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Elevated survey uncertainty after the Great Recession: a non-linear approach

Natalia Levenko[*]

Abstract

The European Survey of Professional Forecasters (SPF) is a dataset that is widely used to derive measures of forecast uncertainty. Participants in the SPF provide not only point estimates but also density forecasts for key macroeconomic variables. The mean individual variance, defined as the average of the variances of individual forecasts, shifted up during the Great Recession and has remained elevated since the crisis. This shift is not typical since proxies for uncertainty are usually counter-cyclical. The paper seeks to explain this puzzling lack of counter-cyclicality by applying a smooth transition analysis on data from the European SPF. The analysis indicates that the mean individual variance has a non-linear relationship with the share of non-rounded responses in the survey and consequently the upward shift in individual variance is likely to be associated with changes in the modelling preferences of forecasters. The results remain robust after potential endogeneity has been accounted for.

JEL Codes: C25, C32, C83, D81, E32, E37

Keywords: survey uncertainty; forecast disagreement; density forecasts; surveys of professional forecasters; Great Recession; smooth transition; instrumental variables

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Non-technical summary

Uncertainty is an important concept for macroeconomic analysis, since the real economy may be affected negatively when households and firms are less certain than usual about what will be happing with their incomes and with the economic environment as a whole. Uncertainty among economic agents may lead to economic growth being suppressed, financial markets distorted, and recovery prolonged. This makes uncertainty particularly important for analysis of the Great Recession and the post-recession recovery.

The European Survey of Professional Forecasters (SPF) is a dataset that is commonly used to derive measures of forecast uncertainty. Participants in the SPF provide point forecasts of key economic indicators like the inflation rate, real output growth and the unemployment rate, together with probability distributions of the same variables. Individual forecasts can then be combined and aggregate measures of uncertainty can be computed from the survey data.

A widely-used measure of survey uncertainty is mean individual variance, which is defined as the average of the variances of the individual forecasts. The key exercise in this paper is to analyse and explain the dynamics of this measure of uncertainty. The mean individual variance shifted upwards during the Great Recession and has remained elevated since the crisis. This permanent upward shift is hard to explain since measures of uncertainty are usually counter-cyclical. This means that economic agents are on average more uncertain about the future in bad times and become more certain about their perspectives in good times.

The paper contributes to the literature by showing that although mean individual variance is a theoretically attractive measure of uncertainty, it absorbs information that is irrelevant for quantifying macroeconomic uncertainty. The analysis shows that the mean individual variance is directly associated with changes in the modelling preferences of forecasters, both in the short run and in the long run. The results imply that there is no unexplained upward shift in the survey uncertainty of the sort that a quick look at the individual variance would suggest.

Contents

1. Introduction

Uncertainty is being incorporated extensively into economic analysis and is particularly important for analysis of the Great Recession and the prolonged post-recession recovery. A large body of literature has documented the adverse effects that macroeconomic uncertainty may have on the real economy. Uncertainty may affect the economy through numerous channels, such as precautionary saving by households (Levenko, 2020) or firms taking a wait-and-see attitude to investment (Bloom et al., 2007; Stokey, 2016). In a more general perspective, uncertainty may be associated with a contraction in economic activity, depressing economic growth, creating financial distortions and slowing post-crisis recovery (see among others Cesa-Bianchi et al., 2018; Bloom et al., 2018; Basu & Bundick, 2017; Baker et al., 2016; Gilchrist et al., 2014).

Uncertainty is a wide and subtle concept that can cover quite different developments across different markets. A widely-used source of data on the uncertainty of the macroeconomic forecasts in the euro area is the European Survey of Professional Forecasters (SPF) conducted by the ECB. Participants in the SPF provide point forecasts of key economic indicators like the inflation rate, real output growth and the unemployment rate, accompanied by probability distributions of the forecast variables. The micro-level data of the individual forecasts can then be combined and aggregate measures of uncertainty can be computed from the survey data.

The main focus of this paper is on the mean individual variance of forecasts, which is defined as the average of the variances of the individual density forecasts.[1] An alternative measure of uncertainty, which can be calculated using the same dataset, is the cross-sectional variance of point estimates, often labelled as forecast disagreement or just disagreement. Both measures of uncertainty peaked during the Great Recession, but the while mean individual variance has remained elevated since the crisis, the disagreement returned to its pre-crisis level right after the recession was over. The paper examines the upward shift in the level of the mean individual variance, which is hard to attribute solely to the crisis given that there was no such shift in the forecast disagreement.

Diebold et al. (1999) point out that it is crucial to evaluate the quality of forecasts. The same argument can be found in Rossi (2014, p. 20): “Since density forecasts play such an important role in providing information on the uncertainty around point forecasts, it is crucial to evaluate whether they are well specified. If density forecasts are not correctly specified, then the measure of uncertainty that they provide is incorrect”. This paper examines the forecast uncertainty measured as the mean individual variance and uses this to evaluate the quality of this proxy of uncertainty.

The mean individual variance of density forecasts is often seen as a key measure of uncertainty that gives more informative estimates of uncertainty than the cross-sectional variance of point estimates does, as it is directly related to the concept of probability (Zarnowitz & Lambros, 1987; Giordani & Söderlind, 2003; Wallis, 2008; Abel et al., 2016). Equally

[1] The terms mean individual variance and individual variance are used interchangeably in this paper. In the literature, the mean individual variance is also labelled as the average individual variance, the average individual uncertainty, and the average perceived uncertainty. Survey uncertainty and forecast uncertainty are also treated as synonyms in this paper.

though, disagreement is often found to underestimate uncertainty (Zarnowitz & Lambros, 1987), to be an incomplete approximation of overall uncertainty (Glas & Hartmann, 2016), or just to be a poor proxy for uncertainty (Abel et al., 2016; Lahiri & Liu, 2006). The main argument for labelling disagreement as a weak measure of uncertainty is that there is only a weak relationship between disagreement and mean individual variance (see the references above).

Measures of uncertainty are typically countercyclical, meaning that economic agents are on average more uncertain about the future in bad times than they are in good times. This is documented in many empirical studies; see Abel et al. (2016), Binder (2017) or Cesa-Bianchi et al. (2018) among several others. Forecast disagreement peaked during the Great Recession and then subsequently returned to its pre-crisis level, demonstrating behaviour typical of a proxy for uncertainty, whereas the mean individual variance of the SPF density forecasts has shifted upwards since 2008 and never come back. To the best of my knowledge no formal research has investigated this puzzling pattern of the mean individual variance.

This paper addresses this gap in the literature. It models the mean individual variance by applying a logistic smooth transition regression (LSTR) analysis and finds that the shift in the level can in large part be explained by changes in the methodology used by forecasters. In other words, the mean individual variance reflects information that may not be relevant for quantifying changes in uncertainty. The main message of the paper is that mean individual variance might not be the best proxy of macroeconomic uncertainty, at least for comparing uncertainty levels before and after the Great Recession.

A key to understanding the shift in uncertainty is the rounding behaviour of forecasters. Rounding behaviour means that forecasters may or may not round the probabilities they assign to the different outcomes of the variables being forecast. The paper examines how the inclination to round probabilities affects the measures of uncertainty derived from the SPF.

Various attributes of the forecasts that result from forecasters using different approaches to rounding are examined thoroughly in Glas & Hartmann (2018), who document that more responses were non-rounded after the Great Recession. They state that one possible explanation for the increased uncertainty after the crisis could be the increase in the share of survey participants who did not round, but still find that the mean individual variance is a better proxy for measuring uncertainty than forecast disagreement is. Disagreement, in contrast, is not considered a reliable measure of uncertainty, though no evidence is found that disagreement between forecasters is affected by the rounding behaviour of forecasters.[2]

This paper contributes to the empirical literature on measures of forecast uncertainty in several ways. The paper finds that not only are short-run fluctuations in the cyclical component of the share of non-rounders transmitted into the changes in the mean individual variance, but also, more importantly, that the shift in the level of uncertainty after the Great Recession as measured by individual variance but not by disagreement can be attributed to changes in the forecast methodology that have been taking place since the early 2000s. These findings are relevant for applied empirical research.

The rest of the paper is organised as follows: Section 2 briefly discusses issues around the rounding behaviour of forecasters; Section 3 describes the data, estimation methods, and results; and finally, Section 4 concludes.

[2] Glas & Hartmann (2018, p. 27) posit that there is “no evidence of substantial differences in the means of the histograms reported by rounders and non-rounders, measures of forecast disagreement for both groups are likely to be relatively similar”.

2. Rounding behaviour of forecasters

The rounding behaviour of forecasters is central to the paper. This section gives a short review of the relevant literature, discusses the properties of forecasts by rounders and non-rounders, and explains how methodology and rounding behaviour are related.

The SPF provides no information on the methodology applied by each individual forecaster, but whether or not forecasters round the probabilities they report can be observed. Different definitions for rounders are used in the literature, so a forecaster can be defined as a rounder if all the numbers they report are integers that are multiples of one, or multiples of five, or multiples of ten.[3] All of these definitions are considered in this paper, and so three series of the share of non-rounders are computed for each forecast variable and each forecast horizon.

Non-rounders typically use more forecast intervals, or bins, and their density forecasts typically have larger variance than those of the rounders (Glas & Hartmann, 2018). If individual variance is taken as a direct measure of uncertainty, then it follows that rounders are systematically more certain about their forecasts than non-rounders are about theirs. Zarnowitz & Lambros (1987) and Boero et al. (2015) make the opposite point though, stating that rounding behaviour might indicate uncertainty in forecasters. The same conclusion is reached by the extensive literature on cognition, linguistics and communication; see Binder (2017) for an overview. A round number signals less knowledge and more uncertainty about the subject, a feature known as the “Round Numbers suggest Round Interpretations” (RN/RI) principle (Krifka, 2002).

It is often emphasised that uncertainty means less predictability (Knight, 1921; Jurado et al., 2015), so if the RN/RI principle is accepted, rounders would produce less accurate forecasts than non-rounders. Rounding might also happen, or uncertainty might arise, because less effort has been invested in completing a task (Dechow & You, 2012). This would also make the forecast less accurate. However, Glas & Hartmann (2018), who made their analysis using the same dataset as the one used in this paper, find no noticeable difference in forecast accuracy between rounders and non-rounders. The absence of any correlation between rounding patterns and forecast accuracy can be taken as indirect evidence that RN/RI does not hold for professional forecasters.

Having said that there is no information on the methodology used by an individual forecaster, it should be acknowledged that the approaches used by forecasters in general are known. Surveys report that SPF forecasts can be judgement-based, model-based or model-based with judgemental adjustment (Meyler & Rubene, 2009; ECB, 2014, 2019). It seems a reasonable assumption that a judgement-based approach will generally produce forecasts with rounded numbers, while a model-based approach will produce forecasts with non-rounded numbers. The surveys find the share of forecasters using model-based approaches has increased from 21% to around 27% since 2008 (Meyler & Rubene, 2009; ECB, 2014, 2019). This is in line with the upward trend in the share of non-rounders (see Figure 1).

[3] Defining a forecaster as a rounder using the approach of multiples of 5 is not very common, but this definition can be found in for example Binder (2017) and Glas & Hartmann (2018).

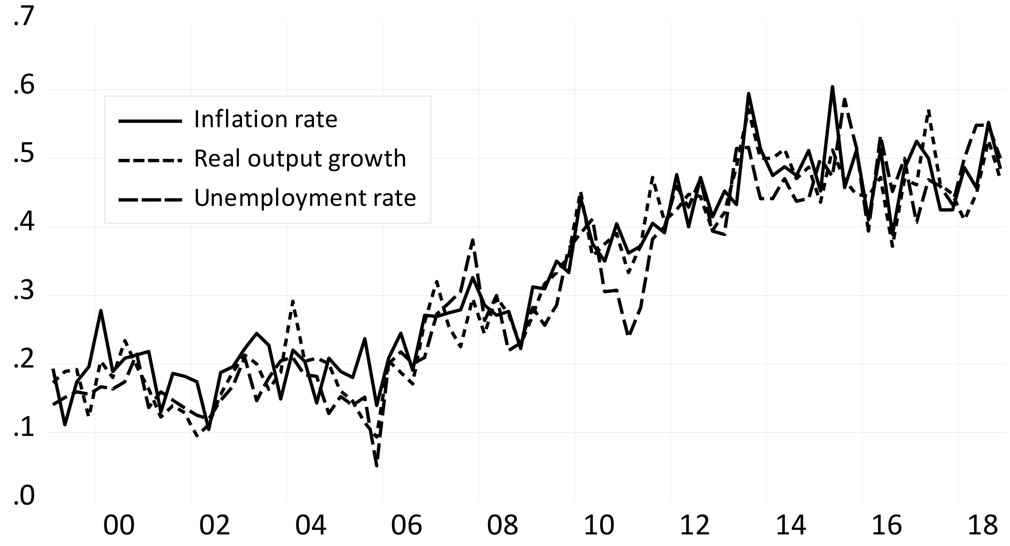

Figure 1: Share of non-rounders in the one-year-ahead forecasts

Note: Forecasters are defined as rounders if all reported probabilities in density forecasts are multiples of five.

An indirect argument in favour of linking non-rounded responses to the model-based forecasts is the finding that judgement-based consumer forecasts have the opposite characteristics to SPF forecasts. As reported in Binder (2017), increased uncertainty in consumer forecasts is associated with rounding behaviour, as rounded forecasts are less precise and are subject to more frequent revisions.

Another argument supporting the idea of a connection between non-rounding behaviour and methodology is the persistence of uncertainty measured at the individual level, as discussed in Boero et al. (2015). If individual variance is persistent, it is more likely to be because of the persistence in the methodology used by a forecaster rather than a constant level of individual uncertainty. This assumption is in line with the sticky information theory, which suggests that there is a cost associated with updating information and the methods used for forecasting (Mankiw & Reis, 2002).

This means that the share of non-rounders can be considered a valid proxy for the choice of methodology employed by professional forecasters, and the upward trend in the share of non-rounders can be interpreted as a trend towards increased digitalisation of the forecasting methodology, a switch to more sophisticated software, or a switch from a purely judgement-based approach to a model-based one.

3. Data, method, and results

In the European SPF, the forecasters are asked to provide point forecasts and density forecasts for the inflation rate, real output growth and the unemployment rate in the euro area at different horizons. Following Wallis (2005), I calculate mean individual variance and the disagreement between forecasters for all three variables for the one-year-ahead horizon (H1) and the two-year-ahead horizon (H2). The sample contains data from 1999Q1 to 2018Q4. Wallis (2005) shows that the aggregate variance of the combined density forecast σ_C^2 for the variable considered can be decomposed into mean individual variance and the variance of point estimates:

$$\sigma_C^2 = \frac{1}{n}\sum_{i=1}^{n} \sigma_i^2 + \frac{1}{n}\sum_{i=1}^{n} (\bar{y}_i - \bar{y}_C)^2 \,,$$

where σ_C^2 is the combined density forecast; n is the number of forecasters; σ_i^2 is the variance of the probability distribution of forecaster i; $\bar{y}_i$ denotes the mean of the individual density; and $\bar{y}_C$ is the cross-sectional mean of the point forecasts. The first term on the right-hand side is the mean individual variance and the second term is the cross-sectional variance of the point estimates, also labelled forecast disagreement. When calculating the mean individual variance, I assume that the numerical value of each probability is concentrated at the midpoint of the corresponding interval or bin. See Figures 2 and 3 for the one-year-ahead forecasts.

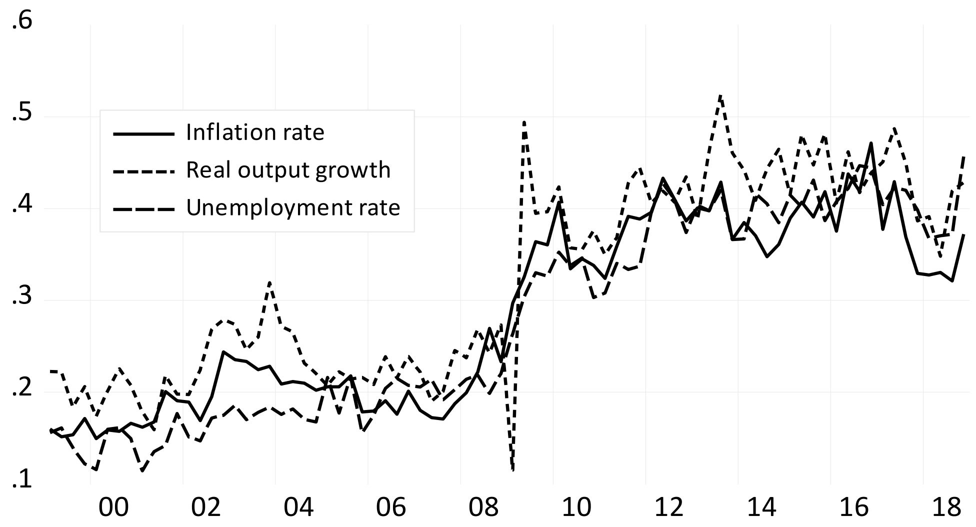

Figure 2: Mean individual variance of one-year-ahead forecasts

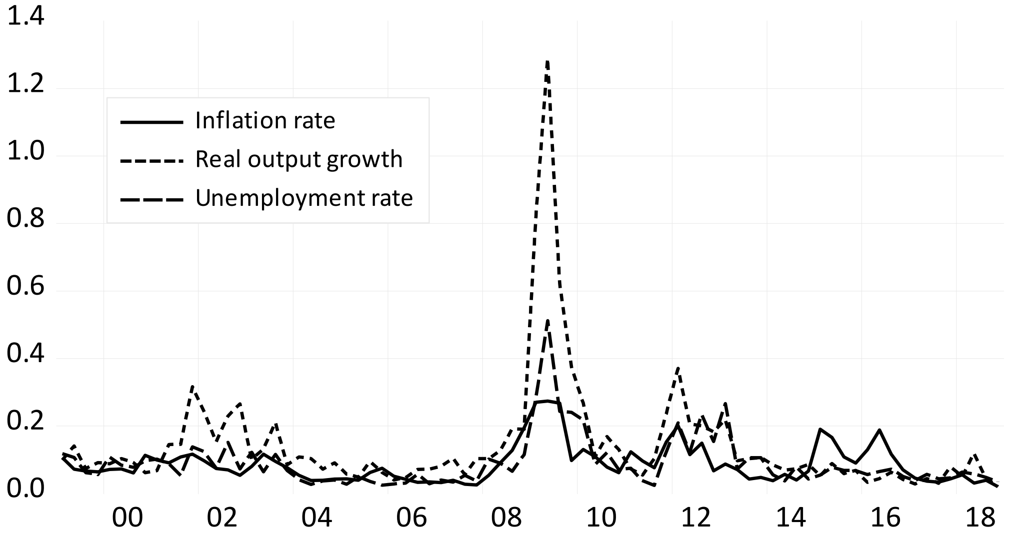

Figure 3: Disagreement in the one-year-ahead forecasts

The two proxies for uncertainty have very different dynamics. While the disagreement in Figure 3 returns to its pre-crisis level after the Great Recession with a small peak around 2012–2013 during the later recession documented by the Euro Area Business Cycle Dating Committee[4], the mean individual variance appears to be non-stationary or to have a structural break at the time of the crisis.[5]

3.1 Transformation of the data

Uncertainty can be calculated for three forecast variables using data for the one-year-ahead horizon and the two-year-ahead horizon, which results in six series of mean individual variance and six series of disagreement. All these series are highly correlated among themselves (see Tables A.1 and A.2 in Appendix A) as the correlation coefficients vary between 0.88 and 0.99 in the individual variance group of variables and between 0.45 and 0.92 in the group of the disagreement series.

In addition to the 12 series of uncertainty proxies, there are 18 series of the share of non-rounders, which arise from the different approaches to defining non-rounders[6] discussed in Section 2. They are also highly correlated among themselves, with correlation coefficients varying in the range of 0.62 to 0.96.

It should be stressed that the survey uncertainty associated with the forecast of a specific macroeconomic variable is not the focus of interest in this paper. The main interest of this paper is in choosing and examining an appropriate measure of *overall uncertainty* using SPF

[4] https://cepr.org/sites/default/files/news/EABCDC_Findings_November2019.pdf (accessed 24.12.2019).

[5] To make this analysis a bit more formal, it should be added that disagreement is highly correlated with the output gap, with correlation coefficients varying between 0.5 and 0.8 and statistically significant at the 1% level, while the correlation of mean individual variance with the output gap is effectively zero. This is valid for the principal components and for the original series of uncertainty proxies.

[6] As was discussed in Section 2, a forecaster can be defined as a rounder if all the numbers they report are integers that are multiples of one, or multiples of five, or multiples of ten.

data. The shares of non-rounders show that none of these measures of the rounding behaviour of forecasters is ideal as a proxy of the methodology used by forecasters and all of them have similar dynamics.

A suitable solution for dealing with noise and redundancy in the data is a principal component analysis (PCA), which should reduce the dimensionality of the data and extract the principal information from a given set of variables. One of the questions that needs to be answered for the PCA is how many principal components (PC) should be retained. Various approaches are possible and the ones used most often in the literature are the scree plot and the cumulative proportion of the variance explained by the first *n* principal components (see Appendix B).

The following analysis is restricted to the first PCs as they explain from 75% to 94% of the variance of the variables.[7] Further on, references to mean individual variance, disagreement or the share of non-rounders mean the transformed series of the underlying variables. Simple averages of the groups are used for a robustness check (see Subsection 3.3). The resulting series of mean individual variance, disagreement and shares of non-rounders are shown in Figures 4 and 5. To make the preliminary analysis more illustrative, each measure of uncertainty is combined with the share of non-rounders.

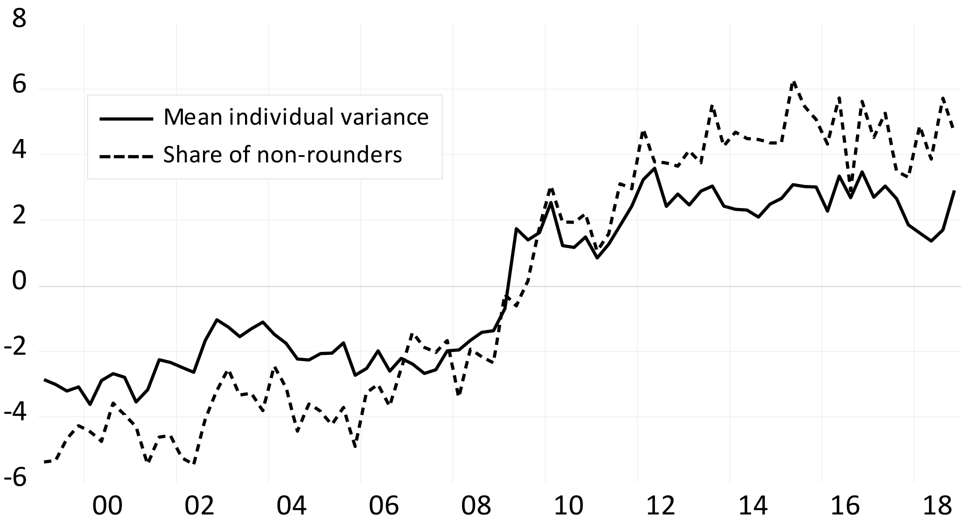

Figure 4: First principal component of the mean individual variance and of the share of non-rounders

[7] Factor loadings (eigenvectors) of the first PC are around 0.41 for the individual variance series, and vary in the range of 0.35–0.44 in the disagreement group and around 0.22–0.25 for the shares of non-rounders.

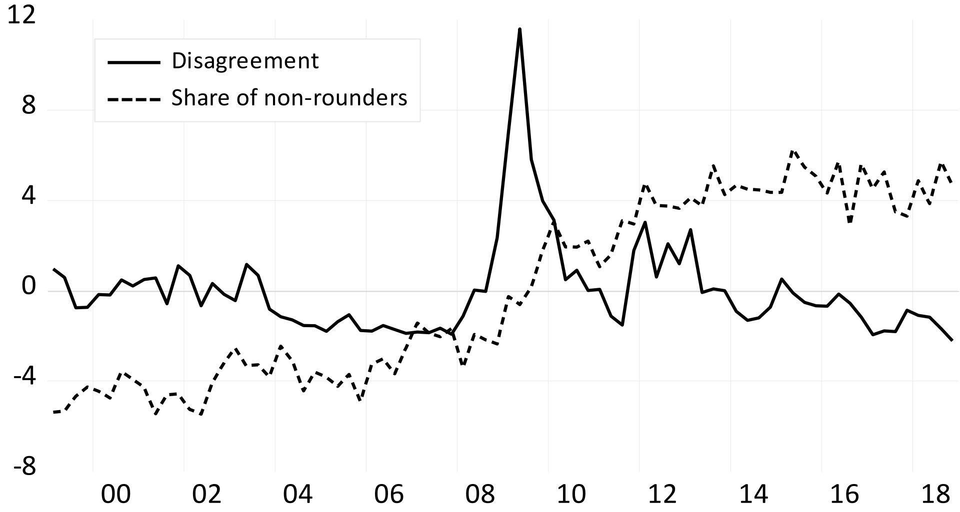

Figure 5: First principal component of disagreement and of the share of non-rounders

3.2 Time series properties of the data

A quick visual analysis of Figures 4 and 5 suggests that individual variance and the share of non-rounders are not stationary. An ADF test corroborates this preliminary inference (the results are not reported) and shows that the individual variance series and share of non-rounders have unit root, while the series for forecast disagreement are stationary.[8]

However, unit root tests are known to give biased results if there are structural breaks or regime shifts in the series. Perron (1989) points out that unit root tests tend not to reject the null hypothesis of a unit root in the presence of a break. The same findings are obtained in Zivot & Andrews (1992), Skalin & Teräsvirta (2000), and Choi et al. (2010) among others.

To account for a possible structural break at the time of the Great Recession, I run the Zivot-Andrews unit root test allowing for a break in level (Zivot & Andrews, 1992). The results suggest that all the series are stationary with a structural break at the time of the recession (see Table 1).[9] These results corroborate the findings of Dovern & Kenny (2019), who find structural breaks in the series of SPF inflation forecasts.

Table 1: Zivot-Andrews unit root test with structural break

Variable	Break	t-Statistic	Prob.
Individual variance	2009Q2	–5.119	0.000
Non-rounders	2009Q1	–4.504	0.000
Disagreement	2008Q2	–4.440	0.002

Note: t-Statistics refer to Zivot-Andrews test statistics. Probability values are calculated from a standard t-distribution.

[8] The same applies for the original series, that is all the series of mean individual variance and all the series of shares of non-rounders have unit roots, while the series for the disagreement between forecasters are stationary. The results are the same if the years of the crisis 2008-2009 are excluded from the sample.

[9] The ADF test with structural breaks gives similar results.

On the other hand, Dijk et al. (2002, p. 7) highlight that it might be difficult to distinguish between non-linearity and structural change: "[N]onlinearity, and regime-switching behaviour in particular, and structural change can be regarded as competing alternatives to linearity and it might be difficult to distinguish between the two". Keeping in mind that there may be non-linearities in the series, I estimate smooth transition models with a logistic transition function (LSTR), as discussed in the next subsection. An argument for applying the smooth transition approach is that even in the presence of a large shock to the economy, experts are unlikely to adjust their expectations at once. Besides, the information that is available to different forecasters may be different, as may the speed that new information is incorporated into the forecasts. Given all this, it is plausible to assume that the aggregate change in the uncertainty level is smooth rather than abrupt.

3.3 LSTR model estimations

Smooth transition regression models (STR) were first introduced in Chan and Tong (1986) and were developed in Luukkonen et al. (1988), Granger & Teräsvirta (1993), Teräsvirta (1994, 1998), and Dijk et al. (2002). The focus of this paper is on the shift from the low level of uncertainty before the Great Recession to the new higher level after the Great Recession, and the most appropriate type of STR model for examining a switch between two regimes is a model with a logistic transition function, which has the following form:

$$y_t = \varphi'_1\omega_{1,t} + (\varphi'_2\omega_{2,t}) \cdot (1 + exp[-\gamma(s_{t-d} - c)])^{-1} + \varepsilon_t,$$

where y_t is the dependent variable, $\omega_{1,t} = (1, y_{t-1}, \dots, y_{t-p}, X_{1,t}, \dots, X_{k,t})'$, $\omega_{2,t} = (1, y_{t-1}, \dots, y_{t-q}, Z_{1,t}, \dots, Z_{m,t})'$, $\varphi_i = (\varphi_{i,0}, \ \varphi_{i,1}, \dots, \varphi_{i,n})', i \in (1,2)$, $n \in (k, m)$, $X_{j,t}$ and $Z_{h,t}$ are vectors of explanatory variables that may partly coincide, s_{t-d} is a threshold variable lagged d periods, γ is the speed of transition between regimes and $\gamma > 0$, c is a threshold parameter, t is the time index, and ε_t is an error term with the distribution $Nid(0, \sigma_\varepsilon^2)$.

The smooth transition function is a continuous function and is bounded between 0 and 1. Following Dijk et al. (2002) the model is interpreted as a regime-switching model, with each regime associated with the extreme values of the transition function, rather than as a continuum of different regimes.

The choice of threshold variable is not an obvious one as there is no underlying economic theory for how the rounding behaviour of experts affects survey uncertainty. A common option for the threshold variable is the lagged dependent variable (see Teräsvirta, 1998; or Skalin & Teräsvirta, 2000), but it could also be a non-stationary deterministic trend such as a linear time trend (Lin and Teräsvirta, 1994) or an explanatory variable (Christopoulos & Leon- Ledesma, 2007).

Given the hypothesised relationship between rounded responses and the measure of uncertainty, the share of non-rounders is used as the baseline threshold variable. The number of lags d is chosen endogenously by minimising the sum of squared residuals. A linear time trend is used as an alternative threshold when testing for the stability of the parameters. To evaluate the short-run and long-run dynamics separately in the relationship between the mean individual variance and the share of non-rounders, the non-rounders are disaggregated into trend and cyclical components using a one-sided HP-filter with a smoothing factor of 1600.

The output gap enters the model to account for fluctuations, including seasonal ones. To examine possible asymmetries in the dynamics of uncertainty, positive and negative output gaps are evaluated separately.

One possible problem with this model specification is the potential for reverse causality from mean individual variance, showing uncertainty, to the share of non-rounders, which indicates a model-based approach in forecasting. As was discussed in Section 2, frequent updates of the data or methodology are not in line with sticky information theory, but reverse causality could be an example of rational inattention theory, in which a high level of uncertainty, during a recession say, might motivate survey participants to switch to more sophisticated methods of forecasting.[10] To be on the safe side, a two-stage instrumental variable approach is employed. Instrumental variables have been used within the STR framework by Fouquau et al. (2008), who propose an extension of the STR methodology and point out that STR models are estimated with non-linear least squares and that an IV estimator can be used to take potential endogeneity into account.

I use two instruments. The first is the share of the value added of computer programming, consultancy and related activities in total value added calculated as a simple average of the shares for the EU member states. The data originate from the WIOD database (Timmer et al., 2015) and are annual and cover the period 2000–2014. Quarterly series are calculated using cubic spline and are extrapolated to 2018. The second instrument used for an alternative estimation is the number of scholarly articles found on Google Scholar that use popular statistical software such as SAS, Stata and R.[11]

The main idea behind using these instruments is that a model-based approach to forecasting is likely to be associated with the development and use of advanced software and forecasting techniques, which is likely to be related to developments in computer programing and can be also mirrored by the use of statistical software reported by researchers.

In both auxiliary regressions, the share of non-rounders is regressed on an instrumental variable and the model is estimated with logistic STR with a linear trend as the threshold variable:

$$NONR_t = \varphi_1 IV_t + (\varphi_2 IV_t) \cdot (1 + exp[-\gamma(T - c)])^{-1} + \varepsilon_t,$$

where $NONR_t$ is the share of non-rounders, IV_t is an instrumental variable, φ_1 and φ_2 are the parameters, T is the linear trend, γ is the speed of transition between regimes and $\gamma > 0$, c is a threshold parameter, and ε_t is an error term with the distribution $Nid(0, \sigma_\varepsilon^2)$. Table 2 shows the results of the auxiliary estimations.

[10] Forecasting becomes more challenging during recessions but recessions might equally encourage forecasters to update their information more frequently or invest in producing better forecasts in other ways, for example by improving the models or methods used, which in turn might affect how the forecasts are presented (Mackowiak & Wiederholt, 2009; Sims, 2003).

[11] The data are used by kind permission of Bob Muenhen; see the data description and analysis on http://r4stats.com. The original series contains data from 1995 to 2016; this paper extrapolates the time series for 2017 and 2018 and uses cubic spline to convert annual data to quarterly.

Table 2: Estimations of the auxiliary regression

	(2.1)	(2.2)	(2.3)
Instrument	WIOD	WIOD	Articles
Linear part			
φ_1	–323.429	–306.671	–0.419
	(23.280)	(21.822)	(0.031)
Nonlinear part			
φ_2	565.473	508.27	0.843
	(40.148)	(26.773)	(0.045)
γ	0.157	0.20	0.150
	(0.029)	(0.035)	(0.021)
c	39.373	38.77	41.042
	(1.421)	(1.160)	(1.241)
Sample	2001Q1–2014Q1	2001Q2–2018Q4	1999Q1–2018Q1
Number of observations	57	75	77
R-squared	0.94	0.95	0.95
Durbin-Watson stat	1.31	1.47	1.37

Note: The dependent variable is the share of non-rounders. Models are estimated with the standard non-linear least square estimators. HAC errors are in parentheses. The parameter γ is the speed of transition between regimes and $\gamma > 0$, c is a threshold parameter. All the estimated parameters are statistically significant at the 1% level.

Columns 2.1 and 2.2 show the results when the share of non-rounders is regressed on the share of the value added from computer programming, consultancy and related activities in gross value added. While Column 2.1 uses the original data sample 2000-2014, Column 2.2 uses a longer sample with four additional years of data being extrapolated to cover 2000–2018. In Column 2.3 the instrument is the number of scholarly articles that use popular statistical software. All the parameters are highly significant and all the model specifications have successfully passed model diagnostics for linearity, remaining non-linearity and stability of parameters. Fitted values from the auxiliary regressions are used in the non-linear part of the main regression (see Table 3 below).

The baseline specification of the main model includes mean individual variance (*INDVAR*) as a dependent variable and its lagged value as a regressor (*INDVAR*(-1)); the cyclical component of the share of non-rounders (*NONR_CY*) is included in the linear part of the regression and the trend of the share of non-rounders (*NONR_TR*) is included in the non-linear part; the output gap lagged one period (*OGAP*(-1)) enters the linear part; when examined separately, both a positive output gap (*OGAPPOS*(-1)) and a negative output gap (*OGAPNEG*(-1)) enter the linear part of the equation, and both variables are lagged one period. The models are estimated with standard non-linear least square estimators; γ and c are estimated using grid search. The results are shown in Table 3.

Table 3: Estimations of the LSTR model

	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)
	Baseline	Asymmetry	No disaggregation	Fitted values (WIOD)	Fitted values (Articles)
Linear part					
$\varphi_{1,0}$	–1.309	–1.487	–1.245	–1.205	–1.401
	(0.196)	(0.328)	(0.230)	(0.183)	(0.181)
INDVAR(-1)	0.409	0.373	0.420	0.466	0.367
	(0.098)	(0.113)	(0.072)	(0.080)	(0.087)
NONR_CY	0.315	0.260		0.338	0.356
	(0.085)	(0.073)		(0.072)	(0.069)
OGAP(-1)	–0.304		–0.297	–0.284	–0.299
	(0.060)		(0.048)	(0.046)	(0.047)
OGAPPOS(-1)		–0.293			
		(0.128)			
OGAPNEG(-1)		–0.297			
		(0.131)			
Non-linear part					
$\varphi_{2,0}$	1.400	1.551	1.327	1.519	1.611
	(0.274)	(0.331)	(0.315)	(0.382)	(0.359)
NONR_TR	0.370	0.383			
	(0.086)	(0.084)			
NONR			0.370		
			(0.052)		
NONR_FITTED				0.324	0.432
				(0.104)	(0.100)
γ	1.221	1.394	0.834	0.943	0.699
	(0.515)	(1.444)	(0.323)	(0.272)	(0.214)
c	–2.869	–3.158	–3.547	–1.912	–2.383
	(0.838)	(0.921)	(0.468)	(0.698)	(0.752)
Threshold variable	*NONR*(–6)	*NONR*(–3)	*NONR*(–6)	NONR(–6)	*NONR*(–6)
No of observations	74	77	74	74	74
R-squared	0.97	0.97	0.97	0.97	0.98
Durbin-Watson stat	1.83	1.83	1.87	1.96	1.91

Note: The dependent variable is mean individual variance INDVAR. Models are estimated with the standard non-linear least square estimators. HAC errors are in parentheses. Parameter γ is the speed of transition between regimes and $\gamma > 0$, c is a threshold parameter. Column 3.4 uses fitted values from the auxiliary regression shown in Column 2.2 in Table 2, while Column 3.5 uses fitted values from the auxiliary regression in Column 2.3 in Table 2.

There are five model specifications in Table 3. The baseline model in Column 3.1 includes the share of non-rounders in disaggregated form. The trend (*NONR_TR*) is included in the non-linear part of the equation and the cyclical component (*NONR_CY*) in the linear part. In Column 3.2, the positive and negative output gaps enter the model separately. Column 3.3 shows the results if the share of non-rounders enters the model without being disaggregated. Finally, Columns 3.4 and 3.5 report the estimations when an instrumental variable approach (IV) is applied, so the fitted values of the share of non-rounders from auxiliary regressions are used instead of the trend (*NONR_FITTED*); here the fitted values from the auxiliary regression shown in Columns 2.2 and 2.3 in Table 2 are used. All the parameters in all the model specifications including constant, slope parameter and threshold parameter are statistically significant at the 1% level with one exception: γ is not statistically significant in the model with the positive and negative output gaps, see Column 3.2.

It follows from Table 3 that the estimated parameters are quite stable across the various specifications. The autoregressive coefficient of the individual variance is around 0.4 in all the specifications, and the short-run coefficient of the cyclical component of the share of non-rounders is roughly 0.3; see Columns 3.1, 3.2, 3.4 and 3.5. The parameters of the proxy of non-rounders that enter the non-linear part of the equation vary in the range of 0.32 to 0.43, and the largest one is in the model with scholarly articles as instrumental variables, see Column 3.5. It is of note that the differences in the estimates of the baseline model (Column 3.1) and the specification with the instrumented share of non-rounders (Columns 3.4 and 3.5) are in effect of the same magnitude.

The output gap has a negative effect on the uncertainty level, as a positive gap reduces uncertainty and a negative gap makes forecasters more uncertain. However, the effect of the output gap is quantitatively marginal, see Figure 7. It is interesting that there is no asymmetry in the effect the output gap has on the perceived uncertainty. The parameters of both the positive and negative output gaps are numerically the same, see Column 3.2.

As Dijk et al. (2002) point out, the modelling cycle consists of specification, estimation and evaluation stages. Evaluation includes testing for linearity against STR alternatives, for remaining non-linearity, and for parameter constancy. All the model specifications shown in Table 3 have successfully passed both linearity tests, the Teräsvirta sequential test and the Escribano-Jorda test, and the linear model is rejected at the 5% significance level. Neither are there any remaining non-linearities according to the additive non-linearity and encapsulated non-linearity tests, meaning the first-order logistic type of threshold is correct. The residuals of the models discussed above are normally distributed, not serially correlated, but they are mostly heterogeneous. However, HAC errors can cope with this problem. The transition function of the baseline model specification is shown in Appendix C.

For a robustness check, simple averages of the original variables are used instead of the first principle components; the results are mainly the same and for that reason they are not reported here. However, the effect of the output gap on uncertainty disappears when averages are used. The parameters are statistically significant, but are effectively equal to zero. This might be an argument in favour of using principal components for analysis, as the results where the cyclical and seasonal fluctuations are quantitatively significant appear to be more robust.

The empirical analysis in this subsection suggests that the mean individual variance is heavily affected by the changes in the share of non-rounders, both in the short run and in the long run. A new result for the literature is that the relationship between these variables is non-linear. To get a better visual estimation of how much the forecast methodology affects the level of the mean individual variance, Figure 7 shows the contributions of both the cyclical component and the trend component as elements of the share of non-rounders, and the contributions of the output gap and the lagged dependent variable. As can be seen, almost half of the post-crisis rise in the uncertainty level measured by individual variance can be attributed to the increased share of non-rounded responses. Given the size of the autoregressive coefficient at 0.4, the shift in the level of uncertainty can be attributed to the increased share of non-rounders.

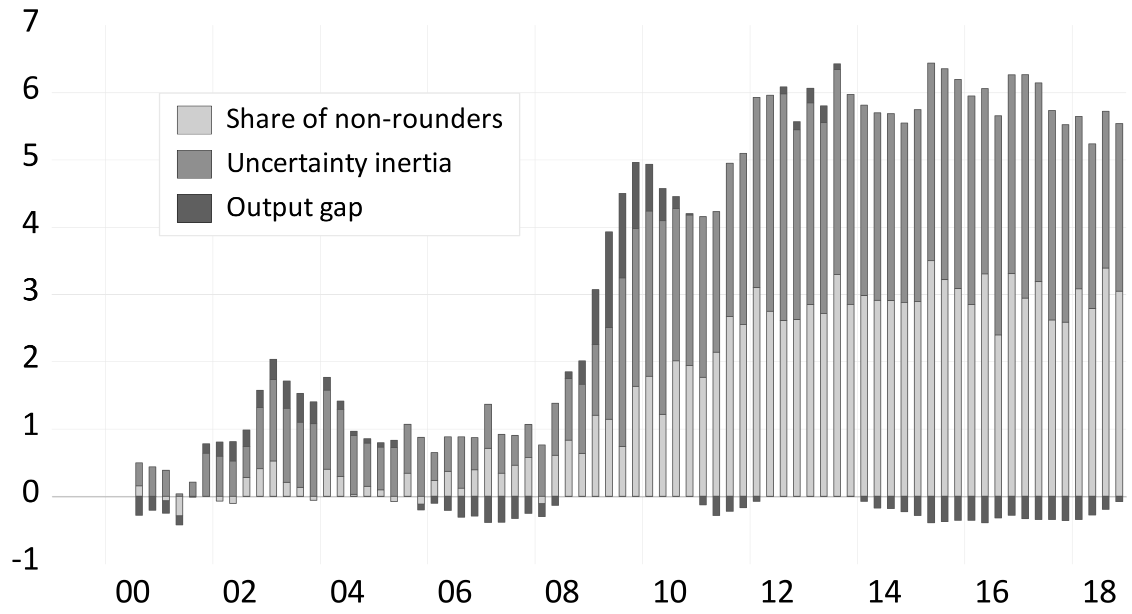

Figure 7: Contribution of the share of non-rounders and the output gap to the increased level of the mean individual variance

Note: The contributions are calculated using the baseline model specification with scaled variables.

Another important finding is that the output gap, which shows actual recessions, plays only a minor role in the changes in the forecast uncertainty. It lowers the uncertainty level to some extent between recessions and increases the perceived uncertainty in the years of crises, but the contribution of the output gap to the overall level of uncertainty is close to insignificant. This means that without exogenous digitalisation, changes in the methodology, and most probably the use of more advanced software by forecasters, the level of the mean individual variance after the Great Recession would have been the same as before the crisis, and this measure of uncertainty would have behaved much more like the disagreement time series did.

3.4 Robustness check

As a robustness check, the baseline specification is estimated on the original data, using not the principal components but the initial time series of mean individual variance and the share of non-rounders for different forecast variables and time horizons. The results are shown in Table 4.

Table 4: Estimations of the LSTR baseline model on the original data

	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
Forecast	Inflation		Output growth		Unemployment	
Horizon	H1	H2	H1	H2	H1	H2
Linear part						
$\varphi_{1,0}$	0.108	0.093	0.177	0.196	0.059	0.103
	(0.027)	(0.017)	(0.026)	(0.026)	(0.016)	(0.017)
INDVAR(–1)	0.447	0.644	0.193	0.360	0.651	0.555
	(0.123)	(0.068)	(0.121)	(0.09)	(0.088)	(0.078)
NONR_CY	0.163	0.290	0.419	0.266	0.191	0.255
	(0.068)	(0.086)	(0.069)	(0.123)	(0.07)	(0.086)
OGAP(–1)	–0.009	–0.008	–0.014	–0.026	–0.004	–0.010
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)
Non-linear part						
NONR_TR	0.236	0.153	0.391	0.324	0.186	0.289
	(0.054)	(0.035)	(0.064)	(0.055)	(0.043)	(0.053)
γ	49.250	43.787	80.387	53.747	40.744	47.173
	(27.361)	(27.496)	(73.389)	(38.098)	(29.282)	(30.618)
c	0.253	0.302	0.261	0.341	0.227	0.275
	(0.02)	(0.023)	(0.004)	(0.016)	(0.016)	(0.021)
Lags of threshold variable	6	7	6	3	6	4
Number of observations	70	73	74	76	74	76
R-squared	0.93	0.93	0.89	0.91	0.95	0.93
Durbin-Watson stat	2.05	2.02	2.37	1.82	2.23	1.95

Note: The dependent variable is the mean individual variance of the forecast INDVAR. The variable INDVAR(–1) is a one-period lagged dependent variable, NONR_CY and NONR_TR are the cyclical and trend components of the share of non-rounders where the multiple-of-five definition of rounding is employed, and OGAP(–1) is the one-period lagged output gap. The parameter γ is the speed of transition between regimes, while c is a threshold parameter. The threshold variable is the share of non-rounders. The models are estimated using the standard non-linear least square estimators. H1 and H2 are the one-year-ahead forecast horizon and the two-year-ahead forecast horizon. HAC errors are in parentheses.

There is more variety in the parameter estimates when the original, noisier, data are used. However, both components of the shares of non-rounders are statistically and quantitatively significant for all the forecasts, and all the models have passed stability diagnostic tests. The model estimates shown in Table 4 suggest that the main results discussed earlier in this subsection are fairly robust.

To conclude the analysis of the measures of uncertainty in the survey, forecast disagreement needs brief mention. As was discussed, it is a stationary, mean-reverting variable with peaks at the times of the recessions in 2009Q2 and in 2012Q1. The same properties of asset-specific realised volatility, which is another proxy for uncertainty, are discussed in Cesa-Bianchi et al. (2018). When this is tested for structural breaks, the break is found in 2008Q2 (see Subsection 3.2), but no structural break is found when the Great Recession is excluded. The unconditional correlation with the share of non-rounded responses is effectively zero, as the correlation coefficient is 0.03, and t-statistic is 0.296; this is in line with the findings in Glas & Hartman (2018) discussed in Sections 1 and 2.

Given the sensible time-series properties of the disagreement and particularly the absence of any interrelation between disagreement and the forecast methodology, this measure of uncertainty could be considered a justified proxy for modelling forecast uncertainty. Having compared average individual variance and disagreement, Giordani & Söderlind (2003) also reach the conclusion that disagreement of forecasters is a reasonable proxy for changes in uncertainty.[12]

4. Final comments

The key exercise of this paper is to analyse and explain the dynamics of the mean variance of individual density forecasts, a widely-used measure of survey uncertainty, and to compare it to the other component of the aggregate distribution of density forecasts, which is the cross-sectional variance of point forecasts.

The paper contributes to the literature by showing that although mean individual variance is a theoretically attractive measure of uncertainty, it absorbs information that is irrelevant for quantifying macroeconomic uncertainty, since it mirrors changes in the methodology used by professional forecasters.

A key novelty of this paper is its application of a smooth transition regression approach to the survey uncertainty, through which it shows that changes in the share of non-rounders are directly transmitted into the changes in mean individual variance, both in the short run and in the long run. The results suggest that there is no unexplained upward shift in the survey uncertainty of the sort that a quick look at the individual variance would suggest. Exogenous growth in the share of non-rounders among forecasters has caused the shift in the mean individual variance. The results remain robust after possible endogeneity has been accounted for.

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[12] Giordani & Söderlind (2003, p. 1038) state that "[u]sing improved (more robust) estimation techniques, we conclude that disagreement on the point forecast, a readily available but (at present) theoretically unfounded measure of uncertainty, is a better proxy for more theoretically appealing measures than previously thought".

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Appendices

Appendix A. Correlation of uncertainty proxies

Table A.1: Correlation coefficients of the individual variance series

	INFL_H1	INFL_H2	RGDP_H1	RGDP_H2	UNEM_H1
INFL_H2	0.99	1			
RGDP_H1	0.93	0.91	1		
RGDP_H2	0.94	0.94	0.92	1	
UNEM_H1	0.95	0.94	0.91	0.88	1
UNEM_H2	0.94	0.95	0.91	0.91	0.97

Notes: INFL is the inflation forecast, RGDP is the real output growth forecast, UNEM is the unemployment forecast; H1 and H2 are the one-year-ahead and two-year-ahead forecasts. The probability values for all the correlation coefficients are zero.

Table A.2: Correlation coefficients of disagreement series

	INFL_H1	INFL_H2	RGDP_H1	RGDP_H2	UNEM_H1
INFL_H2	0.63	1			
RGDP_H1	0.69	0.58	1		
RGDP_H2	0.57	0.45	0.78	1	
UNEM_H1	0.68	0.62	0.88	0.76	1
UNEM_H2	0.69	0.62	0.81	0.76	0.92

Notes: INFL is the inflation forecast, RGDP is the real output growth forecast, UNEM is the unemployment forecast; H1 and H2 are the one-year-ahead and two-year-ahead forecasts. The probability values for all the correlation coefficients are zero.

Appendix B. Cumulative proportion of explained variance

Table C1. Cumulative proportion of explained variance of individual variance, disagreement, and the share of non-rounders

PC	Individual variance		Disagreement		Non-rounders	
	Eigenvalue	Cumulative proportion	Eigenvalue	Cumulative proportion	Eigenvalue	Cumulative proportion
1	5.67	0.94	4.51	0.75	15.31	0.85
2	0.14	0.97	0.63	0.86	1.10	0.91
3	0.10	0.99	0.35	0.92	0.28	0.93
4	0.06	0.99	0.26	0.96	0.21	0.94
5	0.02	1.00	0.19	0.99	0.20	0.95
6	0.01	1.00	0.06	1.00	0.16	0.96

Note: There are 18 PC of the shares of non-rounders; eigenvalues and cumulative proportion only of the first six are reported for the sake of space.

Appendix C. Transition function of the baseline LSTR model

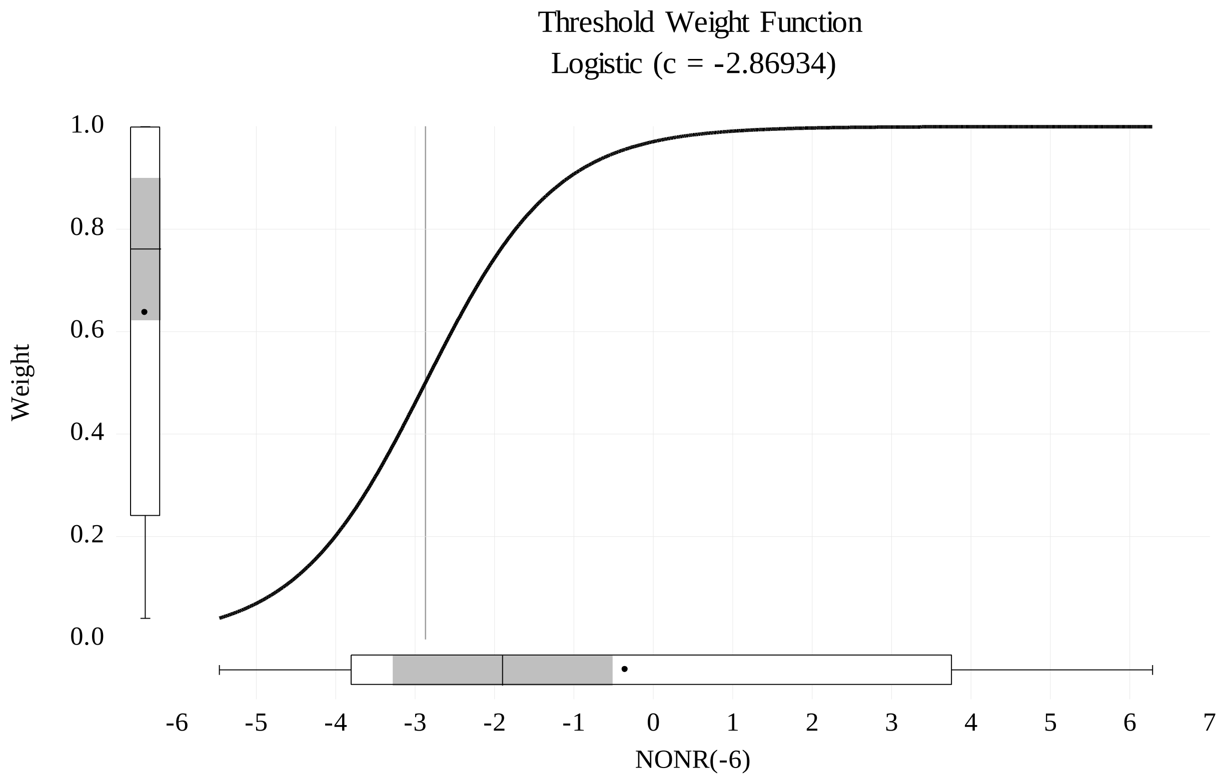

Figure D1: Transition function of the baseline LTSR model with the share of non-rounders as threshold variable

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