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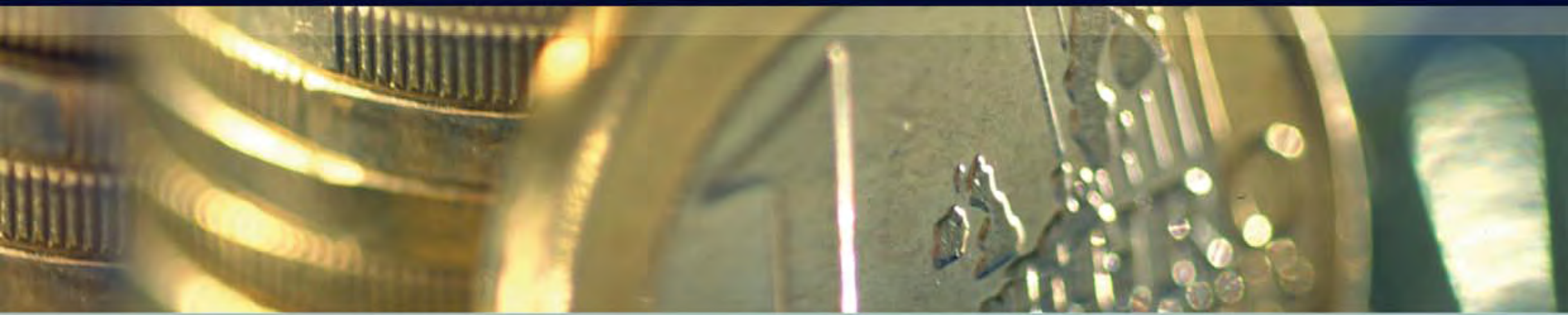

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Did the introduction of the Euro impact on inflation uncertainty ? - An empirical assessment

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Abstract

We study the impact of the introduction of the European Monetary Union on inflation uncertainty. Two groups of economies, one consisting of three European Union members which are not part of the EMU and one of six OECD member economies, are used as control groups to contrast the effects of monetary unification against the counterfactual of keeping the status quo. We find that the monetary unification provides a significant payoff in terms of lower inflation uncertainty in comparison with the OECD. Regarding the difficulty of quantifying the latent inflation uncertainty, results are found to be robust over a set of four alternative estimates of inflation risk processes.

JEL classification: C53, E31, E42.
Keywords: Monetary policy regimes, Euro introduction, inflation uncertainty, uncertainty measurement.

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1 Introduction

Inflation uncertainty (IU) is commonly believed to bear several risks for the evolution of the real economy. Yet an empirical assessment of sources and implications of IU is hindered by the high and positive correlation between inflation and IU. Friedman (1977) and Ball (1992) regard inflation as a cause for IU. If it were the dominant cause, a focus on controlling inflation by means of an inflation targeting strategy might be sufficient to ensure stable future dynamics of inflation along with well anchored expectations about the inflation process. However, as noted by Mankiw, Reis and Wolfers (2003), there might be other influential determinants of IU, like, for instance, the uncertainty about exchange rates, stock prices or real output. Moreover, it might be IU which actually determines the level of inflation, as it has been asserted by Cukierman and Meltzer (1986).

The costs of excess uncertainty about the development or the current state of inflation accord with the following categories. Firstly, decisions about long term savings are biased towards real assets, since investors may be more reluctant to engage in long-term investment strategies. This, in turn, might impact on the real economy through distortions of optimal capital allocation (Ratti 1985, Elder 2004). Secondly, the signal-to-noise ratio inherent in relative prices deteriorates if IU rises (Silver and Ioannidis 1995). If prices reflect more erroneous signals, the relative price dispersion among different groups of goods and services is likely to increase. This may confound the price mechanism, inducing misallocations of goods and welfare losses due to imperfect substitutability among commodities. Thirdly, excess IU might involve inefficient choices of durations of nominal contracts. Vroman (1989) describes the trade-off that employers and employees face in wage negotiations under relatively high IU. She argues that although frequent renegotiations are costly, they might be regarded as beneficial in times of significant changes of unanticipated inflation. This argument applies analogously to contracts on financial markets, where long-term investments result in overall lower transaction costs. Risk adverse investors might, however, favour assets with shorter maturities in a more uncertain inflation environment. Further adverse implications of nominal uncertainty are unanticipated wealth effects due to the predominantly nominal definition of various sorts of assets (Okun 1975), the distortion of firms' price setting decisions ('menu costs') or changes in the structure of tax regulations, which are usually formulated in nominal terms (Fischer and Modigliani 1978).

Economic theory provides numerous explanations for the sources of IU and how it might affect the state of an economy. Empirical assessments of determinants of nominal uncertainty, however, encounter the problem of how to measure this latent quantity. Typically, uncertainty is supposed to be linked to some sort of variation. Ball, Cecchetti and Gordon (1990), for example, distinguish between inflation *variability* as the variance of changes in inflation over time and inflation *uncertainty* as the variance of unanticipated changes of inflation. Evans and Wachtel (1993) examine a hypothesis of Friedman (1977) that the correlation between inflation and its variability is due to uncertainty about the future state of inflation. They note that an assessment of the sources of IU should incorporate the impact of changes in the institutional framework. One of the most important institutional changes in the recent European monetary policy setting has been the introduction of the Euro. It is the purpose of this paper to investigate the impact of the monetary unification on IU.

A fundamental distinction for IU measures is to separate *ex-ante* from *ex-post* quantities. The former family of estimators is based on inflation expectations, which are formed prior to the period of consideration. Expectations might be obtained e.g. from econometric forecasting models or by reference to experts, as it is the case for survey based measures. Regarding ex-ante estimators, Ball, Cecchetti and Gordon (1990) note that the choice of the forecast horizon could be an important determinant for the outcomes of subsequent analyses. Ex-post measures, on the other hand, quantify the extent of uncertainty which prevails up to the current time instance. As an example of this type of measure one may regard the dispersion of relative prices, which is proposed as an estimate of IU e.g. by Silver and Ioannidis (1995). In this paper we consider a set of alternative IU measures at distinct horizons to provide a robust assessment of the monetary unification effect on IU.

Once supposedly appropriate measures of uncertainty are defined, the question about the determinants of IU immediately arises. One approach is to relate uncertainty to the type of monetary administration within economies. With the formation of the European Monetary Union (EMU), a group of European economies concentrated their formerly national monetary policy administrations within the European Central Bank (ECB). The Euro effect on IU has to be analysed carefully, since this regime shift falls into a period of marked changes of inflation dynamics. Prior to the formation of the EMU, the observation of a considerable decline in output and inflation volatility across numerous economies has coined the notion of *great moderation* (Meltzer 2005). Furthermore, the recent coincidence of a decline in inflation variation and stable or even accelerating financial market volatility has invoked a rethinking of the relation between inflation and financial markets expressed in the *new environment hypothesis* (Cecchetti 2000). The hypothesis highlights fundamental changes in the way financial indicators interact with inflation and IU. Moreover, during recent years, the majority of central banks has been adopting inflation targeting (Svensson 2005).

This means that the primary focus of monetary policy lies on the achievement and maintenance of a stable inflation path, which might affect inflation expectations and IU in several ways (Huang, Meng and Xue 2009). In the presence of such dynamic changes in the global IU environment, it is important to consider a counterfactual situation, where monetary unification does not come into effect. We include European Union members outside the EMU and OECD economies outside the European Union as control groups and, moreover, consider a set of other potential (country specific) triggers of IU to isolate the institutional impact on IU in the Euro area. Thereby the analysis is safeguarded against potentially spurious conclusions from a counterfactual effect that is factually driven by global trends in IU or other time varying triggers of macroeconomic risks.

The remainder of the paper begins with an outset of several autoregressive distributed lag (ADL) models to determine inflation expectations as a prerequisite for the derivation of second order inflation characteristics. These specifications might be integrated in the framework of extended Phillips curve (PC) models, which have become a common way to exploit the predictive content of alternative inflation indicators (Stock and Watson 2007). The forecasting abilities of these models and combined predictors are evaluated according to a statistical loss criterion, namely the model specific root mean squared forecast error (RMSE). This provides insight into the relative performance of alternative modelling approaches as (complementary) means to determine ex-ante idiosyncratic IU. Section 3 introduces the cross-sectional data. Section 4 provides an overview of alternative estimators of IU and a regression design to uncover the constitutional impact on IU. Section 5 collects the empirical results. In the first place the relative performance of alternative prediction schemes is described to justify a particular benchmark approach employed to determine particular IU statistics. Secondly, alternative IU measures are compared with financial market or survey based processes of inflation risks. Thirdly, the impact of the Euro on IU is isolated and discussed. Section 6 summarizes the main findings and concludes.

2 Linear specifications of expected inflation

To assess IU it is natural, first, to determine inflation expectations since IU is mostly regarded as uncertainty about future inflation dynamics (Ball, Cecchetti and Gordon 1990). To extract IU we consider a variety of ADL models for two purposes. Firstly, to determine model based ex-ante uncertainty measures at a later stage it appears most effective if the considered model has proven to offer accurate forecasting precision within a set of rival models. Secondly, implementing a variety of forecasting models offers an extra perspective on IU since choosing a particular model always bears the risk of disregarding information that is relevant to describe the space of future states of inflation. Therefore, forecast dispersion measured over a variety of time series models is regarded as a further quantification of IU.

2.1 Estimation and evaluation design

In total, we consider a set of seven prediction schemes for inflation, including a linear autoregressive benchmark and combined forecasts. The quantity that is forecasted throughout is $\pi_{t+h} - \pi_t$, where $\pi_t = \ln(P_t/P_{t-12})$ is the annual inflation rate and P_t is the consumer price index (CPI) in month t. We focus on the CPI since broader indices like the GDP deflator, or the Harmonised Index of Consumer Prices, as the primary target variable of the ECB, are in most countries not available at the monthly frequency (ECB 1999). Throughout, h-step ahead ex-ante forecasts of inflation changes determined in time t are denoted $\widehat{\pi}_{t+h|t}$, with alternative forecast horizons $h \in \{1, 3, 6, 12\}$. The forecast performance of alternative model recitations is evaluated in a pseudo out-of-sample context. From the data which is available over time instances $t = 1, ..., T$, the more recent part, comprising observations $[\mathcal{T}_0, \mathcal{T}_0 + 1, \ldots, T - 1, T]$, is used to evaluate out-of-sample predictions. To center the evaluation sample almost symmetrically around the time instance of the Euro introduction in 1999M1, $\mathcal{T}_0$ is chosen as of January 1991. Estimation is conducted exploiting a rolling sample window of fixed size E for all forecast horizons h. Thus, with $\mathcal{T}$ denoting a particular forecast origin, rolling forecasts are based on observations $t = \mathcal{T} - E - h + 1, ..., \mathcal{T} - h$. Counterfeiting a real time forecasting situation, we obtain a total of $T - \mathcal{T}_0 + 1$ forecasts for evaluation and model comparison.

2.2 Prediction schemes

For the purpose of benchmarking we employ a model which relates inflation changes to their own past. The AR scheme is

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h \pi_t + \varepsilon_{t+h}, \quad t = \mathcal{T} - E - h + 1, ..., \mathcal{T} - h, \tag{1}$$

with ε_t assumed $iid(0, \sigma_\varepsilon^2)$. In (1) L denotes the lag operator such that e.g. $L\pi_t = \pi_{t-1}$, $\Delta_s = 1 - L^s$, and $\beta(L) = 1 + \beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$ is a lag polynomial. The flexible filtering approach implemented for inflation observations in the right hand side of (1) has been proposed recently by Kurz-Kim (2008). It is justified noting the definition of the dependent variable such that the flexible filter is most likely to offer a balanced regression design. In fact, forecasting at higher horizons $h \geq 3$ the autoregression in (1) turns out to offer smaller average squared forecast errors as (quasi) autoregressions where fixed filter operators, Δ or Δ_{12} say, are used for transforming the conditioning variables. Owing to linearity of (1) the determination of an ex-ante forecast by means of parameter estimates and time series information available in time $\mathcal{T}$ is straightforward.

An alternative model in the spirit of Cogley (2002) incorporates the deviation of inflation from its long run trend, denoted $\widetilde{\pi}_t = \pi_t - \overline{\pi}_t$. The CO model is

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \theta(L)\widetilde{\pi}_t + \varepsilon_{t+h}, \tag{2}$$

where $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_p L^p$. Given the autoregressive dynamics the model in (2) exploits additional time series information similar to error correction adjustments. In states deviating markedly from the long run inflation trend additional adjustment dynamics might impact on inflation changes.

Augmenting the baseline AR in (1) with lagged values of the output gap, $\widetilde{y}_t = y_t - \overline{y}_t$, yields the backward looking PC following e.g. Stock and Watson (2007), i.e.

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \gamma(L)\widetilde{y}_t + \varepsilon_{t+h}. \tag{3}$$

To examine the predictive content of monetary variables, Stock and Watson (2008) predict inflation changes with the money augmented Phillips curve (MPC), initially proposed by Gerlach (2004). Similarly, the growth rate of core money, denoted $\overline{m}_t$, is typically interpreted as a proxy for inflation expectations. Introducing a further lag polynomial, $\delta(L)$, the MPC model is

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \gamma(L)\widetilde{y}_t + \delta(L)\Delta\overline{m}_t + \varepsilon_{t+h}. \tag{4}$$

Neumann and Greiber (2004) propose to augment (4) with an indicator of energy prices obtaining

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \gamma(L)\widetilde{y}_t + \delta(L)\Delta\overline{m}_t + \zeta(L)\Delta^2 oil_t + \varepsilon_{t+h}. \tag{5}$$

In (5) $\Delta^2 oil_t$ denotes second differences of the log oil price in terms of domestic currency and $\zeta(L)$ is a further lag polynomial. Note that (5) implicitly comprises log foreign exchange (FX) rate changes as predictors of inflation. We refer to this model as OMPC.

Finally, the adjustments of long run real interest rates Δr_t may be interpreted as an indicator of future inflation expectations (Woodford 2007). To contrast the predictive content of monetary aggregates with the scope of interest based modelling we replace $\Delta\overline{m}_t$ in (4) by Δr_t and obtain a further recitation, the IPC model

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \gamma(L)\widetilde{y}_t + \delta(L)\Delta r_t + \varepsilon_{t+h}. \tag{6}$$

2.3 Implementation

Given that the prediction models are implemented at the monthly frequency, the maximum order of the autoregressive lag polynomial $\beta(L)$ is chosen as $q = 15$, whereas the maximum order of all other lag polynomials $\gamma(L), \delta(L), \zeta(L)$ and $\theta(L)$ is set to $p = 6$. From the set of potential (ADL) covariates effective predictors are selected by means of a *specific-to-general* predictor selection proposed in Herwartz (2009). It is basically a pretest method in the spirit of Judge and Bock (1978) that is carried out sequentially with nominal significance of 5% at each step of model comparison. The iteration starts from an admittedly false baseline model. Single autoregressive distributed lags with the highest marginal explanatory content are subsequently included in the model according to Lagrange Multiplier (LM) statistics (Godfrey 1988). The iteration stops once additional variables fail to provide significant explanatory content. In Herwartz (2009) this strategy is found to be particularly efficient in terms of out-of-sample forecasting performance when estimation sample sizes are small to moderate or the column dimension of potential explanatory variables is large.

The predictions obtained from all models (1) to (6) are direct multistep forecasts in the sense of Clements and Hendry (1998). This is the most straightforward method if other regressors than lags of the dependent variable enter the model. Direct multistep forecasts have also been found more robust in comparison with iterated h-step ahead forecasts under potential model misspecification. In particular, the direct approach is supposed to feature smaller biases in situations when the true lag order of a process exceeds the maximum number of lags that is admitted for subset model selection (Marcellino, Stock and Watson 2006, Chevillon 2007).

2.4 Forecast combination

The ADL models listed in Section 2.2 are parsimonious, yet rather simplistic devices to model inflation expectations. Therefore, it appears sensible to expect some conditional misspecification for each of these schemes, i.e. they might suffer from insufficient capability to explain short run deviations from the steady-state at business cycle frequencies.

In light of conditional misspecification of unknown form an integration of the informational content of alternative models could be helpful to quantify inflation expectations or IU more precisely. Notably, such an assertion follows the ECB methodology of forming a combined expectation that is based on distinct indicators and models for the short- and long run view at inflation risks (ECB 1999). For instance, Gerlach (2004) interprets the MPC model in (4) as the unification of a short- and a long run pillar in the spirit of the ECB's strategy.

A further avenue to integrate information from distinct sources is to combine alternative model based predictions. The ECB's cross checking strategy can also be regarded as a form of forecast combination. Forecast combinations are a means to cope with various sorts of misspecification, as argued in a broad literature initiated by Bates and Granger (1969) and reviewed recently by Timmermann (2006).

Similar to the forecasting approach in Stock and Watson (2004), the individual models entering forecast combinations are the AR model in (1) and ADL specifications based on past inflation and single indicator variables, $w_t = \widetilde{\pi}_t, \widetilde{y}_t, \Delta\overline{m}_t, \Delta^2 oil_t, \Delta r_t$, as employed in the structural models (2) to (6), i.e.

$$\pi_{t+h} - \pi_t = \nu + \beta(L)\Delta_h\pi_t + \gamma(L)w_t + \varepsilon_{t+h}. \tag{7}$$

To combine predictions from individual models, unconditional averaging has been found to be among the most successful approaches for predicting GDP growth and inflation (Stock and Watson 2004). We adopt this method to combine $J = 6$ inflation forecasts obtaining $\widehat{\pi}^{AV}_{t+h|t} = (1/J)\sum_j \widehat{\pi}_{j,t+h|t}$, where the $\widehat{\pi}_{j,t+h|t}$ denote model specific predictions. Apart from unconditional weighting, a time varying combination scheme based on a state space approach (Sessions and Chatterjee 1989, Stock and Watson 2004) has also been considered, which obtains forecast characteristics close to those of $\widehat{\pi}^{AV}_{t+h|t}$. Hence this method is not considered any further in the following discussion.[1]

[1]Results for this forecast combination approach are available upon request.

2.5 Forecast evaluation

To assess forecasting accuracy over a variety of (combined) time series models and thereby to identify a most suitable specification, the RMSE serves as a measure of the predictive success of distinct inflation indicators, i.e.

$$\mathrm{RMSE}_h = \sqrt{\frac{1}{T - \mathcal{T}_0 + 1} \sum_{t=\mathcal{T}_0 - h}^{T-h} \left(\pi_{t+h} - \widehat{\pi}_{t+h|t}\right)^2}. \tag{8}$$

For simplicity, our notation does neither indicate that inflation forecasts $\widehat{\pi}_{t+h|t}$ are model specific nor that RMSE_h statistics are determined by country. To decide if the RMSEs from two prediction schemes differ significantly, we use the Giacomini and White (2006) (GW) test which is suitable for both nested and nonnested specifications, if parameter estimates are obtained from a rolling window design. A-priori one might also think of other, more economic, forecast evaluation criteria like directional accuracy or explicit economic loss functions. However, the RMSE_h criterion appears favourable in our context of identifying a time series framework isolating most effectively the idiosyncratic noise attached to future inflation.

3 Data

The data set comprises monthly observations for the period 1979M1 to 2008M8 and 14 economies and the Euro area. The forecast evaluation sample starts in $\mathcal{T}_0$ =1991M1 to position the evaluation window almost symmetrically around the time instance of the Euro introduction in 1999M1. The size of the estimation window is chosen as $E = 96$ comprising eight years of data. Collected time series include the CPI, industrial production as a measure of output and the broadest monetary aggregate (see Table 1 below) available for each economy. Moreover, the data set contains oil prices in domestic currencies and long term (expected) real interest rates, as obtained by inverting the Fisher equation. Formally, we have $r_t = i_t - \pi_t^e$, where r_t and i_t denote the real and nominal interest rate of government bonds with maturities of at least 5 years, respectively. Following Frankel (1982) the expected rate of inflation π_t^e is estimated by means of the term spread between long- and short term rates which, in turn, determines the horizon of expected inflation. In most economies, a lack of comprehensive long term interest rates for the entire sample period hinders the incorporation of monthly quotes in the data. Hence, quarterly data were transformed to the monthly frequency by means of EViews[2]. As argued before, we investigate the effect of the Euro introduction by comparing IU in the EMU and selected member states with the uncertainty prevailing in two control groups. The first control group, denoted $\overline{\text{EMU}}$, consists of three economies which are part of the EU, but not EMU members (Denmark, Sweden and the UK). The second control group, $O6$, comprises six OECD economies, which are not part of the EU. Table 1 shows a classification of the economies.

[2] The version we use is EViews 5.0, where monthly values are interpolated as a constant function of quarterly data.

Group	Country	m_t	freq. transformations for r_t
	Belgium	M2	1974M1-2008M8
EMU economies	France	M2	1974M1-2008M8
	Germany	M3	-
	Italy	M1	1974M1-2008M8
	Netherlands	M2	1974M1-2008M8
	EU11	M2	-
EU, but not-EMU ($\overline{\text{EMU}}$)	Denmark	M3	1974M1-2008M8
	Sweden	M3	1974M1-2008M8
	UK	M1	1974M1-2008M8
	Canada	M3	1974M1-2008M8
	Japan	M3	1974M1-2008M8
Other OECD economies ($O6$)	Norway	M3	1974M1-2008M8
	South Korea	M2	1974M1-2008M8
	Switzerland	M3	1974M1-2008M8
	US	M2	1974M1-2008M8

Table 1: Groups of economies, monetary variables and periods of frequency transformation

The inclusion of data for the 11 original EMU member economies (E11) is thought as a means to utilize sample information for smaller economies, for which detailed data is lacking. The approach, though, bears the drawback of 'double-counting' some EU11 members, which are also considered on a single economy basis.

All series are obtained from Datastream and seasonally adjusted by the Census X12 method. Estimates of the output gap, $\widetilde{y}_t$, core money, $\bar{m}_t$, and the inflation gap, $\widetilde{\pi}_t$, are calculated by means of the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) with smoothing parameter 129600 (Ravn and Uhlig 2002). To implement the out-of-sample forecasting exercises in the most realistic way, trend estimates are computed at each prediction step conditional on available data which is used to form the current prediction. To alleviate the weak precision of the HP filter at the end of the estimation window $\mathcal{T}$, level series y_t, m_t and π_t are predicted over the period $[\mathcal{T}+1,\ldots,\mathcal{T}+12]$ by means of an ARIMA(6,1,0) model and, then, subjected to HP filtering. For the case of output and monetary aggregates, Canova (2007) employs exponential smoothing to guard against unreliable HP filter estimates in the neighborhood of the forecast origin $\mathcal{T}$. Another possibility is to estimate long run components by means of the Christiano-Fitzgerald band pass filter (Christiano and Fitzgerald 2003). The results provided in this study are mostly invariant with respect to the choice of the filter method. Furthermore, outcomes are largely unaffected by attempts to include higher frequency components of money growth by means of the approach in Christiano and Fitzgerald (2003)[3].

In a couple of studies, IU is considered to be related to volatility on financial markets, since returns, being streams of nominal income, should reflect uncertainty about inflation. The effect of stock market volatility on IU is investigated by Kontonikas, Montagnoli and Spagnolo (2005). They find a positive relation between stock market volatility and IU in the UK, but also point out that the relation turns negative after the Bank of England has adopted an inflation targeting policy scheme. Gosh et al. (1995) find that the dynamics of FX rates affect both the level and volatility of inflation. Barsky and Kilian (2002) describe the transmission of oil price shocks onto inflation, IU and real economic processes. To incorporate measures of aggregate financial and commodity risks, we consider realised volatility estimates (Schwert 1989, Andersen, Bollerslev and Diebold 2004) as explanatory variables in the analysis of IU determinants in Section 4. Linking IU to observable economic volatility measures, we focus on the realised standard deviations of log FX rates (FX), log prices of crude Brent oil (Oil) and the log Dow Jones Industrials Average Index (Dow).

[3] The results of these robustness checks are available from the authors upon request.

Realised standard deviations are determined as

$$\mathrm{RS}_t(x) = \sqrt{\sum_{m \in t} (\Delta \ln x_m)^2}, \tag{9}$$

where an observation at day m is denoted x_m and x is either FX, Oil or Dow. FX rates are measured as the price of the US Dollar in country i in local currency for all economies, except the US, for which the price of the Euro in US Dollar is used to determine realised standard deviations.

4 Measures of IU

Clearly, when assessing the impact of a shift in the monetary constitution on the latent IU process, final conclusions might crucially depend on the employed IU measure. From the variety of time series models a couple of IU estimates can be derived and, alternatively, conditional second order characteristics could be extracted from the inflation series. Regarding the latter one might distinguish parametric volatility models, GARCH say, or filtering techniques like RiskMetrics (Zangari 1996). Since GARCH models are likely infeasible to estimate over (small) windows of monthly time series, the GARCH model class is disregarded for IU extraction in this study. Apart from time series approaches external information as public perceptions collected in survey data (Gallo et al. 2002) or IU implied by arbitrage relations linking financial instruments (ECB 2006) have become prominent tools to assess inflation risks. In this study we consider a set of alternative IU measures, derived from (systems of) time series processes to give robust conclusions regarding the constitutional impact on IU. To assess the accuracy of time series based IU measures we compare these systematically with external information processed from survey data or inflation protected treasury bonds. Owing to data availability or market liquidity this comparison concentrates, however, on selected economies and a subperiod relative to the time span for which model based quantities are determined.

In the following IU statistics are introduced that can be derived from a cross section of time series models and external IU approximations are mentioned in some more detail. Moreover, we recall the definition of the rank correlation coefficient (Spearman 1904) that is employed to compare model based and financial market or survey related IU statistics.

4.1 Ex-ante and ex-post IU measures

There is no generally accepted definition of IU, and, accordingly, its measurement may follow alternative avenues. Four distinct measures of IU are considered in this work and briefly described in turn.

Firstly, since the AR model turns out to be reasonably effective in terms of the RMSE criterion, we consider this benchmark to quantify the forecast error variance. According to (1) the estimated forecast error standard deviation at forecast origin $\mathcal{T} = \mathcal{T}_0 - h, ..., T - h$ is

$$\widehat{\sigma}_{\mathcal{T}}(h) = \sqrt{\widehat{\sigma}^2_{\varepsilon}(1 + \boldsymbol{x}'_{\mathcal{T},h}(X'_{\mathcal{T}} X_{\mathcal{T}})^{-1}\boldsymbol{x}_{\mathcal{T},h})}, \tag{10}$$

where $\widehat{\sigma}^2_{\varepsilon}$ is the usual in-sample error variance estimator, $X_{\mathcal{T}}$ is a rolling (subset) autoregression design matrix and $\boldsymbol{x}_{\mathcal{T},h}$ collects a constant and the autoregressive lags selected to have predictive content.

Secondly, an estimate of local IU in the spirit of RiskMetrics (Zangari 1996) is

$$\mathrm{RM}_{\mathcal{T}} = \sqrt{0.05(\Delta\pi_{\mathcal{T}-1})^2 + 0.95\overline{(\Delta\pi)^2}}, \tag{11}$$

where $\overline{(\Delta\pi)^2} = (1/(B-1))\sum_{t=\mathcal{T}-B}^{\mathcal{T}-2} (\Delta\pi_t)^2$ and $B = 24$ is the magnitude of the time window employed to determine IU at the actual end of the sample information. The RiskMetrics estimator in (11) might be seen as an ex-ante alternative to (estimated) (G)ARCH models (Engle 1982, Bollerslev 1986) that are widely applied for IU measurement (Engle 1982, Baillie et al. 1996). Note that while a 'local' implementation of GARCH type models in rolling windows of size $E = 96$ is most likely infeasible, full sample GARCH model estimates would leave the framework of ex-ante IU determination.

A third IU measure is the disparity of forecasts from the $J = 6$ alternative prediction models (1) to (6), i.e.

$$s_{\mathcal{T}}(h) = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}(\widehat{\pi}_{j,\mathcal{T}+h|\mathcal{T}} - \overline{\pi}_{\mathcal{T}+h|\mathcal{T}})^2}, \tag{12}$$

with $\overline{\pi}_{\mathcal{T}+h|\mathcal{T}} = (1/J)\sum_{j=1}^{J}\widehat{\pi}_{j,\mathcal{T}+h|\mathcal{T}}$. Notably, the model dispersion measure in (12) is similar to IU assessment by means of public disagreement about future inflation that can be approximated by means of survey data. According to dispersion approaches individual expectations are supposed to differ by larger amounts in periods of relatively high IU (Bomberger 1996).

Finally, as a realised measure of IU complementing the ex-ante quantities, the absolute forecast error from the benchmark AR model in (1) is considered, i.e.

$$a_{\mathcal{T}+h}(h) = |\widehat{\pi}_{\mathcal{T}+h|\mathcal{T}} - \pi_{\mathcal{T}+h}|. \tag{13}$$

It is worthwhile to point out that the quantities in (10) to (12) on the one hand and (13) on the other hand assess IU conditional on distinct information sets. The former may describe the (public's) perception of future inflation risks while the latter might (also) reveal a central banks ability to actually control such threats or to establish a narrow corridor of unanticipated inflation dynamics. It is reasonable to expect, however, that the public's experience as highlighted in ex-post measures like (13) might enter the subsequent ex-ante formation of expectations of both the level of inflation and IU. Moreover, IU statistics in (10) and (11) are (conditional) standard deviations that could be used to specify prediction intervals, while $s_{\mathcal{T}}(h)$ in (12) focuses on the robustness of forecasts determined from a variety of sets of sample information. Taking these considerations into account, it is sensible to allow for alternative IU measures when addressing its dependence on shifts in the monetary constitution.

4.2 Assessment of IU measures

In the previous Section, a variety of time series based IU measures has been proposed to quantify the Euro effect on IU from distinct perspectives and information sets. However, apart from the model based approaches listed in Section 4.1, IU is often extracted alternatively from financial instruments or survey data. We compare the series of IU statistics in (10) to (13) with so-called breakeven inflation volatilities for a subset of economies namely Canada, France, the UK and the US. Inflation expectations are determined from the spread between daily price quotes of nominal and inflation indexed government bond yields (Söderlind and Svensson 1997). The associated monthly breakeven volatility ($\mathrm{BV}_{\mathcal{T}}$) is estimated in a nonparametric fashion as realised standard deviations of breakeven inflation rates. Moreover, the time series based quantities are compared with the dispersion of survey expectations ($\mathrm{SD}_{\mathcal{T}}$) of inflation in the G7.

Notably, markets for inflation protected securities have been launched only recently or suffer from weak liquidity in the 1990s. Due to limited data availability or to ensure a homogeneous time period for measure comparison, model based IU estimates are compared with financial market or survey based quantities for the period 2001M4 ($\mathcal{T}_l$) to 2006M6 ($\mathcal{T}_u$).[4] To evaluate the coherence between the measures in Section 4.1 and the (market or survey) benchmark approaches, we compute rank correlation coefficients (Spearman 1904) between the former, $\xi_{\mathcal{T}} = \sigma_{\mathcal{T}}(h), \mathrm{RM}_{\mathcal{T}}, s_{\mathcal{T}}(h), a_{\mathcal{T}}(h)$, and the latter, $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$. The rank correlation between a model based IU estimate $\xi_{\mathcal{T}}$ and $\mathrm{BV}_{\mathcal{T}}$ (or analogously $\mathrm{SD}_{\mathcal{T}}$) is

$$\hat{\rho}(\xi_{\mathcal{T}}, \mathrm{BV}_{\mathcal{T}}) = 1 - \frac{6\sum_{k=1}^{K} d_k^2}{K\left(K^2-1\right)}, \quad K = \mathcal{T}_u - \mathcal{T}_l + 1, \tag{14}$$

where $d_k = r_k - r_k^*$, and r_k and r_k^* denote the kth order statistic of the $\xi_{\mathcal{T}}$ and $\mathrm{BV}_{\mathcal{T}}$ quotes over the time interval $[\mathcal{T}_l, \mathcal{T}_u]$, respectively.

4.3 IU and the Euro introduction

To determine the effect of the monetary unification on IU, we specify an analysis of variance (ANOVA) regression isolating a net effect of the Euro introduction,

[4]We thank Jan Roestel for providing us with $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ measures as analysed in Herwartz and Roestel (2010).

compared with a counterfactual situation where no common currency is in effect. For providing the ANOVA design in an explicit fashion we now introduce an extra index $i = 1, \ldots, 15$ that characterizes country specific quantities. Controlling for measurable triggers of global trends in IU, the monthly realised standard deviations $\boldsymbol{z}_{i,\mathcal{T}} = (\mathrm{RS}_{i,\mathcal{T}}(FX), \mathrm{RS}_{\mathcal{T}}(Oil), \mathrm{RS}_{\mathcal{T}}(Dow))'$ (see eq. (9)) are used for conditioning the IU measures. Four ANOVA regressions are considered, namely

$$\begin{aligned}\xi_{i,\mathcal{T}} &= \mu_{\mathcal{T}} + \nu_{i,\mathcal{T}} + \boldsymbol{z}'_{i,\mathcal{T}-1}\boldsymbol{\theta} + u_{i,\mathcal{T}}, \quad \mathcal{T} = \mathcal{T}_0 - h, \mathcal{T}_0 - h + 1, ..., T - h, \\ &\quad \text{with } \xi_{i,\mathcal{T}} \in \{\sigma_{i,\mathcal{T}}(h), \mathrm{RM}_{i,\mathcal{T}}, s_{i,\mathcal{T}}(h)\}, \qquad (15) \\ a_{i,\mathcal{T}}(h) &= \mu_{\mathcal{T}} + \nu_{i,\mathcal{T}} + \boldsymbol{z}'_{i,\mathcal{T}-1}\boldsymbol{\theta} + u_{i,\mathcal{T}}, \quad \mathcal{T} = \mathcal{T}_0, \mathcal{T}_0 + 1, ..., T. \qquad (16)\end{aligned}$$

Due to potential endogeneity (Hooker 1996) $\boldsymbol{z}_{i,\mathcal{T}}$ is lagged by one month for the conditioning of IU statistics. Deterministic time features of IU are specified as a low-order time polynomial augmented with a set of trigonometric terms (Gallant 1981). To be precise, $\mu_{\mathcal{T}}$ in (15) and (16) is formalised as

$$\mu_{\mathcal{T}} = \beta_0 + \sum_{c=1}^{C} \beta_c s^c + \sum_{d=1}^{D} \{\phi_d \cos(ds) + \varphi_d \sin(ds)\}, s = 2\pi(\mathcal{T} - \mathcal{T}_0 + h)/(T - \mathcal{T}_0). \quad (17)$$

Eubank and Speckman (1990) refer to the polynomial trigonometric (PT) model in (17) primarily as an efficient means of detrending, but also point out its applicability as a filtering method for nuisance effects within the blocks of an ANOVA design. Following their recommendations we set $C = 2$ and determine the trigonometric order D by means of a goodness of fit criterion, i.e.

$$\widehat{D} = \min_{D} \ \mathrm{CV}(D) = \frac{(T - \mathcal{T}_0 + 1)\mathrm{RSS}(D)}{(T - \mathcal{T}_0 - 2D - 2)^2}, \quad (18)$$

with RSS(D) denoting the residual sum of squares from (15) or (16) implied by a particular choice of D from $1 \leq D \leq D_{max}$, $D_{max} = 8$. Notably, the maximum order implies that the highest admitted frequency is characterized by a period of ≈2.25 years which might be seen as a conservative lower threshold to capture business cycle dynamics. As an alternative is turned out that fixed IU time effects offer a rather similar perspective at the 'global trend' in IU. Since the PT regression in (17) is by far more parsimonious we do not consider unrestricted time effects any further.

Constitutional determinants of IU are addressed in (15) and (16) by means of a function of dummy variables,

$$\nu_{i,\mathcal{T}} = \gamma_1 \mathrm{D}_i^{(\overline{\mathrm{EMU}})} + \gamma_2 \mathrm{D}_i^{(O6)} + \gamma_3 \mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})} + \gamma_4 \mathrm{DE}_{i,\mathcal{T}}^{(O6)}. \quad (19)$$

On the one hand dummy variables are employed to distinguish economies that are not subjected to monetary unification. Two control groups are set out, EU members outside the monetary union ($\overline{\mathrm{EMU}}$) and a set of OECD economies ($O6$) (see Table 1). The association of economies to these groups is controlled by $\mathrm{D}_i^{(\overline{\mathrm{EMU}})}$ and $\mathrm{D}_i^{(O6)}$, respectively. On the other hand dummy variables separate the time periods around the advent of the common currency (AE) and are specified to interact with the control groups. Interaction variables $\mathrm{DE}_{i,\mathcal{T}}^{(\bullet)}$, $\bullet = \overline{\mathrm{EMU}}, O6$, are defined as

$$\mathrm{DE}_{i,\mathcal{T}}^{(\bullet)} = \begin{cases} 1 & \text{if } i \text{ belongs to } \bullet \text{ and } \mathcal{T} \geq AE \\ 0 & \text{otherwise.} \end{cases}$$

5 Empirical results

The discussion of empirical results in this section proceeds in basically 3 steps. In the first place we try to identify a most promising (or at least 'robust') benchmark prediction scheme from the set of alternative forecasting models introduced in Section 2. As already pointed out the simple autoregressive model turns out to offer reasonable forecasting accuracy over the cross section of considered economies. Then, AR model based and further IU measures are compared with IU statistics derived from financial and survey data to describe both the difficulty inherent in the issue of measuring IU and the reliability of alternative measurement approaches. Then, with distinct quantifications of IU at hand we discuss the outcomes of the ANOVA regression given in Section 4 to quantify the impact of the Euro's advent on IU. If not stated otherwise the significance of inferential results is determined according to the 5% nominal level.

5.1 Forecasting performance

The predictions from the econometric specifications introduced in (2) to (6) and a combined forecast (AV) are evaluated against the autoregressive benchmark (1). Table 2 summarises the results of the forecast comparisons, where entries are the numbers of economies for which the AR model is outperformed in terms of smaller RMSE statistics obtained by particular rival prediction schemes. Each tuple $(a; b; c)$ collects the number of outpredictions, unconditionally (a), and conditional on the significance of the GW statistic at the 10% (b) and 5% level (c).

	eq.	$h = 1$	$h = 3$	$h = 6$	$h = 12$
		$E = 84$			
CO	(2)	(6;1;1)	(7;4;2)	(6;3;1)	(6;3;3)
PC	(3)	(7;2;1)	(5;4;3)	(5;2;2)	(5;2;1)
MPC	(4)	(7;0;0)	(8;7;3)	(7;4;4)	(6;4;4)
OMPC	(5)	(5;0;0)	(4;2;2)	(4;4;3)	(3;3;2)
IPC	(6)	(3;0;0)	(5;3;3)	(3;2;1)	(2;2;2)
AV		(7;3;1)	(7;1;0)	(8;4;2)	(6;2;1)
		$E = 96$			
CO	(2)	(5;1;1)	(6;5;2)	(5;4;4)	(6;4;4)
PC	(3)	(4;1;1)	(4;3;2)	(4;2;2)	(5;3;2)
MPC	(4)	(5;0;0)	(6;5;4)	(5;5;3)	(5;5;4)
OMPC	(5)	(6;0;0)	(4;2;1)	(4;4;4)	(5;5;4)
IPC	(6)	(5;0;0)	(2;0;0)	(5;3;3)	(3;2;1)
AV		(7;1;1)	(7;2;2)	(7;1;0)	(5;3;1)
		$E = 108$			
CO	(2)	(6;1;1)	(5;3;1)	(5;5;3)	(4;2;1)
PC	(3)	(5;2;2)	(3;1;1)	(4;2;0)	(5;2;1)
MPC	(4)	(7;1;0)	(6;5;2)	(7;5;4)	(4;2;2)
OMPC	(5)	(5;0;0)	(4;2;1)	(5;4;4)	(4;3;3)
IPC	(6)	(5;0;0)	(2;0;0)	(5;3;3)	(4;3;3)
AV		(6;1;1)	(5;2;2)	(5;2;2)	(8;2;2)

Table 2: Forecast comparison results. Entries show the number of cases where RMSE(•)/RMSE(AR)<1 and '•' indicates a particular rival model. Count statistics in the tuple $(a; b; c)$ are either unconditional (a) or conditional on significance of the GW statistic at the 10% (b) and 5% level (c). The number of economies is 15. For model abbreviations see also Section 2.

Model comparison results are tabulated for three alternative selections of the size of estimation windows $E = 84, 96$ and $E = 108$ to illustrate that the relative performance of the AR model is robust in this dimension of the forecasting design. Diagnostic results both unconditional and conditional on the significance of the GW statistic clearly indicate the benchmark property of the AR model, which is not uniformly dominated by any particular competing model, including the forecast combination approach. For instance, for the set of 15 cross section members (14 economies and the Euro area) particular ADL specifications offer RMSE statistics smaller than the AR based counterpart for at most 8 entities. Significant outperformance of the AR model at short horizons ($h = 1$) is generally exceptional. Regarding the forecast horizon h and relative to the AR benchmark, the PC specification obtains most favourable results for low to medium horizons, whereas the Cogley model, the MPC and the OMPC specification are most successful relative to the AR benchmark at medium to large horizons h. These results are intuitive noting that the former models incorporate some long run inflation indicators, namely the inflation gap or monetary aggregates (Canova 2007).

To summarise, performance comparisons for alternative econometric models (including several ADLs, an autoregression and forecast combinations) confirm a finding of Stock and Watson (2007) who note that the pure AR model has become increasingly successful to predict inflation over the last three decades. For this reason, the AR model is selected as the basis for computing the IU measures $\sigma_{\mathcal{T}}(h)$ and $a_{\mathcal{T}}(h)$ defined in (10) and (13), respectively.

The results collected in Table 2 do, however, not indicate that the ADL and forecast combination methods fail to provide useful ex-ante information since conditional on single cross section members particular model specifications offer more accurate forecasting precision in comparison with the AR benchmark. To decide if the prediction schemes yield unbiased ex-ante inflation estimates, we specify (cross section and model specific) diagnostic regressions (Mincer and Zarnowitz 1969),

$$\pi_{t+h} - \pi_t = \delta_1 + \delta_2 \left(\widehat{\pi}_{t+h|t} - \pi_t\right) + \epsilon_{t+h}, \quad t = \mathcal{T}_0 - h, \mathcal{T}_0 - h + 1, ..., T - h, \qquad (20)$$

and test the composite hypothesis $H_0 : \delta_1 = 0, \delta_2 = 1$. In determining the relevant $F-$statistic we choose a heterskedasticity robust covariance estimator also accounting for serial forecast error correlation of order $h-1$ (Newey-West 1987). Not rejecting H_0 is seen as evidence for a well specified forecasting model. Diagnostic results over distinct prediction schemes and forecast horizons are documented in Table 3. In the majority of cases, no misspecification is indicated, which holds even at higher horizons h for a number of prediction models. Notably, for 7 to 9 (out of 15) cross sectional entities, biased one year ahead predictions ($h = 12$) are detected that are determined by means of the AR benchmark, the PC, the Cogley model and the forecast combination approach. Again, model specifications exploiting the informational content of monetary aggregates (MPC, OMPC) perform most accurately in providing unbiased long term predictions. In summary, diagnosing unbiasedness for rival prediction schemes it appears reasonable to consider the dispersion statistic $s_{\mathcal{T}}(h)$ in (12) to provide a valuable measure of IU or (at least) of its underlying time variation.

h	1	3	6	12	h	1	3	6	12
AR	15	15	9	7	OMPC	15	15	15	15
PC	15	15	12	8	IPC	15	15	13	12
CO	15	15	10	7	AV	15	14	9	6
MPC	15	15	15	15					

Table 3: Mincer regression results. Entries are the number of economies (out of 15) for which the null hypothesis of unbiased forecasts cannot be rejected at the 5% level. For model abbreviations see also Section 2.

5.2 Relations between IU measures

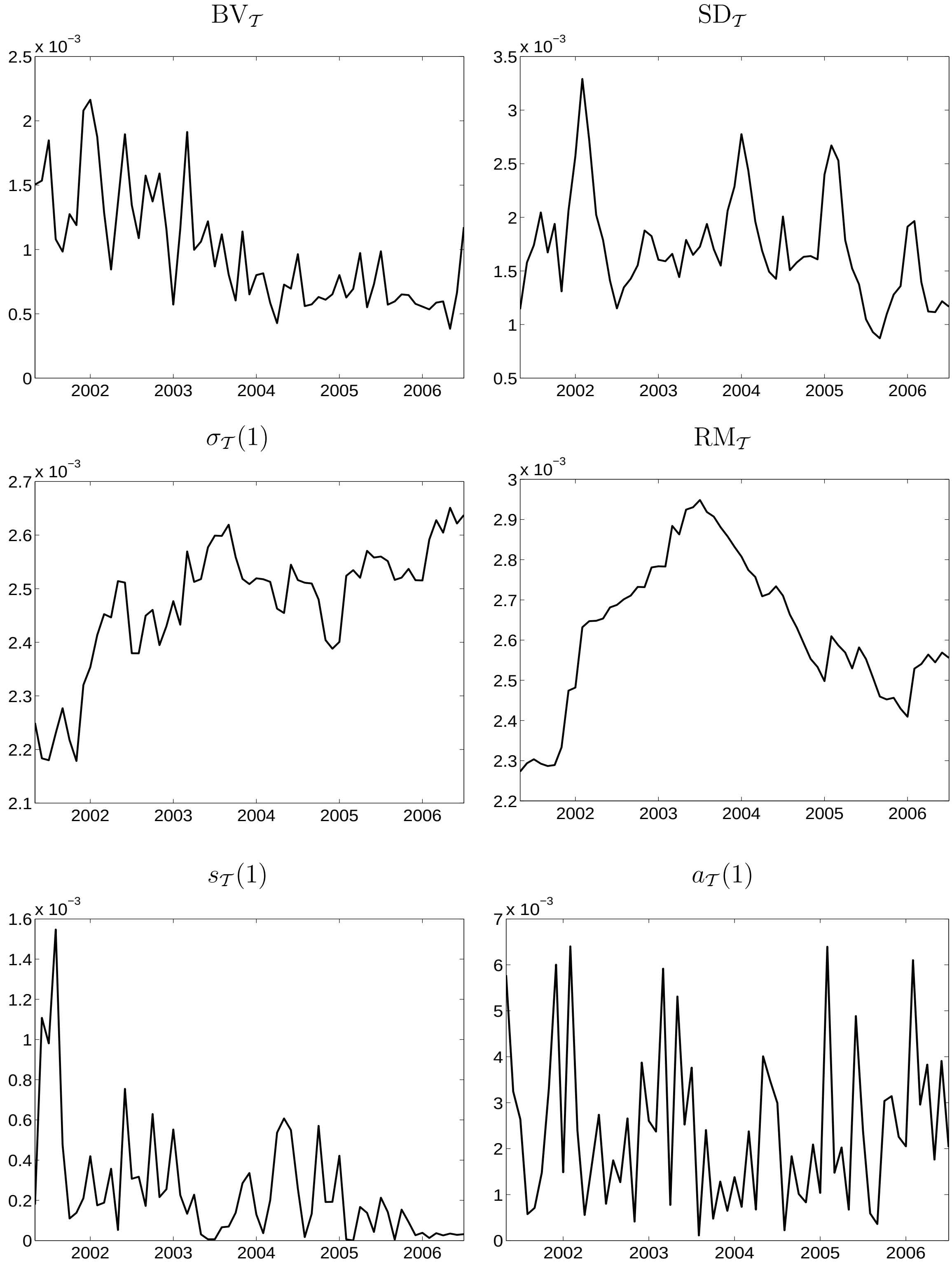
In this section, the coherence between IU estimates, $\xi_{\mathcal{T}} = \sigma_{\mathcal{T}}(h), \mathrm{RM}_{\mathcal{T}}, s_{\mathcal{T}}(h), a_{\mathcal{T}}(h)$, and the $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ benchmark, respectively, is characterized in terms of rank correlation estimates for the subperiod 2001M4 to 2006M6 comprising $K = 63$ time instances. To emphasise the difficulty inherent in IU measurement the following display, first, lists estimated rank correlations of $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ for Canada (CA), France (FR), the UK and the US

i	CA	FR	UK	US
$\hat{\rho}(\mathrm{BV}_{\mathcal{T}}, \mathrm{SD}_{\mathcal{T}})$	**-0.55**	0.21	**0.62**	-0.01

To facilitate the interpretation of correlation estimates bold entries indicate statistics that exceed an informal critical threshold of $2/\sqrt{63} = .252$ in absolute value. Obviously, the empirical relation between established measures of IU is rather instable and varies from being significantly negative to positive while for two economies $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ fail to exhibit a significant comovement. To illustrate country specific IU dynamics Figure 1 shows the four model based IU processes for $h = 1$ along with $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ for the case of France. First of all it is to mention that $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ do only tentatively agree according to a (likely insignificant) estimated rank correlation $\hat{\rho}(\mathrm{SD}_{\mathcal{T}}, \mathrm{BV}_{\mathcal{T}}) = 0.21$. The downward trend visible in $\mathrm{BV}_{\mathcal{T}}$ and also, to a lesser extent, in $\mathrm{SD}_{\mathcal{T}}$ is in contrast to the displayed recent uprise featuring $\sigma_{\mathcal{T}}(h)$ and $\mathrm{RM}_{\mathcal{T}}$, and is weakly paralleled only by the $s_{\mathcal{T}}(h)$ process. These contradictory observations further accentuate the sublime difficulties inherent in the measurement of IU. If $\xi_{\mathcal{T}}$ measures are qualified according to their coherence with financial instruments or survey data, $s_{\mathcal{T}}(h)$ appears most favorable according to eyeball inspection of Figure 1. Distinct trajectories of model based estimates on the one hand and $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$ on the other hand are characteristic for almost all economies considered. Respective rank correlation estimates are collected in Table 4. For $h = 1$, $\sigma_{\mathcal{T}}(h)$ shows marked negative rank correlations with the benchmark approaches. All $\mathrm{BV}_{\mathcal{T}}$ and 5 out of seven $\mathrm{SD}_{\mathcal{T}}$ processes are characterised by negative and mostly significant rank correlations with their $\sigma_{\mathcal{T}}(h)$, $h = 1, 3$, counterparts. The disagreement between model based and benchmark quantities, however, vanishes at higher horizons, which might reflect that the latter are market and survey based quantifications of IU at longer horizons of at least one year.

For several economies $\mathrm{RM}_{\mathcal{T}}$ exhibits positive and significant rank correlations with $\mathrm{SD}_{\mathcal{T}}$ at short horizons which speaks in favour of the $\mathrm{RM}_{\mathcal{T}}$ measure in comparison with $\sigma_{\mathcal{T}}(h), h = 1, 3$. The most reliable approximation of the benchmark IU processes is, however, the forecast dispersion statistic $s_{\mathcal{T}}(h)$, which is characterised by the highest fraction of significantly positive rank correlations with both $\mathrm{BV}_{\mathcal{T}}$ and $\mathrm{SD}_{\mathcal{T}}$. The ex-post estimates $a_{\mathcal{T}}(h)$ also show mostly positive rank correlations, but, owing to excess variation, these are generally of smaller magnitude than those reported for the other model based statistics.

In summary, the distinct model based measures provide more reasonable approximations of external IU statistics at higher horizons, $h = 6, 12$. Among the model based measures, forecast dispersions $s_{\mathcal{T}}(h)$ exhibit the strongest correspondence with market or survey based IU processes according to the sign, magnitude and significance of rank correlation estimates. Hence, this IU statistic might be regarded to be the most reliable choice. However, external measures determined for a particular cross section member do not necessarily agree in their assessment of the state of future inflation. It appears that IU measurement is basically a matter of definition, with outcomes depending on the choice of the methodology. Accordingly, any analysis of the determinants of IU is conditional on its quantification at hand. Put differently, to identify the constitutional impact of monetary unification on IU it pays to consider a variety of uncertainty measures.


$\mathrm{BV}_{\mathcal{T}}$
$\mathrm{SD}_{\mathcal{T}}$
$\sigma_{\mathcal{T}}(1)$
$\mathrm{RM}_{\mathcal{T}}$
$s_{\mathcal{T}}(1)$
$a_{\mathcal{T}}(1)$
x 10^{-3}
2002
2003
2004
2005
2006

	$h=1$				$h=3$			$h=6$			$h=12$		
	$\sigma_{\mathcal{T}}(h)$	$\mathrm{RM}_{\mathcal{T}}$	$s_{\mathcal{T}}(h)$	$a_{\mathcal{T}}(h)$	$\sigma_{\mathcal{T}}(h)$	$s_{\mathcal{T}}(h)$	$a_{\mathcal{T}}(h)$	$\sigma_{\mathcal{T}}(h)$	$s_{\mathcal{T}}(h)$	$a_{\mathcal{T}}(h)$	$\sigma_{\mathcal{T}}(h)$	$s_{\mathcal{T}}(h)$	$a_{\mathcal{T}}(h)$
	Correlations with $\mathrm{BV}_{\mathcal{T}}$												
Canada	**-0.64**	-0.20	**0.36**	**0.31**	**-0.63**	0.11	**0.38**	0.22	**0.36**	0.21	0.07	**0.61**	0.17
France	**-0.62**	0.11	**0.43**	0.23	**-0.56**	-0.02	0.19	**-0.33**	0.24	-0.05	0.16	0.23	**0.51**
UK	**-0.48**	**0.64**	**-0.26**	0.20	**0.65**	0.18	**0.27**	**0.67**	**0.54**	0.09	**0.68**	**0.60**	0.22
US	**-0.83**	**-0.83**	**0.33**	0.07	**-0.83**	**0.31**	-0.06	**-0.83**	0.16	-0.17	**-0.79**	-0.08	0.00
	Correlations with $\mathrm{SD}_{\mathcal{T}}$												
Canada	**-0.77**	**-0.45**	**0.29**	**0.32**	**-0.75**	0.10	**0.36**	0.13	**0.33**	-0.01	**0.35**	**0.65**	0.12
France	-0.12	**0.79**	0.07	-0.01	**0.37**	**0.29**	0.16	**0.52**	**0.44**	0.18	**0.80**	**0.53**	0.02
Germany	**-0.78**	0.06	**0.53**	0.02	**-0.63**	-0.12	0.13	**-0.27**	0.23	-0.00	**0.33**	**0.40**	**0.44**
Italy	**0.80**	**0.70**	**0.35**	0.03	**0.77**	0.15	0.17	**0.78**	0.22	**0.14**	**0.80**	**0.25**	**0.62**
Japan	**0.77**	**0.32**	0.20	-0.10	**0.78**	**0.25**	-0.23	**0.78**	**0.38**	-0.23	**0.67**	**0.28**	**-0.25**
UK	**-0.40**	**0.55**	**-0.32**	**0.27**	**0.55**	0.24	0.17	**0.63**	**0.35**	0.06	**0.64**	**0.52**	0.18
US	0.01	0.03	0.05	**-0.24**	0.03	0.01	0.17	0.05	0.21	0.13	0.01	**0.23**	0.04
	ANOVA estimates ($\times 10^{-3}$)												
$\mathrm{D}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$	**2.28**	**1.64**	**0.34**	**0.60**	**3.56**	**0.62**	**1.37**	**6.06**	0.66	**8.59**	**4.19**	**1.83**	**2.56**
	(12.03)	(8.25)	(6.35)	(2.73)	(9.19)	(3.27)	(2.47)	(5.92)	(0.38)	(4.10)	(9.28)	(3.92)	(2.89)
$\mathrm{D}_{i,\mathcal{T}}^{(O6)}$	**0.96**	**0.86**	**0.10**	**0.70**	**1.68**	0.18	**1.22**	**3.15**	**−4.28**	1.17	**1.88**	**1.01**	**1.74**
	(6.23)	(5.31)	(2.18)	(3.94)	(5.35)	(1.17)	(2.71)	(3.78)	(−2.61)	(0.69)	(5.14)	(2.65)	(2.42)
$\mathrm{D}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}},AE)}$	**−2.00**	**−1.49**	**−0.50**	−0.46	**−3.18**	**−0.66**	−1.08	**−4.25**	−0.52	**−5.71**	**−4.08**	**−1.34**	**−2.50**
	(−7.91)	(−5.60)	(−6.97)	(−1.56)	(−6.10)	(−2.58)	(−1.46)	(−3.03)	(−0.26)	(−2.03)	(−6.44)	(−2.03)	(−2.11)
$\mathrm{D}_{i,\mathcal{T}}^{(O6,AE)}$	**0.45**	**0.59**	0.02	0.44	**1.31**	0.33	**1.21**	−0.41	**4.78**	1.07	**1.15**	−0.15	0.45
	(2.23)	(2.77)	(0.33)	(1.85)	(3.14)	(1.61)	(2.01)	(−0.36)	(2.12)	(0.47)	(2.26)	(−0.27)	(0.47)
$\mathrm{RS}_{i,\mathcal{T}}^{FX^{\bullet}}$	**−6.10**	−1.35	**−2.14**	**10.7**	−7.84	−1.23	**22.5**	**−40.6**	−24.1	**−14.83**	−1.66	5.32	−10.38
	(−2.08)	(−0.44)	(−2.30)	(2.46)	(−1.30)	(−0.39)	(2.21)	(−2.50)	(−0.69)	(−3.95)	(−0.23)	(0.66)	(−0.69)
$\mathrm{RS}_{\mathcal{T}}^{Oil}$	1.30	1.12	0.23	**9.01**	1.80	0.84	5.33	2.91	10.57	13.74	−0.65	**5.78**	−6.74
	(1.34)	(1.10)	(0.66)	(4.81)	(0.97)	(0.89)	(1.35)	(0.65)	(1.05)	(1.18)	(−0.29)	(2.48)	(−1.26)
$\mathrm{RS}_{\mathcal{T}}^{Dow}$	−0.17	−0.55	0.06	−3.28	−0.23	1.25	−0.60	0.23	11.06	4.70	−1.56	−1.03	−7.78
	(−0.09)	(−0.27)	(0.08)	(−0.91)	(−0.06)	(0.57)	(−0.08)	(0.02)	(0.42)	(0.21)	(−0.31)	(−0.19)	(−0.76)
	ANOVA estimates with alternative AE date ($\times 10^{-3}$)												
$\mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$	**−1.90**	**−1.92**	**−0.50**	−0.47	**−2.90**	**−0.73**	**−1.59**	−0.03	−0.06	**−9.39**	**−3.75**	**−1.57**	**−3.10**
	(−7.09)	(−7.03)	(−6.58)	(−1.53)	(−5.26)	(−2.74)	(−2.05)	(−0.02)	(−0.02)	(−3.21)	(−5.74)	(−2.34)	(−2.51)
$\mathrm{DE}_{i,\mathcal{T}}^{(O6)}$	0.38	**0.52**	0.08	0.43	**1.07**	0.37	0.98	1.41	**5.16**	−0.57	**1.05**	0.27	0.74
	(1.75)	(2.36)	(1.36)	(1.70)	(2.40)	(1.69)	(1.54)	(1.19)	(2.29)	(−0.24)	(2.00)	(0.50)	(0.74)

Table 4: Correlation between IU measures and ANOVA results. The upper panel documents results for the correlation of the model based measures with realised standard deviations of breakeven inflation ($\mathrm{BV}_{\mathcal{T}}$) and the second block contains correlation measures with survey based IU processes ($\mathrm{SD}_{\mathcal{T}}$). The $\mathrm{BV}_{\mathcal{T}}$ measure is based on the spread of 10 year nominal and inflation indexed government bond yields, $\mathrm{SD}_{\mathcal{T}}$ is obtained from the database of *Consensus Economics*. Bold entries indicate rank correlations which are significant at the 5% level with critical values $\pm 2/\sqrt{K} = \pm 0.252$, where $K = T_u - T_l + 1 = 63$. The lower part of the table reports ANOVA regression estimates with t-ratios in parentheses. The t statistics are based on robust covariance matrix estimates (Newey and West 1987). Significant estimates are in bold face. The last two rows show coefficient estimates of interaction variables $\mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$ and $\mathrm{DE}_{i,\mathcal{T}}^{(O6)}$ for an alternative AE date 1997M1.

5.3 The Euro impact on IU

Before we discuss time properties and deterministic characteristics of IU first consider the impact of its potential stochastic triggers. The lower part of Table 4 documents coefficient estimates of the ANOVA regressions (15) or (16). The estimated influence of FX volatility differs in sign and significance over distinct IU measures and horizons. Apparently the relation between these uncertainty measures is nontrivial and likely not captured within our model framework. The impact of oil price volatility on IU is mostly positive, although coefficient estimates are in many cases not significant. Finally, the effect of the US stock market volatility on global IU is ambiguous, which is in line with Kontonikas, Montagnoli and Spagnolo (2005).

The ANOVA regressions in (15) and (16) obtain estimates of a 'global trend' in IU, $\hat{\mu}_{\mathcal{T}}$. For space considerations we do not provide explicit parameter estimates for the model in (17) that are, however, available from the authors upon request. Figure 1 illustrates the time paths of trend estimates for the distinct measures at anticipation horizons $h = 1$ and $h = 6$, which are representative for other horizons since the graphs for $h = 3$ and $h = 12$ are similar to $h = 1$ and $h = 6$, respectively. The figures reflect a relatively similar path of the distinct measures except for the dispersion statistic $s_{\mathcal{T}}(h)$ at $h = 1$. For all measures, IU is found to decrease in the 1990s and, since then, to stabilize or even increase during most recent time instances. An impression suggested by all measures is that IU has been largely reduced prior to the year 2000. Notably this large reduction of overall IU might reflect the success of the inflation targeting strategy that was first adopted in New Zealand (1990) and, since then, has become a world wide important and often successful strategy of monetary policy. According to the $\sigma_{\mathcal{T}}(h)$ process, IU reaches its minimum level in 2001, whereas for other measures minimum 'average' IU is diagnosed somewhat earlier. Obviously the introduction of the common currency almost coincides with an economic state featuring smallest overall IU. Apparently, any analysis of the institutional impact on IU should account for such local characteristics, as otherwise an analyst might draw spurious conclusions with regard to the Euro effect.

Parameter estimates for the functional in (19) are also displayed in Table 4. First of all, note that the coefficients of $\mathrm{D}_{\mathcal{T}}^{(\overline{\mathrm{EMU}})}$, $\mathrm{D}_{\mathcal{T}}^{(O6)}$, $\mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$ and $\mathrm{DE}_{i,\mathcal{T}}^{(O6)}$ are in almost all cases significant. These estimates indicate that both control groups are characterised by unconditionally higher IU in comparison with EMU members. In any event, IU is on average less abundant within the EMU. After the advent of the Euro, the $\overline{\mathrm{EMU}}$ economies (Denmark, Sweden and the UK) have been experiencing a convergence process in IU as compared to the EMU, whereas $O6$ economies have faced additional uncertainty according to our estimates. This pattern regarding coefficient signs and significance holds over almost all anticipation horizons and IU measures. A few parameter estimates differing from this overall pattern are mostly insignificant at the 5% level.

To check for robustness of these results with respect to the choice of the time instance of the advent of the Euro, the ANOVA regression is also implemented for an alternative break date AE=1997M1. The resulting alternative coefficient estimates for $\mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$ and $\mathrm{DE}_{i,\mathcal{T}}^{(O6)}$ are given in the last rows of Table 4. The sign, magnitude and significance of these coefficient estimates is in almost all cases numerically very close (and qualitatively identical) to the results documented for the official Euro introduction in AE =1999M1[5].

[5]In addition, the results of the ANOVA analysis in (15) and (16), carried out with quarterly data as a further robustness check, are in most cases qualitatively identical to the outcomes for the monthly frequency in the case of IU estimates $\sigma_{\mathcal{T}}(h)$, $\mathrm{RM}_{\mathcal{T}}$ and $a_{\mathcal{T}}(h)$. For the $s_{\mathcal{T}}(h)$ measure, a Euro effect adverse to the one described for monthly data is obtained for higher horizons of anticipation. However, due to the reduced number of observations available at the quarterly frequency, the corresponding coefficients for $s_{\mathcal{T}}(h)$ are in most cases not significant at the 5% level. Detailed

These results can be interpreted to uncover a stabilising influence of the introduction of a common monetary policy among the EMU economies. This is particularly suggested by significant uprise of IU in the OECD control group after 1997 or 1999. The convergence of IU towards the overall lower EMU level after 1999 in Denmark, Sweden and the UK seems at first sight to confound this interpretation. However, the convergence appears to be incomplete according to the parameter estimates attached to $\mathrm{DE}_{i,\mathcal{T}}^{(\overline{\mathrm{EMU}})}$, which are mostly smaller in absolute terms than those of $\mathrm{D}_i^{(\overline{\mathrm{EMU}})}$ over alternative IU measures. That is, although convergence seems to occur after the advent of the Euro, the $\overline{\mathrm{EMU}}$ economies are still characterized, on average, by a higher level of IU as it is the case for EMU members. Moreover, these economies might contribute less clear a counterfactual signal as it is the case for $O6$. Since Denmark, Sweden and the UK are important trade partners of the EMU, they are likely to be subjected to spillover effects from the low IU prevalent in the EMU.

results for IU prediction are available from the authors upon request.

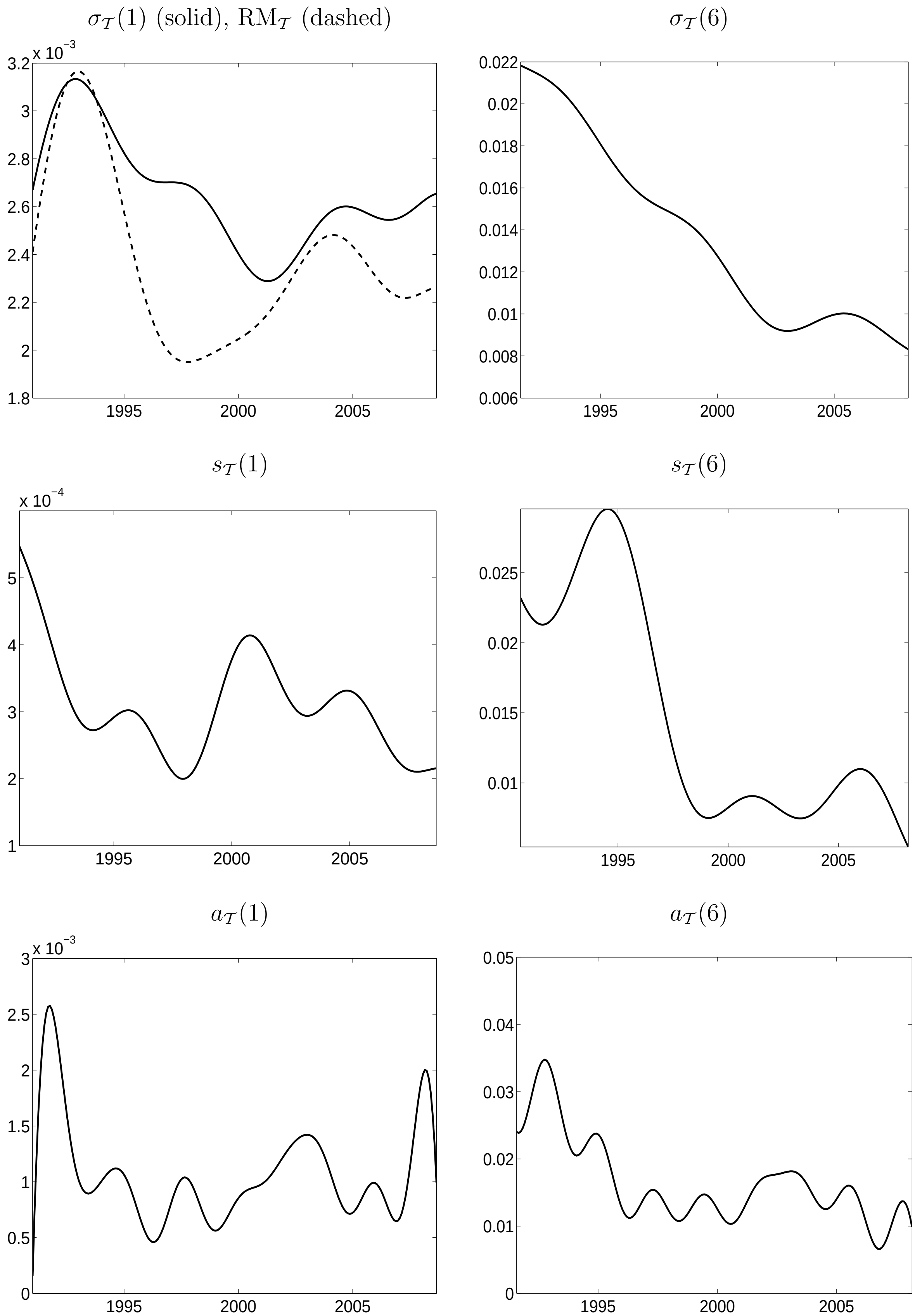


Figure 1: Trend estimates $\hat{\mu}_{\mathcal{T}}$ for $h = 1$ (left hand side panels) and $h = 6$ (right hand side) and distinguished model based IU processes.

6 Conclusions

In this paper, we focus on the question if the formation of the EMU as a major shift in the framework of European monetary policy had a measurable influence on IU. We address the subtle issue of IU measurement by constructing a set of alternative estimators, which take complementary views on IU from distinct modelling perspectives. Based on these IU measures, we assess the impact of the monetary unification on IU by conducting an ANOVA analysis for a large international data set. A number of economies not involved in the EMU serve as control groups in order to gauge the Euro effect against the counterfactual situation of keeping monetary independence. The empirical evidence underpins that IU has not only been unconditionally higher outside the EMU members, but moreover the monetary union has provided effective insulation against rising 'global' IU. It is noteworthy that this core conclusion is invariant with respect to the choice of different IU estimation methods including ex-ante and ex-post quantifications on the one hand and forecast error standard deviations and forecast dispersions on the other hand.

In the current times of both a rampant worldwide economic crisis and freehanded fiscal stimulation programmes, the concept of inflation uncertainty (IU) might be more tangible and acute as it has been over the last decades of *great moderation* and successful inflation targeting policies. A main source of such uncertainty is the indeterminacy about whether a low level of inflation is due to low demand during the recession or rather a rising inflation stemming from the monetary and fiscal expansion will ultimately result from the current developments. To these structural threats it is noteworthy that according to evidence provided in this work a recently positive trend of global IU appears to add to the current overall inflation risk. Noting that long term investments could be discouraged in states of excess IU its stabilization or reduction becomes a first order policy issue. Given the diagnosed development of IU in the EMU on the one hand and other OECD economies on the other hand the former might currently offer a more attractive climate for longer term investment.

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