefficients is zero. Regressions (4) to (6) are related to the annu-

[15] See appendix 3.A.4 for a description of inflation data and the estimation of the UC-SV model.

alized quarterly rate of inflation. When the value of past inflation is above 2.5 percentage points, we do not document a significant change in the expectations formation process. In contrast, there is a significant decrease in the underlying degree of information rigidity for states with inflation above a value of 3 percentage points or within the 90$^{\text{th}}$ percentile. Concerning the Wald test displayed in the lower part of table 3.6, there is again evidence of full-information rational expectations or overshooting expectations. The results based on threshold values of expected trend inflation and past inflation emphasize our previous findings that state-dependence is inherent in the process of inflation expectations formation.

Table 3.6: Testing for state-dependence in inflation expectations given the level of actual inflation

Dependent variable: $\pi_{t+3} - F_t\pi_{t+3}$	Trend inflation > 2.5 (1)	Trend inflation > 3 (2)	Trend inflation $\in 90^{\text{th}}$ percentile (3)	QoQ inflation > 2.5 (4)	QoQ inflation > 3 (5)	QoQ inflation $\in 90^{\text{th}}$ percentile (6)
$\Delta F_t\pi_{t+3}$	0.48***	0.48***	0.49***	0.30*	0.41***	0.46***
	(0.09)	(0.07)	(0.08)	(0.14)	(0.09)	(0.09)
D_t^{HI}	0.39***	0.30***	0.25**	0.41***	0.42***	0.59***
	(0.07)	(0.08)	(0.11)	(0.09)	(0.10)	(0.18)
$\Delta F_t\pi_{t+3} \times D_t^{HI}$	−0.44***	−0.63***	−0.66***	−0.31	−0.62***	−0.96***
	(0.10)	(0.19)	(0.12)	(0.19)	(0.15)	(0.24)
p-value ($\beta_1 + \beta_3 = 0$)	0.80	0.43	0.18	0.91	0.12	0.03
R-squared	0.30	0.28	0.26	0.30	0.30	0.29
# observations	255	256	256	258	259	258

Driscoll-Kraay standard errors in parentheses. Each specification includes country-fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Concluding remarks

The focus of this paper was to analyze the process of inflation expectations formation in high-income countries. Specifically, we assess the degree of information rigidity in inflation forecasts following an approach by Coibion and Gorodnichenko (2010). Their test is directly based on models of imperfect information and allows for the inference of the economic significance as well as the underlying mechanisms of a departure from full-information rational expectations. We apply their approach to a unique dataset provided by the CESifo World Economic Survey. Our sample comprises inflation forecasts for 16 high-income countries from 1996 to 2012. Since WES participants are also asked to evaluate the importance of the economic problem “inflation”, we can identify periods where inflation concerns are prevailing. Consequently, we analyze to what extent the level and changes in the importance of the problem “inflation” influence the underlying expectations formation process.

Our main results can be summarized as follows. First, we provide evidence of information rigidity with WES experts updating their information set every three to four months. However, the degree of information rigidity crucially depends on the forecast horizon. Second, we document state-dependence in the process of forecasting inflation. When the majority of WES experts assess the economic problem “inflation” as being highly important, the implied degree of information rigidity is lower. We actually find that forecasters can be characterized by having full-information rational expectations during times of higher inflation concerns. This conclusion seems robust when considering the level of expected and past inflation. Whenever the value of expected trend inflation or past quarterly inflation is above a critical threshold, forecasters are on average more attentive.

For economic modeling, two implications arise from our empirical findings. Since the degree of information rigidity varies across forecast horizons, this validates noisy-information models (Woodford, 2001; Sims, 2003; Maćkowiak and Wiederholt, 2009) rather than sticky-information models which assume a constant updating frequency. A more prominent role of noisy information in forecasters’ expectations formation process is also consistent with findings by Coibion and Gorodnichenko (2010) and Dovern et al. (2013). Moreover, we document that the degree of information rigidity varies with the importance attached to the forecasting variable inflation. This finding suggests a state-dependent rule of information updating, as recently addressed in theoretical models by Gorodnichenko (2008) and Woodford (2009).

Appendix

3.A.1 Wording of WES questions

Table 3.A.1: Wording of WES question on inflation rate

from 07/1990 **to** 04/1991 (except in 10/1990) The rate of inflation will be: _____%*
from 07/1991 **to** 07/1994 **and in** 04/1995 The rate of inflation by the end of the next 6 months will be: _____% (p.a.)
from 10/1994 **to present** (except in 04/1995) The rate of inflation on average of this year will be: _____% (p.a.)**

* Expected tendency of consumer prices within the next 6 to 12 months.
** The remark "(compared to average of previous year)" was used from 10/1994 to 10/1998, in 10/1999 and 10/2000. The number of the year was used instead of "this year" in every January survey of each year from 2002 onwards, as well as in all 2004 surveys, 10/2005, 07/2006, 10/2006, and from 07/2011 onwards.

Table 3.A.2: Wording of WES question on economic problems

from 03/1983 **to** 04/1991

The most important problems for the economy in this country are at present:

- Inflation	☐

from 07/1991 **to** 10/2003

Please try to assess the **importance** of the following **problems** the economy of your country is facing **at present:**

	most important	also very important	not so important/ not relevant*
- Inflation	☐	☐	☐

from 04/2004 **to present**

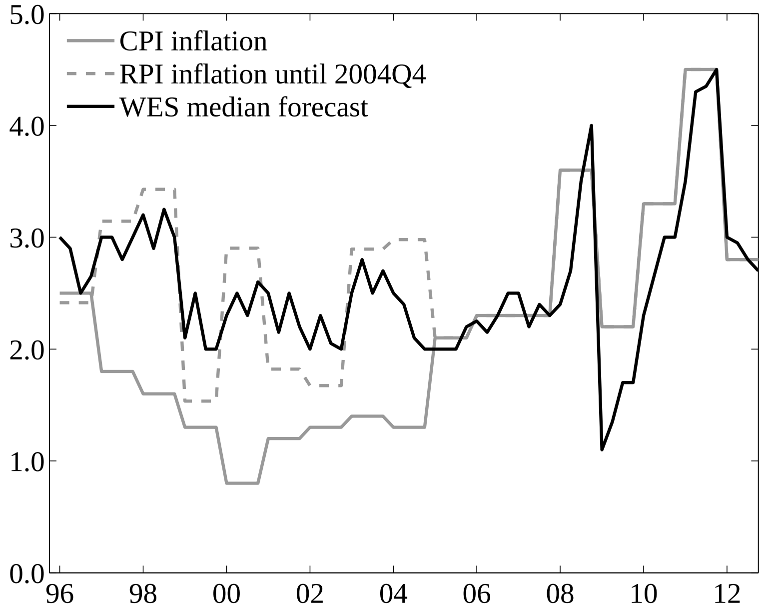
Please try to assess the **importance** of the following **problems** the economy of your country is facing **at present:**

	most important	important	not so important
- Inflation	☐	☐	☐

* The word "so" was omitted in 04/1998 and 07/1998; "not relevant" was omitted in 04/2002, 10/2002, and 10/2003.
In 04/2003, "very important" was used instead of "most important" and "important" was used instead of "also very important".
The questions were included in the WES with a periodicity as follows. In 1983: March, August. From 1984 to 1988: March, June, October. From 1989 to 01/2002: January, April, July, October. From 04/2002 to present: April, October.

3.A.2 Comparison of UK WES forecasts to CPI and RPI inflation

Figure 3.A.1: Comparison of UK WES forecasts to CPI and RPI inflation



3.A.3 Descriptive statistics on economic problems

Table 3.A.3: Average number of assessments per economic problem

Country	Pr. 01	Pr. 02	Pr. 03	Pr. 04	Pr. 05	Pr. 06	Pr. 07	Pr. 08	Pr. 09	Pr. 10
Australia	10	10	10	10	10	10	10	10	10	10
Austria	13	13	14	14	14	14	14	14	14	14
Belgium	15	15	16	16	16	16	16	16	16	15
Canada	11	11	11	12	11	11	12	11	11	11
Finland	19	19	19	19	19	19	19	19	19	19
France	18	18	18	18	18	18	18	18	18	18
Germany	54	53	54	54	54	54	54	54	54	53
Italy	23	23	23	23	23	23	23	23	23	23
Japan	32	32	32	32	32	32	32	32	32	31
Netherlands	16	16	16	16	15	15	16	16	16	15
New Zealand	10	10	10	10	10	11	10	10	10	10
Spain	25	25	25	25	25	25	25	25	25	24
Sweden	15	15	15	15	15	15	15	15	15	14
Switzerland	13	14	13	13	13	13	14	13	13	13
United Kingdom	18	18	18	18	18	18	18	18	18	18
United States	29	29	29	29	29	29	29	29	29	29
Average	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**

Note: Sample average is referring to questionnaires conducted in April and October of a respective year (1996:Q2-2012:Q4). Legend: Pr. 01: Lack of confidence in the government's economic policy. Pr. 02: Insufficient demand. Pr. 03: Unemployment. Pr. 04: Inflation. Pr. 05: Lack of international competitiveness. Pr. 06: Trade barriers to exports. Pr. 07: Lack of skilled labour. Pr. 08: Public deficits. Pr. 09: Foreign debts. Pr. 10: Capital shortage.

3.A.4 Description of inflation data and the UC-SV model

Inflation is measured as the annualized quarterly percent change in the Consumer Price Index (CPI) as given by $400 \times \log(CPI_t/CPI_{t-1})$. For the UK, the inflation rate of the Retail Price Index is taken until 2004:Q4 and the inflation rate of the CPI thereafter. All inflation series are seasonally adjusted. Moreover, we tracked and replaced outliers in the data beforehand as reported in table 3.A.4. Thereby, we detect observations that deviate more than a certain threshold (here, four) times the interquartile range from the median (Stock and Watson, 2003a). These outliers are marked with an asterisk in table 3.A.4 and were replaced with the median over a symmetric window of six observations. Furthermore, we replaced five outliers either due to major VAT rate changes (in Japan, the Netherlands, and Sweden) or exceptional observations such as the German reunification in 1991.

Table 3.A.4: Detection of outliers in quarterly CPI inflation rate

Country	**Dates of replaced outliers**		
Australia	2000:Q3*		
Canada	1991:Q1*		
Germany	1991:Q3	1991:Q4	1993:Q1*
Japan	1997:Q2		
Netherlands	2001:Q1		
New Zealand	2010:Q4*		
Sweden	1991:Q1*	1992:Q1	1993:Q1*
United States	2008:Q4*		

To measure trend inflation, we estimate an unobserved components model with stochastic volatility (UC-SV) as proposed by Stock and Watson (2007). The underlying state-space model decomposes inflation into a stochastic trend and a transitory component. The UC-SV model is defined as:

$$\pi_t = \bar{\pi}_t + \eta_t \qquad \eta_t \sim N(0, \sigma^2_{\eta,t}) \tag{3.A.1}$$

$$\bar{\pi}_{t+1} = \bar{\pi}_t + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma^2_{\epsilon,t}) \tag{3.A.2}$$

$$\log \sigma^2_{\eta,t+1} = \log \sigma^2_{\eta,t} + \nu_{1,t} \tag{3.A.3}$$

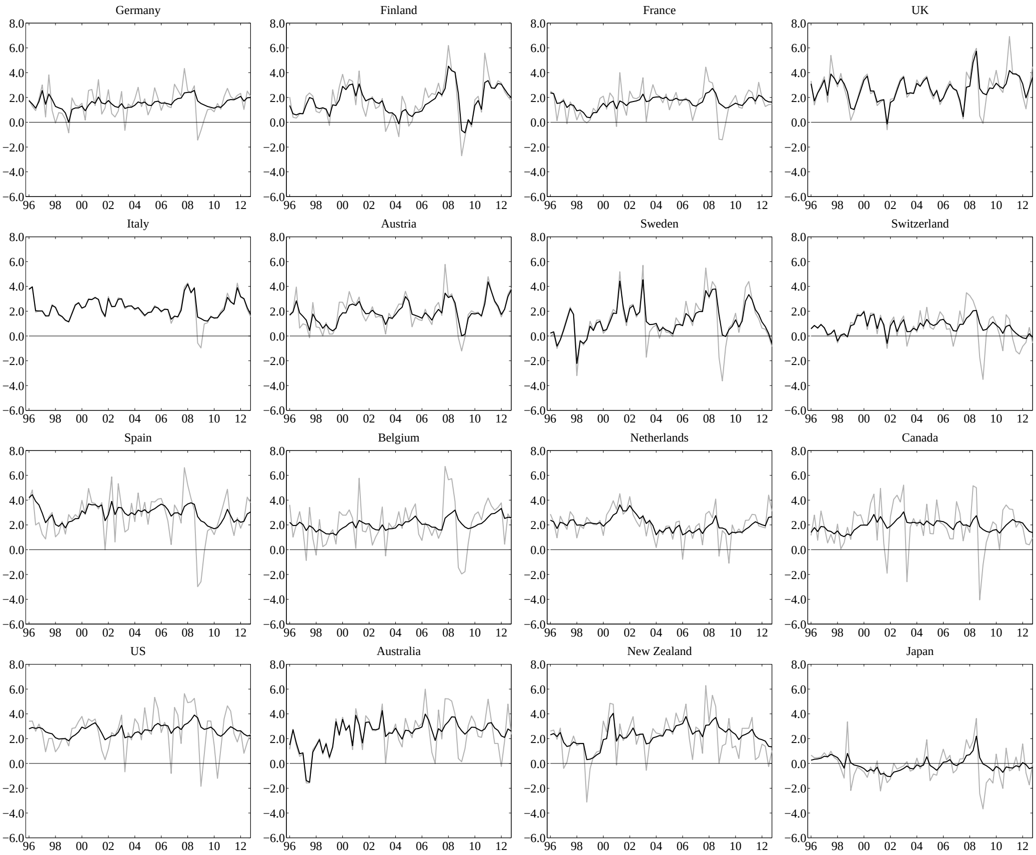
$$\log \sigma^2_{\epsilon,t+1} = \log \sigma^2_{\epsilon,t} + \nu_{2,t} \tag{3.A.4}$$

$$\begin{pmatrix} \nu_{1,t} \\ \nu_{2,t} \end{pmatrix} \sim N(0, \gamma I_2) \tag{3.A.5}$$

The trend component is denoted by $\bar{\pi}_t$ whereas the transitory component is modeled as the innovation process η_t. The variances of the trend and transitory innovations are allowed to vary over time by following a geometric random walk. This, in turn, leads to a time-varying estimate of trend inflation. The model includes only one scalar parameter γ which affects the time variation of the shock variances. Following Stock and Watson (2007), we compute the UC-SV model with $\gamma = 0.20$ for quarterly inflation. Estimation is carried out with the Gibbs sampler.

For the purpose of our analysis, we want to obtain a real-time measure of trend inflation. To this end, estimation of the UC-SV model is performed recursively with the same starting point in 1991:Q1 for all countries and an increasing data window from 1996:Q1 through 2012:Q4. Using only inflation data available up to t yields a one-sided estimate of the trend component of inflation $\bar{\pi}_{t|t}$. Note that, according to equation (3.A.1), the model's unbiased forecast of inflation is the trend component of inflation, irrespective of the forecast horizon. As suggested by Stock and Watson (2010), the estimate of $\bar{\pi}_{t|t}$ provides a proxy of long-term inflation expectations at time t. Figure 3.A.2 displays the resulting trend measure together with the annualized quarterly rate of inflation.

Figure 3.A.2: Recursive estimates of the trend component of inflation



Note: The gray line represents actual annualized quarterly inflation. The dark line represents the estimate of trend inflation.

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