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Uncertainty and Measurement in Macroeconomics

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted elsewhere for a doctoral or equivalent academic degree.

Natalia Levenko

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NATALIA LEVENKO

KIRJASTUS

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List of Publications

The list of the author's publications, on the basis of which the thesis has been prepared:

I Levenko, N., Oja, K., & Staehr, K. (2019). Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis. *Post-Communist Economies*, Vol. 31, No. 2, 137–160. DOI: doi.org/10.1080/14631377.2018.1460713. (ETIS 1.1)

II Levenko, N. (2020). Perceived uncertainty as a key driver of household saving. *International Review of Economics & Finance*, Vol. 65, 126–145. DOI: doi.org/10.1016/j.iref.2019.10.005. (ETIS 1.1)

III Levenko, N. (2020). Rounding bias in forecast uncertainty. *Research in Economics,* forthcoming. DOI: doi.org/10.1016/j.rie.2020.08.001. (ETIS 1.1)

Author's Contribution to the Publications

Contribution to the publications in the thesis is:

I The author of the thesis had a leading role in writing the paper and acted as the corresponding author in the publishing process.

II The author of the thesis is the sole author of the paper.

III The author of the thesis is the sole author of the paper.

Introduction

The thesis contains three studies on applied macroeconomics that cover a range of topics on growth accounting, household saving, and measuring forecast uncertainty. The motivation for them came from different observations. Publication I was motivated by the sluggish recovery after the global financial crisis, while Publications II and III got their inspiration from the quite vague economic prospects and the massive wave of uncertainty that accompanied the financial crisis and the recession after the crisis.

An overarching theme for the three studies can be broadly defined as analysis of economic uncertainty with a special focus on data quality and data measurement. This holds for all three papers, including Publication I, on total factor productivity (TFP), which is unobservable and fairly uncertain, as that paper puts a lot of effort into constructing informative underlying series. The main attention of the publications in the thesis is on measurement and economic uncertainty, and they take a closer look at what was happening during the global financial crisis and in the post-crisis recession, seeking to shed light on the dynamics of economic growth.

Long-term economic growth and short-term economic fluctuations are two phenomena that are very different but are closely linked together (Martin & Rogers, 2000). Business cycles can theoretically affect long-term growth both positively and negatively, and the empirical evidence on this interaction is mixed. (Aghion & Saint-Paul, 1998; Malley & Muscatelli, 1999). Martin & Rogers (2000) find that increased fluctuations affect long-term growth negatively in a large sample of OECD and European countries, though this relation does not hold for developing countries. Given this, growth accounting, which is the focus of Publication I, could be crucial for understanding the different patterns of economic cycles across economies and could be of particular importance for the economies of Central and Eastern Europe (CEE) that have volatile growth; see Arratibel et al. (2007).

Short-run fluctuations in output around its long-term trend can be explained using the mechanics of capital flows or investment formation, while an explanation for the negative effect of short-run volatility on long-run growth may be rooted in uncertainty (Staehr, 2015; Ramey & Ramey, 1995). Dimelis & Dimopoulou (2002) argue however that a starting point for understanding the cyclical nature of economic growth could be capital accumulation and TFP growth. This might also be useful for assessing the sustainability of growth. Analysis of this kind is performed in Publication I.

The high levels of economic uncertainty seen during the global financial crisis invigorated the literature on the role of uncertainty in the cyclical fluctuations of economic growth. Ilut & Schneider (2014) point out that variations in ambiguity, or Knightian uncertainty, are a major source of business cycle fluctuations. This source of output volatility is examined in Publication II in the context of household saving. Bloom et al. (2018) point out that one of the key questions with uncertainty and business cycles is the direction of causality. They find that uncertainty grows endogenously during recessions, and as it is high, it amplifies the negative effects of downturns. The same conclusions on a bidirectional relationship between output and uncertainty are reached in Straub & Ulbricht (2015), Van Nieuwerburgh and Veldkamp (2006), and Kozlowski et al. (2020a) to name but a few.

Among the channels through which uncertainty may affect the real economy are precautionary saving by households, a wait-and-see stance towards investment at firms, a higher cost of borrowing, distortions in financial markets, and increased capital costs that lead to lower capital accumulation; see Fernández-Villaverde et al. (2015), Basu and Bundick (2017), Bloom et al. (2007), Stokey (2016), Bernanke (1993), and Kozlowski et al. (2020a). These channels may not only amplify a recession but may also slow the recovery after the crisis and so affect the economy for a long time (Bloom et al. 2018).

The persistent dynamics of a large shock to the economy may be explained by productivity loss and accelerated capital obsolescence. This may happen because changes in the habits, tastes and behaviour of agents persist after the shock has faded away. Kozlowski et al. (2020b) label this mechanism the belief-scarring effect as it reflects a persistent change in beliefs about the probability of an extreme, negative shock to the economy; see also Nordhaus et al. (1974) and Barro (2006).

In the short run, the effects of a crisis are a decline in output accompanied by decreasing consumption and investment, but in the longer run the consequences might be more painful, including problems in the labour market resulting in lower employment and subsequent drops in income and consumption (Gali 2020). Further worsening of market conditions might be partly caused by increased economic uncertainty, as this has a substantial impact on the confidence that households and firms feel about their consumption and investment plans. The impact of uncertainty is twofold, as it amplifies recessions and might slow a recovery (Barrero & Bloom 2020). This is what was observed in 2010-2014 when the European economy was recovering at a very slow pace from the recession induced by the financial crisis, and a similar effect might be expected as a consequence of the current Covid-19 pandemic.

In addition to its direct effects on the economy, the global financial crisis also provoked drastic changes in the global economic environment. The main features of the new economic conditions are a slowdown in productivity; interest rates that are close to zero and so leave less space for monetary policy; and a flattening of the Phillips curve, and in consequence of all this an increasing need for new frameworks for monetary policy and a greater role for fiscal policy (Gali & Gambetti 2019). Moreover, the recession had a large impact on labour market conditions, worsening not only the current state of the market but also the future perspectives perceived by market participants. Given the changed economic and social environment, it is important to have updated empirical evidence on these topics of productivity, household saving, and forecast uncertainty. The thesis contributes towards this objective.

A key issue with economic uncertainty is measuring it, given that uncertainty itself is not directly observable, and that it is often challenging to find a proper proxy for it. Numerous uncertainty variables are used in the economic literature and there is no single recognised definition of macroeconomic uncertainty. Knight (1921) distinguished between risk and uncertainty as two different types of randomness, with uncertainty defined as the unpredictability of an event. However, this concept is not generally followed in the literature and the most commonly used proxies are various measures of volatility.

One categorisation of types of uncertainty is made by considering the different approaches to measurement. Ex-post measures of uncertainty are all the measures that use past data such as volatility indices, the variance of macroeconomic indicators, and conditional variance estimated with ARCH-type models (Bloom 2014). Ex-ante measures use information on expectations about future projections and are typically based on survey data. Text mining and machine learning techniques have more recently been added to the arsenal of methods used to produce indicators of uncertainty in addition to the conventional measures of uncertainty noted above; see Priyaranjan & Pratap (2020) for an overview. Publication III focuses on the dynamics of a survey-based measure of uncertainty. The main scope of Publication III is to ascertain how far this indicator depends on exogenous factors that are not related to the actual level of uncertainty perceived by economic agents.

The issues discussed above of the decline in productivity and the dynamics and decomposition of economic growth, the deterioration of labour market conditions and the role of expectations in determining the behaviour of households, and the challenges of measuring and aggregating expectations are considered in this thesis. The three publications of the thesis focus on the developments and cyclical fluctuations of European economies. Europe is of particular interest to this study as it is one of the largest economic areas in the world and it is studied less than the US economy. The samples in the publications are, however, different. Publication I studies the fast growing CEE countries, Publication II considers a larger sample of the countries in the European Union (EU), and Publication III looks at the euro area as a whole.

The thesis contributes to three different areas of applied macroeconomics. Publication I decomposes economic growth in the sample of CEE countries into the contributions of labour, capital, utilisation of capital, and TFP. Decomposing growth helps to give a better idea of how important total factor productivity was and is for economic growth before and after the global financial crisis. The first step of the analysis is to compute a new series of physical capital as the existing data were found to be of poor quality. An important innovation is that the capital series are adjusted for capital utilisation. Another novelty of the paper is that it splits the sample into subsamples to reflect business cycles in the region, and analyses the developments of TFP over different stages of the business cycle.

Publication II examines precautionary saving, one of the channels through which uncertainty is transmitted to economic activity, with special attention paid to the financial crisis and the post-crisis period. The main innovation of the study is two proxies for labour income uncertainty. One proxy is based on the actual changes in the labour market conditions, and the other uses expectational data. The buffer-stock saving model is tested on a large up-to-date sample of European countries. As expectations are found to be one of the main determinants of the saving behaviour of households, it can be modified by changing the expectations that agents have for future developments in the labour market. These findings might have policy implications that could be particularly important during recessions when the labour market is depressed.

Publication III contributes to the literature on economic measurements by examining a widely-used proxy of forecast uncertainty and showing that the indicator considered is a function of the modelling preferences of forecasters and for that reason should be treated with caution. As uncertainty cannot be measured directly, it is of crucial importance to ensure that the proxies used in economic modelling are adequate for the purpose.

One of the key contributions of the thesis is its focus on the quality and interpretation of data. Each publication in the thesis pays close attention to finding suitable proxies for the variables being modelled and to transforming the data appropriately; moreover, Publication III is dedicated entirely to assessing the quality of a widely-used proxy for uncertainty.

The three publications use a variety of empirical methods. In Publication I, a growth accounting approach is used, while simulation exercises are conducted to obtain the distributions of possible outcomes with different parametrisation. Publication II uses the system GMM estimator in the baseline estimations and difference GMM for the robustness check. GMM estimators make it possible to account for the possible endogeneity of uncertainty in the saving behaviour of households and to address a possible Nickell bias (Wooldridge 2010, chs. 5 and 8, Nickell 1981). Publication III uses principal component analysis to reduce the dimensionality of the data, and smooth transition estimations to analyse the relationships between the variables of interest. Simulations are used to show the effect on density forecasts when rounding is used.

The thesis is organised as follows. Section 1 gives an overview of Publication I and discusses the economic fluctuations in the CEE countries, and growth accounting decomposition. Section 2 gives an overview of Publication II, focusing on measures of labour income uncertainty and the saving behaviour of households. Section 3 discusses the main points of Publication III, including the measurement of uncertainty, issues with the quality of uncertainty indicators, and the modelling preferences of forecasters. Finally, Section 4 concludes by outlining the contributions of the thesis and discussing potential avenues for future research. Appendices I-III contain the three publications.

1 Business cycles and economic growth

Publication I, "Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis", decomposes economic growth into the contributions of factors of production, and looks at the dynamics of the decomposition over the different stages of business cycles. It breaks down the growth rate of GDP in the sample of eleven CEE countries, using a growth accounting approach to gain insights into the dynamics of economic growth across the business cycle in these countries.

Growth accounting was introduced by Solow (1957) and is typically used to shed light on different patterns of economic growth. Empirical evidence of this kind might be useful for policymaking, particularly during recessions and recoveries, when the growth rates may be far from steady. Decomposing economic growth might also be instructive for assessing the sustainability of growth.

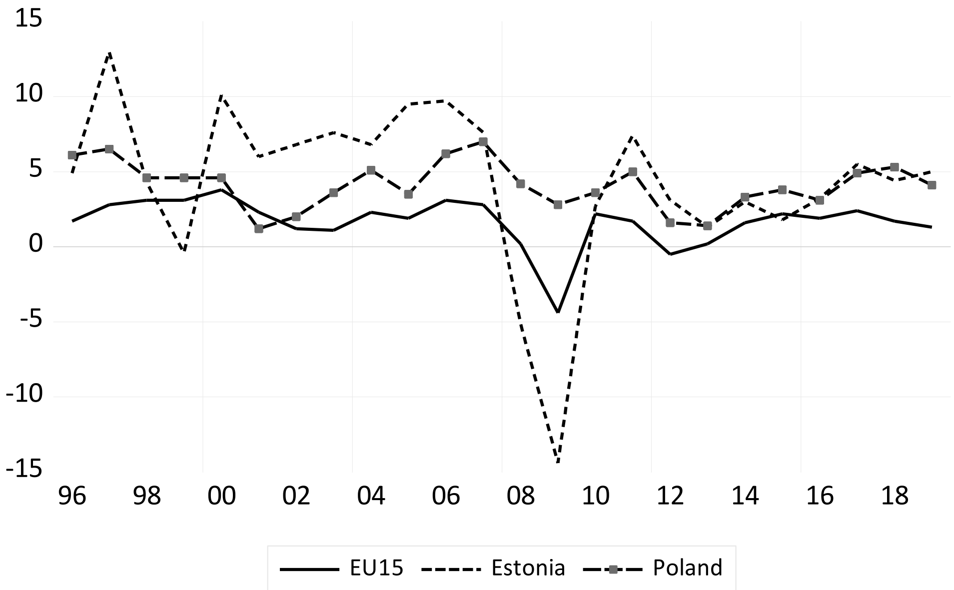

Figure 1. Output growth in Estonia, Poland and the EU15, %
Sources: Eurostat [table code: nama_10_gdp]

The countries in the sample were growing rapidly on average from the middle of the 1990s to 2007, and they then experienced deep recessions during the global financial crisis and sluggish economic recovery in 2010-2014. There is however some heterogeneity in the sample, in how the global financial crisis affected the CEE economies for example. While the Baltic states experienced an average aggregate decline of about 20%, Poland had positive rates of output growth even during the time of the crisis (see Figure 1).

The growth accounting exercise can give insights into the drivers of the divergences between the countries in the sample and the slowdown in economic growth during the years after the crisis. Growth decomposition might also be of interest in the light of the Covid-19 crisis, given the general slowdown in the economy and the expected reduction in total factor productivity (Dimelis & Dimopoulou, 2002; Elenev et al., 2020; Dietrich et al., 2020).

Growth in TFP, which is the focus of Publication I, is generally interpreted as technical or institutional change or as a change in production technology and as a measure of productivity (Solow, 1957; Dimelis & Dimopoulou, 2002; Baier et al., 2006). Externalities like changes in the sectoral composition of production and in the quality of government or management might also be reflected in the changes in TFP (Easterly & Levine, 2002; Fischer, 1993). However, this paper does not seek to explain the factors behind TFP growth. The aim is merely to characterise the dynamics of TFP growth and to link it to the trends in the business cycle in the sample period.

Before running the growth accounting exercise, the paper takes a few steps to identify and overcome the caveats in the underlying data. The first is to compute new series for physical capital using the perpetual inventory method, as the data available from the Eurostat and AMECO databases cannot be considered satisfactory for a number of reasons. First of all, it should be noted that the capital stock data provided in these databases differ not only in levels but also in dynamics. While AMECO calculates the capital series, Eurostat gets them from the national accounts. In both cases, the perpetual inventory method is used, though the approaches to calculating the initial capital are different.

AMECO uses a mechanistic approach of equating the capital-to-output ratio in 1995, the initial year in the sample, to two for all the CEE countries except Czechia, where the capital-to-output ratio is set to three. In the national accounts, which provide the data made available in Eurostat, the initial capital stock is calculated in many different ways. Czechia, Hungary Estonia, Slovenia and Lithuania use data from surveys, census data, or expert estimates; company records and administrative data are used in Poland, Romania and Croatia; while Latvia and Slovakia use the cumulative flows of investment approach to calculate initial capital. In some sense, the national accounts could be expected to provide more accurate estimates of capital stock than the AMECO approximation, but the use of different methods to estimate the initial capital make the series less comparable, and some of these methods, like cumulative flows of investment, are of questionable quality. Besides, the time series provided in Eurostat are much shorter than those of AMECO and for some countries the data are missing.

When calculating the capital series, we assume the depreciation rate to be constant across countries and over time, the underlying assumption being that the sectoral composition of the sample countries is largely similar and that it does not change much during the period examined. Keeping the depreciation rate constant follows from the literature, but for a robustness check, we use different depreciation rates in the main specification of the model and in the simulation exercise.

Second, the paper takes the utilisation of capital into account, as Solow (1957) pointed out that capital in use rather than capital in place is what is important when decomposing output growth. We use capacity utilisation in manufacturing as a proxy of economy-wide capital utilisation, with the assumption that capital is utilised in other sectors of the economy at the same rate as in manufacturing. This is a simplification but not an oversimplification. Our argument in favour of this proxy is that capacity utilisation in manufacturing captures cyclical components quite well. In the paragraph above, questions were raised about the quality of the official data on the physical capital available in the Eurostat and AMECO databases. This does not mean, however, that all the data in these databases are considered to be of low quality. In addition, the data on the capital stock come directly from the national accounts and face a measurement and comparability problem, while the data on capacity utilisation are quarterly survey-based data from a survey that is conducted by the Directorate General for Economic and Financial Affairs of the European Commission. Solow (1957) uses the unemployment rate to adjust the capital series for utilisation, arguing that capital is generally used at the same rate as labour. The paper exploits the same approach in a robustness check.

The main idea behind adjusting capital for its uneven utilisation over cycles is to remove all or at least some of the cyclicality from the final TFP series. This can also be done by employing a more precise measure of labour and considering employment as hours worked instead of as the number of employees. This is also done in the paper but only as a robustness check since the data on working hours are not available for a number of countries.

Finally, the paper decomposes output growth and provides annual and average TFP growth figures for the CEE countries in the sample. The analysis shows that before the global financial crisis, Slovenia, Hungary and Slovakia were the countries where TFP growth contributed most to growth in output, while capital accumulation was more important in the Baltic states, Poland and Czechia.

The contributions of TFP growth and capital growth at the time of the global financial crisis were very different in the countries in the sample, reflecting the diverse dynamics of the crisis and the heterogeneity of the measures taken to mitigate the negative consequences of the crisis. In the years after the crisis, modest output growth in all the sample countries was accompanied by negligible TFP growth. The results remain robust after numerous robustness checks, including different methodologies and parametrisations used to identify which assumptions are most important for the results and which are less important. To get a better idea of how different parameters affect the results, simulations are used to generate the distributions of TFP across the sample countries.

The paper discusses the contraction in the CEE economies during the years after the global financial crisis in the context of the slowdown in TFP. Alternative explanations are possible however, and Akcigit & Ates (2020) point out for example that aggregate productivity growth, as the essential source of sustainable economic growth, is supported by business dynamism and factor reallocation. They bring evidence of declining business dynamism and entrepreneurship in the USA over the past several decades, which in turn might be related to increasing market concentration and a decline in the intensity of knowledge diffusion. Emerging economies might suffer in addition to declining transmission of knowledge from the low availability and high cost of credit, especially for small and medium-sized firms (Kukk & Levenko, 2020).

The main contribution of this paper alongside providing reliable data on the capital stock and the TFP series in a sample of CEE countries is to give an insight into the differences in growth patterns over time, with the idea of finding which factor contributed the most to the slowdown after the crisis. The paper shows that the growth rates of output after the global financial crisis were modest mostly because the contributions of TFP growth were small. In this context, it could be interesting to speculate on whether TFP is procyclical, countercyclical or acyclical, and to what extent it is affected by the type of shock. According to textbook theory of the real business cycle, TFP is a measure of changes in technology and as such it should be affected by a supply shock. However, TFP is also called a "measure of our ignorance" (Abramovitz, 1956, p. 11) as it is the share of output growth that cannot be explained by other factors of production. Explaining the dynamics of TFP and its causal relations with movements in output is beyond the scope of this paper, but the yearly patterns of TFP across the sample appear to exhibit procyclicality even when capital utilisation is included in the calculations.

Growth accounting is a conceptually simple exercise, but it requires careful collection of data and sound judgement in how the methodology is applied, and it can be stated that the resulting figures are very informative estimates of TFP growth, given the available data. The estimations of how production factors contribute to aggregate productivity can give insights into the overall dynamics of the economies being examined, and the slowdowns in economic growth. The main contributions of the paper are in providing new and reliable capital stock series, taking the capital utilisation rate into account, and building on that by computing figures for TFP growth for a set of CEE countries.

The paper was presented at the 16th Annual Conference of the European Economic and Finance Society in 2017 in Ljubljana, Slovenia and at the 9th International Conference Challenges in Enlarged Europe in 2017 in Tallinn, Estonia. Before being published in *Post-Communist Economies*, an earlier version of this paper was issued in the Eesti Pank Working Paper series (No. 8/2017).

2 Expectations and consumption

Consumption and saving are among the key performance indicators extensively studied at both the macro and micro levels; see Mikesell & Zinser (1973), Balassa (1993), Loayza et al. (2000), and Meghir & Pistaferri (2011) to name but a few. Publication II, "Perceived uncertainty as a key driver of household saving", focuses on how labour income uncertainty affects the saving behaviour of households, examining realised uncertainty and uncertainty in expectations about the future separately. The paper uses a dynamic panel of 22 European countries and applies system GMM on the aggregate country-level data.

The method used makes it possible to account for the endogeneity of the right-hand side variables and to address Nickell bias (Wooldridge, 2010, chs. 5 and 8; Nickell, 1981). The sample period includes several business cycles in the years 1996-2017. Since the macroeconomic environment has changed quite substantially over the past few decades, it is important to get an updated view of the drivers of household saving in Europe as saving behaviour is a flip side of household consumption, and as such it could be thought of as an important determinant in the dynamics of output growth.

According to textbook consumption theories like the Permanent Income Hypothesis or the Life-Cycle Hypothesis, a recession in which incomes decline gives a good excuse for dissaving (Friedman, 1957; Ando & Modigliani, 1963). Nevertheless, household saving rates have grown quite substantially since the global financial crisis both in Europe and in the USA. The same kind of behaviour has been observed during the Covid-19 crisis, which makes the topic particularly relevant. It is of note that increases in saving rates appear to be accompanied by increases in expectations of unemployment; see Figure 2.

Figure 2. The saving rate and unemployment expectations in the euro area.
Note: The saving rate (left scale) and annual change in unemployment expectations in the euro area computed as the difference between positive and negative answers (right scale)
Sources: Eurostat [table codes: nasq_10_ki, ei_bsco_m]

Uncertainty about the future dynamics of labour income if labour market conditions deteriorate is associated with the precautionary motive for saving. The need to build up a reserve against unforeseen contingencies, as defined by Keynes (1936), is one of the main incentives for households to save. This is also confirmed by more recent data from surveys like the Survey of Consumer Finances run by the Federal Reserve Board in the USA, or the Household Finance and Consumption Survey conducted in Europe.

Precautionary saving is typically explained by the concavity of the utility function of consumption, implying that increased uncertainty is followed by higher expected marginal utility for a given value of expected consumption (Romer, 1996, ch. 7). The precautionary motive can be also considered in the context of the cost of real options, meaning that firms put their investment decisions on pause while households reduce their consumption, mainly at the expense of durables; see Barrero & Bloom (2020) for an overview.

The precautionary motive of saving for households is investigated in Publication II in the framework of the buffer-stock saving model of Carroll (1997). To explain fluctuations in household saving, Carroll combines uncertainty about labour income, the impatience of consumers, and the target wealth-to-income ratio. The pattern where consumers save while their wealth is below their target wealth-to-income ratio and spend when it is above is called buffer-stock saving behaviour. Carroll's (1997) model is close to the models developed by Houthakker & Taylor (1970), Taylor (1971), Zeldes (1989) and Deaton (1992). What makes Carroll's buffer-stock saving model different from earlier theories is that it incorporates uncertainty in the form of unemployment expectations.

The main focus of Publication II is on the role of labour market uncertainty when saving decisions are made. A key contribution of the paper is that it distinguishes between realised labour income uncertainty and expectations about future uncertainty, and shows that both components of perceived uncertainty are economically and statistically significant for the dynamics of household saving. The paper gives evidence that expectations affect household saving in Europe, and so it might be of interest for policymaking since consumers' expectations can be influenced, and through this, their behaviour can too.

In the literature on saving, uncertainty is frequently modelled in a fairly straightforward manner. Macroeconomic variables such as the inflation rate or the unemployment rate are often used as proxies for macroeconomic uncertainty (Gupta, 1987; Loayza et al., 2000; Bande & Riveiro, 2013). A key contribution of Publication II is that the modelling of uncertainty is approached in a more elaborate way.

The paper decomposes labour income uncertainty into two components, one that accounts for actual change in labour market conditions and the other that covers the perceived expectations about possible changes. To get at those expectations, the paper uses data from the Joint Harmonised EU Consumer Survey, which is one of the novelties of this study as survey data are not typically used in macroeconomic studies.

The correlation between unemployment expectations and the lead of the unemployment rate is different from zero at around 0.26, which would be expected as both indicators are tightly connected to the dynamics of the labour market. However, the co-movements are not very strong as households might not be very accurate in their forecasts for labour market developments, but their perception of these developments still affects their saving behaviour.

As mentioned above, the unemployment rate is often used to construct proxies for labour income uncertainty. The unemployment rate can be thought of as a two-dimensional indicator of uncertainty. An increasing unemployment rate signals that there is a higher probability of workers being laid off, and at the same time it is a signal of a higher probability of reduced future income.

For that reason, it is important to distinguish between the unemployment rate in levels and the rate in first differences, as these are proxies for different processes. A high unemployment rate correlates with a lower income, and so saving could be expected to fall because there is a reduced ability to save. Equally, a positive change in unemployment indicates uncertainty about the future, and saving could be expected to grow in response to precautionary motives. In other words, the level of unemployment is a proxy for labour income, while a change in the unemployment rate is a proxy for uncertainty about labour income.

The main specification of the model estimated in the paper includes changes in unemployment as an explanatory variable while a specification with unemployment in levels is estimated as a robustness check. The unemployment rate in levels, indicating the capacity to save, is not statistically significant whenever income growth is present in the model as a more direct proxy for the capacity to save.

The paper finds that household saving is very persistent, with an autoregressive coefficient of around 0.8, and that saving is driven by income growth as well as by labour market uncertainty. These results are in line with previous studies. Credit availability, interest rates, inflation, and other macroeconomic and expectational variables are often included in models of household saving, but these are not found to affect household saving in the sample examined. The positive conditional correlation of income growth with saving rates can be explained by the persistence of consumption habits (Taylor 1971), while the concavity of the consumption function implies that consumption has diminishing utility with respect to income (Carroll & Kimball 1996). Given the size of the autoregressive coefficient, the long-run effects of all the drivers of household saving rates are around four times the size of their short-run effects.

Numerous robustness checks corroborate the main findings of the study and show that indicators of overall economic volatility and other expectational variables have no discernible effect on the household saving rates in the panel of European countries, while increases in the unemployment rate and in unemployment expectations can depress consumption for quite a long time. These findings may explain the slow recovery after the global financial crisis and might also be relevant during the Covid-19 crisis given sky-rocketing unemployment rates and a pessimistic economic outlook.

The paper was presented at the 20th IWH-CIREQ-GW Macroeconometric Workshop in 2019 in Halle, Germany, and at the 10th International Conference Economic Challenges in Enlarged Europe in 2018 in Tallinn, Estonia. Before being published in the *International Review of Economic and Finance*, an earlier version of this paper was issued in the Eesti Pank Working Paper series (No. 9/2018).

3 Measuring uncertainty

The main challenge when incorporating uncertainty into economic analysis is that it is not directly observable. This makes the need to identify a valid proxy for uncertainty a key issue when dealing with this variable. The focus of Publication III, “Rounding bias in forecast uncertainty”, is on the features of a widely-used measure of forecast uncertainty, the mean individual variance of the density forecasts of the European Survey of Professional Forecasters (SPF), a dataset that is extensively used to derive measures of perceived macroeconomic uncertainty.

The mean individual variance of density forecasts is defined as the average of the variances of individual forecasts. The variance of density forecasts is often seen as a direct measure of uncertainty and is often used in macroeconomic analysis. A noticeable shift of this indicator to a higher level at the time of the global financial crisis was expected, but it is puzzling that uncertainty, measured as the mean individual variance, has remained broadly unchanged after the crisis.

The paper seeks to shed light on the lack of counter-cyclicality in individual variance, as measures of uncertainty are known to follow business cycles quite closely. The paper analyses whether this uncertainty indicator actually quantifies changes in perceived uncertainty and provides evidence that it may be related to the modelling preferences of forecasters. As no information about the methods and models used by the experts is available at the individual level, the argumentation of the paper is based on the rounding behaviour of forecasters.

Rounding refers to the way the forecasts are presented and the probability that the numbers in them have been rounded to the nearest integer, five or ten, or have not been rounded at all. Rounding has been studied both in the economic literature and in the literature on cognition, linguistics and communication. Rounding is typically associated with a high level of uncertainty, and Krifka (2002) labelled this behavioural pattern the “Round Numbers suggest Round Interpretation” (RN/RI) principle. This principle is found to hold in consumer survey data for example (Binder, 2017). A possible positive relation between rounding and the level of perceived uncertainty is discussed in Zarnowitz & Lambros (1987) and Boero et al. (2008).

Publication III contributes to the empirical literature on forecast uncertainty by considering the puzzling lack of counter-cyclicality in the mean individual variance of the SPF forecasts after the global financial crisis. The paper first shows that the RN/RI principle is not supported by the data from the European SPF at the aggregate level, meaning that rounded forecasts have lower variance on average, which is interpreted as a lower level of uncertainty. The paper uses simulations to provide evidence that the rounding of histograms is likely to reduce the variance of density forecasts by introducing additional noise in the data, which it is then impossible for the end user to isolate.

Second, the paper analyses the relationship between the rounding of forecasts, used as a proxy for the modelling preferences of forecasters, and the uncertainty indicator based on the mean variance of individual density forecasts. The paper applies smooth transition regression analysis to ascertain whether a link between these two variables can be identified. The instrumental variable approach is used to account for the possible endogeneity of modelling preferences towards the state of the economy.

The smooth transition regression approach is an alternative to the models with structural breaks. As Dijk et al. (2002) point out, it is often difficult to distinguish between a structural break and a nonlinearity. However, if a regime shift is under examination, a smooth transition is usually a more plausible way to model an economic process. In this particular case, where changes in the modelling preferences of forecasters are being examined, it is not likely that all of the survey participants will change their forecasting behaviour at once in the same quarter. It is more likely that forecasters update information and upgrade their forecasting methodology gradually, which will result in a smooth transition from one state to another.

The underlying micro panel of forecasts is unbalanced, meaning that not all the forecasters are present in the panel for the whole period. However, selection bias is not an issue as the experts are fairly persistent in reporting their forecasts. The statement made in this paper is that rounding affects the variance of forecasts. From this point of view, it makes no difference if a forecaster changes their modelling approach or if one forecaster, who may be a rounder, is replaced in the panel by another forecaster, who may be a non-rounder.

The paper finds that the smooth increase in the level of individual variance may be attributed to changes in the modelling preferences of forecasters and these changes might perhaps have happened in response to developments in the computer software market or improved professional training, while the actual level of forecast uncertainty might have completely different dynamics. The results indicate that a widely-used measure of forecast uncertainty, the mean individual variance of density forecasts, is a noisy indicator that may be dependent on modelling preferences and the habits of professional forecasters, and for that reason it should be treated with caution as a proxy for forecast uncertainty.

The paper was presented at the Estonian Economic Association Conference in 2020 in Laulasmaa, Estonia. Before being published in *Research in Economics*, an earlier version of this paper was issued in the Eesti Pank Working Paper series (No. 2/2020).

4 Concluding remarks

The thesis was motivated by the aftermath of the global financial crisis when economic growth was weak and uncertainty was high. The thesis takes a closer look at the mechanics of uncertainty and various issues regarding economic measurement, contributing to applied macroeconomics, and specifically to the empirical literature on growth accounting, consumption, expectations, and data measurement. The thesis restricts its analysis to European economies as empirical evidence on this economically important region is limited compared to the number of studies on the US economy.

The thesis contains a number of contributions. Publication I decomposes output growth into the contributions of utilised capital, labour, and total factor productivity to gain insights into the dynamics of the post-recession slowdown in economic growth, while the focus of the two other papers is on macroeconomic uncertainty and expectations. Publication II examines the relationships between household saving, labour income uncertainty and other macroeconomic indicators, and provides evidence that expectations along with income growth are the two main drivers of household saving behaviour. Publication III takes a closer look at measuring uncertainty and finds that a popular uncertainty indicator is affected by the modelling preferences of forecasters, a variable that is exogenous to the dynamics of uncertainty.

Potential avenues for future studies are numerous. The growth accounting exercise can be done using data on the sectoral decomposition of output, such as data from the World Input-Output Database (Timmer et al. 2015). The saving behaviour of households can be analysed from a larger sample of countries, or saving can be decomposed into financial assets, liabilities and purchases of durables. In Publication III, the uncertainty indicator is computed in a conventional manner as a second moment of density forecasts. To enrich the analysis, third and fourth moments can be computed and analysed for the rounding behaviour of forecasters. Taking a broader perspective on the uncertainty in macroeconomics, the changed macroeconomic environment could be taken into account with possible monetary and fiscal interventions at the zero lower bound and along the flattening Phillips curve. In this context, a promising avenue for future research is the relationship between business cycles and long-term growth in new economic conditions.

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Abstract

Uncertainty and measurement in macroeconomics

The thesis consists of three publications covering selected macroeconomic topics with a special focus on economic uncertainty and measurement. The analysis is restricted to European economies as these countries play an important role in the global economy and are typically less studied than the US economy. While the unifying theme for the thesis is economic uncertainty and data quality, the papers focus on different topics, covering growth decomposition, consumer expectations and household saving, and issues related to measuring forecast uncertainty.

Publication I, “Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis”, consists of a growth accounting exercise for 11 CEE countries for the years 1996-2016. The paper focuses on the contributions of production factors to economic growth in order to gain insights into the differences in economic growth in the sample countries. The main contributions of the paper are in providing reliable new capital stock series, taking account of the capital utilisation rate, and computing TFP figures for a set of CEE countries. The results indicate that TFP growth and capital deepening were the main contributors to output growth in the sample countries before the global financial crisis. During the crisis, the patterns of growth decomposition were quite heterogeneous across the countries, while weak output growth after the crisis was paired with sluggish TFP growth in all of the sample countries.

Publication II, “Perceived uncertainty as a key driver of household saving”, focuses on household saving behaviour in the context of labour income uncertainty. The paper distinguishes between realised uncertainty and uncertainty from expectations about the future. This may be considered a key contribution of the paper. To account for expectations, the paper incorporates survey data into its analysis, which is one of the novelties of the paper. The paper uses a dynamic panel of 22 European countries and applies system GMM on aggregate country-level data. The method chosen is able to account for endogeneity and Nickell bias. The paper finds that the household saving rate is persistent and is mostly driven by income growth and labour income uncertainty, the quantitative effects of these two drivers being roughly the same. Credit availability, interest rates, and inflation have little or no effect on saving. The findings of the paper that expectations matter for the saving behaviour of households might be of importance for policymaking.

Publication III, “Rounding bias in forecast uncertainty”, examines a widely-used measure of forecast uncertainty, the mean individual variance of density forecasts derived from the European SPF dataset. The paper uses smooth transition regression analysis to show that individual variance is a function of the rounding behaviour of forecasters, and simulations to demonstrate how the rounding of density forecasts affects their variance. The paper shows that the mean individual variance of density forecasts, which is often referred to in the literature as a direct measure of uncertainty, is a noisy proxy for uncertainty and is a function of exogenous processes such as developments in the computer software market or improved professional training. The findings imply that the actual movements in forecast uncertainty might have different dynamics from what might be concluded from looking at the mean individual variance of the forecasts.

The publications of the thesis look at the developments in the European economy from different angles, decomposing economic growth and examining different features of economic uncertainty. The findings of all three publications are relevant for empirical studies, particularly studies of recessions as times when it might be important to have a precise idea of the dynamics of growth and the movements of uncertainty.

Lühikokkuvõte

Ebakindlus ja mõõtmine makroökonoomikas

Doktoritöö koosneb kolmest artiklist, mis käsitlevad valitud makromajanduslikke teemasid, pöörates erilist tähelepanu majanduslikule ebakindlusele ja mõõtmisele. Analüüsis vaadeldakse Euroopa riikide majandusi, kuna neil riikidel on globaalses majanduses oluline roll ja neid uuritakse tavaliselt vähem kui Ameerika Ühendriikide majandust. Ehkki doktoritöö siduvaks teemaks on majanduslik ebakindlus ja kasutatavate andmete kvaliteet ja mõõtmine, keskenduvad artiklid erinevatele teemadele nagu majanduskasvu dekomponeerimine, majapidamiste säästud ja ootused ning tajutava ebakindluse mõõtmisega seotud küsimused.

Artikkel I, “Kogutootlikkuse kasv Kesk- ja Ida-Euroopas enne üleilmset finantskriisi, kriisi ajal ja pärast seda”, kirjeldab majanduskasvu allikaid 11 Kesk- ja Ida-Euroopa (KIE) riigis, mis liitusid Euroopa Liiduga alates 2004. aastast. Artikli peamine panus erialakirjandusse seisneb selles, et genereeritakse uued usaldusväärsed kapitali aegread, võetakse arvesse andmeid kapitali rakendatuse kohta tootmises ja arvutatakse KIE riikide kogutootlikkus. Tulemused näitavad, et enne üleilmset finantskriisi olid valimisse kuuluvate riikide majanduskasvu peamiseks panustajaks kapitali ja kogutootlikkuse kasv. Kriisi ajal olid majanduskasvu dekomponeerimise tulemused KIE riikides üsna heterogeensed, kuid pärast üleilmset kriisi oli nõrk majanduskasv kõigi valimis sisalduvate riikide puhul seotud tagasihoidliku kogutootlikkuse kasvuga.

Artikkel II “Tajutav ebakindlus kui peamine kodumajapidamiste säästmiskäitumist mõjutav tegur” keskendub kodumajapidamiste säästukäitumisele tööturuga seotud ebakindluse kontekstis. Uuringus eristatakse tegelikku ja tajutavat ebakindlust. Sellist lähenemist võibki pidada töö põhiliseks panuseks. Tegelik ebakindlus tuleneb šoki realiseerumisest, samas kui tajutavaks ebakindluseks võib pidada tulevikus esineda võivate šokkide ootust. Uuringus kasutatakse 22 Euroopa riigi dünaamilisi paneelandmeid, mille analüüsimiseks kasutatakse GMM hinnangfunktsiooni. Valitud meetod võimaldab arvestada tunnuste endogeensuse ja Nickelli nihega. Artiklis leitakse, et kodumajapidamiste säästumäär on püsiv ning selle taga on peamiselt sissetulekute kasv ja tööturuga seotud ebakindlus, kusjuures nende kahe teguri kvantitatiivne mõju on ligikaudu sama. Laenude kättesaadavus, intressimäärad ja inflatsioon mõjutavad säästmist vähe või üldse mitte. Uuringu peamine järeldus, et tarbijaootused mõjutavad kodumajapidamiste säästmiskäitumist, võib olla oluline eeskätt poliitika kujundamise kontekstis.

Artiklis III „Ümardamise nihe majandusprognoose ümbritsevas ebakindluses“ uuritakse sellist prognoosidega seotud ebakindluse levinud mõõdikut nagu keskmine individuaalne dispersioon, mida defineeritakse kui individuaalsete prognooside dispersioonide keskmist. Uuringus kasutatakse sujuva ülemineku regressioonanalüüsi ja simulatsioone funktsiooni, et uurida, kuidas prognooside ümardamine mõjutab nende dispersiooni. Artiklis ilmneb, et keskmises individuaalses dispersioonis, mida kirjanduses sageli nimetatakse otseseks ebakindluse indikaatoriks, on müra ning see on välisprotsessi funktsioon, nagu näiteks arvutitarkvara turu areng või paremad erialase koolituse võimalused. Analüüs näitab, et majandusprognoose ümbritseva ebakindluse dünaamika puhul ei esine säärast seletamatut kasvu, millele viitab pealiskaudne individuaalse dispersiooni vaatlus.

Doktoritöö artiklites vaadeldakse Euroopa majanduse tsükliliste kõikumiste dünaamikat erinevate nurkade alt, dekomponeerides majanduskasvu ja uurides majandusliku ebakindluse erinevaid omadusi. Kõigi kolme artikli tulemused on asjakohased empiiriliste uuringute jaoks, eriti majanduslanguste aegadel, kui võib tekkida vajadus kasvudünaamikast ja ebakindluse liikumisest täpse ettekujutuse järele.

Appendix 1. Publication I

TOTAL FACTOR PRODUCTIVITY GROWTH IN CENTRAL AND EASTERN EUROPE BEFORE, DURING AND AFTER THE GLOBAL FINANCIAL CRISIS

Publication I
Levenko, N., Oja, K., & Staehr, K. (2019). Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis. *Post-Communist Economies*, Vol. 31, No. 2, 137–160. DOI: doi.org/10.1080/14631377.2018.1460713. (ETIS 1.1)

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Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis

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ABSTRACT
This article presents growth accounting results for 11 EU countries from Central and Eastern Europe for the years 1996–2016. Its contributions include the estimation of new capital stock series and adjustment for the utilisation of capital stock. Before the crisis, growth in total factor productivity (TFP) was the main contributor to output growth in Slovenia, Hungary and Slovakia, while capital deepening was more important in the Czech Republic, Croatia and Poland. During the global financial crisis the contributions of TFP and capital growth differed markedly across the countries, reflecting the very diverse dynamics of the crisis. After the crisis the contribution of TFP growth has been negligible in all of the sample countries coinciding with generally weak output growth. The results are generally robust to changes in estimation methods and parametrisations, but some assumptions regarding the construction of the capital stock series are critical for the results.

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Growth accounting; capital stock; perpetual inventory method; total factor productivity; global financial crisis; Central and Eastern Europe

1. Introduction

This article presents the results of growth accounting for 11 countries from Central and Eastern Europe (CEE), which joined the European Union in 2004, 2007 or 2011. Growth accounting involves the decomposition of growth in output into contributions from growth in production inputs and the residual total factor productivity (TFP). Growth accounting is of key importance for understanding the drivers of economic growth (Arratibel et al., 2007). Growth accounting is particularly important for the CEE countries as they have experienced rapid but unusually volatile economic growth since the mid-1990s, implying an uneven catching-up process. Official statistics do not provide reliable data on total factor productivity in the CEE countries for the full period from 1995 to 2016 due to the challenges stemming from the transition process and the strong business cycles. Earlier academic studies have typically covered only the period to the mid-2000s implying that updated and longer time series are warranted.[1]

Most CEE countries saw rapid economic growth, rapid capital accumulation and large current account deficits in the years before the global financial crisis. Growth accounting

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may provide important insights into the dynamics and sustainability of such growth spurts. Krugman (1994) and Young (1995) noted that the very rapid economic growth of 6–7% per year experienced by the East Asian tiger economies before 1997 came mainly from accumulation of capital, not total factor productivity growth. Krugman (1994) used this finding to question the longer-term sustainability of the growth performance of the tiger economies, arguing that they were vulnerable to changes in international financing conditions. These worries proved vindicated when the Asian crisis broke out in 1997.

The global financial crisis affected the CEE countries very differently; output declined in total by 20% or more in the Baltic states over 2008 and 2009, while Poland maintained positive rates of growth throughout the crisis. How various factors contributed to GDP growth during the crisis may provide insights into the reasons for these diverging developments. Fernald and Matoba (2009) argue that GDP declined in the USA largely because employment fell and the utilisation of the capital stock was reduced, while TFP growth held up relatively well. Economic growth has generally been subdued in the CEE countries since the global financial crisis. This has led to concerns that the CEE countries may risk getting caught in a middle income trap with low growth and very slow catching-up (Staehr, 2015).[2] A first step towards understanding the growth slowdown would be to examine how far it is associated with slower growth rates of capital and total factor productivity (Dimelis & Dimopoulou, 2002). Such an analysis may also give an indication of the prospects for economic growth in the years ahead.

Growth accounting provides an immediate gauge of the challenges for growth in an economy (Hulten, 2001). Total factor productivity growth is the residual that is left when the effects of other factors that impact economic growth have been accounted for. This residual has been labelled the Solow residual, and has been called 'manna from heaven' because TFP growth boosts GDP growth without requiring the use of additional resources. A less favourable labelling of the Solow residual is as a 'measure of our ignorance' (Abramovitz, 1956, p. 11). TFP growth has been depicted as a rough proxy of technical change (Solow, 1957); a measure of changes in production technology or technical progress (Pena-Lopez, 2008); a measure of productivity, efficiency and technological change, or unexplained growth (Dimelis & Dimopoulou, 2002); and changes in institutions and a backwash of armed conflicts (Baier, Dwyer, & Tamura, 2006). TFP growth may also embody the effects on production of externalities, changes in the sectoral composition of production (Easterly & Levine, 2002), or the quality of institutional factors and management of the economy (Fischer, 1993). We simply take TFP growth as the share of economic growth that is not determined by changes in employment or physical capital utilised; we focus on the developments of TFP growth and do not seek to explain the factors behind these developments.

Numerous studies have reported results from growth accounting since the pioneering work of Abramovitz (1956) and Solow (1957). Rapacki and Prochniak (2009) provide a list of publications using growth accounting and which are published between 1994 and 2005. A key finding is that the level and dynamics of the estimated TFP growth vary considerably across countries and sample years, and this indeed underscores the need for such analyses for each case of interest. A number of studies provide results for a large number of countries.[3] Baier et al. (2006) consider 145 countries over 57 years and find that TFP growth makes an unimportant contribution to average output growth. TFP growth is on average only 0.13% per year and amounts to approximately 8% of the growth in total output per worker. TFP growth in Western European countries and in Newly Industrialised Countries contributes

18–25% of overall growth, while countries in Central and Eastern European, Central and Southern Africa, and the Middle East often exhibit negative TFP growth.

Dimelis and Dimopoulou (2002) decompose economic growth in the EU countries before and after the introduction of the Maastricht Treaty in 1992. The period 1981–1996 is divided into three sub-periods and TFP growth is found to have been the main source of growth in all three sub-periods. However, most of the EU countries experienced recessions at some point in 1986–1991 and TFP growth generally decelerated in those years. Though growth accounting studies are numerous, there are only a few that cover the CEE countries and then they typically only cover the catching-up phase before the global financial crisis. Vanags and Bems (2005) is an early study covering the three Baltic states and the years 1996–2003. The contribution of TFP growth is found to vary between 45 and 60% of total GDP growth. The authors conclude that the growth dynamics of the Baltic states in the early transition phase resembled those of major European countries during the Bretton Woods era but not those of the Asian tiger economies.

Arratibel et al. (2007) find that TFP growth contributed more to GDP growth than capital accumulation did during the catching-up process in the eight CEE countries that joined the EU in 2004. They argue however that the importance of accumulation might be underestimated given that investment may promote innovation and knowledge transfer. Iradian (2007) examines the contribution of capital, labour and TFP growth in the transition countries for the years 1996–2006. TFP growth accounted for 25–49% of overall growth in the CEE countries, which is a higher contribution from TFP growth than is often found in fast growing economies. Rapacki and Prochniak (2009) consider 27 transition economies in Europe for the years 1990–2003. They calculate the capital stock series using the perpetual inventory method, but the initial capital stock is determined simply by setting the capital–output ratio at either 3 or 5. The Baltic states had the fastest rates of TFP growth among the CEE countries in the sample while the Czech Republic and Hungary had the lowest rates.

The only study to include the crisis period and its immediate aftermath is Dombi (2013a). The study provides growth accounting results for 10 CEE countries in 1996–2012.[4] The main source of economic growth is found to be capital accumulation, which is probably due to the low capital intensity and comparatively low TFP growth in the beginning of the sample. The results are different however for the catching-up years 1996–2007 and the crisis years 2008–2012. Dombi (2013a) also finds notable differences between a group consisting of the Visegrad countries and Slovenia and a group of lesser-developed countries consisting of Bulgaria, Romania and the Baltic states.

This article contributes to the literature on growth accounting for the CEE countries in several ways. First, it extends the sample of earlier studies to the years 1996–2016, providing an extended period with one or two full business cycles in most of the countries. Second, the long sample affords a detailed analysis of the contributions of capital and TFP growth before, during and after the global financial crisis. Third, the capital stock is computed using the perpetual inventory method as is customary in the literature, but the data are filtered to remove cyclical components. Fourth, the analysis takes into account the utilisation of the capital stock by using data on capacity utilisation in manufacturing. Finally, the article contains numerous robustness checks and sensitivity analyses, including simulation studies, providing important insights into the importance of various assumptions.

The rest of the article is organised as follows. Section 2 describes the methodology of growth accounting, including the challenges that the perpetual inventory method raises.

Section 3 discusses the data sources and model parameters used. Section 4 presents the baseline results using the full time sample and various sub-samples. Section 5 provides the results of various robustness checks, including simulation exercises. Conclusions are presented in the final section.

2. Methodology

The starting point for all growth accounting studies is a hypothesised aggregate production function (Abramovitz, 1956; Solow, 1957). We prefer the rather general specification $Y_t = A_t F_t(h_t K_t, L_t)$. The variable Y_t is output or value added in period t. The variable K_t is the economy-wide capital stock available at the beginning of period t, while $h_t \in (0, 1)$ is the rate of capital utilisation in period t so $h_t K_t$ is the capital actually utilised for the production of Y_t. The variable L_t is employment, $F_t(.)$ is an aggregator function and A_t is a factor scaling the aggregator typically interpreted as total factor productivity (TFP). If the production function is time differenced and perfect competition and constant returns to scale are assumed, the growth rate of output can be written as:

$$\frac{\Delta Y_t}{Y_{t-1}} \approx (1-\alpha_t^K)\frac{\Delta L_t}{L_{t-1}} + \alpha_t^K \frac{\Delta K_t}{K_{t-1}} + \alpha_t^K \frac{\Delta h_t}{h_{t-1}} + \frac{\Delta A_t}{A_{t-1}} \tag{1}$$

The operator Δ denotes the first difference. The term α_t^K is the elasticity of output to capital utilised in period t; it is assumed to be time-varying, reflecting that the aggregator function $F_t(.)$ can vary over time. Notice that we do not impose the assumption of the aggregator function $F_t(h_t K_t, L_t)$ being a Cobb–Douglas function. This is indeed the reason for the elasticity α_t^K being allowed to vary over time.

Equation (1) decomposes output growth into components stemming from growth in employment, growth in available capital, growth in capital utilisation and, finally, the Solow residual or TFP growth, $\Delta A_t/A_{t-1}$. Data on output and employment are readily available, but data on the available capital stock, capital utilisation and elasticity of output to capital must be computed.

2.1. The capital stock

Existing data on the capital stock for the CEE countries are generally subject to some concern as there are many missing observations while the dynamics do not appear reasonable for many of the countries (see Subsection 4.1). This applies to data from Eurostat (2017) and Ameco (2017), the macroeconomic database of the European Commission. The key endeavour is thus to produce reliable estimates of the available capital stock. Most studies in the literature use the perpetual inventory method, which computes the capital stock as the sum of past investments net of depreciation. The starting point is the capital accumulation equation according to which the capital stock K_t in the beginning of period t can be written as:

$$K_t = K_{t-1} - \delta K_{t-1} + I_{t-1} \tag{2}$$

The variable I_{t-1} is the investment in period t–1. It is assumed that a fixed fraction $\delta \in (0, 1)$ of the capital stock is worn out or depreciated every period, so δK_{t-1} is the capital depreciation in period t–1. Iterating Equation (2) gives the capital stock as a weighted infinite sum of all historical investment rates:

$$K_t = \sum_{i=1}^{\infty} (1-\delta)^i I_{t-1-i} \tag{3}$$

Investments are evidently not known for an infinite number of periods. If, however, the capital stock can be calculated for one particular period, then the capital stock series for the entire sample period can be computed by forward or backward iteration of Equation (1). The known capital stock serves essentially as an 'anchor' for the whole capital series and we therefore label it the anchor capital stock and the corresponding period the anchor period.

Most growth accounting studies use the first year of the sample as the anchor year. This choice reduces the importance of the estimate of the anchor capital stock for the estimates of the capital stock for the later parts of the sample. Given the extreme volatility in the CEE countries in the beginning of the sample, we believe that it is not suitable to use 1995 or 1996 as the anchor year but prefer instead to use a later year when the transition process was largely complete and all of the CEE countries had relative stable environments with positive rates of economic growth.

This discussion raises the issue of how to find an estimate of the anchor capital stock given that no reliable capital stock data are available.[5] Using Equation (2) it is straightforward to show that the growth rate of the capital stock is $\Delta K_t/K_{t-1} = I_{t-1}/K_{t-1} - \delta$. If the economy is in a steady state in the anchor period T, then the capital stock grows at a constant rate, $\tilde{g}_K$. The investment in the anchor period T is labelled $\tilde{I}_T$, where the tilde indicates that it is the steady-state investment for the anchor period, not necessarily the actual investment in the period. The capital stock in the anchor period, $\tilde{K}_T$, is then:

$$\tilde{K}_T = \frac{\tilde{I}_T}{\tilde{g}_K + \delta} \tag{4}$$

It follows from Equation (4) that to compute the anchor capital stock we need measures of the steady-state investment $\tilde{I}_T$ in the anchor period, the steady-state growth rate of capital $\tilde{g}_K$ and the depreciation rate δ.

The investment $\tilde{I}_T$ in steady state is time dependent and this underscores the importance of choosing the anchor year carefully so that the economy can reasonably be considered to be in a steady state in the year chosen. The actual investment in the chosen anchor year will in any case be affected by various shocks and these need to be eliminated.

The steady-state growth rate of capital, $\tilde{g}_K$, can be computed in various ways. One option is to use the growth rate of investment (Berlemann & Wesselhöft, 2014; de la Fuente & Doménech, 2006; OECD, 2009), while another option is to use the growth rate of output since the growth rates of the capital stock and output are identical in steady state (Harberger, 1988). It may be necessary to remove the effects of various shocks to the growth rate of investment or output. The steady-state growth rate of capital can for instance be found by HP-filtering or averaging the growth rate of investment or output. Alternatively it can be found by regressing the log investment on time (Berlemann & Wesselhöft, 2014).[6]

The depreciation rate δ is of key importance both for the capital stock in the anchor period and for computing the capital stock from period to period, cf. Equation (2). It is customary in the literature to assume that the depreciation rate is constant over time and typically also across countries. We follow the same approach, partly to ensure that any differences in the results across countries do not arise from different depreciation rates being used. An arguably superior way of estimating the depreciation rate would be to use a weighted average using the shares of different types of capital stock as weights. In practice this is not feasible due to data availability issues.

2.2. Capital utilisation

Solow (1957) stressed that it is capital in use that enters the production function, not capital in place. The estimates of TFP growth will incorporate changes in capacity utilisation if the capital stock is not adjusted to match changes in the utilisation of it (Mourre, 2009). Leaving out the utilisation of the capital stock would typically lead to TFP growth being underestimated during downturns when capital is left idle, and overestimated during booms when capital utilisation is high.

It is particularly important to account for the utilisation of capital in the CEE countries for two reasons. First, during the transition process in the 1990s the CEE countries experienced structural reforms and large declines in output. This created dead capital, or structurally unused capital, that was left over from the era of central planning and which was unusable under the new market economic conditions (Bah & Brada, 2009; Campos & Coricelli, 2002; Izyumov & Vahaly, 2008). Estimates of dead or unused capital in the transition economies differ a lot across various studies.[7] Second, the CEE countries have had unusually large business cycles throughout the sample years resulting in downturns with notable underutilisation of the installed capital stock. This was for instance prevalent after the global financial crisis when many of the countries experienced deep recessions.

A key question is how the rate of utilisation of the capital stock can be measured and incorporated into growth accounting. Solow (1957) uses the unemployment rate to estimate the utilisation of capital, arguing that labour and capital may more or less be utilised to the same degree. He admits that this is not the best proxy for capital in use, but it does to some extent take account of cyclical movements in the economy.

Izyumov and Vahaly (2008) argue that it is possible to account for the weak capacity utilisation in the early transition period by applying a higher rate of depreciation during this period. This method is however only applicable in the early transition period in the 1990s and not in later periods. Moreover, some CEE countries saw very large output declines after the transition while others saw smaller declines so there is no reason to expect that the same higher depreciation rate would apply for all CEE countries (Brada, 1989).

We believe the most appropriate approximation is obtained by using the capacity utilisation in manufacturing as a proxy for the utilisation of capital in the entire economy, effectively assuming that capital is utilised in other sectors of the economy at the same rate as in manufacturing. The same approach is used in Kuboniwa (2011).[8] An advantage of using capacity utilisation as a proxy for the economy-wide utilisation of capital is that it can account both for idle or dead capital that is due to the transition process, and for idle capital that is due to standard business cycles.

The utilisation of capital may be incorporated in growth accounting either by adjustment of the capital stock series using data on capacity utilisation, or by inclusion of changes in capacity utilisation as a separate factor. This article uses the second approach and thus obtains a separate estimate for the importance of changes in the utilisation of the available capital stock.

2.3. The elasticity of output to capital

The elasticity of output to capital is another key variable in the decomposition. The variable is not directly observable but the assumptions of constant returns to scale and competitive markets mean that the elasticity of output to capital, α_t^K, is equal to the share of capital income in total income or, alternatively, to one minus the estimate of the share of labour income in total income.

Estimating the elasticity from the income shares can lead to biased estimates if the assumptions are not satisfied. This may for instance be the case if spillovers of capital or other sources of increasing returns to scale are quantitatively important (Barro, 1998). Caselli and Feyrer (2007) note that capital income includes not only the returns to reproducible capital, but also the returns to non-reproducible capital such as land and natural resources. The perpetual inventory method implies that the capital stock is computed using investment flows that represent only the reproducible capital stock, and so standard measures of the elasticity of output to capital may lead to the marginal productivity of reproducible capital being overestimated.

Some growth accounting studies compute the elasticity of output to capital using annual data on income shares, with the result that the elasticity is time-varying. This is the approach followed in this article. Other studies use averages over longer periods, implying that the elasticity is constant over time. A typical estimate of the elasticities is 0.33 for capital and 0.67 for labour (Romer, 2001, ch. 1).[9]

3. Data and modelling choices

The sample consists of 11 CEE countries: Bulgaria, the Czech Republic, Estonia, Croatia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia and Slovenia. For comparison we also include aggregate data for the EU15, the Western European EU members with relatively high levels of per capita income. The data cover the years 1995–2016, so growth rates can be computed for the years 1996–2016.

If not mentioned otherwise, the data source is Eurostat. The gross domestic product, gross value-added, gross fixed capital formation (investments) and compensation to employees are from the ESA2010 national accounts (code: *nama_10_gdp*). Since ESA2010 data are not available for some countries for the whole sample, we impute some observations using the growth rates for the ESA95 definitions of the same variables (codes: *nama_gdp_c*, *nama_gdp_k*).[10] The data for the total number of employees and people employed follow the domestic employment concept in the ESA2010 national accounts (code: *nama_10_pe*). However, some observations are missing and these have been imputed using the growth rates for employment according to the ESA2010 national concept or the ESA95 domestic concept (code: *nama_aux_pem*).[11]

3.1. Anchor capital stock

The anchor capital stock is calculated from Equation (4) using 2003 as the anchor year. The year 2003 is chosen because it occurs in the short interval after the transition process was largely completed in the CEE countries and before the countries were to experience the exceptional booms that preceded the global financial crisis and the subsequent downturns. The year 2003 was indeed a year in which the output gap was small or non-existent in all of the sample countries.

The actual investment variable may be affected by the business cycle or other shocks, so to compute the investment in the anchor year, $\tilde{I}_T$, we smooth the actual investment and GDP series, both in logs, using a Hodrick–Prescott filter with λ=100. Next we compute the investment-to-GDP ratio using the smoothed series and then take the average over the years 2001–2005. Finally, to get the steady-state level of investment in 2003, we multiply the average smoothed investment-to-GDP ratio by the smoothed GDP in 2003. As discussed in Subsection 3.1 we proxy the steady-state growth rate of the capital stock with the growth rate of GDP, since that exhibits less volatility than the growth rate of investment and may be less susceptible to catching-up effects.

The steady-state growth rate of the capital stock, $\tilde{g}_K$, is proxied by the smoothed growth rate using an HP filter with $\lambda = 100$. However, we do not use the filtered growth rate directly, but calculate a five year average growth rate that includes the filtered growth rate from two years before and two years after the anchor year. The averaging is meant to eliminate possible cyclical effects which the filtered growth rate may contain and which could distort the results.

The depreciation rate is taken to be constant over time and equal to 0.05 for the 11 CEE countries and the EU15. The same depreciation rate is used by de la Fuente and Doménech (2006) and it is within the range between 0.04 and 0.10 used in the literature.[12]

3.2. Capital utilisation

In the baseline computations the rate of capital utilisation is proxied by the rate of capacity utilisation in manufacturing (codes: *BS_ICU_PC*, *ei_bsin_q_r2*). The quarterly data are annualised by taking averages. Data for capacity utilisation for the EU15 are computed as the capacity utilisation in each of the countries weighted for the relative size of the economy. No data are available for Ireland so the country does not enter the calculations; this should be inconsequential given the size of the Irish economy. The data on the capacity utilisation of Austria and Sweden for 1995 are also missing, so these countries are not included in the average capacity utilisation for the EU15 for that year.

For the CEE countries there are no data on capacity utilisation for Croatia in 1995–2008, for Hungary in 1995 and for Romania in 1995–2000. To avoid losing these observations, we predict the rate of capital utilisation using information on the dynamics of output growth in these countries. This is done by regressing the change in the rate of capacity utilisation on relative output growth using panel data estimations for the 11 CEE countries in the sample. The estimated relationship is then used to predict the missing observations for the rate of capacity utilisation.[13]

3.3. Elasticity of output to capital

The time-varying elasticity of output to capital, α_t^K, is computed as one minus the share of labour income in total income. We calculate the labour elasticity by dividing the total labour income by gross value added, which is the difference between GDP and net product taxes. Total labour income is equal to compensation to employees and the income of the self-employed. We assume that the income of the self-employed is equal to the pay of employees so that total labour income is compensation per employee times total employment. Due to a lack of data for some countries we use the closest observation available to calculate α_t^K.[14]

The capital elasticities computed vary over time and countries. The average is 0.41 for the 11 CEE countries and 0.37 for the EU15. The lowest share of capital is 0.16 in Romania, while the highest figure is 0.54 in Slovakia. These results are within the range of findings in Mankiw, Romer, and Weil (1990).

4. Baseline results

We use the methodology set out in Section 2 and the assumptions in Section 3 to compute baseline series for the stock of available capital. For comparison across countries it is useful to consider the capital–output ratio, here computed as the real capital stock relative to real output. Figure A.1 in Appendix 1 shows the capital–output ratio of the capital stock series for each of the 11 CEE countries and the EU15 along with the available capital–output ratios from Eurostat and Ameco.

We find capital–output ratios that are typically higher than those in Ameco and lower than those in Eurostat, when data from Eurostat are available. The differences between our results and the Ameco data are very small for the EU15 suggesting that the computation method is inconsequential for this country group. Our estimate of the capital–output ratio for Poland is also close to the estimates from Eurostat and Ameco. There are however very large differences for Latvia but this is unsurprising given that the ratios from Eurostat and Ameco both appear unreasonable. The differences are also noticeable for the Czech Republic, Hungary, Slovenia and Slovakia, the most developed CEE countries in the mid-1990s. In conclusion, the capital series computed in this article result in capital–output ratio that appear reasonable when compared across countries and over time.

4.1. Full sample

Table 1 presents the baseline results for the full sample 1996–2016. The table exhibits the average annual GDP growth over the period and the average annual contributions from changes in employment, capital utilisation, capital and TFP. Evidently, the average contributions sum to the average output growth apart from deviations due to rounding.

The average output growth varies from 2.1 to 4.3% in the CEE countries, while it is 1.6% for the EU15. The fastest growing countries, which are the Baltic states, Poland and Slovakia, exhibit contributions from the growth of capital of 1.7–2.4 percentage points and from the growth of TFP of 1.0–1.8 percentage points. The contribution from the growth in capital utilisation is noticeably higher in the Baltic states than in Poland and Slovakia. This is consistent with the transitional recessions being much deeper in the Baltic states than in the more developed CEE countries such as Poland or Slovakia.

Table 1. Decomposition of output growth, 1996–2016.

	Output growth	Contributions			
		Employment	Capital	Utilisation	TFP
EU15	1.60	0.51	0.59	0.00	0.50
Bulgaria	2.37	−0.04	1.26	0.49	0.67
Czech Rep.	2.46	0.09	1.49	0.25	0.63
Estonia	4.08	−0.06	1.67	0.70	1.77
Croatia	2.05	0.33	0.67	0.40	0.65
Latvia	4.13	−0.12	1.86	1.09	1.30
Lithuania	4.31	−0.22	2.00	1.30	1.24
Hungary	2.24	0.25	0.99	0.12	0.89
Poland	3.99	0.20	1.80	0.19	1.80
Romania	2.87	−0.96	1.43	−0.05	2.45
Slovenia	2.55	0.12	0.74	0.47	1.22
Slovakia	3.96	0.22	2.36	0.42	0.96
CEE average	3.18	−0.02	1.48	0.45	1.27

Notes: All values are annual averages for 1996–2016. Output growth is average annual growth in percent. The annual contributions of employment, utilisation, capital and TFP are denominated in percentage points. The sum of the contributions may not add up to output growth due to rounding. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

The contributions of labour, capital and TFP are effectively equal in the EU15, with the contribution from capital utilisation being zero, but the contribution of labour in the CEE countries is negligibly small with the sole exception of Romania where the relative contribution of labour is negative due to a diminishing labour force.

In contrast to Dombi (2013a), we do not find capital accumulation to have been the main source of economic growth in the period as a whole. Our findings indicate it to have been so only for the Czech Republic and Slovakia, where the contribution from capital growth is more than one half of average output growth. If the contribution of capital utilisation is added to that of capital, then the number of countries with substantial physical capital growth of greater than 50% of output growth is six out of eleven countries. This suggests that the growth of physical capital played an important role during the period being examined, but it was not the main source of growth. Indeed, in line with Arratibel et al. (2007) our results show that the contribution of TFP growth was quite significant in all the sample countries, varying between 0.63 and 2.45 percentage points, which corresponds to between 26 and 85% of the contribution, with a mean of 1.25 percentage points or 39%.

4.2. Sub-periods

The CEE countries experienced pronounced boom–bust cycles and large changes in annual GDP growth over the sample years. These features make it pertinent to repeat the growth decomposition for various sub-samples. We consider four sub-periods; the years 1996–2001 are the late transition period, the years 2002–2007 are the pre-crisis period when most CEE countries experienced economic booms, 2008–2009 are the years in which the global financial crisis affected the CEE countries, and the years 2010–2016 are the post-crisis recovery period.

Table 2 reports the growth accounting results for the late transition period. During this stage, almost all the sample countries show relatively high output growth, with Bulgaria and Romania lagging behind. There are generally large contributions from TFP growth, with the Czech Republic and Slovakia as exceptions. High TFP growth during these years of the

Table 2. Decomposition of output growth, 1996–2001.

		Contributions			
	Output growth	Employment	Capital	Utilisation	TFP
EU15	2.76	0.93	0.61	−0.04	1.25
Bulgaria	−0.66	−0.81	−0.49	−0.36	1.00
Czech Rep.	2.01	−0.43	1.65	0.77	0.01
Estonia	6.21	−0.70	0.74	1.85	4.33
Croatia	3.44	−0.47	0.28	0.46	3.17
Latvia	5.39	0.11	0.57	1.84	2.87
Lithuania	5.02	−0.88	1.26	2.47	2.18
Hungary	3.12	0.54	0.80	0.29	1.49
Poland	4.60	−0.42	1.50	−0.68	4.20
Romania	0.76	−1.05	0.46	−0.35	1.69
Slovenia	4.05	−0.05	0.72	1.39	1.99
Slovakia	3.53	−0.28	3.21	1.18	−0.58
CEE average	3.41	−0.40	0.97	0.75	2.09

Notes: All values are annual averages for 1996–2001. Output growth is average annual growth in percent. The annual contributions of employment, utilisation, capital and TFP are denominated in percentage points. The sum of the contributions may not add up to output growth due to rounding. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

catching-up period may be related to the transition process as new production technologies were introduced and better managerial practices were applied (Arratibel et al., 2007, p. 11).

Very high contributions from TFP are recorded in the Baltics, primarily in Estonia, but they are also seen in Croatia and Poland and to a lesser extent in Hungary, Romania and Slovenia.[15] Romania takes a special position as the economy was growing slowly while TFP growth was relatively high. Growth in employment is negative in the majority of the CEE countries during the first sub-period. The average contribution of capital growth is roughly one third, while the average contribution of capital utilisation is one fifth. Nevertheless, the total of the contributions of growth in the capital stock and in the rate of utilisation is on average less than the contribution of TFP growth during this sub-period.

Table 3 presents the results of the growth accounting for the pre-crisis years 2002–2007. Average growth in the CEE countries is almost double what it was in the previous sub-period as is the contribution of growth in physical capital. The contribution of employment growth was positive in almost all the sample countries. The TFP contribution was also notable and in this sub-period it again exceeds both the capital contribution and the overall capital contribution which takes account of capacity utilisation. The quite strong growth in physical capital not only in the CEE countries but also in the EU15 is also worthy of note.

Table 4 shows the growth accounting results for the crisis years 2008–2009. The output performance during the crisis varied markedly across the 11 CEE countries. The contribution from capital accumulation is still high during these two years, but the contribution of capacity utilisation is negative in all the CEE countries. The contribution of TFP to output growth varies from −4.83 percentage points in Estonia to 2.88 percentage points in Slovakia, indicating different dynamics during the crisis. The Baltic states saw very large declines in GDP stemming from large declines in employment, utilisation and TFP growth, while capital continued to contribute positively to GDP growth. Poland exhibited relatively rapid economic growth during the crisis years 2008–2009 and, notably, this was accompanied by substantial positive TFP growth.

Dimelis and Dimopoulou (2002) find that the slowdown experienced by the majority of the EU15 countries during the recession in Western Europe in the early 1990s was due mostly

Table 3. Decomposition of output growth, 2002–2007.

		Contributions			
	Output growth	Employment	Capital	Utilisation	TFP
EU15	2.10	0.66	0.74	0.15	0.55
Bulgaria	6.48	1.35	2.08	2.10	0.95
Czech Rep.	4.84	0.43	1.55	0.40	2.46
Estonia	7.86	0.82	2.78	0.48	3.79
Croatia	4.83	2.37	1.07	0.71	0.69
Latvia	9.40	1.13	3.20	1.27	3.80
Lithuania	8.35	0.65	2.58	1.49	3.62
Hungary	3.67	−0.08	1.35	0.23	2.17
Poland	4.57	0.58	1.43	1.22	1.34
Romania	6.36	−1.39	1.33	0.50	5.91
Slovenia	4.61	0.68	1.09	0.30	2.53
Slovakia	6.87	0.53	2.31	0.25	3.78
CEE average	6.17	0.64	1.89	0.75	2.88

Notes: All values are annual averages for 2002–2007. Output growth is average annual growth in percent. The annual contributions of employment, utilisation, capital and TFP are denominated in percentage points. The sum of the contributions may not add up to output growth due to rounding. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

Table 4. Decomposition of output growth, 2008–2009.

		Contributions			
	Output growth	Employment	Capital	Utilisation	TFP
EU15	−2.14	−0.30	0.83	−2.72	0.04
Bulgaria	1.22	0.16	3.91	−3.00	0.15
Czech Rep.	−1.07	0.10	2.06	−3.45	0.23
Estonia	−10.07	−3.30	2.92	−4.86	−4.83
Croatia	−2.67	1.08	1.40	−0.92	−4.23
Latvia	−8.97	−4.47	3.96	−5.48	−2.98
Lithuania	−6.09	−2.52	3.98	−3.76	−3.81
Hungary	−2.84	−1.30	1.36	−3.19	0.30
Poland	3.53	1.19	2.62	−2.04	1.77
Romania	0.70	−0.61	4.18	−2.75	−0.13
Slovenia	−2.25	0.23	1.44	−2.51	−1.40
Slovakia	0.10	0.26	2.78	−5.81	2.88
CEE average	−2.58	−0.83	2.78	−3.45	−1.08

Notes: All values are annual averages for 2008–2009. Output growth is average annual growth in percent. The annual contributions of employment, utilisation, capital and TFP are denominated in percentage points. The sum of the contributions may not add up to output growth due to rounding. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

to declining contributions from capital and labour. Our results for the crisis period in the CEE countries are consistent with this finding if capital is adjusted for capacity utilisation. However, we also find very large negative TFP contributions in some of the countries most affected by the crisis.

Table 5 shows that output growth was slower in the post-crisis period than it was before the crisis. The distinctive result from the growth decomposition in this sub-period is that growth in all the countries in the sample is largely due to the accumulation of capital stock and a growing rate of capital utilisation. Bulgaria, Poland, Romania and Slovenia are the only countries with positive, though quite small, contributions from TFP growth.

Table 5. Decomposition of output growth 2010–2016.

	Output growth	Contributions			
		Employment	Capital	Utilisation	TFP
EU15	1.25	0.25	0.37	0.68	−0.04
Bulgaria	1.79	−0.62	1.30	0.83	0.28
Czech Rep.	1.81	0.24	1.15	0.72	−0.29
Estonia	3.06	0.68	1.15	1.50	−0.27
Croatia	−0.16	−0.96	0.47	0.47	−0.14
Latvia	2.29	−0.14	1.22	2.16	−0.96
Lithuania	3.23	0.26	1.55	1.57	−0.16
Hungary	1.73	0.74	0.73	0.82	−0.56
Poland	3.10	0.13	2.12	0.68	0.16
Romania	2.32	−0.60	1.57	0.49	0.87
Slovenia	0.86	−0.24	0.25	0.67	0.18
Slovakia	2.96	0.38	1.55	1.71	−0.68
CEE average	2.09	−0.01	1.19	1.06	−0.14

Notes: All values are annual averages for 2010–2016. Output growth is average annual growth in percent. The annual contributions of employment, utilisation, capital and TFP are denominated in percentage points. The sum of the contributions may not add up to output growth due to rounding. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

4.3. Annual data

The business cycle affects the results substantially and it may therefore be instructive to consider the growth accounting results for each year separately. Figure 1 shows the contribution from TFP growth for the 11 CEE countries and the EU15 for each year from 1996 to 2016. It is notable that changes in capital utilisation are included separately suggesting that the TFP estimates do not include changes in capital utilisation stemming from the business cycle.

The rate of TFP growth is generally higher in the CEE countries than in the EU15, but it is also much more volatile. The larger volatility is particularly pronounced around the global financial crisis but it also appears in individual years elsewhere. Negative rates of TFP growth often coincide with economic and financial crises like the inflation crisis in Bulgaria in 1996, the exchange rate crisis in the Czech Republic in 1997 and the deep downturn in Slovakia in the late 1990s. Positive TFP growth rates are prevalent in the years before the global financial crisis. A part of these annual changes in TFP growth may be explained by the swift and substantial sectoral changes as shown in Kuusk, Staehr, and Varblane (2017).

5. Robustness analyses

The calculation method and parametrisation of the baseline computations in Section 4 largely follow those used in the literature while taking into account the particularly volatile economic environment in the CEE countries. This section shows the sensitivity of the results by, first, changing the calculation methods and assumptions individually and, then, by simulating the distribution of the contribution of TFP growth to economic growth using various distributional assumptions.

5.1. Changing assumptions

The robustness check involves changing the key assumptions and parameters of the model to assess the sensitivity of the results to these changes. The TFP growth contributions of the

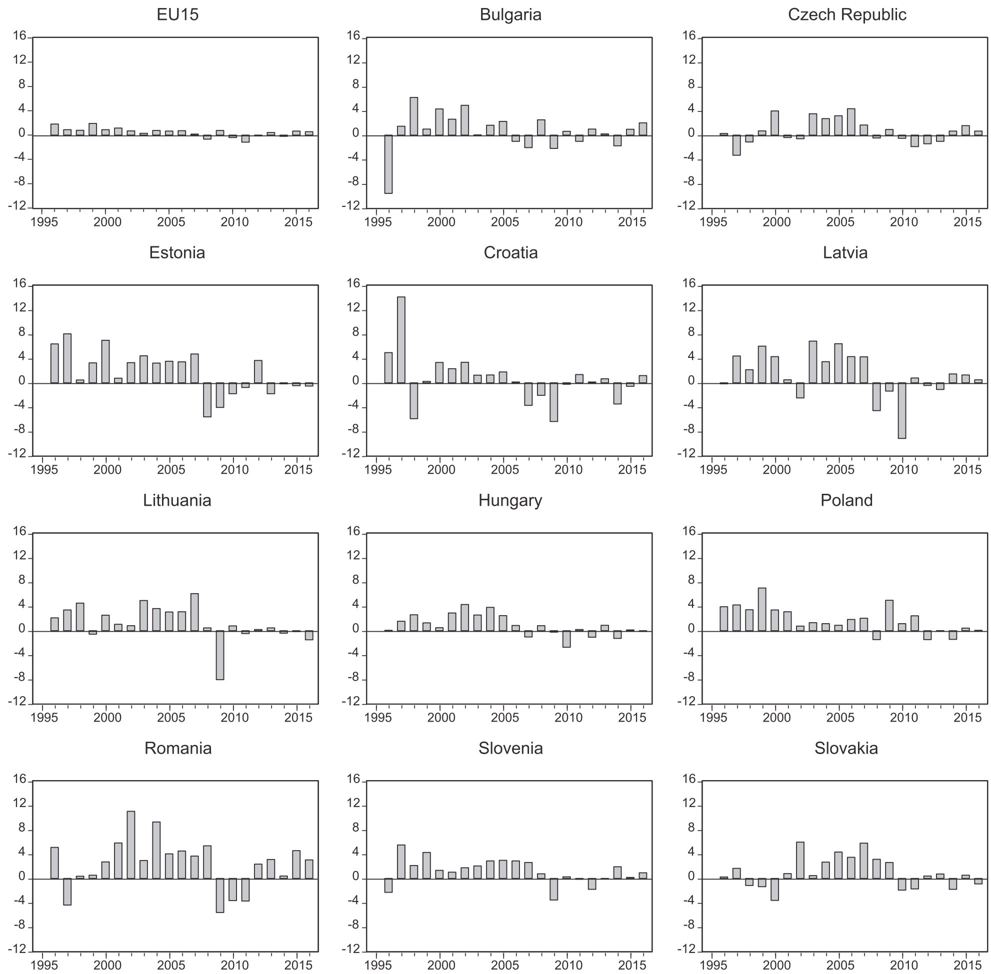

Figure 1. Contribution of TFP growth to output growth in 11 CEE countries and the EU15. Source: Authors' calculations, see text.

baseline and under various assumptions are presented in Table 6 for the entire sample period 1996–2016 and in Table 7 for the post-crisis period 2010–2016.

The anchor year is the year for which the capital stock is computed using assumptions about the steady state; see Equation (4) in Subsection 2.1. Most studies use the first year as the anchor year but this study uses 2003 because economic conditions were relatively stable in the CEE countries at this time. We assess the sensitivity of the results using different anchor years. The results when the anchor year is 1998 and 2014 are reported in Tables 6 and 7; we cannot use earlier or later anchor years because the computation of the anchor capital stock uses a Hodrick–Prescott filter and subsequent averaging over five years. The contributions from TFP growth are generally somewhat smaller than in the baseline case when 1998 is chosen as the anchor year, while the contributions are larger when 2014 is the anchor year. The largest differences can be found for the Baltics and Bulgaria and to some extent for Croatia and Poland.

Table 6. Contribution from TFP growth, baseline and robustness checks, 1996–2016.

	(6.1)	(6.2)	(6.3)	(6.4)	(6.5)	(6.6)	(6.7)	(6.8)
	Baseline	Anchor year 1998	Anchor year 2014	Growth rate of invest.	Unempl. for cap. util.	Empl. in hours	Elasticity $\alpha^K = 0.33$	Deprec. rate $\delta = 0.08$
EU15	0.50	0.32	0.76	0.48	0.48	0.67	0.54	0.56
Bulgaria	0.67	−0.31	1.50	−2.80	..	0.76	1.07	0.92
Czech Rep.	0.63	0.84	1.45	0.60	0.88	0.75	1.17	0.68
Estonia	1.77	0.69	2.98	0.36	..	..	2.31	2.02
Croatia	1.02	0.52	2.01	0.20	..	..	0.98	1.18
Latvia	1.30	−0.02	2.72	−0.73	..	1.36	2.17	1.61
Lithuania	1.24	0.57	2.59	0.21	..	1.00	2.20	1.47
Hungary	0.92	0.57	1.45	0.64	..	1.25	1.10	1.03
Poland	1.80	1.74	2.69	1.57	..	..	2.16	1.78
Romania	2.45	2.30	3.26	0.99	..	2.46	2.65	2.57
Slovenia	1.22	0.97	1.40	1.08	..	1.35	0.99	1.32
Slovakia	0.96	1.54	1.01	1.87	..	1.11	1.86	0.91
CEE average	1.27	0.86	2.10	0.36	..	1.26	1.70	1.41

Notes: All values are annual averages for 1996–2016. The contribution of TFP growth is in percentage points. The symbol .. indicates that data for computation of the TFP growth are not available. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

Table 7. Contribution from TFP growth, baseline and robustness checks, 2010–2016.

	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)	(7.7)	(7.8)
	Baseline	Anchor year 1998	Anchor year 2014	Growth rate of invest.	Unempl. for cap. util.	Empl. in hours	Elasticity $\alpha^K = 0.33$	Deprec. rate $\delta = 0.08$
EU15	−0.04	−0.13	0.09	−0.05	0.64	0.29	0.05	0.08
Bulgaria	0.28	−0.12	0.77	−0.64	1.22	0.30	0.75	0.49
Czech Rep.	−0.29	−0.19	0.13	−0.30	0.23	−0.25	0.21	−0.15
Estonia	−0.27	−0.60	0.33	−0.68	0.74	−0.38	0.15	0.03
Croatia	−0.14	−0.35	0.50	−0.45	0.47	..	−0.30	0.06
Latvia	−0.96	−1.34	−0.26	−1.47	0.56	−0.78	0.04	−0.55
Lithuania	−0.16	−0.40	0.57	−0.50	0.92	−0.26	0.81	0.17
Hungary	−0.56	−0.73	−0.26	−0.70	−0.09	0.27	−0.33	−0.37
Poland	0.16	0.13	0.76	0.04	0.70	0.18	0.91	0.14
Romania	0.87	0.78	1.46	0.25	1.31	1.12	1.55	1.11
Slovenia	0.18	0.09	0.25	0.13	0.93	0.15	−0.02	0.41
Slovakia	−0.68	−0.46	−0.66	−0.31	0.83	−0.51	0.34	−0.48
CEE average	−0.14	−0.29	0.33	−0.42	0.71	−0.02	0.37	0.08

Notes: All values are annual averages for 2010–2016. The contribution of TFP growth is in percentage points. The symbol .. indicates that data for computation of the TFP growth are not available. The CEE average is the unweighted average for the 11 CEE countries.
Source: Authors' calculations, see text.

If the growth rate of output is replaced by the growth rate of investment in the formula for anchor capital as discussed in Subsection 2.1, the contribution from TFP growth for the full sample 1996–2016 is considerably smaller across all the countries except Slovakia, and it even becomes negative for two countries, Bulgaria and Latvia. These results are in large part due to the volatility of investment and the very high investment rates for some of the CEE countries. The differences are however much less pronounced in the last sub-period 2010–2016, as shown in Table 7.

The next robustness exercise follows Solow (1957) and uses the unemployment rate to compute capacity utilisation. The new measure is calculated as one minus average annual unemployment as a percentage of the labour force (code: *une_rt_a*). The unemployment rate for the EU15 is found using weights computed from the average population each year (code: *demo_gind*). However, as data for 1995–1999 are missing for all or some years for all the countries except the Czech Republic, we do not present the TFP numbers for the full sample but only for the post-crisis years 2010–2016. Using the unemployment rate to compute capacity utilisation gives considerably higher contributions from TFP growth than those found in the baseline estimations. Unemployment was more stable than the capacity utilisation in manufacturing used in the baseline computation so using the unemployment rate reduces the contribution of capital utilisation.

As an additional robustness check we use employment in hours instead of persons in employment (code: *demo_gind*). This measure of employment could be expected to be more precise.[16] The data are missing for Estonia and Poland for 1995–1999 and for Croatia for 1995–2007, and the TFP figures are therefore not reported for these countries for the full sample period. The results are very close to those of the baseline. The only noticeable differences are observed for the EU15 and for Hungary in the post-crisis period when the negative contributions from employment become positive.

As a further robustness check the country-specific and time-varying values of the share of capital in total income, α_t^K, are changed to a constant value of 0.33, which is a value commonly used in the growth accounting literature. This change increases the TFP contributions for all the countries except Slovenia, whose original average share of capital was 0.29.

Changing the depreciation rate δ from 5 to 8% does not change the results much. It increases the contributions from TFP growth a little as the computed level of the available physical capital is typically reduced.

To sum up, the sensitivity analyses in this subsection show that the results are reasonably robust to the specific modelling choices and parameterisations used. The key exception relates to assumptions about the computation of the anchor capital, in particular the anchor year chosen and the measure of the growth of capital in steady state. We believe that the choices of 2003 as the anchor year and the smoothed output growth rate as a proxy for the steady-state growth rate of the capital stock are appropriate given the very volatile environment of the CEE countries during the two decades considered.

5.2. Simulations

In practice several of the assumptions about modelling choices are highly uncertain and it might therefore be pertinent to consider the outcome of simulations in which it is assumed that various parameters follow distributions, not singular points. We run simulations to ascertain the distribution of the TFP contributions given selected assumptions for the depreciation rate and the anchor year, as these variables seem to matter a great deal for the results. We draw the depreciation rate from a normal distribution $N(0.05, 0.01)$. The anchor year is drawn from a set of years between and including 1998 and 2014, each having an equal probability of appearing as the anchor year. This is the largest sample that can be used in the robustness test, as the years before 1998 and after 2014 are lost due to smoothing of the equilibrium indicators. The anchor year and the depreciation rate are drawn independently.

The simulated distributions shown in Figures 2 and 3 visualise the uncertainty of the estimates of the contribution of TFP growth, taking into account the uncertainty around both the value of the depreciation rate and the anchor year. However, these distributions

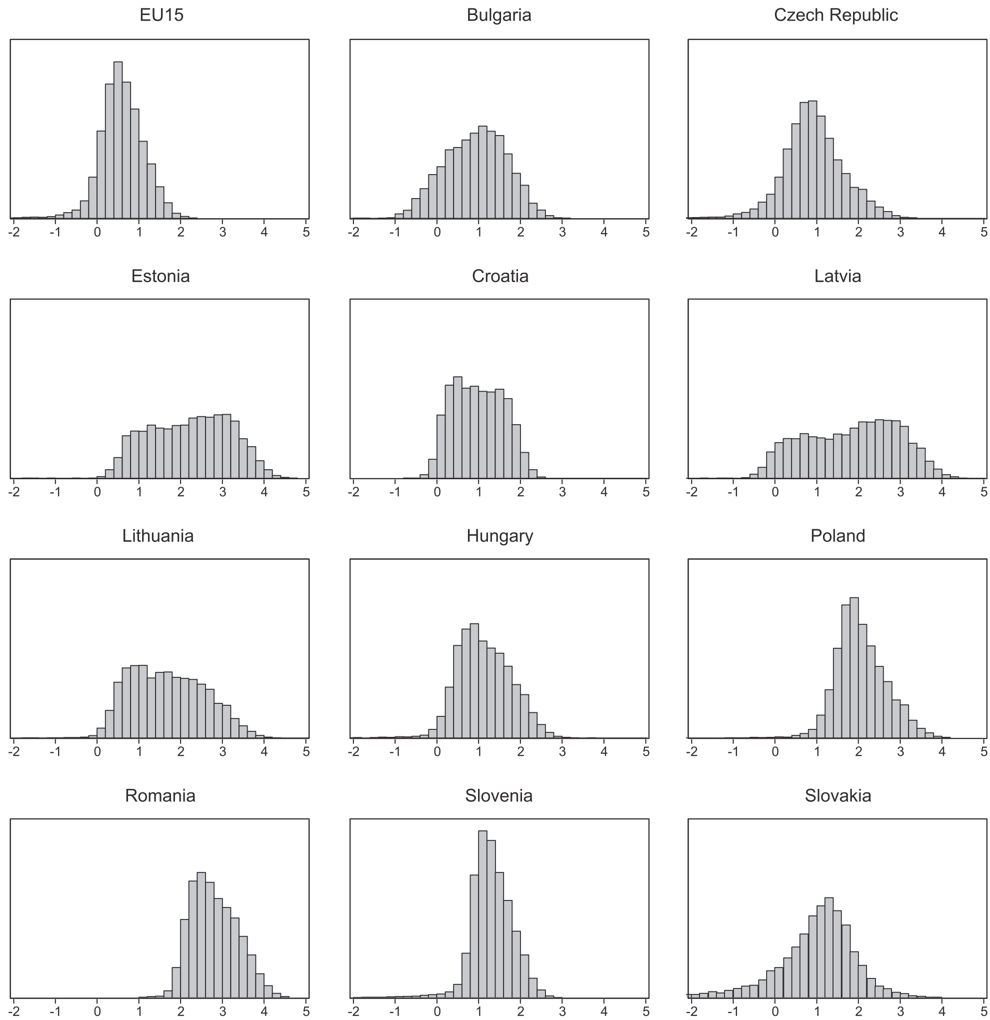

Figure 2. Simulated distribution of the contribution of TFP growth, 1996–2016. Source: Authors' calculations, see text.

cannot be interpreted as exact measures of estimation errors and confidence bands should not be derived from these distributions.

Figure 2 reveals that the simulated distributions of TFP contributions are flatter for most of the CEE countries than for the EU15. This is largely driven by the choice of the anchor year. The anchor year should matter less for countries and economic areas which are on their steady-state growth path. This is indeed the case for the EU15 and also Slovenia, which had a higher income level in the 1990s than the other CEE countries. The Baltic states, on the other hand, have quite flat simulated TFP contribution distributions, suggesting the estimates of the contribution of TFP growth to GDP growth in these countries are rather uncertain.

Figure 3 shows the distributions of the TFP contributions for the post-recession period. They vary less than those for the full sample because the relevance of the anchor year declines in time as the anchor capital stock depreciates. As for the full sample, the simulated

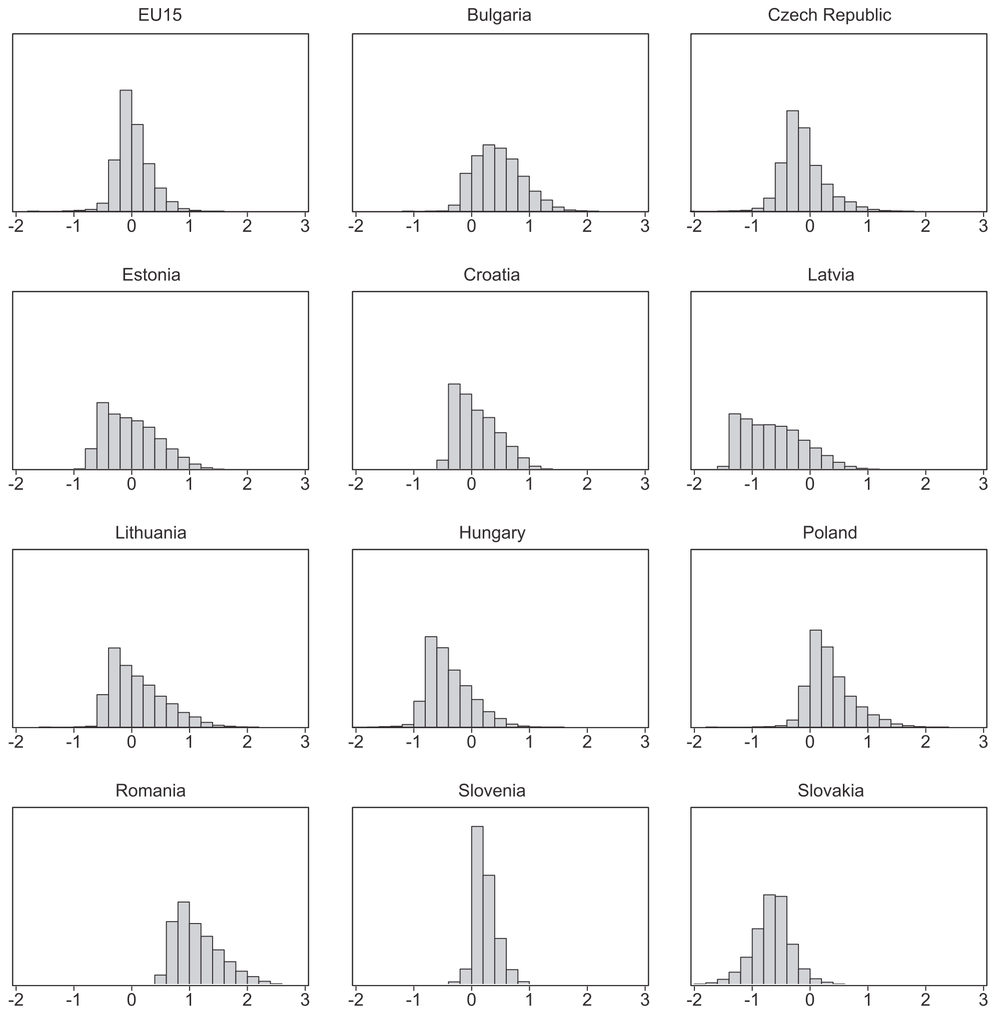

Figure 3. Simulated contributions of TFP growth, 2010–2016. Source: Authors' calculations, see text.

TFP contributions of the EU15 and Slovenia have narrower distributions than those in most CEE countries. For several of the countries the TFP contributions are not indisputably different from zero, but the masses of the distributions are still concentrated on either the positive or the negative side of the vertical axis. For most of the countries the mode of the distribution is on the negative side for the post-recession sub-sample, while for Bulgaria, Romania and Slovenia the mode of the TFP contribution is on the positive side. For Poland and the EU15 the mode of the simulated distribution is close to zero, as are the baseline results.

The simulation results presented in Figures 2 and 3 illustrate that estimations from growth accounting are necessarily associated with substantial uncertainty. This is a reminder that the results in Section 4 should be interpreted with some caution. The simulations however also revealed clear patterns or tendencies in the results and this is particularly the case for the post-crisis period.

6. Conclusion

This article decomposes GDP growth in the 11 CEE countries over the years 1996–2016. The exercise is complicated by the countries exhibiting highly unusual growth dynamics over the two decades due to the impact of transition and strong business cycles.

Official statistics do not provide reliable data on the capital stock as the computations typically use ad hoc estimates of the capital stock in the mid-1990s and these estimates are bound to be imprecise due to the on-going transition process at the time. We use the perpetual inventory method but anchor the capital stock in a year not affected by transition or an unusual business cycle. The choice of anchoring year is of substantial importance for the results. We also include the capital utilisation directly in the computations to ensure that a strong business cycle does not influence the results unduly. The results are generally robust to changes in modelling assumptions and parametrisations, especially for the later part of the sample.

For the full sample 1996–2016, average GDP growth was generally higher in the CEE countries than in the reference group of the 15 EU countries from Western Europe. On average capital deepening accounted for approximately half, TFP growth for approximately one third, and increased utilisation of capital for the remaining one sixth of GDP growth, while changes in employment did not matter much. These results are however averages; there is indeed substantial variation over time and across the countries. During the boom in 2002–2007, TFP growth accounted for approximately half of GDP growth and capital deepening for around one third, while higher employment and capital utilisation accounted for the rest. There is substantial heterogeneity across the countries. Slovakia and the Baltic states stand out for very high rates of economic growth and large contributions from TFP growth, while economic growth in Poland, Hungary, the Czech Republic and Slovenia was less brisk and TFP growth was less important in at least some of these countries. This somewhat heterogeneous pattern across the CEE countries is also noticed in Dombi (2013a, 2013b).

The substantial contribution of TFP growth during the boom may be seen to set the CEE countries apart from the experiences of the newly industrialised countries (NIC) in Southeast Asia during the boom preceding the 1997–1998 Asian crisis. Young (1995) found that the NICs had exceptionally high ratios of investment to GDP, implying that capital deepening was thus the predominant source of economic growth while TFP growth was of little importance. Krugman (1994) indeed argued that the financing of the capital accumulation could threaten financial stability, a conjecture that proved accurate. TFP growth was an important contributor to GDP growth in the CEE countries, suggesting that the causes of the crisis in CEE countries differed from those of the NIC countries.

Developments differed markedly across the CEE countries during the global financial crisis in 2008–2009. The Baltic states experienced very large output declines, while Poland and to a lesser extent Bulgaria, Romania and Slovakia weathered the crisis without a substantial loss of output. It is notable that the capital stock continued to grow at a brisk rate in all CEE countries during the crisis years, but the rate of utilisation of the capital stock decreased markedly. This shows the importance of taking capital utilisation into account in growth accounting as the TFP contribution will otherwise be underestimated during downturns like those experienced by many CEE countries after the global financial crisis (Fernald, 2014; Fernald & Matoba, 2009).

Economic growth has been subdued in the CEE countries since the global financial crisis. The growth accounting analysis presented here reveals that capital deepening and increased capital utilisation have contributed in equal proportions to economic growth, while TFP growth has been virtually absent in most CEE countries in this period. The lack of TFP growth is holding back the catching-up process and casts doubt on the ability of these countries to sustain growth without increased use of resources (Vuegelers, 2011). The modest TFP growth and its causes in the CEE countries after the global financial crisis are areas that warrant further analysis and research.

Notes

1. The data series are available from the corresponding author upon request.
2. A related discussion emerged in the USA after Summers (2013) asked whether the USA was caught in secular stagnation after the crisis.
3. Maddison (2007) and Summers and Heston (1991) report data on TFP growth for a very large number of countries but do not explicitly state the method and assumptions used.
4. Dombi (2013b) covers the period 1996–2007 but provides more detailed documentation of the method and data used.
5. Besides the perpetual inventory method two alternative methods have been used for calculating the initial or anchor capital stock. One is to compute the capital–output ratio in the first year from, for instance, the capital–output ratio in the last observable years or from the labour–output ratio in the first years (Berlemann & Wesselhöft, 2014; Nehru & Dhareshwar, 1993). Another way is to construct a very long artificial investment series assuming a constant growth rate for investment (Jacob, Sharma, & Grabowski, 1997; Kamps, 2006). These methods have substantial limitations for catching-up economies.
6. The methods give identical results if the smoothing parameter is sufficiently large.
7. It is uncertain how much of the capital stock was made obsolete during the transition period. Bah and Brada (2009) consider different studies and conclude that the decline in the capital stock in the early transition period was about 50%. Izyumov and Vahaly (2006) report figures between 15 and 50% of the capital stock. Campos and Coricelli (2002, p. 806) simply state: 'We do not know much about what happened to communist capital. Did it depreciate very fast? How much of it was reallocated to the emerging private and informal sector?'.
8. The issue of capital utilisation is discussed in Rapacki and Prochniak (2009) and Vanags and Bems (2005) but the capital stock series in the papers are not adjusted.
9. Solow (1957) computes a time-varying share of capital income in total income using US data and finds an average of 0.35. Fischer (1993) and Nehru and Dhareshwar (1993) use a constant share of 0.40, Baier et al. (2006) and Vanags and Bems (2005) use a constant share of 0.33, Gollin (2002) estimates the capital share to be between 0.25 and 0.35, while Rapacki and Prochniak (2009) use shares of 0.30 and 0.40.
10. The imputed national accounts data are the volume of the gross domestic product, value added and gross fixed capital formation for Bulgaria in 1995, and compensation to employees for Poland from 1995 to 1999.
11. For Croatia the data for employees and the self-employed for 1996–1999 are imputed using growth rates from the ESA95 data, the data for 1995 are imputed using data for 1996, and both the total employment and the number of employees for 2016 were imputed using the data of the national concept. For Poland the total employment for 1995–1999 is imputed using the national concept and the number of employees is imputed using the ESA95 data of domestic concept.
12. See for instance, Baier et al. (2006), Berlemann and Wesselhöft (2014), Griliches (1980), Harberger (1988), Kamps (2006), Nadiri and Prucha (1996), Nehru and Dhareshwar (1993), Rapacki and Prochniak (2009), Romer (1988) and Vanags and Bems (2005).

13. The change in the capacity utilisation is regressed on GDP growth and a constant in a panel estimation for the 11 CEE countries (but not the EU15) using all the available data. If this is estimated using a fixed effect estimation, the fixed effects are small and statistically insignificant so we prefer to use panel OLS. The result is shown below with standard error in brackets:

    $\Delta CU = -1.018+0.519 \cdot GY.$

    $(0.519)\ \ (0.055).$

    The variable ΔCU is the change in the capacity utilisation in percentage points and GY is the growth rate of output in percent per year. The relationship is used to predict the missing observations for the capacity utilisation.
14. The compensation to employees as a share of value added for Poland in 2016 is replaced by the same indicator from 2015, as newer data are not available. The share of employees in total employment for Croatia in 1995 is replaced by the same variable for 1996.
15. The five countries with the highest contributions from TFP growth in 1996–2002 coincide with those identified in Rapacki and Prochniak (2009). The large contribution of TFP growth in the Baltic states is also in line with the findings in Bah and Brada (2009). The results for the Baltic states are broadly in line with those in Vanags and Bems (2005), who reported TFP growth of 2.8, 2.6 and 2.9 percentage points for Estonia, Latvia and Lithuania, respectively.
16. We do not use employment measured in hours for the baseline results because data are missing at the beginning of the period for several of the sample countries.

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Appendix 1. Capital–output ratios

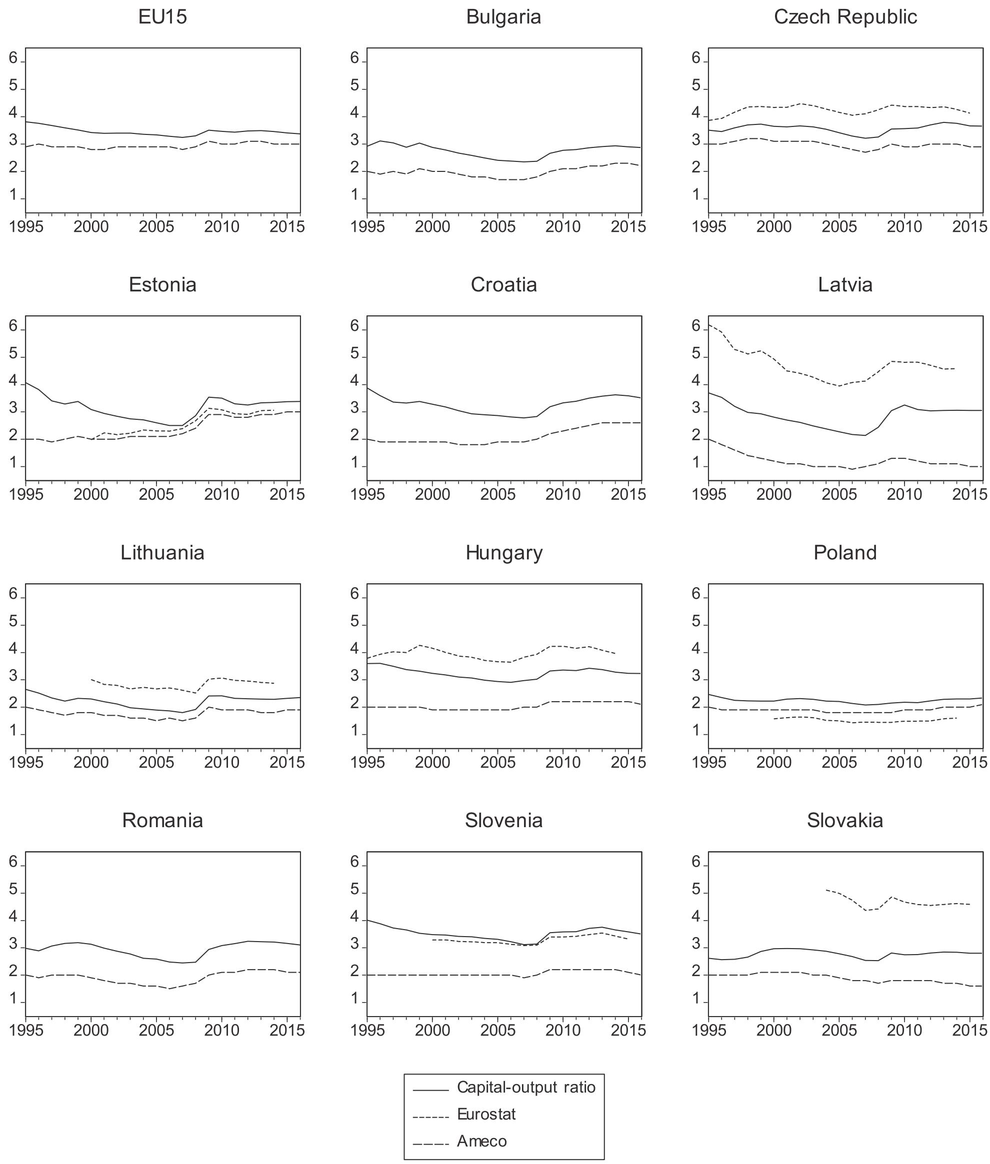

Figure A.1. Capital–output ratio for 11 CEE countries and the EU15. Source: Eurostat (codes: *nama_10_gdp, nama_10_nfa_st, nama_10_*an6), Ameco (code: *8.1 AKNDV*) and authors' calculations, see text.

Appendix 2. Publication II

PERCEIVED UNCERTAINTY AS A KEY DRIVER OF HOUSEHOLD SAVING

Publication II

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Perceived uncertainty as a key driver of household saving☆

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ABSTRACT

The paper studies the determinants of household saving in Europe with particular focus on the impact of labour income uncertainty. Panel data models are estimated on aggregate national-level data for 22 European countries in 1996–2017 using system GMM. The household saving rate is highly persistent and is driven in large part by income growth and by changes in labour income uncertainty, which can be dissected into two components: realised uncertainty and expectations about future uncertainty. Credit availability, interest rates, inflation, and other macroeconomic and expectational variables have little or no effect on saving.

1. Introduction

A deep recession accompanied by declining incomes and high unemployment in 2008–2010 could have been a good reason for dissaving. Instead though, household saving rates have grown substantially since then both in Europe and in the USA. The accumulation of savings accompanied by a high level of economic uncertainty has created a new wave of interest in the dynamics of household saving behaviour.

Christelis, Georgarakos, and Jappelli (2015) point out that three shocks occurred simultaneously during the crisis, as there was a drop in housing prices, declines in stock market indexes, and a dramatic deterioration of labour market conditions, the latter causing great uncertainty about labour income, which is the main source of income for households. This paper examines the links between household saving rates and uncertainty as a trigger of the precautionary saving behaviour that could explain high saving rates during and after the crisis. A key innovation of this paper is that it introduces two measures of perceived[1] labour uncertainty, both of which are important for household saving.

The focus of the paper is on aggregate saving, which is defined residually as disposable income including asset income, less consumption. This is the most commonly used definition of saving because of its simplicity and the availability of the data. Other approaches are also feasible, especially in the microeconomic literature, for example making a distinction between the consumption of durables, which can be considered a form of accumulation of capital, and nondurables (Campbell, 1987; Pistaferri, 2001), or

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[1] The terms "perceived" and "subjective" are used here interchangeably.

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distinguishing personal cash saving, which is the difference between total cash receipts and total cash expenditures on anything except capital expenditures (Howrey & Hymans, 1978).

Saving could be also decomposed into different components using data from different sources.[2] The problem with different data sources is that they give different results due to statistical discrepancies, conceptual differences, and differences in sectoral coverage, as Wachtel (1977) showed. Although it could be of interest to disaggregate different types of saving (Wachtel, 1979), or to disaggregate income because the marginal propensity to save out of different types of income could be different (Campbell, 1987; Taylor, 1971), this paper restricts its analysis to the response of aggregate household saving to uncertainty and other macroeconomic shocks. As Denison (1958) pointed out, it is gross saving as a whole that is crucial, and disaggregating is of interest in finding the implications for this total.

Saving rates as one of the key indicators for economic performance have been studied extensively at both the macro and micro levels; see Mikesell and Zinser (1973), Balassa (1993), Loayza, Schmidt-Hebbel, and Servén (2000), and Meghir and Pistaferri (2011) for overviews. However, the dynamics of saving since the recent crisis have made it clear that there is still only a little empirical evidence for the determinants of the saving rates and particularly for economic uncertainty as a possible explanatory variable. The paper addresses this issue by focusing on labour income uncertainty as a key driver of household saving.

The paper contributes to the literature on household saving in several ways. First of all, it explores new ways of looking at the uncertainty. It accounts for the uncertainty arising from the actual change in labour market conditions, and for the subjectively assessed expectations about what might happen in the labour market in the future. To account for that, data from the Joint Harmonised EU Consumer Survey are employed, which is rarely done in macroeconomic studies.[3]

The survey data represent a forward-looking expectational component of the uncertainty, while changes in the unemployment rate can be considered a backward-looking component as they contain information from past periods. The paper shows that both indicators of uncertainty have a pronounced and statistically significant effect on saving rates and together with income growth they can be considered the key determinants of household saving rates.

The findings reveal that household saving rates are highly persistent; it follows that the negative effect of unemployment on consumption is inflated in the long-run, not only reducing current consumption but also keeping it at low level over a long time span. Moreover, the results demonstrate how the consumption-credit environments in Europe and the USA are different, as Europeans have less debt-driven consumption than Americans do.[4]

The study uses a large up-to-date sample covering a panel of 22 European economies over multiple full business cycles in 1996–2017. The data used are aggregate national-level annual data. Given how the economic environment changed after the crisis, with low inflation, a zero lower bound, and unconventional monetary policy, it is instructive to obtain empirical evidence of what is now driving household saving rates in Europe as an economically and politically important region.

The models are estimated with system GMM, which makes it possible to account for the endogeneity of the regressors and to resolve a dynamic panel bias. Numerous robustness checks prove the validity of the results.

The paper is organised as follows: Section 2 briefly reviews the existing literature; Section 3 describes the sample, data, model, and estimation method; Section 4 discusses the results and robustness checks; and finally, Section 5 concludes.

2. Brief literature review

The following section provides a brief literature review. Subsection 2.1 discusses the basics of precautionary saving theory. Subsection 2.2 is dedicated to a discussion of uncertainty and expectations, and it also provides a short overview of income growth, interest rates, and credit constraints as possible drivers of household saving.

2.1. Precautionary saving

A typical textbook explanation of precautionary saving (Leland, 1968; Sandmo, 1970) would follow from the positive third derivative of the utility function of consumption, $u(C)$, implying that $u^{'}(C)$ is convex. This implies that the higher the income uncertainty is, the higher the expected marginal utility is for a given value of expected consumption. Thus when uncertainty increases, the incentive to accumulate a precautionary buffer increases as well (Romer, 1996, ch. 7).

Menegatti (2007) points out that for every given level of consumption, the marginal utility associated with a higher level of consumption is less than the marginal disutility[5] associated with a lower level of consumption. It follows that risk-averse economic agents will accumulate a reserve as an insurance against uncertainty, which is supposed to reduce the disutility due to uncertainty if consumption is reduced.[6] This observation is in line with loss aversion theory, which claims that people prefer to avoid losses rather than achieve gains (Tversky and Kahneman, 1992).

Another textbook model of precautionary saving is Carroll's (1997) buffer-stock saving theory. At the core of this theory is labour

[2] Wachtel (1977) points out that saving is essentially the sum of three different movements: the increase in financial assets, the decrease in net liabilities, and the increase in durables.

[3] There are some studies that use survey data (see for example Alessie & Lusardi, 1997; Harris, Loundes, & Webster, 2002; Jappelli & Pistaferri, 2000; Pistaferri, 2001), but these are mostly microeconomic studies.

[4] See for example Carroll et al. (2012) for empirical evidence on the large impact of credit on consumers' behaviour in the USA.

[5] Disutility due to uncertainty is defined as a reduction in utility due to consumption of the random quantity y_1 instead of the certain quantity $E[y_1]$.

[6] "The precautionary saving motive is the desire to reduce the disutility due to uncertainty, generated by risk aversion" (Menegatti, 2007).

income uncertainty combined with the impatience of consumers. If a consumer's wealth is below the target wealth-to-permanent-income ratio, then the effect of prudence dominates the effect of impatience and the consumer saves; if wealth exceeds the target wealth ratio, impatience will dominate over prudence. Carroll (1997) calls this pattern buffer-stock saving behaviour.

Given the interaction of the impatience and the prudence of the consumer, it is not optimal for the consumer to let wealth become arbitrarily large with respect to income; however, when the level of wealth falls, prudence begins to dominate and it affects saving behaviour positively (Carroll & Toche, 2009, p. 15265).

The buffer-stock saving model is closely related to the models developed by Zeldes (1989) and Deaton (1992), with the difference that Carroll's model incorporates unemployment expectations to take account of labour income being one of the main sources of household income. In the empirical study based on the buffer-stock saving theory, Carroll, Slacalek, and Sommer (2012) document a considerable rise in private saving in the USA after the global financial crisis of 2008–2009 and explain this by the increased uncertainty and the expectations of high unemployment after the crisis.

The earlier "zero-depreciation" theory[7] of saving elaborated by Houthakker and Taylor (1970) and Taylor (1971), referred to as the HT model, is fairly close to the buffer-stock model. The basic notion underlying the HT model is that "the consumer adjusts his saving so as to bring his stock of financial assets into line with his level of income" (Taylor, 1971), meaning saving is a linear function of wealth and there is a target wealth-income level as in the buffer-stock saving model. The HT model is used quite extensively in the literature (see for example the augmented model in Juster & Wachtel, 1972b) and it was later generalised and expanded in Bergstrom and Chambers (1990, pp. 279–319) and in Taylor and Houthakker (2009).

2.2. *Uncertainty and other drivers of saving rates*

Theory says that uncertainty can affect the real economy, one of the key channels being precautionary saving by households.[8] For that reason it would be instructive to include uncertainty variables in the saving model, the only problem being that it is fairly challenging to find an appropriate proxy for uncertainty.

Bloom (2014) argues that uncertainty can be measured in numerous ways and he names a few types of proxy for uncertainty, the most commonly used being the volatility of an economic indicator like output, inflation, or stock market indexes.[9] In the literature on the saving rates, the most frequently used proxy for macroeconomic uncertainty is the inflation rate (Gupta, 1987; Loayza et al., 2000), or the unemployment rate if the focus is on labour income uncertainty (Bande & Riveiro, 2013; Mody, Ohnsorge, & Sandri, 2012).

Inflation can affect saving through different channels like the money illusion, intertemporal substitution or uncertainty, including indirect ones that operate through the interest rate and wealth (Wachtel, 1977)[10]. The inflation rate can be disaggregated into anticipated and unanticipated inflation as in Juster and Wachtel (1972b); uncertainty is created and savings are pumped up by unanticipated inflation, while a "fully anticipated change in inflation has no effect on real economic behaviour in the long run".

It is worth stressing that the theoretical effect of inflation on saving is ambiguous. It can discourage saving because it creates distortions in returns on saving, since taxes and interest rates are specified in nominal terms, but it can also increase saving if households perceive the economic environment to be more uncertain because of higher inflation (Wachtel, 1979).

The key indicator in the context of labour income is the unemployment rate. For those who are working, rising unemployment gives two signals at once, a signal that there is a higher probability of losing their job and a signal that there is a higher probability of lower future income as the bargaining power of employees is weakened in an environment of high unemployment. The unemployment rate is a straightforward proxy that is meant to quantify this two-dimensional risk from labour income. The higher unemployment is, the higher the risk is of the main source of income being lost or of income becoming lower.

Juster and Wachtel (1972a) distinguish between the unemployment rate in levels and in first differences. The idea behind this is that these variables are proxies of different processes. When the unemployment rate is high, a large share of the population receive relatively low income; this means that the *capacity* to save (Hussein & Thirlwall, 1999) is lower and it could be expected that saving will fall. However, when the change in unemployment is positive, the fear of losing a job and uncertainty about future income become larger, so saving could be expected to rise because of precautionary motives. To summarise, the level of unemployment could be a proxy for labour income, and a change in the unemployment rate appears to be a suitable proxy for uncertainty about labour income.

Distinguishing between levels and first differences is also important because uncertainty is effectively a reflection of a change as discussed in Bachmann, Carstensen, Lautenbacher, and Schneider (2018). They show on microdata from firms that a change in sales, either good or bad, makes firms more uncertain, and perceived uncertainty increases even more if the change is temporary. Arrow et al. (1995) examine how the economy affects the environment and introduce the concept of *familiar* and *unfamiliar* changes; they argue that "changes from familiar to unfamiliar states increase the uncertainties associated with the environmental effects of economic activities" (p. 521).

Two empirical studies that focus on the macroeconomic determinants of household saving rates, Pesaran, Ul Haque, and Sharma

[7] The name of the theory refers to the assumption that households own non-depreciating financial wealth.

[8] For empirical evidence see for example Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Basu and Bundick (2017).

[9] It can also be measured as the dispersion of productivity shocks to firms or the volatility of sales and profits, which are called micro level uncertainty; as political uncertainty by calculating the frequencies of certain words such as "uncertainty" in the news; or as forecast error coming from survey data.

[10] Wachtel (1977) analyses how different components of saving are affected by inflation-induced uncertainty and shows that it reduces the propensity to incur liabilities, but has no effect on financial assets.

(2000) and Kukk and Staehr (2017), include the unemployment rate in the set of the explanatory variables but they do not find any significant effect from it. Carroll et al. (2012) combine the unemployment rate with data from surveys of consumers on the expected change in the unemployment rate, which produces one proxy for labour income uncertainty. However, it might be useful to bring in expectational variables explicitly to account for subjectively assessed uncertainty.

The reason for evaluating the impact of changes in unemployment rate and expectations of unemployment separately is that they are conceptually different. If unemployment increases, consumers feel less confident about their labour market perspectives and save more than in the previous period. This can be classified as the backward-looking component of the uncertainty as it is based on data from a past period. Along with actual developments on labour market, forward-looking expectations about future labour market conditions also affect household saving. These expectations may be labelled the forward-looking expectational component of uncertainty.

Alternatively, these two proxies may be thought of as familiar and unfamiliar uncertainty, or as a measure of realised uncertainty and a measure of expectations about future uncertainty. The line between them is very fine, though, as changes in the unemployment rate can be also considered an expectational variable if consumers have statistical expectations and make projections of earlier developments in the labour market into the future. However, these variables have different dynamics (this is to be expected as they refer to different periods,[11] see Fig. 1 for a sample of 24 EU countries), and this is an additional reason to include them both in the model.

As discussed in Subsection 2.2, a desirable buffer is defined by the income level, and while the income variable can be thought of as an indicator of the *capacity* to save (Hussein & Thirlwall, 1999), the *willingness* to save might depend on other determinants, the most important of which are macroeconomic stability or the lack of uncertainty, interest rates, and credit conditions, but which also include transfers,[12] the stage of the business cycle,[13] income distribution,[14] demography,[15] the life cycle,[16] and so on.

Changes in the interest rate can theoretically have an ambiguous effect on the saving rate, as the total of the wealth, income and the substitution effect of changes in the interest rate is not predictable (Browning & Lusardi, 1996; Wachtel, 1977).

Household saving can be subject to borrowing constraints (Attanasio & Weber, 2010). Carroll et al. (2012) explain for example that the fall in the saving rate to a mere one per cent in the mid-2000s in the USA can be interpreted in the context of financial liberalisation or credit-loosening. Davis and Palumbo (2001) explain these short-run fluctuations, however, by changes in household wealth.

3. The data, the model and the estimation method

The paper uses a panel covering 22 EU countries over multiple full business cycles in 1996–2017. The annual data used are aggregate national-level data. The sample covers Austria, Belgium, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom. Four EU countries – Croatia, Greece, Malta and Romania – are not included in the sample due to a lack of data. The baseline model excludes Bulgaria and Luxembourg as these countries have many outliers.

3.1. Model

The reduced-form buffer-stock saving model discussed in Subsection 2.1 includes a lagged dependent variable[17] to account for saving inertia and following the literature it is augmented with income growth, the real interest rate, inflation rate, and demographic variables as controls. All the explanatory variables enter the model in first differences (Taylor, 1971; Juster and Wachtel, 1972a,b).

The reduced-form saving rate model is:

$$\begin{aligned}\text{Saving rate}_{it} &= \rho\text{Saving rate}rg_{\,it-1} + \beta_U\Delta\text{Unemployment}_{it} + \beta_E\Delta\text{Unempl.expectations}_{it} + \beta_I\Delta\text{Income}_{it} + \beta_C\Delta\text{Credit}_{it}\\ &+ \beta_R\Delta\text{Real interestrate}_{it} + \beta_\pi\Delta\text{Inflation}_{it} + \beta_X X_{it} + \eta_i + \varepsilon_{it},\end{aligned}$$

The subscript t refers to the time period and i is the country. The variable Saving rate$_{it}$ is the household saving rate as a share of disposable income. The autoregressive coefficient ρ is expected to be less than 1. The variable Δ Unemployment is the first difference of the unemployment rate in percentage points; ΔUnempl.expectations is the first difference of expectations of unemployment; Δ Income stands for the growth of household real disposable income per capita; Δ Credit is the net flow of loans for households as a fraction of output; Δ Real interest rate is the first difference of the real short-term interest rate; η_i is an unobserved country-specific time-invariant effect, which allows for heterogeneity across the countries; and ε_{it} is an error term. The coefficients ρ, β_U, β_E, β_W, β_C, β_I, β_R are to be estimated, X_{it} is a matrix of control variables (life expectancy, the old-age dependency ratio, and the young-age dependency ratio), and β_X is a vector of their coefficients.

While Carroll et al. (2012) combine the data from the surveys with actual unemployment data, this paper treats them separately, and

[11] One is the change from last year to this year and the other is the expected change in unemployment in the following 12 months.

[12] Juster and Wachtel (1972a) document the large positive effect that social transfers have on saving, suggesting that economic agents receiving transfers have a very high short-run marginal propensity to save. The same findings are obtained in Taylor (1971).

[13] See for example Abel, Rich, Song, and Tracy (2016) on the countercyclicality of uncertainty indicators.

[14] See Malinen (2013) for an empirical study on saving and inequality.

[15] One of the pioneering studies is Leff (1969).

[16] Taylor (1971).

[17] When adding the lagged dependent variable to the right-hand side of the equation, we account for the changes in the wealth stock and can avoid adding this variable explicitly like in the HT model.

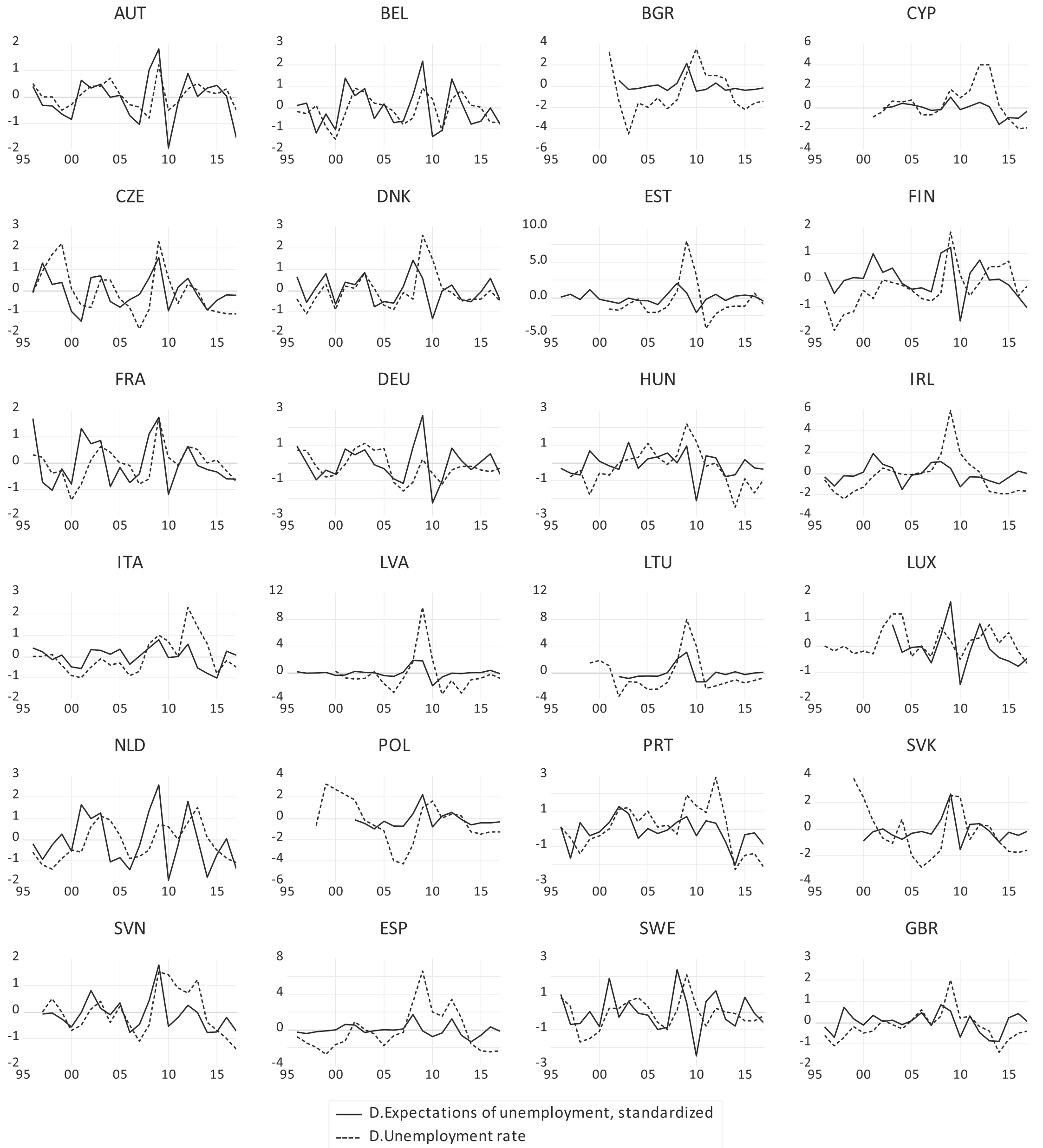

Fig. 1. Changes in the unemployment rate and changes in the index of expectations of unemployment.
Notes: The variable "D.Expectations of unemployment, standardised" denotes the first difference of the standardised expectations of unemployment (dashed line), while the variable "D.Unemployment rate" denotes the first difference of the unemployment rate (solid line). For country codes see Appendix A. *Source*: Eurostat.

that results in there being two different measures of uncertainty. This is done to distinguish between two layers of uncertainty, and both proxies of uncertainty are expected to have a positive sign, meaning more uncertainty leads to a higher saving rate. The credit flow variable is a proxy of credit availability and the coefficient of the variable is expected to have a negative sign, meaning credit easing is supposed to reduce household saving.

The effects of income growth and the interest rate on the saving rate are theoretically undetermined. Higher income growth can be accompanied by higher saving rates, but the effect can also be negative if consumers perceive higher income growth to be permanent. If

Table 1
Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Saving rate	484	10.1	5.2	−8.5	21.3
ΔUnemployment	460	−0.1	1.5	−4.4	9.8
ΔUnempl.expectations	461	−0.1	0.8	−2.5	3.1
Credit flow	487	3.1	4.0	−9.0	28.6
Income growth	465	2.1	3.4	−13.7	22.5
ΔReal interest rate	470	−0.2	2.8	−22.4	28.6
ΔInflation	458	−0.2	2.1	−14.4	5.4
ΔLife expectancy	474	0.3	0.3	−0.8	2.2
ΔYoung dependency ratio	484	−0.2	0.4	−1.9	0.9
ΔOld dependency ratio	484	0.4	0.3	−0.4	1.3

Notes: See the description of variables in Appendix B.
Source: Eurostat, AMECO, ECB

the substitution effect of the higher interest rate prevails over the wealth and income effects, then the estimated coefficient of the interest rate will have a positive sign, otherwise the sign will be negative. Summary statistics for the main variables are shown in Table 1.

The paper uses a rich set of explanatory variables to ascertain the determinants of the household saving rates; these variables include the Gini index, the pension replacement ratio, the female participation rate, the output growth rate, the output gap, and others. Additional uncertainty variables from the EU Consumer Survey and volatility measures are used for robustness checks.

Period dummies are not included in the baseline model as they may lead to overfitting; instead, the country-invariant VIX index and the mean average forecast error (MAFE) from the ECB Survey of Professional Forecasters are included in the model to account for time effects that are not country-specific. All variables except the control variables are instrumented, and two external instruments are used.

3.2. *Estimation method*

The model presented in the previous subsection is a dynamic panel data model. Nickell (1981) shows that in dynamic panels the error terms and lagged dependent variable are typically correlated and so fixed effects estimators are asymptotically biased downwards. With T growing, the Nickell bias becomes less pronounced (Bun & Kiviet, 2001; Judson & Owen, 1999), but it never disappears if standard estimators such as fixed effects or pooled least squares are used (Baltagi, 2013, ch. 8).

Another concern arising from the model specification is that most of the explanatory variables are not strictly exogenous, meaning that reverse causality bias is present. The problem of endogeneity can be solved by using instrumental variables. This suggests a conventional remedy for both problems would be generalised method-of-moments (GMM) estimators developed by Hansen (1982), Holtz, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).[18] The GMM estimator is also known to be consistent when heteroscedasticity of the unknown form is present (Baum et al., 2003).

Arellano and Bond (1991) suggested an estimator that differences the model to eliminate the time-invariant individual effects, where the differenced regressors are then instrumented with the lagged levels of the regressors.[19] Blundell and Bond (2000) showed that when the modelled process is highly persistent or there is a high level of heterogeneity between groups, difference GMM may perform very poorly as the lagged levels will be weak instruments for the differenced variables. They introduced system GMM, an estimator that combines the results of a transformed equation in differences instrumented using lagged levels, and the original equation in levels instrumented using lagged differences[20].

The present dataset exhibits a relatively large number of periods $T = 23$ and a fairly small number of groups $N = 22$. If all the possible lags are used, the number of instruments will approach or exceed the number of observations. To avoid overfitting of the instrumented variables, the number of instruments used in the model is reduced. Instead of creating one instrument for each time period, variable, and lag distance, instruments are created for each variable and lag distance. Furthermore, only lags from two to three are used, while lags up to eight are used for a robustness check.

The baseline model is estimated with one-step system GMM, and the two-step estimator is used when testing for robustness.[21] The bias in the two-step standard errors are corrected by Windmeijer's (2005) correction procedure. Two external instruments are used, these being the volatility of expectations of unemployment measured as the standard deviation of monthly balances of survey answers,

[18] See Baltagi (2013) ch. 8 for a summary of the methods appropriate for estimating dynamic panel data models.
[19] The disadvantages of the first-difference transformation are that it eliminates country-specific information and it magnifies gaps in the unbalanced panels (Arellano & Bover, 1995).
[20] Using Monte Carlo simulations, Blundell, Bond and Windmeijer (2001) show that the system GMM estimator performs better than the difference GMM estimator in finite samples, improving the precision and reducing bias.
[21] The consistency of the system GMM estimator can be verified by using the Hansen test of over-identifying restrictions. The null of the Hansen test is that instruments and the error term are orthogonal, meaning the over-identifying instruments are valid. Another specification test used is the first-order and second-order autocorrelation tests for the error term. First-order serial correlation of the residuals is expected to be present, while second-order serial correlation is expected to be absent. The absence of second-order autocorrelation is important because it confirms the consistency of the GMM estimator (Baltagi, Demetriades, & Law, 2009; ch. 8). All three statistics and their respective p-values are reported for each model specification.

and the volatility of income measured as the standard deviation of the quarterly compensation of employees deflated with the HICP.

4. Results

4.1. Baseline model

Table 2 presents the estimates of the baseline model and four different subsamples to assess whether possible heterogeneity affects the results unduly. According to the baseline model presented in column (2.1), household saving rates have high inertia and are driven by uncertainty and income growth.

Column (2.1) reports the estimations of the baseline sample with 22 countries; Column (2.2) reports the results without the years of crisis 2007–2009; in Column (2.3) the subsample without France, Germany and United Kingdom is estimated; Column (2.4) shows a subsample without Denmark, Finland and Sweden; Column (2.5) estimates a subsample without Italy, Spain and Portugal.

The coefficient for the lagged saving rate is statistically significant at the one per cent level in the baseline model and in all subsamples. These findings are mainly in line with the literature.[22] The persistence of the saving rates can be explained with Denison's law. Denison (1958) and later David and Scadding (1974) show on US data that private saving rates are extremely stable and there is no long-run trend in the saving rate, and that this is more pronounced in good years.

The estimated effects of the changes in the unemployment rate are also significant in all the model specifications at the one per cent level; the expectational variable is significant, both statistically and economically, but it is a little less precisely estimated. This is to be expected as unemployment expectations are apparently a noisier measure of uncertainty than the unemployment rate.

Income growth is positively correlated with the saving rate and the coefficient is highly significant in the baseline model and in all subsamples. The finding that the saving rate grows together with income can be explained by the high persistence of consumption habits (Taylor, 1971); a more trivial explanation would be the diminishing utility of consumption with respect to income.

The credit variable has the expected minus sign but large standard errors in all the model specifications, so effectively it has a coefficient of zero. The inflation rate and the real interest rate have no effect on the saving rate of households.

The quantitative effect of the statistically significant drivers of the saving rate is fairly large. If the change in the rate of unemployment is 1.5 percentage points, which is one standard deviation of this sample, the change in the saving rate will be 1.2 percentage points; if expectations of unemployment change by one standard deviation, the saving rate will change by 0.6 percentage point. During the years of the recent recession, the average change in the unemployment rate was 1.5 percentage points and the change in the expectations of unemployment was on average 1.2 percentage points, which means that the change in the level of uncertainty has contributed to an increase of 2.1 percentage points in household saving rates, which is one fifth of the average saving rate.

A change of one standard deviation in income growth, or around 3.4 percentage points, will induce a change in saving rates of 1.9 percentage points. The effects of both drivers of household saving, uncertainty (taking into account both proxies) and income growth, are of roughly the same magnitude and are economically significant.

The high persistence of saving behaviour implies that every driver has a long-term effect on saving rates that considerably exceeds the short-term effect. Given the autoregressive coefficient of 0.78 in the baseline model, the long-run effects of all drivers of household saving rates are more than 4 times larger than their short-run effects.

Columns (2.2)–(2.5) report the results for different subsamples. To make sure that the results are not driven by the crisis period, when unemployment and expectations of unemployment were very high, the years 2007–2009 are excluded from the sample. Column (2.2) shows the results without three years of the crisis and they are very similar to the results of the baseline estimates.

Column (2.3) reports the results without three large economies, namely France, Germany and United Kingdom; column (2.4) excludes three Nordic countries, Denmark, Finland and Sweden; finally, column (2.5) reports the results for the subsample without Italy, Portugal and Spain. The results suggest that the results of the baseline model are stable for the different subsamples.

The point estimates of the variables in the subsamples are compared to the baseline model estimates using the *Z*-test for the equality of the regression coefficients (Paternoster, Brame, Mazerolle, & Piquero, 1998). This test shows that the coefficients of all the subsamples are not significantly different from the baseline estimates (the results are not reported here).

4.2. The contribution of uncertainty measures to the changes in household saving rates by country

To get an idea of the relationship between labour income uncertainty measures and household saving rates in particular countries, the contributions of the changes in the unemployment rate and changes in the unemployment expectations are calculated and plotted against changes in the saving rates from year to year.[23] The results are presented separately for three country groups of core Western

[22] Swamy (1968) reports an average coefficient for the lagged saving rate of 0.936 for developed countries and 0.778 for less developed countries; the estimation method is referred to as three-pass least squares and the sample contains 19 countries. The estimates for the lagged saving rate in Loayza et al. (2000) are 0.59 for the whole sample and 0.67 for the OECD countries, using a system GMM estimator and a sample of 69 countries. According to Kukk and Staehr (2017), the coefficient of the lagged saving rate in ten CEE countries before the crisis was 0.65, but it is considerably lower after the crisis at 0.36. Bande and Riveiro (2013) consider Spanish regions and the point estimate for the lagged saving rate is around 0.64 (OLS and GMM). The estimate by Carroll et al. (2012) for the USA is 0.574 (OLS). Horioka and Wan (2007) report a lagged saving rate coefficient that varies in the range of 0.774 to 0.476 depending on the model specification; the method used is GMM on panel data from Chinese provinces.

[23] The contributions of the uncertainty measures are calculated using the baseline model coefficients, see Table 2, Column (2.1).

Table 2
Baseline model and subsamples.

	(2.1) Baseline	(2.2) w/o crisis years	(2.3) w/o largest	(2.4) w/o Nordic	(2.5) w/o Southern
Saving rate, lagged	0.784***	0.803***	0.770***	0.777***	0.791***
	(0.050)	(0.064)	(0.051)	(0.058)	(0.049)
ΔUnemployment	0.794***	0.657***	0.759***	0.809***	0.862***
	(0.240)	(0.170)	(0.234)	(0.257)	(0.283)
ΔUnempl.expectations	0.760**	0.711***	0.881**	0.674**	0.738**
	(0.298)	(0.202)	(0.332)	(0.295)	(0.343)
Income growth	0.560***	0.361***	0.562***	0.561***	0.604***
	(0.087)	(0.089)	(0.087)	(0.095)	(0.089)
Credit flow	−0.107	0.005	−0.113	−0.103	−0.151
	(0.091)	(0.075)	(0.096)	(0.108)	(0.108)
ΔReal interest rate	0.045	0.122	0.015	0.039	0.052
	(0.078)	(0.080)	(0.082)	(0.083)	(0.083)
ΔInflation	0.069	0.050	0.017	0.057	0.099
	(0.153)	(0.099)	(0.147)	(0.157)	(0.187)
Observations	402	336	344	340	344
Number of countries	22	22	19	19	19
Number of instruments	31	31	31	31	31
Hansen J-stat	12.280	12.630	7.480	6.167	5.540
p value	0.906	0.893	0.995	0.999	0.999
AR(1)	−2.610	−2.535	−2.588	−2.552	−2.438
p value	0.009	0.0112	0.009	0.010	0.014
AR(2)	−1.592	0.911	−1.445	−2.033	−1.751
p value	0.111	0.362	0.148	0.042	0.080

Notes: The dependent variable is the household saving rate as a share of disposable income. Panel estimates with one-step system GMM, with volatility of expectations of unemployment and income volatility as external instruments. All the estimated models include life expectancy, the young-age dependency ratio and the old-age dependency ratio as control variables, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

European countries, Central and Eastern European countries, and Southern Europe together with Ireland and Great Britain; see Figs. 2–4, and note that the scale varies across countries.

The increase in household saving rates during the great recession and subsequent decrease in them is fully or to a large extent supported in almost all countries by a rise in unemployment and in expectations of unemployment. In many countries, the contribution of the survey-based measure of uncertainty to the changes in saving rates is comparable in magnitude to the contribution of the unemployment rate. This means that ignoring the expectational component of uncertainty might be misleading for the dynamics of saving rates.

The Western European countries that saw the largest shifts in household saving behaviour in 2008–2009 were the Nordic countries and the Netherlands (see Fig. 2). In Austria and Germany the rise in uncertainty among consumers was as large as it was in Finland or Denmark, but this did not translate into increased saving rates; indeed the households in these countries dissaved during the crisis, demonstrating more orthodox, textbook behaviour.

In the Central and Eastern European countries the magnitude of the fluctuations in saving rates is on average larger than it is in the core European countries, and the patterns of movements in saving rates are very different. However, the changes in the uncertainty level during the great recession are fully transmitted into the changes in saving behaviour with the exception only of Slovenia, which demonstrates saving behaviour that is more typical for Austria or Germany.

Fig. 4 shows that with the exception of Italy, where the saving pattern is procyclical, uncertainty about labour income contributed most substantially to the rise in saving during the great recession, after which the lower saving rates are associated with falling unemployment rates and more optimism.

A quick visual analysis suggests that unemployment expectations have a more pronounced effect in the core European countries and in some Central and Eastern European countries such as Czechia, Slovakia and Hungary, while in the Southern Europe, where unemployment rates are on average higher, unemployment is much more important in driving the saving rates of households.

4.3. Results using additional explanatory variables

The aim of the analysis in this subsection is to ascertain whether there are signs of omitted variable bias or instability of the regression coefficients. Different specifications of the model are examined and the results are reported in Table 3.

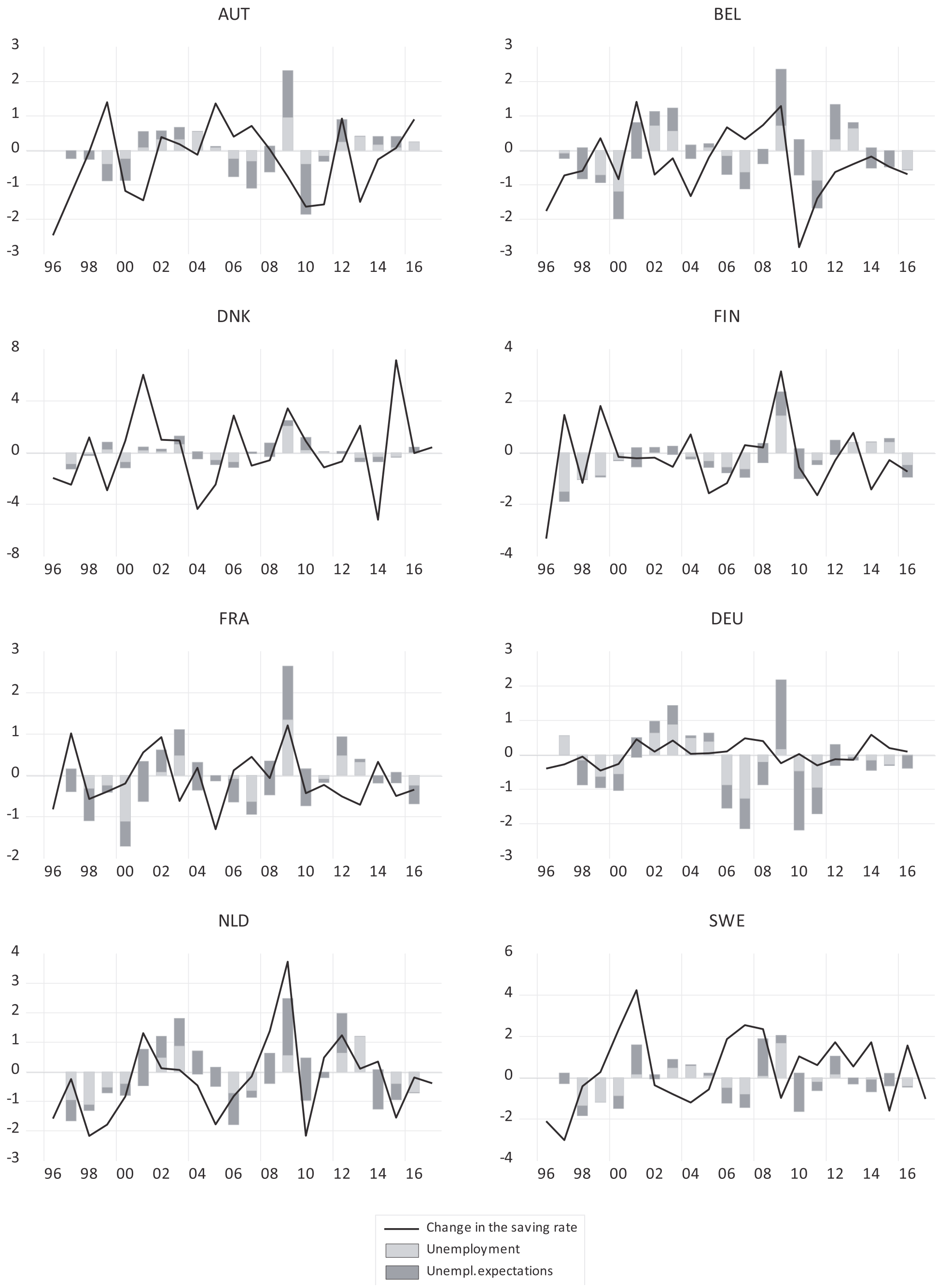

Fig. 2. The contribution of uncertainty measures to the changes in household saving rates in Western European countries.
Notes: The change in the saving rate is the first difference of the household saving rates. Unemployment and Unempl.expectations refer respectively to the contribution in percentage points of the changes in the unemployment rate and to the contribution in percentage points of the survey-based measure of uncertainty to the changes in household saving rates.
Source: Eurostat, author's calculations

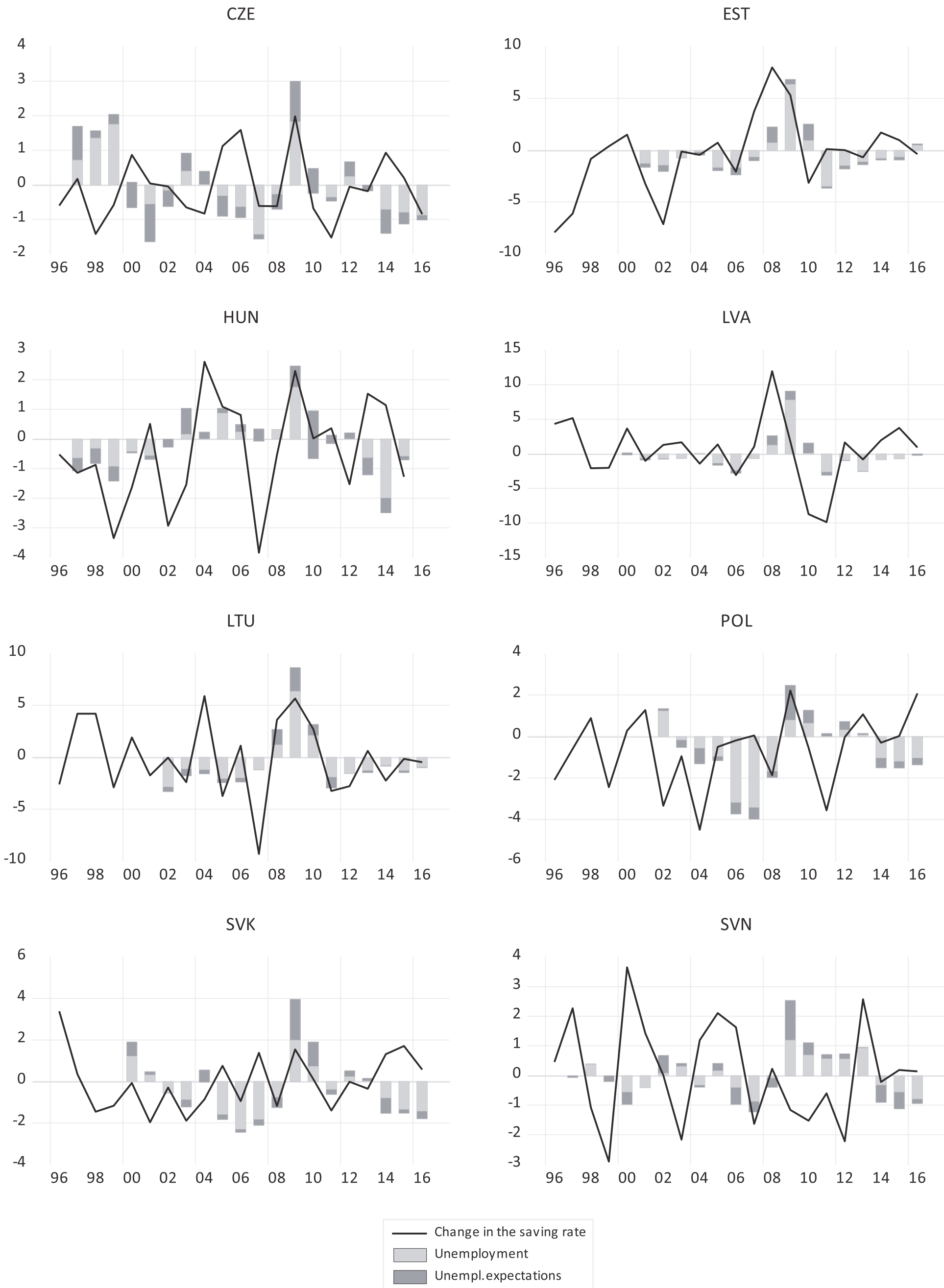

Fig. 3. The contribution of uncertainty measures to the changes in household saving rates in Central and Eastern European countries.
Notes: See notes to Fig. 2.
Source: Eurostat, author's calculations

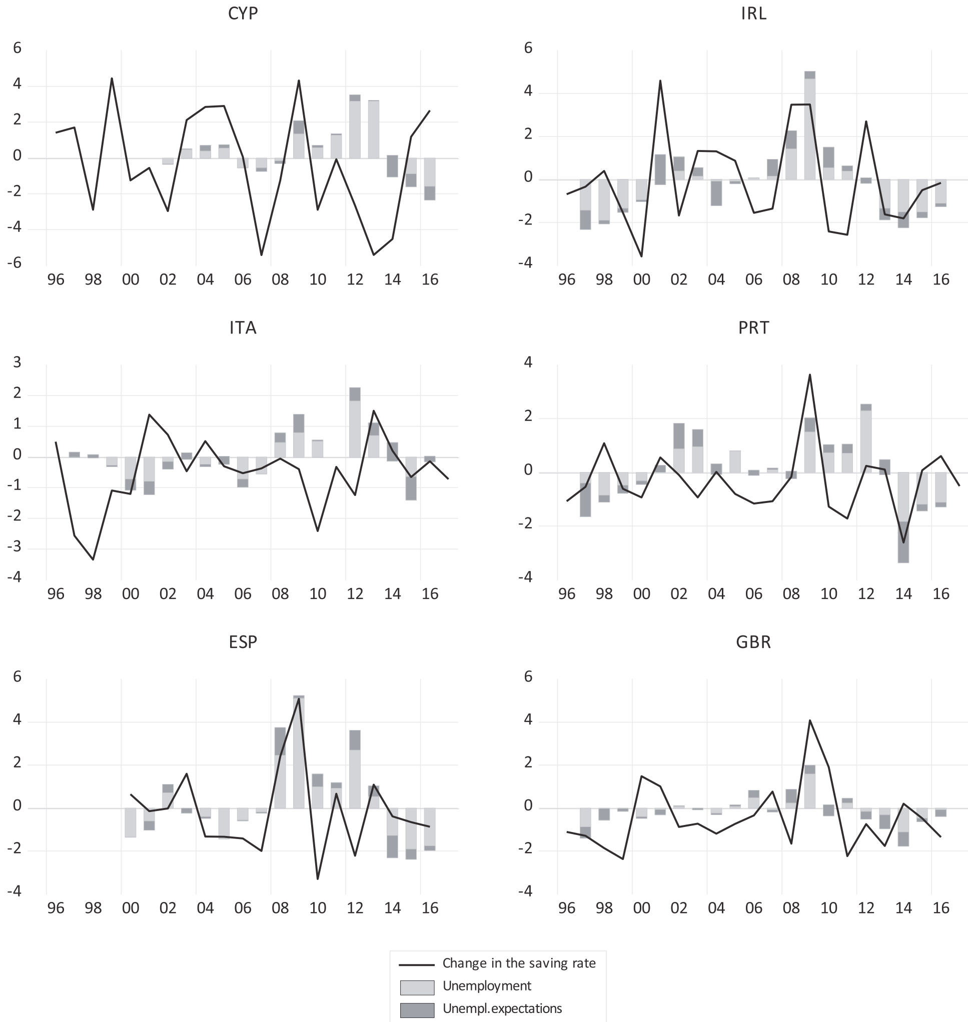

Fig. 4. The contribution of uncertainty to the changes in household saving rates in Southern European countries, Ireland and Great Britain.
Notes: See notes to Fig. 2.
Source: Eurostat, author's calculations

For convenience, column (3.1) repeats the estimations of the baseline model. The Gini index is added to the model in column (3.2). The female participation rate is used to account for different saving patterns across genders, as shown in column (3.3). Following Juster and Wachtel (1972b), the level of unemployment is added to the model in column (3.4).[24] Additionally, the model is augmented with social transfers (3.5). A few other macroeconomic variables are also added to the model (the results are not reported here). Age structure is accounted for by three control variables, which are life expectancy (Taylor, 1971) and the dependency ratios.

The results in the specifications with the additional variables are largely unchanged, as the coefficients of the uncertainty proxies and income growth are statistically and economically significant, and they are broadly of the same magnitude as in the baseline model.[25] Meanwhile, the coefficients of the other main and additional variables are insignificant.

[24] However, when the income variable is present, the unemployment rate in levels does not appear to have an effect on the saving rate.
[25] The point estimates of the variables in different model specifications are compared to the baseline model estimates using the *Z*-test as in the previous subsection. This is done for all model specifications in this and the following subsections.

Table 3
Baseline model and additional variables.

	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)
	Baseline	Gini index	Female particip.rate	Unemploy-ment level	Transfers
Saving rate, lagged	0.784***	0.820***	0.765***	0.776***	0.779***
	(0.050)	(0.069)	(0.056)	(0.050)	(0.048)
ΔUnemployment	0.794***	0.694***	0.668**	0.862***	0.936***
	(0.240)	(0.151)	(0.259)	(0.265)	(0.331)
ΔUnempl.expectations	0.760**	0.857**	0.839**	0.837**	0.932**
	(0.298)	(0.342)	(0.322)	(0.387)	(0.414)
Income growth	0.560***	0.532***	0.544***	0.547***	0.579***
	(0.087)	(0.088)	(0.107)	(0.094)	(0.090)
Credit flow	−0.107	−0.118	−0.061	0.044	−0.115
	(0.091)	(0.099)	(0.090)	(0.140)	(0.094)
ΔReal interest rate	0.045	0.007	0.062	0.064	0.086
	(0.078)	(0.065)	(0.093)	(0.086)	(0.078)
ΔInflation	0.069	0.014	0.123	0.150	−0.040
	(0.153)	(0.099)	(0.118)	(0.216)	(0.120)
ΔGini coefficient		0.336			
		(0.381)			
ΔFemale participation rate			−0.309		
			(0.254)		
Unemployment, level				0.193	
				(0.185)	
ΔTransfers					−0.535
					(0.479)
Observations	402	388	383	402	402
Number of countries	22	22	22	22	22
Number of instruments	31	34	34	34	34
Hansen J-stat	12.28	6.612	11.60	10.19	13.22
p value	0.906	0.999	0.965	0.985	0.927
AR(1)	−2.610	−2.362	−2.594	−2.614	−2.626
p value	0.009	0.018	0.009	0.008	0.008
AR(2)	−1.592	−1.377	−1.871	−1.349	−1.608
p value	0.111	0.169	0.061	0.177	0.108

Notes: The dependent variable is the household saving rate as a share of disposable income. Panel estimates with one-step system GMM with two external instruments: volatility of expectations of unemployment and income volatility. All the estimated models include three control variables of life expectancy, the young-age dependency ratio and the old-age dependency ratio, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

4.4. Results using additional variables of uncertainty

A few additional measures of uncertainty are added to the model to ensure that the measures of uncertainty used in the baseline specification are the most appropriate ones, see Table 4. These measures are inflation volatility, output volatility, and the volatility of unemployment expectations measured as the standard deviation of the expectations variable. Two country-invariant volatility measures, the Volatility Index (VIX) and the Mean Average Forecast Error (MAFE) calculated using the data from the Survey of Professional Forecasters are also used.

The results suggest that the model is stable and that the household saving rates are driven by the proxies of labour income uncertainty but not by the measures that describe general economic volatility. It is interesting that the second moment of the expectational variable, which is the standard deviation of unemployment expectations, has no effect on the saving rate and it does not kill the first moment. A change in expectations of unemployment is what matters for household saving.

4.5. Results using additional data from the survey

Unemployment expectations can potentially be correlated with other expectational variables, for example with expectations of the general economic situation or the future financial position of households, or the intentions of households to save or to purchase durables, and it turns out that they are (see Table 5). All the survey-based variables are highly correlated among themselves, and they equally correlate with the changes in the unemployment rate. The only two variables that are not correlated are the intentions of future saving and expectations about consumer prices, with the latter only marginally correlated with expectations about the future financial position.

Table 4
Baseline model and uncertainty measures.

	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)
	Inflation volatility	Output volatility	MAFE	VIX	Volatility of expectations
Saving rate, lagged	0.795***	0.770***	0.762***	0.791***	0.773***
	(0.044)	(0.048)	(0.067)	(0.044)	(0.054)
ΔUnemployment	0.759***	0.723***	0.807***	0.793***	0.757***
	(0.233)	(0.223)	(0.226)	(0.236)	(0.220)
ΔUnempl.expectations	0.745**	0.602*	0.815**	0.769**	0.693**
	(0.283)	(0.340)	(0.325)	(0.344)	(0.300)
Income growth	0.553***	0.561***	0.559***	0.550***	0.601***
	(0.088)	(0.093)	(0.100)	(0.092)	(0.089)
Credit flow	−0.097	−0.094	−0.106	−0.114	−0.105
	(0.092)	(0.099)	(0.102)	(0.088)	(0.104)
ΔReal interest rate	0.052	0.006	−0.030	0.048	0.083
	(0.075)	(0.091)	(0.093)	(0.077)	(0.112)
ΔInflation	0.036	−0.009	0.074	0.051	0.082
	(0.162)	(0.135)	(0.096)	(0.145)	(0.146)
Price volatility	0.561				
	(1.155)				
Output volatility		45.505			
		(33.039)			
MAFE			0.058		
			(0.327)		
VIX				−0.019	
				(0.026)	
Volatility of unempl.expectations					0.122
					(0.086)
Observations	402	385	379	402	402
Number of countries	22	21	22	22	22
Number of instruments	34	34	32	32	31
Hansen J-stat	10.94	13	10.13	8.411	6.681
p value	0.976	0.933	0.966	0.989	0.996
AR(1)	−2.718	−2.644	−2.494	−2.623	−2.852
p value	0.006	0.008	0.0126	0.008	0.004
AR(2)	−1.621	−1.405	−1.759	−1.376	−2.372
p value	0.105	0.160	0.078	0.169	0.017

Notes: The dependent variable is the household saving rate as a share of disposable income. Panel estimates with one-step system GMM with two external instruments: volatility of expectations of unemployment and income volatility. All the estimated models include three control variables of life expectancy, the young-age dependency ratio and the old-age dependency ratio, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

Table 5
Correlation of survey-based measures of consumer expectations and changes in the unemployment rate.

	ΔUnemploy-ment	ΔUnempl. expectations	ΔEconomic situation	ΔFinancial position	ΔConsumer prices	ΔMajor purchases
ΔUnempl. expectations	0.313 (0.000)					
ΔEconomic situation	−0.232 (0.000)	−0.843 (0.000)				
ΔFinancial position	−0.284 (0.000)	−0.560 (0.000)	0.486 (0.000)			
ΔConsumer prices	−0.347 (0.000)	−0.352 (0.000)	0.389 (0.000)	−0.087 (0.055)		
ΔMajor purchases	−0.466 (0.000)	−0.464 (0.000)	0.446 (0.000)	0.586 (0.000)	0.251 (0.000)	
ΔIntentions of saving	−0.393 (0.000)	−0.404 (0.000)	0.397 (0.000)	0.610 (0.000)	0.020 (0.666)	0.483 (0.000)

Notes: Probabilities that the correlation coefficient is equal to zero are given in parentheses.

Table 6
Other expectational variables.

	(6.1)	(6.2)	(6.3)	(6.4)	(6.5)
	Economic situation	Financial position	Consumer prices	Major purchases	Saving
Saving rate, lagged	0.809***	0.771***	0.819***	0.806***	0.775***
	(0.046)	(0.049)	(0.041)	(0.043)	(0.044)
ΔUnemployment	0.797***	0.763***	0.764***	0.744***	0.846***
	(0.242)	(0.227)	(0.201)	(0.233)	(0.275)
ΔUnempl.expectations	0.743*	0.658**	0.983***	0.738**	0.828**
	(0.427)	(0.237)	(0.303)	(0.287)	(0.348)
Income growth	0.553***	0.543***	0.522***	0.531***	0.552***
	(0.096)	(0.101)	(0.096)	(0.075)	(0.087)
Credit flow	−0.131	−0.086	−0.098	−0.091	−0.097
	(0.114)	(0.096)	(0.086)	(0.103)	(0.095)
ΔReal interest rate	0.091	0.010	0.066	0.042	0.028
	(0.076)	(0.084)	(0.071)	(0.082)	(0.066)
ΔInflation	0.079	0.023	0.035	0.083	0.096
	(0.147)	(0.133)	(0.118)	(0.140)	(0.170)
ΔExpectations of economic situation	0.005				
	(0.240)				
ΔExpectations of financial position		−0.529			
		(0.645)			
ΔExpectations of consumer prices			0.293		
			(0.265)		
ΔPlans of major purchases				−0.439	
				(0.984)	
ΔIntentions of saving					1.086
					(1.864)
Observations	387	402	401	401	401
Number of countries	21	22	22	22	22
Number of instruments	34	34	34	34	34
Hansen J-stat	9.911	7.919	6.519	11.66	12.13
p value	0.987	0.997	0.999	0.964	0.955
AR(1)	−2.647	−2.581	−2.760	−2.655	−2.581
p value	0.008	0.009	0.005	0.007	0.009
AR(2)	−1.217	−1.616	−1.446	−1.479	−1.516
p value	0.224	0.106	0.148	0.139	0.129

Notes: The dependent variable is the household saving rate as a share of disposable income. All independent variables except credit flow and income growth are in first differences. Panel estimates with one-step system GMM with two external instruments: volatility of expectations of unemployment and income volatility. All the estimated models include three control variables of life expectancy, the young-age dependency ratio and the old-age dependency ratio, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

The largest correlation coefficient is between expectations about the future economic situation and unemployment expectations. The financial position is also tightly correlated with plans for major purchases and saving intentions.

To test whether the proxy for labour income uncertainty can be substituted by a wider measure of overall optimism or other future expectations, the model is augmented with the other expectational variables discussed above, see Table 6 for the results. This analysis uses all the forward-looking questions from the same survey. The only variable omitted is a composite index of consumer expectations, which is the unweighted average of four questions.

As these variables are highly correlated, they are added to the model one variable at a time. The analysis shows that none of the additional expectational variables has any effect on saving rates and the effect of unemployment expectations remains of the same magnitude when the uncertainty proxies are added to the model one by one. If expectations of unemployment are excluded from the specification and other survey-based measures are added all together, Ireland drops out from the sample and the effect of none of the expectational variables can be precisely estimated, as shown in Column (7.2).

If Luxembourg and Bulgaria are added to the sample, then the expectations for the general economic situation, the variable that correlates the most with unemployment expectations (see Table 7), becomes marginally significant. The absolute value of the parameter is however less than half that for unemployment expectations, as seen from comparing Columns (7.1) and (7.3). If expectations for the economic situation are excluded and the baseline sample is restored with Ireland in and Luxembourg and Bulgaria out, the expectations for consumer prices become marginally significant, as Column (7.4) shows.

Table 7
Baseline model and other expectational variables.

	(7.1)	(7.2)	(7.3)	(7.4)
	Baseline	All expectational	All expectational	All expectational
Saving rate, lagged	0.784***	0.830***	0.810***	0.802***
	(0.050)	(0.049)	(0.045)	(0.051)
ΔUnemployment	0.794***	0.799***	0.818***	0.694**
	(0.240)	(0.266)	(0.261)	(0.268)
ΔUnempl.expectations	0.760**			
	(0.298)			
Credit flow	−0.107	−0.071	−0.067	−0.058
	(0.091)	(0.118)	(0.119)	(0.106)
Income growth	0.560***	0.473***	0.467***	0.484***
	(0.087)	(0.105)	(0.111)	(0.100)
ΔReal interest rate	0.045	0.002	0.057	−0.058
	(0.078)	(0.089)	(0.104)	(0.094)
ΔInflation	0.069	0.062	0.088	−0.040
	(0.153)	(0.117)	(0.111)	(0.120)
ΔExpectations of economic situation		−0.296	−0.302*	
		(0.196)	(0.168)	
ΔExpectations of financial position		−0.919	−0.207	−1.661
		(1.184)	(1.199)	(1.044)
ΔExpectations of consumer prices		−0.194	−0.071	−0.427*
		(0.308)	(0.293)	(0.235)
ΔPlans of major purchases		−0.627	−1.196	−0.499
		(0.689)	(0.710)	(0.773)
ΔIntentions of saving		3.456	3.229	3.107
		(2.230)	(3.054)	(2.290)
Observations	402	387	416	401
Number of countries	22	21	23	22
Number of instruments	31	43	43	40
Hansen J-stat	12.280	10.690	9.259	5.524
p value	0.906	0.999	0.999	0.999
AR(1)	−2.610	−2.593	−2.846	−2.771
p value	0.009	0.009	0.004	0.006
AR(2)	−1.592	−0.278	0.153	−0.746
p value	0.111	0.781	0.879	0.456

Notes: The dependent variable is the household saving rate as a share of disposable income. All independent variables except credit flow and income growth are in first differences. Panel estimates with one-step system GMM with two external instruments: volatility of expectations of unemployment and income volatility. All the estimated models include three control variables of life expectancy, the young-age dependency ratio and the old-age dependency ratio, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

The results suggest that in some specifications of the model the association between one survey-based variable or another and saving rates may be found and estimated. However, if they are added to the model together with expectations of unemployment, the unemployment expectations kill the effect of the other expectational variables, meaning labour income uncertainty is presumably the most important component of uncertainty for household saving rates.

Column (7.1) reports for the reader convenience the estimations of the baseline model. Column (7.2) reports the estimations of the baseline sample without Ireland; Column (7.3) – a sample without Ireland and with Bulgaria and Luxembourg; Column (7.4) – baseline sample. In the last model specification expectations of economic situation are excluded from the model.

Keeping in mind that the main source of income for households is labour income, it seems reasonable that precautionary saving is driven by unemployment expectations, as these are expectations of the factor that will directly affect future labour income through the higher probability of losing a job or having diminished bargaining power.

4.6. Different configurations of the model

The results reported in Tables 2–5 show that the baseline model is stable on different specifications and subsamples. Nevertheless, system GMM is known to be sensitive to changes in the model settings, and for this reason the baseline model is estimated in different configurations (Table 8).

Table 8
Different configurations of the model.

	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
	Two-step	AB	6 lags	No const.	LSDV
Saving rate, lagged	0.779***	0.612***	0.792***	0.791***	0.832***
	(0.060)	(0.112)	(0.041)	(0.057)	(0.029)
ΔUnemployment	0.688**	0.755**	0.582***	0.788***	0.640***
	(0.286)	(0.284)	(0.199)	(0.244)	(0.075)
ΔUnempl.expectations	0.542**	0.634*	0.586**	0.658**	0.361***
	(0.239)	(0.332)	(0.211)	(0.309)	(0.105)
Income growth	0.504***	0.475***	0.439***	0.535***	0.464***
	(0.143)	(0.139)	(0.075)	(0.097)	(0.040)
Credit flow	−0.043	−0.114	−0.084	−0.088	−0.098***
	(0.116)	(0.128)	(0.061)	(0.093)	(0.027)
ΔReal interest rate	0.059	−0.045	0.025	0.070	0.146***
	(0.108)	(0.098)	(0.102)	(0.074)	(0.032)
ΔInflation	0.036	0.018	−0.097	−0.008	0.011
	(0.225)	(0.131)	(0.141)	(0.146)	(0.049)
Observations	402	380	402	402	402
Number of countries	22	22	22	22	22
Number of instruments	31	21	58	30	
Hansen J-stat	12.28	12.62	10.25	14.65	
p value	0.906	0.319	1	0.796	
AR(1)	−2.618	−2.374	−2.534	−2.654	
p value	0.008	0.017	0.011	0.007	
AR(2)	−1.199	−1.644	−1.409	−1.762	
p value	0.231	0.100	0.159	0.078	
R-squared					0.721

Notes: The dependent variable is the household saving rate as a share of disposable income. All independent variables except credit flow and income growth are in first differences. Panel estimates with one-step system GMM with two external instruments: volatility of expectations of unemployment and income volatility. All the estimated models include three control variables of life expectancy, the young-age dependency ratio and the old-age dependency ratio, all in first differences. Lags 2 to 3 are used for the transformed equation and lags 1 to 2 are used for the equation in levels. Robust standard errors are in parentheses. Superscripts ***, **, * indicate levels of statistical significance at 1, 5 and 10 per cent respectively.

Column (8.1) in Table 6 reports the results obtained with a two-step estimator instead of the one-step estimator used in the baseline model. Column (8.2) reports the results obtained with the Arellano-Bond estimator. A different number of lags[26] is used in column (8.3) and there is no constant term in (8.4). The model in column (8.5) is estimated with the least square estimator with a country dummy variable and clustered errors.

The only notable difference between the baseline model and the LSDV estimates is that the coefficients of the explanatory variables are somewhat smaller and the autoregressive coefficient is larger. However, this is an expected outcome as the Nickel bias present in OLS estimates drives all coefficients downwards, while autoregressive is biased upwards. The coefficients in all the other model configurations are very close to those of the baseline model.

Column (8.1) reports the estimations with the two-step estimator with Windmeijer (2005) corrected standard errors. In column (8.2) the model is estimated with the Arellano-Bond estimator. The model in column (8.3) uses 8 and 5 lags instead of 3 and 2. The model in column (8.4) supresses the constant. Finally, the model in column (8.5) is estimated with the Least Square Dummy Variable estimator.

All the point estimates of the different model configurations are compared to the baseline estimates using the Z-test as described above (results are not reported). According to the test, none of the coefficients, even those of LSDV estimates, are statistically different from the baseline estimates. In summary, the baseline model appears to be very stable and the reported findings may be considered robust.

5. Conclusions

This paper studies the determinants of household saving rates in 22 European countries in 1996–2017 using system GMM to account for the dynamic panel bias and the potential endogeneity of the regressors. The findings reveal that household saving rates are highly persistent and that there are two key determinants of saving, the first one being income growth, and the second one being labour income uncertainty or the precautionary motive.

[26] Models with 4 and 8 lags instead of 3 and a model without external instruments were also estimated but the results are not reported here as they are largely the same.

Keynes (2016) notes the need to build up a reserve against unforeseen contingencies as one of the essential incentives for households to save, and little has changed since the 1930s. According to consumer surveys, a buffer for unexpected events is still the primary motive for saving.[27] The empirical evidence yielded in this paper confirms that the precautionary motive is indeed the one that drives household saving.

Among the novelties of this paper is the incorporation of data from micro-level surveys into a macroeconomic study introducing two channels for the labour income uncertainty that affects household saving behaviour. The core finding of this paper is that both types of uncertainty have a pronounced and statistically significant effect on saving rates, meaning that changes in the level of unemployment rate and the expectations of consumers for future changes in the level of unemployment can severely affect saving rates.

Credit conditions do not explain saving behaviour in Europe and it can be concluded that the credit-consumption environment is different to that in the USA (see Carroll et al. (2012) for the US data), at least in the past two decades. The interest rate and inflation do not have any pronounced effect on saving rates either. The results are robust to the inclusion of other macroeconomic variables and uncertainty measures.

The results show that the negative effect that unemployment is believed to have on the economic growth is amplified through the household saving channel, reducing current consumption and keeping it low over a long time span. These observations may help explain the slow recovery in Europe after the crisis of 2008–2009, when the high unemployment rate was followed by low consumer confidence, which induced high levels of saving and low consumption.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2019.10.005.

Appendix A

AUT	Austria
BEL	Belgium
BGR	Bulgaria
CYP	Cyprus
CZE	Czechia
DNK	Denmark
EST	Estonia
FIN	Finland
FRA	France
DEU	Germany
HUN	Hungary
IRL	Ireland
ITA	Italy
LVA	Latvia
LTU	Lithuania
LUX	Luxembourg
NLD	Netherlands
POL	Poland
PRT	Portugal
SVK	Slovakia
SVN	Slovenia
ESP	Spain
SWE	Sweden
GBR	United Kingdom

Appendix B

The household saving rate is defined as household gross disposable income less household consumption expenditure as a share of household gross disposable income, taken from Eurostat [table code *nasa_10_nf_tr*]. Households refer to households and non-profit institutions serving households (NPISH). It is common practice to study households and NPISH together, as NPISH are supposed to act like households. Gross disposable income is adjusted for the change in the net equity of households in pension fund reserves. Saving rates fluctuate in the range of 8.5–21.3, with an average of 10.1 and standard deviation of 5.2 (484 observations). See Figure C1 in Appendix C.

[27] Carroll (1997) refers to the Survey of Consumer Finances conducted by the Federal Reserve Board in 1983 in the USA, and points out that 43 per cent of the respondents said that having a buffer for emergencies was the most important reason for saving, while only 15 per cent mentioned accumulating funds for retirement as their primary motivation for saving. In Europe the Household Finance and Consumption Survey (HFCS) conducted in 2010/2011 found that about 53 per cent of respondents cited making provisions for unexpected events as the most important reason for saving (Rodriguez-Palenzuela & Dees, 2016). The data come from the first wave of the HFCS and cover the eight first-wave euro area countries other than Finland, France and Italy.

The data for the expectations of unemployment are taken from the business and consumer survey, which is a joint harmonised EU programme of the European Commission, Eurostat code *DG ECFIN*, question7[28] [table code *ei_bsco_m*]. The question is: "How do you expect the number of people unemployed in this country to change over the next 12 months? The number will …" There are five answer choices: increase sharply, increase slightly, remain the same, fall slightly, or fall sharply, and don't know.

Aggregate balances are calculated in the following way. Where there are six options, PP denotes the percentage of respondents who have chosen "increase sharply", MM denotes the percentage of respondents who have chosen "fall sharply", E is the percentage of respondents who think that the unemployment rate will remain the same, and N is the percentage with no opinion, and so the balance is calculated as $B = (PP + ½P) - (½M + MM)$.

The average of monthly balances of answers is globally standardised (demeaned and divided by the standard deviation) using the full sample of 24 countries including Bulgaria and Luxemburg, using the means and standard deviations for the whole sample to make the interpretation of the results more intuitive. The same is done for the other expectational variables used for the robustness check (questions 2, 4, 6, 9 and 11).

The unemployment rate is taken from the same database [table code *une_rt_a*]. The growth rate of income is the growth rate of household disposable income per capita [table code *nasa_10_nf_tr*] deflated with the harmonised index of consumer prices (HICP) [table code *ei_cphi_m*].

For a robustness check, the volatility of inflation (change of HICP) is used as an uncertainty proxy. It is measured as the standard deviation of rolling five-year windows of year-on-year HICP. Besides price inflation, volatility of output, measured as the standard deviation of quarterly output, and stock market volatility, expressed as the VIX and VDAX indexes, are controlled for. VIX measures the market's expectation of future volatility and is based on options for the S&P 500® Index.[29] VDAX is the VDAX NEW index, and it expresses the implied volatility of the DAX, *Deutscher Aktienindex* (German stock index). The VDAX series are markedly shorter than those of the VIX. Both stock market volatility indexes are country-invariant.

Besides stock market volatility, a more general measure of uncertainty is employed, which is the mean average forecast error (MAFE) calculated using the data from the ECB Survey of Professional Forecasters. The forecast is for the inflation rate in the euro area and the forecast horizon is one year.

Credit availability is accounted for as the net flow of loans to households as a fraction of GDP, [table code *nasa_10_f_tr*], ESA 2010. A weakness of this indicator is that it reflects not only the supply side through credit constraints but also the changes in credit demand. However, it is the best proxy of credit conditions available for the given period. The debt-to-income ratio is used for the robustness check [table code *nasa_10_f_bs*]. The data source for the short-term real interest rate is the AMECO database [table code *ISRV*].

The set of control and additional variables includes the young-age dependency ratio (the ratio of the population younger than 15 to the population aged 15–64 [table code *demo_pjanind*]); the old-age dependency ratio (the ratio of the population older than 64 to the population aged 15–64 [table code *demo_pjanind*]); life expectancy [table code *demo_mlexpec*]); proxies of income inequality, which are the income share of the bottom 40 per cent of the population as a percentage of total disposable household income, [table code *sdg_10_50*] and the Gini index, [table code *ilc_di12*]; social benefits as a fraction of GDP, which shows transfers received by households in such circumstances as sickness, unemployment or retirement, or facing changes in housing, education or family circumstances, expressed as a share of GDP [table code *gov_10a_main*]; the pension replacement ratio, which is a ratio of income from the pensions of those aged between 65 and 74 and the income from work of those aged between 50 and 59 [table code *ilc_pnp3*]; the female participation rate measured as a percentage of the total population [table code *lfsi_emp_a*]; and the output growth rate in real terms [table code *nama_10_gdp*]. All these data are downloaded from the Eurostat database. The output gap is taken from the EC database AMECO and is measured as a percentage of trend GDP [table code *AVGDGT*].

Appendix C

[28] See http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/bcs_user_guide_en.pdf for details.

[29] See http://www.cboe.com/vix for details.

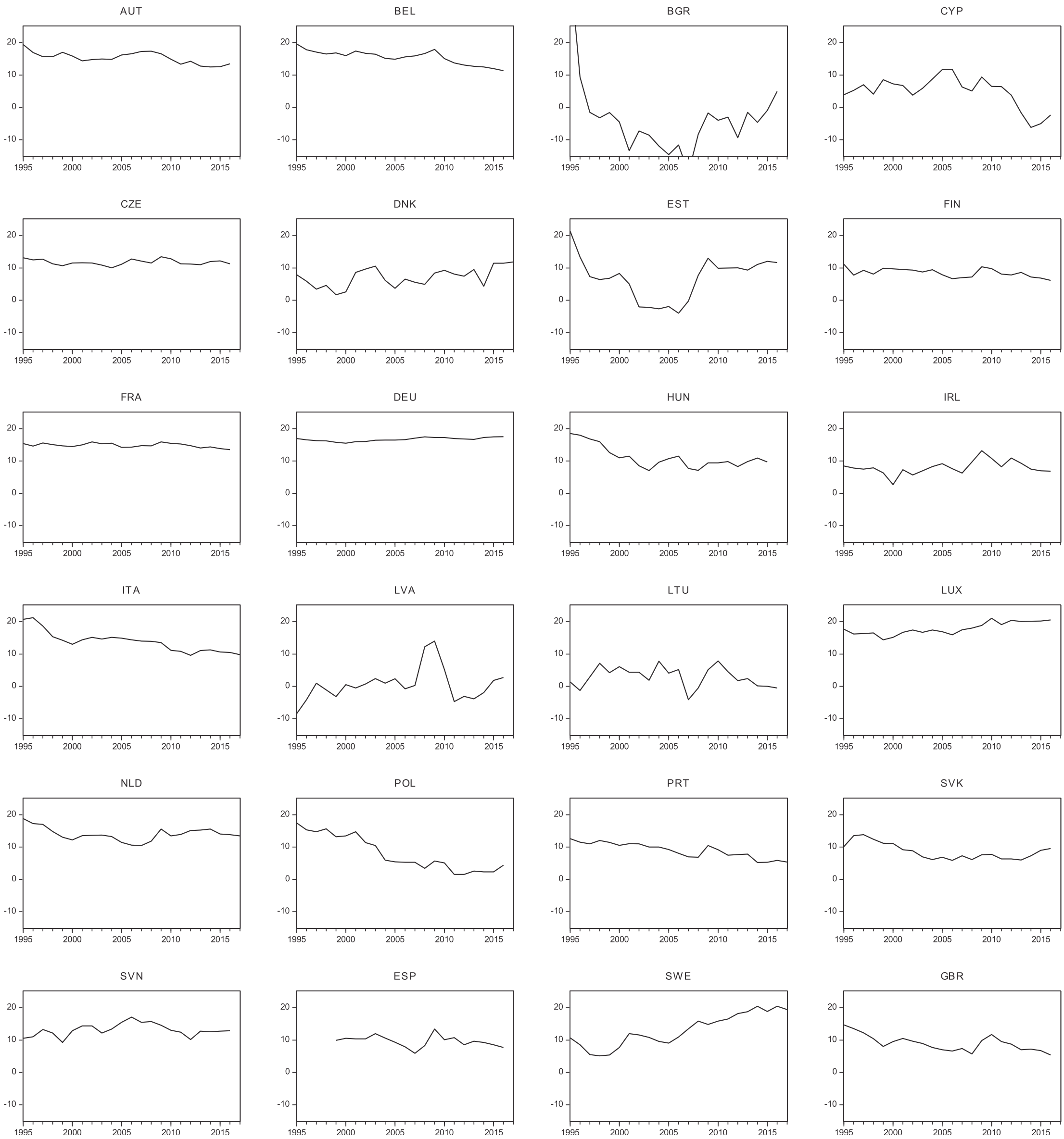

Fig. C1. Household saving rates.
Notes: The household saving rates are expressed as a share of household disposable income.
Source: Eurostat.

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Appendix 3. Publication III

ROUNDING BIAS IN FORECAST UNCERTAINTY

Publication III

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Rounding bias in forecast uncertainty

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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. The paper seeks to explain this puzzling lack of countercyclicality by applying a smooth transition analysis on data from the European SPF. The analysis indicates that the mean individual variance is a function of the modelling preferences of forecasters and consequently shifts in individual variance are likely to be misleading for the actual changes in the perceived uncertainty. The results remain robust after potential endogeneity has been accounted for.

1. Introduction

Uncertainty is now being incorporated extensively into economic research and is particularly relevant in analysis of recessions and post-recession periods, when economic agents are typically more uncertain about the future than they are in normal times. A large body of literature has documented the adverse effects that different types of macroeconomic uncertainty may have on the real economy. Uncertainty may affect the economy through numerous channels, such as precautionary saving by households, or firms taking a wait-and-see attitude to investment (Bloom et al., 2007; Stokey, 2016; Levenko, 2020). 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 (Gilchrist et al., 2014; Baker et al., 2016; Basu and Bundick, 2017; Cesa-Bianchi et al., 2018; Bloom et al., 2018).

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, which are the inflation rate, real output growth and the unemployment rate, together with probability distributions for 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.

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The main focus of this paper is on the quality of the mean individual variance of forecasts, which is a widely used measure of survey uncertainty.[1] Mean individual variance is defined as the average of the variances of the individual density forecasts. The variance of an individual density forecast is supposed to be a direct indicator of how an individual forecaster perceives the uncertainty about the variable being forecast. The larger the variance is, the more uncertain the forecaster is, and the other way round, so the mean individual variance is often considered a direct measure of uncertainty (Zarnowitz and Lambros, 1987; Giordani and Söderlind, 2003; Boero et al., 2008; Abel et al., 2016).

An alternative measure of uncertainty that can be calculated using the same dataset is the cross-sectional variance of the point estimates, which is often labelled forecast disagreement. Both measures of uncertainty peaked during the Great Recession, but while the disagreement returned to its pre-crisis level immediately after the recession was over, mean individual variance has remained elevated since the crisis. This shift in the mean individual variance is puzzling since 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, as has been documented in many empirical studies (Abel et al. 2016; Binder, 2017; or Cesa-Bianchi et al., 2018 to name just a few).

It can be argued that there is no puzzle about the persistence of increased mean individual variance since the level of uncertainty was fairly high not only during the recession but also in the years after the crisis, which saw the sovereign debt crisis in the euro area, the unexpected Brexit vote followed by government crises in the UK, the European migrant crisis, international trade conflicts, and so on. In fact the correlation of mean individual variance with the Economic Policy Uncertainty (EPU) index is quite high.[2]

Even so, this paper offers an alternative explanation for the elevated uncertainty, measured as mean individual variance, and argues that the upward shift cannot be justified solely by the crisis itself or by other economic and political fluctuations in the years since the crisis. The paper provides evidence that the changes in the mean individual variance should in large part be attributed to changes in the modelling preferences and habits of forecasters, and that the evolution of these preferences is a process that is exogenous to the economic and political instabilities in Europe following the crisis. Besides, this paper illustrates how modelling preferences can introduce additional noise into individual variance.

A key to understanding changes in the mean individual variance is the rounding behaviour of survey participants, meaning that forecasters may or may not round the probabilities they assign to the different outcomes of the variables being forecast. Rounding behaviour is likely to be rooted in the modelling preferences of forecasters, such as whether they use a modelling approach or a judgement-based approach. It seems reasonable to assume that density forecasts produced with econometric models would generally be non-rounded while judgement-based forecasts would be rounded. It is shown in Section 3.4 that the share of non-rounded responses in the survey is related to developments in the computer software market, implying that there is a growing tendency for researchers and other professionals to use more sophisticated software and modelling methods.

Rounding itself has a marginal positive effect on the variance of forecasts that can be neglected because of its magnitude.[3] What is important is that when a forecaster rounds the probabilities, the bins at the tails of the probability distribution disappear by becoming nulled, which drives the variance downwards. It is shown by means of simulations in Section 2.2 that due to the different number of bins in rounded and non-rounded density forecasts the difference in variance can be very significant. These findings are perfectly in line with the data. The average number of bins used by rounders is considerably smaller than the number of bins used by those forecasters who do not round their forecasts (Glas and Hartman, 2018).

Rounding is believed to be directly related to the perception of uncertainty. Section 2 discusses how rounding is typically a strong sign of uncertainty from a survey participant (Krifka, 2002). Thus, if rounding and the subsequent reduction in the forecast variance are a product of forecasters perceiving greater uncertainty, then there is problem, since the inferences made by the survey users are the opposite to what is really being perceived by the forecasters. This is of great concern as around three fifths of the short-term and medium-term forecasts examined in this paper use a model-based approach with judgemental adjustment (Meyler and Rubene, 2009; ECB, 2014; ECB, 2019).

Various attributes of the SPF forecasts are examined in Glas and Hartmann (2018), who document that more responses were not rounded after the Great Recession. They state that this increase in the share of survey participants who do not round could be one possible explanation for the increased uncertainty after the crisis, but they still state that mean individual variance is a valid proxy for measuring uncertainty.

While Glas and Hartmann (2018) mostly use statistical and descriptive methods to examine the attributes of the SPF forecasts, this paper applies a more formal econometric approach in the form of smooth transition regression analysis, which to the best of my knowledge has never previously been applied to the SPF data. Apart from its technically not trivial method, the main contribution of this paper is its finding that the shift in the level of uncertainty after the Great Recession as measured by the individual variance can be attributed to the changes that have occurred in the modelling preferences

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

[2] For the European data see www.policyuncertainty.com/europe_monthly.html.

[3] See a discussion on whether rounding introduces variance into estimates stats.stackexchange.com/questions/209260/does-rounding-introduce-variance-into-estimates.

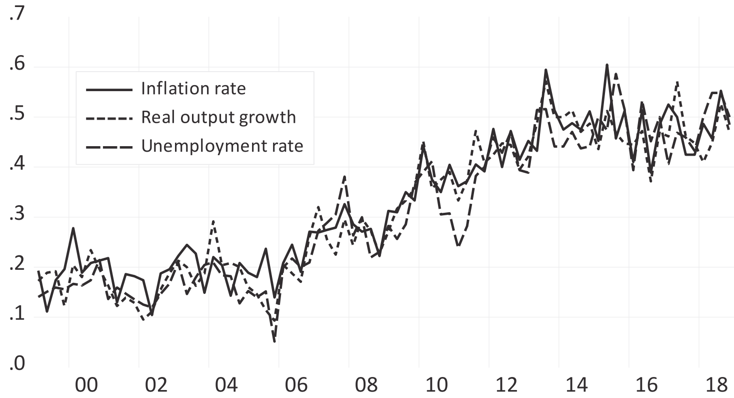

Fig. 1. Share of non-rounders in the one-year-ahead forecasts. *Note*: Forecasters are defined as rounders if all the reported probabilities in the density forecasts are multiples of five. The shares of rounders and non-rounders add up to unity. The dynamics do not change much if other definitions of rounding are applied. If the RN/RI principle holds and the rounding of responses is taken as an indicator of uncertainty, then forecasters were on average much more uncertain about their forecasts in 2000–2006 than they were in 2012–2018.

of forecasters since the mid-2000s. Another contribution of the paper is that it shows by means of simulations that the rounding of density forecasts drives variance down by reducing the number of bins. 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 and runs simulations of rounding applied to density forecasts; Section 3 describes the data, estimation methods, and results; and finally, Section 4 concludes.

2. Rounding behaviour of forecasters

The rounding behaviour of forecasters is central to this paper. This section gives a short review of the literature on it, discusses the properties of forecasts by rounders and non-rounders, explains how modelling preferences and rounding behaviour are related, and runs simulations to show how rounding affects the density forecast variance.

2.1. Attributes of rounded and non-rounded forecasts

A forecaster can be defined as a rounder in different ways. One way is to take an integer approach, in which the forecaster is called a rounder and the forecast is called a rounded forecast if all the numbers in the density forecast are integers. An alternative way would be to define a forecaster as a rounder if all the numbers reported are multiples of five; or similarly, a multiple-of-ten approach can be used. Forecasters may switch between rounding and non-rounding, so they are classified as rounders or non-rounders by the way they present their responses in each individual forecast.

The first point to note is that the mean individual variance of the rounded forecasts is systematically lower than the variance of the non-rounded forecasts, whichever definition of rounding is used. If the multiple-of-five approach is used for example, the average variance in rounded forecasts is smaller by two thirds to a half than in non-rounded forecasts, depending on the underlying forecast variable and the forecast horizon (see Table A.1 in Appendix A).[4]

As was discussed earlier, the variance of density forecasts is typically referred to as a direct measure of uncertainty, from which it follows that rounders are consistently *more certain* about their forecasts than non-rounders are about theirs. Zarnowitz and Lambros (1987) and Boero et al. (2008) 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).

If the RN/RI principle holds true for professional forecasters and the level of uncertainty can be measured by the share of rounded responses, then it can be stated that the level of uncertainty has fallen substantially since 2006 as the share of non-rounders, representing forecasters who are confident in their forecasts according to the RN/RI principle, has been constantly increasing since then (see Fig. 1).

This interpretation of the dynamics of uncertainty does not seem convincing nor does it match with other data like the dynamics of the EPU indicator. This suggests that the interrelations between rounding, uncertainty and forecast variance are not trivial for professional forecasters.

[4] The mechanism of how rounding may reduce variance is discussed in the next subsection.

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Table 1.1
Mean variance calculated on the simulated series. Integer approach.

Standard deviation	Average variance of non-rounded density forecasts	Average variance of rounded density forecasts
0.25	0.0651	0.0635
0.5	0.2667	0.2564
1	1.0226	0.9766
2	4.0813	3.8991
5	26.6062	25.6032

Note: Series are random numbers with mean zero and standard deviations $\in (0.25, 0.5, 1, 2, 5)$.

There is no information available on the methodology used by each individual forecaster, but the approaches used by forecasters in general are known. Special Surveys find that SPF forecasts can be judgement-based, model-based or model-based with judgemental adjustment (Meyler and 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. A model-based forecast with judgemental adjustment can do both.

It is of note that the share of non-rounders in Fig. 1 started to grow not in 2008 or 2009 but a few years earlier and that the transition from a low level at the beginning of the 2000s to a higher level in the 2010s is fairly smooth. It can be assumed from this that the move to the model-based approach that is implied by non-rounding was not necessarily induced by the Great Recession but was affected more by some other process, such as the wider spread of statistical and econometric software, or increased opportunities for professional training.

As reported in ECB (2019), around 12% of short-term and medium-term forecasts are model-based, 24% are judgement-based, and 64% of forecasts can be classified as model-based with judgemental adjustment. Around one half of forecasts were not rounded in 2018 (see Fig. 1). Assuming that all model-based forecasts are non-rounded while the judgement-based forecasts are rounded, it follows that roughly 60% of adjusted forecasts are non-rounded and the rest are rounded. In other words, around one quarter of all forecasts were most probably produced as non-rounded and were then adjusted by rounding. According to the RN/RI principle discussed above, rounding by an individual implies they have less knowledge and less certainty, in which case greater individual uncertainty results in lower variance, but this is then interpreted as less uncertainty.[5]

The link between non-rounding and the model-based approach to forecasting seems quite apparent. There is though a formal argument that supports the idea that rounding behaviour is rooted in the modelling choices of forecasters. This argument is that uncertainty measured at the individual level persists, as discussed in Boero et al. (2008). If individual variance is persistent, it is more likely to be because of the persistence in the methodology used by a forecaster rather than because the level of individual uncertainty is constant. This 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 and Reis, 2010).

2.2. Simulations

To get a better idea of what happens with the variance of density forecasts when forecasters round or do not do so, I run simulations. I generate 1000 random numbers with mean zero and standard deviation of one and draw histograms. The counts in each bin are then divided by 10 to simulate a density forecast. The numbers on the histograms are not rounded, rounded to an integer, rounded to five and to ten. When rounding to an integer, statistician's rounding is used. See Figs. 2–4 (rounding to ten is not shown for the sake of space).

As Figs. 2–4 suggest, the number of bins, becomes smaller as the bins at the tails of the distribution are nulled. I compare two states. First, I want to see if rounding itself affects the variance. To do that, I make the number of bins in the non-rounded histogram the same as the number in the rounded histogram and redistribute the values of the bins cut at the tails proportionally between all the remaining bins. After that, the variance of both histograms is calculated. The simulations are run 1000 times. When the numbers of bins in the histogram are equal in the rounded and non-rounded histograms, there is a little more variance in the rounded one than in the non-rounded one; the difference in variance is numerically small but statistically significant, meaning the rounding itself has introduced additional variance.

However, when the numbers of bins in the rounded and non-rounded forecasts are not equal, the variance in the rounded histogram is smaller than that in the non-rounded one. This is what is likely to happen when a forecaster uses a model-based approach to forecasting and then rounds the density forecast. The difference in variance between the rounded and non-rounded histograms varies depending on the standard deviation that is given initially and on the definition of rounding used, whether to an integer, a multiple of five, or a multiple of ten. See Tables 1.1 and 1.2.

[5] A forecaster may round solely out of habit or because of personal preferences that are not necessarily related to their perception of uncertainty. Even in this case the resulting indicator of uncertainty will be biased as rounding results in a lower variance in the density forecast, see Section 2.2.

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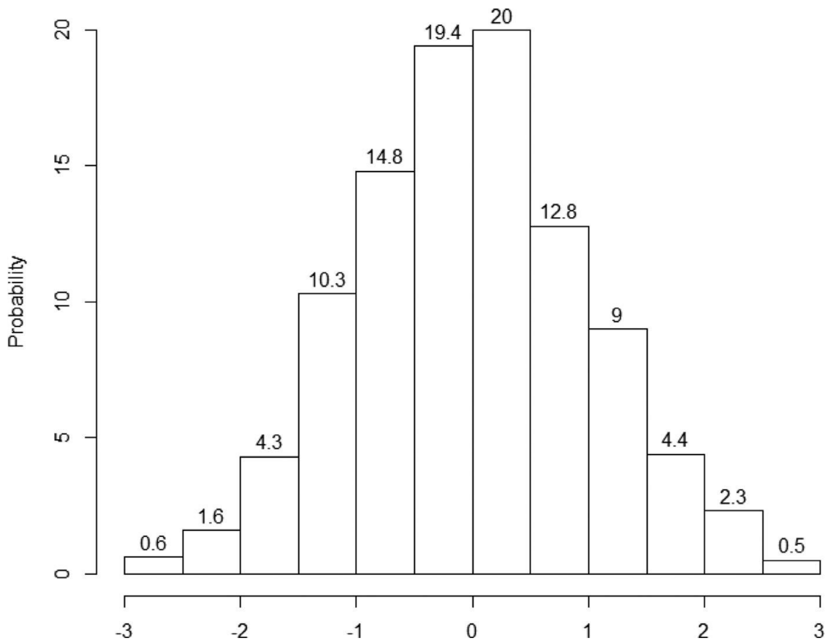

Fig. 2. Simulation of the non-rounded density distribution forecast.

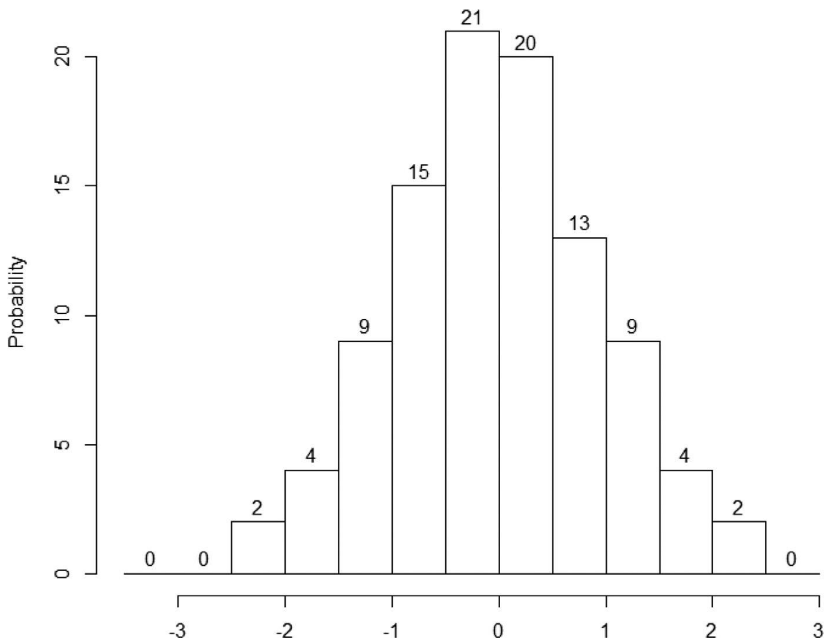

Fig. 3. Simulation of the density distribution forecast with probabilities rounded to an integer.

Tables 1.1 and 1.2 show the difference in the average variance between the rounded and non-rounded series to be quite significant. When the integer definition of rounders is used, the difference between the average variances of the rounded and non-rounded series is smaller than when multiple-of-five approach is employed because fewer bins are nulled; when rounders are defined as those who round to ten, the difference between the variances is close to that of multiple-of-five approach (results are not reported for the sake of space).

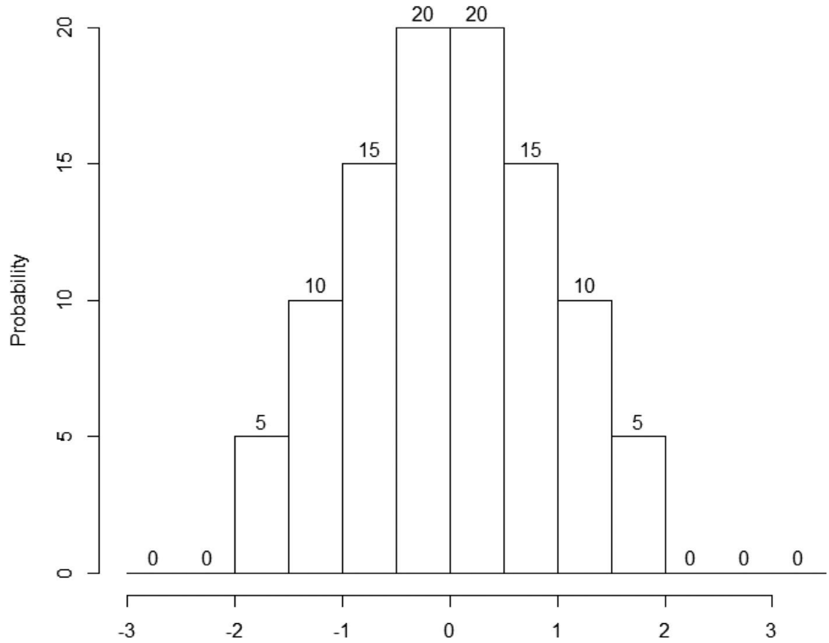

Fig. 4. Simulation of the density distribution forecast with probabilities rounded to multiples of five.

Table 1.2
Mean variance calculated on the simulated series. Multiple-of-five approach.

Standard deviation	Average variance of non-rounded density forecasts	Average variance of rounded density forecasts
0.25	0.0651	0.0560
0.5	0.2659	0.2214
1	1.0221	0.8183
2	4.0708	3.2709
5	26.5278	22.1258

Note: Series are random numbers with mean zero and standard deviations $\in (0.25, 0.5, 1, 2, 5)$.

The next section examines the dynamics of the relationship between the mean individual variance and the share of forecasters who do not round their forecasts. It applies the smooth transition regression approach and shows that the growing share of non-rounders drives the mean individual variance up.

3. Data, method, and results

The European SPF asks the forecasters 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. Wallis (2005) states that mean individual variance can be calculated as a residual of the aggregate variance and disagreement of forecasts (see Eq. 1) or it can be calculated directly from the individual density forecasts as the average of their variances.

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

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; $\overline{y_i}$ 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 as forecast disagreement.

I calculate the mean individual variance using the second approach 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. When calculating the mean individual variance, I assume that the numerical value of each probability is concentrated at the midpoint of the corresponding bin. See Fig. 5 for the one-year-ahead forecasts. The graph shows that either the mean individual variance is non-stationary or it has a structural break at the time of the crisis.

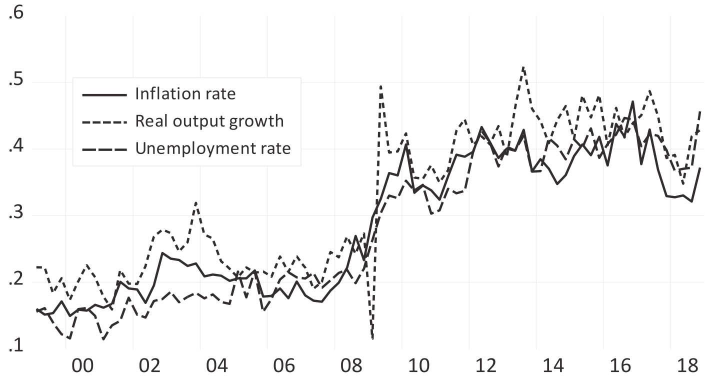

Fig. 5. Mean individual variance of the one-year-ahead forecasts.

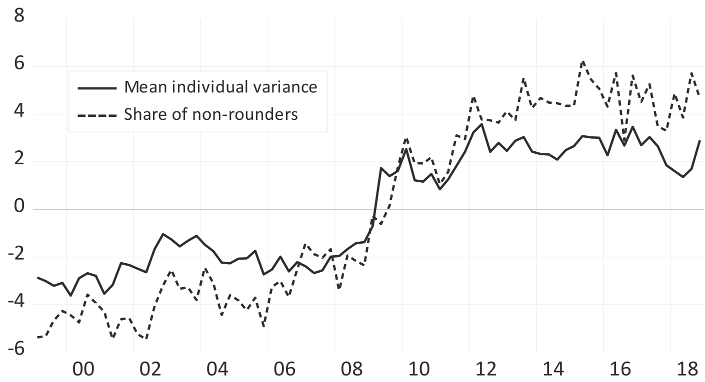

Fig. 6. First principal components of the mean individual variance and of the share of non-rounders.

3.1. Transformation of the data

A measure of uncertainty can be calculated for the three forecast variables using data for the one-year-ahead horizon and the two-year-ahead horizon, and this results in six series of mean individual variance. All these series are highly correlated between themselves with the correlation coefficients varying between 0.88 and 0.99 (see Table B.1 in Appendix B). In addition to the six series of proxies of uncertainty, there are 18 series of the shares of non-rounders, since there are three different approaches to defining non-rounders, three forecast variables and two forecast horizons.[6] These series are also highly correlated between themselves, with correlation coefficients varying in the range of 0.62 to 0.96.

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 issues that needs to be addressed when using 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 C).

The following analysis is restricted to the first PCs as they explain from 85% to 94% of the variance of the variables. Further on, references to the mean individual variance or the share of non-rounders mean the transformed series of the underlying variables. The resulting series for mean individual variance and the shares of non-rounders are shown in Fig. 6.

Further analysis will aim to show that the visible co-movements of the series are not spurious and that the growing share of non-rounders, which happens as forecasters move from a purely judgement-based approach to a model-based approach, is driving the variance of density forecasts up.

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

Table 2
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

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

3.2. Time series properties of the data

A quick visual analysis of Fig. 6 suggests that individual variance and the share of non-rounders are not stationary. An ADF test corroborates this preliminary inference and shows that the individual variance series and the share of non-rounders have a unit root (the results are not reported). 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, and the same findings are obtained in Zivot and Andrews (1992), Skalin and Teräsvirta (2002), 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 and Andrews, 1992). The results suggest that the series are stationary with a structural break at the time of the recession (see Table 2).[7] These results corroborate the findings of Dovern and Kenny (2019), who find structural breaks in the series of SPF inflation forecasts.

The test is against a single structural break and it rejects the null of non-stationarity. However, rejection of a null hypothesis does not automatically validate the alternative hypothesis. As Dijk et al. (2002) discuss, it might be difficult to distinguish between non-linearity, from regime switching for example, and structural change. Lin and Teräsvirta (1994) also point out that it is usually more realistic to assume a smooth transition than a single structural break. In this particular case, Figs. 1, 5 and 6 inform us that there was a smooth shift in the share of non-rounders as well as in the mean individual variance.

Another argument for the smooth transition is that even in the event of a large shock to the economy, experts are unlikely to adjust their expectations at once. The information that is available to different forecasters may be different, as may the speed with which new information is incorporated into forecasts. Given all this, it is plausible to assume that the aggregate change in the level of uncertainty is smooth rather than abrupt. The next subsection examines this in detail.

3.3. Smooth transition

Smooth transition regression models (STR) were first introduced in Bacon and Watts (1971). The autoregressive version of the smooth transition model, the smooth transition autoregressive regression (STAR) model, was introduced in Chan and Tong (1986) and was developed in Luukkonen et al. (1988), Teräsvirta (1994), and van 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:

$$y_t = \varphi_1' \omega_{1,t} + (\varphi_2' \omega_{2,t}) \cdot (1 + exp[-\gamma (s_{t-d} - c)])^{-1} + \varepsilon_t, \tag{2}$$

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

The choice of transition variable is not an obvious one. A common option for the transition variable is the lagged dependent variable (see Teräsvirta, 1998; or Skalin and Teräsvirta, 2002), but it could also be a deterministic trend such as a linear time trend (Lin and Teräsvirta, 1994) or an explanatory variable (Christopoulos and Leon-Ledesma, 2007; Bacon and Watts, 1971). Given the hypothesised relationship between rounded responses and the measure of uncertainty, the share of non-rounders is used as a transition variable. The number of lags d is chosen endogenously by minimising the sum of squared residuals. The output gap enters the model to account for cyclical fluctuations, and EPU is added to control for economic policy uncertainty given the high correlation between the variables.

3.4. Instrumentation

One possible problem with having the share of non-rounders on the right-hand side and the mean individual variance on the left-hand side is the potential for reverse causality. As was discussed in Section 2, frequent updates to the data or the

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

Table 3
Estimations of the auxiliary regression.

	(3.1)	(3.2)
Linear part		
φ_1	-323.429***	-306.671***
	(23.280)	(21.822)
Nonlinear part		
φ_2	565.473***	508.27***
	(40.148)	(26.773)
γ	0.157	0.20
	(0.029)	(0.035)
c	39.373	38.77
	(1.421)	(1.160)
Sample	2001Q1-2014Q1	2001Q2-2018Q4
Number of observations	57	75
R-squared	0.94	0.95

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 location parameter. The estimated parameters φ_1 and φ_2 are statistically significant at the 1% level.

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 might encourage survey participants to switch to more sophisticated methods of forecasting.[8] To be on the safe side, I use a two-stage instrumental variable approach. 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 an IV estimator can be used to take potential endogeneity into account.

The instrument I use 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 main idea behind using this 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.

In both auxiliary regressions, the share of non-rounders is regressed on an instrumental variable, either original series or extrapolated, and the model is estimated with logistic STR (LSTR) with a linear time trend as the transition variable:

$$NONR_t = \varphi_1 IV_t + (\varphi_2 IV_t) \cdot (1 + exp[-\gamma(T - c)])^{-1} + \varepsilon_t, \tag{3}$$

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 rescaled to the interval [0; 1], γ is the speed of transition between regimes and $\gamma > 0$, c is a location parameter, and ε_t is an error term with the distribution $Nid(0, \sigma_\varepsilon^2)$. Table 3 shows the results of the auxiliary estimations.

Table 3 shows 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 3.1 uses the original data sample from 2000-2014, Column 3.2 uses a longer sample with four additional years of data extrapolated to cover all the years in the sample. The estimated parameters φ_1 and φ_2 are highly statistically significant and all the model specifications have successfully passed model diagnostics for linearity, retaining non-linearity and stability of parameters. Residuals from the auxiliary regressions are used in the main regression (see Table 4 in the next subsection).

3.5. Estimations of the main model

The model estimated in this subsection has four variables on the right-hand side. These are mean individual variance lagged one period (*INDVAR*(-1)), the share of non-rounders in the same period (*NONR*), the lagged output gap (*OGAP*(-1)), and the lagged economic policy uncertainty indicator (*EPU*(-1)); the dependent variable is mean individual variance (*INDVAR*). The model is estimated with standard non-linear least square estimators; γ and c are estimated using grid search with coefficients concentrated out of the likelihood.

$$INDVAR_t = \varphi_1' \omega_{1,t} + (\varphi_2' \omega_{2,t}) \cdot (1 + exp[-\gamma(NONR_{t-d} - c)])^{-1} + \varepsilon_t, \tag{4}$$

where $INDVAR_t$ is the dependent variable, $\omega_{1,t} = \omega_{2,t} = (1, INDVAR_{t-1}, \ldots, INDVAR_{t-p}, X_{1,t}, \ldots, X_{k,t})'$, $\varphi_i = (\varphi_{i,0}, \varphi_{i,1}, \ldots, \varphi_{i,n})', i \in (1,2)$, $n \in (k,m)$, $X_{j,\,t}$ is a vector of explanatory variables that contains $NONR$, $OGAP_{t-1}$ and

[8] 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).

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Table 4
Estimations of the LSTR model.

	(4.1) *NONR*	(4.2) *NONR*(IV)
Linear part		
φ1,0	-0.678***	-1.298***
	(0.175)	(0.328)
INDVAR(-1)	0.159*	0.169*
	(0.082)	(0.097)
NONR	0.253***	0.317***
	(0.05)	(0.089)
OGAP(-1)	-0.522***	-0.687***
	(0.059)	(0.113)
EPU(-1)	-0.003	-0.006***
	(0.002)	(0.002)
Non-linear part		
φ2,0	0.711**	2.173***
	(0.298)	(0.397)
INDVAR(-1)	0.186	0.256*
	(0.178)	(0.152)
NONR	0.034	0.081
	(0.087)	(0.111)
OGAP(-1)	0.332***	0.622***
	(0.107)	(0.128)
EPU(-1)	0.005**	0.009***
	(0.002	(0.002)
γ	2.37	1.391
	(1.953)	(0.426)
c	-0.772	-1.092
	(0.433)	(0.300)
Transition variable	*NONR(-4)*	*NONR(-4)*
No of observations	76	75

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 location parameter. Column 4.2 uses innovations of the share of non-rounders from the auxiliary regression shown in Column 3.2 in Table 3.

EPU_{t-1}, $NONR_{t-d}$ is a transition variable lagged d periods, γ is the speed of transition between regimes and $\gamma > 0$, c is a location 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 it is bounded between 0 and 1.

There are two model specifications in Table 4. The model specification in Column 4.1 uses the first principal component of the series of non-rounders and the specification in Column 4.2 uses the residuals from the auxiliary regression with the value added of computer programming, consultancy and related activities in total value added in the EU (Column 3.2 in Table 3). The results with the shorter sample (Column 3.1 in Table 3) are on the whole the same and are not reported. The transition functions of the models in Table 4 are shown in Figs. 7 and 8.

It is apparent from Table 4 that the share of non-rounders is related to the mean individual variance only in the linear part of the equation. These results are fairly reasonable as this is exactly the relationship between variables discussed at the beginning of this paper that when more experts use model-approach, and this results in non-rounded forecasts with a larger number of bins, the mean individual variance becomes higher. It is an important finding that this relationship is not state-dependent. It is interesting that the output gap has statistically significant coefficients in both the linear and non-linear parts of the equation, while economic policy uncertainty is pronounced only in the non-linear part.

It should be stressed that the transition function allows the dependent variable to change from one regime to another with the transition variable (Fouquau et al., 2008). In this particular case, the transition variable is the share of non-rounders, meaning the results can be interpreted as the increase of the share of non-rounders driving the shift in the mean individual variance. It could be explained by an assumption that the higher number of non-zero bins in non-rounded forecasts as compared to rounded forecasts is an attribute of model-based approach.

As van Dijk et al. (2002) point out, the modelling cycle consists of the specification, estimation and evaluation stages. Evaluation includes testing for linearity against STR alternatives, for remaining non-linearity, and for parameter constancy. While the Teräsvirta sequential test does not reject the linearity of the first model specification (Column 4.1), the model which employs residuals from the instrumental variable approach successfully passed all the tests for linearity, remaining non-linearities, and parameter stability (Column 4.2). The residuals of both the models shown above are normally distributed and not serially correlated, but are heterogeneous. However, HAC errors can cope with this problem.

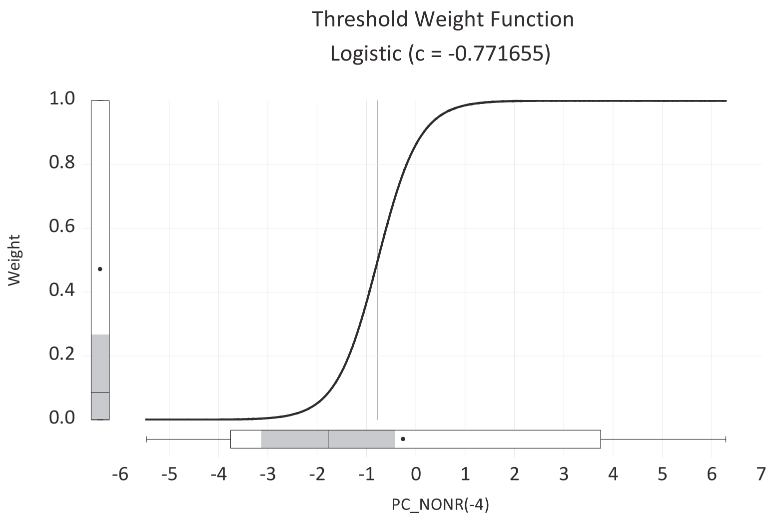

Fig. 7. Transition function of the LSTR model (3.1).

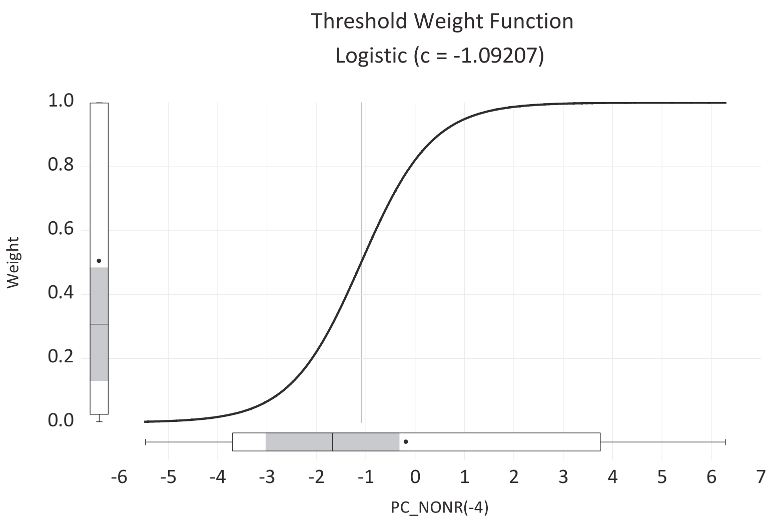

Fig. 8. Transition function of the LSTR model (3.2).

3.6. Robustness checks

To be sure that the results are not driven by the data transformation, the model (see Eq. 4) 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 the different forecast variables and time horizons. The results are shown in Table 5.

There is more variety in the parameter estimates when the original, noisier, data are used. However, the shares of non-rounders are statistically and quantitatively significant for all the forecasts and, as in the baseline estimations, are significant only in the linear part of the equation with one exception of the forecast of output growth for the two-year-ahead horizon. The output gap is negatively related to the mean individual variance linearly and for some forecasts it has a positive non-linear relationship with the uncertainty proxy, while the economic policy uncertainty indicator seems to have no effect on individual forecasts. The model estimates shown in Table 5 suggest that the main results discussed in Section 3.5 are fairly robust.

Table 5
Estimations of the LSTR baseline model on the original data.

	(5.1) INFL_H1	(5.2) INFL_H2	(5.3) RGDP_H1	(5.4) RGDP_H2	(5.5) UNEM_H1	(5.6) UNEM_H2
Linear part						
φ1,0	0.083***	0.076***	0.202	0.104***	0.017***	0.064***
	(0.012)	(0.053)	(0.020)	(0.033)	(0.01)	(0.018)
INDVAR(-1)	0.335***	0.527***	-0.020	0.494***	0.603***	0.494***
	(0.078)	(0.183)	(0.063)	(0.098)	(0.069)	(0.087)
NONR	0.280***	0.209***	0.356***	0.261***	0.237***	0.345***
	(0.067)	(0.070)	(0.064)	(0.060)	(0.055)	(0.069)
OGAP(-1)	-0.023***	-0.017**	-0.044***	-0.036***	-0.007***	-0.015***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.002)	(0.003)
EPU(-1)	0.000	0.000	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-linear part						
φ2,0	0.069	0.069	-0.179***	0.175**	0.341***	0.44***
	(0.076)	(0.079)	(0.047)	(0.087)	(0.072)	(0.142)
INDVAR(-1)	0.051	-0.207	0.456**	-0.220	-0.561**	-0.431**
	(0.269)	(0.244)	(0.193)	(0.202)	(0.245)	(0.209)
NONR	-0.170	0.015	0.111	-0.143	-0.254**	-0.337
	(0.104)	(0.095)	(0.113)	(0.168)	(0.101)	(0.228)
OGAP(-1)	0.022***	0.010	0.054***	0.039***	0.009	-0.003
	(0.005)	(0.009)	(0.009)	(0.010)	(0.007)	(0.021)
EPU(-1)	0.000*	0.000**	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ	79.091	105.408	304.069	2583.363	111.019	52.581
	(28.189)	(107.411)	(3365.191)	(2.40×10^9)	(67.617)	(27.377)
c	0.291	0.341	0.274	0.334	0.411	0.399
	(0.011)	(0.016)	(0.015)	(182.008)	(0.004)	(0.014)
Transition variable	*NONR*(-6)	*NONR*(-3)	*NONR*(-5)	*NONR*(-5)	*NONR*(-4)	*NONR*(-8)
No of observations	74	77	75	75	76	72

Note: The dependent variable is the mean individual variance of the density forecast INDVAR. NONR is the share of non-rounders where the multiple-of-five definition of rounding is used. The parameter γ is the speed of transition between regimes, while c is a location parameter. The transition variable is the share of non-rounders. The models are estimated using the standard non-linear least square estimators. HAC errors are in parentheses. H1 and H2 are the one-year-ahead forecast horizon and the two-year-ahead forecast horizon. INFL, RGDP and UNEM are inflation forecast, output growth forecast, and unemployment forecast respectively.

Given local stationarity of the individual variance series, as another robustness check I run OLS estimations for two subperiods, 1999Q1-2007Q4 and 2011Q1-2018Q4, in levels and for the whole sample in first and seasonal differences. The models estimated are as follows:

$$INDVAR_t = \beta_0 + \rho_1 INDVAR_{t-1} + \beta_{11} NONR_t + \beta_{12} OGAP_{t-1} + \beta_{13} EPU_{t-1} + u_{t1} \quad (5)$$

$$\Delta INDVAR_t = \beta_{21} \Delta NONR_t + \beta_{22} \Delta OGAP_{t-1} + \beta_{23} \Delta EPU_t + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + u_{t2} \quad (6)$$

$$\Delta_4 INDVAR_t = \beta_{31} \Delta_4 NONR_t + \beta_{32} \Delta_4 OGAP_{t-4} + \beta_{33} \Delta_4 EPU_t + u_{t3}, \quad (7)$$

where *INDVAR* is the mean individual variance, *NONR* is the share of non-rounders, *OGAP* is the output gap, *EPU* is the economic policy uncertainty indicator, D_j are seasonal dummies, $j \in (1, 2, 3)$, u_{tj} are error terms, β are the parameters that need to be estimated, and t is a time subscript. The results are shown in Tables 6 and 7.

The results show that the share of non-rounders has a significant effect on the mean individual variance. This result applies for both the series in levels and the series in differences. The results still hold if the years of the Great Recession are excluded from the sample, and so it can be stated that an increase in the share of forecasters who do not round their density forecasts is associated with increased variance. These results hold true after business cycle fluctuations and changes in economic policy uncertainty have been controlled for and they corroborate the results of the main estimations shown in Section 3.5.

4. Final comments

The paper shows that although mean individual variance is theoretically an attractive measure of uncertainty, it absorbs information that is irrelevant for quantifying perceived uncertainty since it mirrors changes in the modelling preferences of professional forecasters.

Rounding poses two problems with density forecasts. The first is that rounding reduces the number of non-zero bins and so results in lower variance in the density forecasts. It follows that the greater perceived uncertainty that is expressed through rounding is read by the survey users as lower uncertainty.

Table 6
Estimations of model (5).

	99Q1-07Q4		
Variable	99Q1-07Q4	11Q1-18Q4	11Q1-18Q4
β_0	0.745	-2.415	-1.856
	(1.314)	(1.88)	(1.124)
INDVAR(-1)	0.140	0.382***	0.444***
	(0.137)	(0.132)	(0.083)
NONR	0.338***	0.273***	0.313***
	(0.069)	(0.073)	(0.046)
OGAP(-1)	-0.637***	-0.136	-0.233***
	(0.123)	(0.124)	(0.079)
EPU(-1)	-0.312	0.551	0.392*
	(0.280)	(0.372)	(0.227)
Observations	35	32	67
R2	0.81	0.62	0.98
DW	1.88	1.79	1.88

Table 7
Estimations of models (6) and (7).

	First differences 99Q1-07Q4		Seasonal differences 99Q1-07Q4	
Variable	99Q1-18Q4	11Q1-18Q4	99Q1-18Q4	11Q1-18Q4
Δ*NONR*	0.256***	0.261***	0.462***	0.363***
	(0.056)	(0.050)	(0.057)	(0.056)
Δ*OGAP*	-0.135	-0.289	-0.24***	-0.240**
	(0.123)	(0.197)	(0.058)	(0.094)
Δ*EPU*	0.230	0.234	0.509**	0.602**
	(0.258)	(0.241)	(0.240)	(0.233)
D1	-0.183	-0.269**		
	(0.121)	(0.107)		
D2	0.260**	0.209**		
	(0.115)	(0.100)		
D3	-0.043	-0.045		
	(0.115)	(0.100)		
Observations	79	67	76	64
R2	0.27	0.41	0.54	0.55
DW	2.19	2.07	1.40	1.18

The second problem is that non-rounded forecasts are associated with a higher number of non-zero bins. This might be a sign of the uncertainty perceived by non-rounding forecasters, but it can equally be an attribute of the model-based approach to forecasting. In that case, increased variance in the density forecasts says little about the uncertainty perceived by forecasters.

Finally, the paper applies a smooth transition regression approach to the survey uncertainty and shows that the mean individual variance is a function of the share of non-rounders. Various robustness checks validate the results. The main findings are that the widely used proxy of uncertainty, mean individual variance, is noisy and can hardly be considered an appropriate measure for evaluating the level of forecast uncertainty.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rie.2020.08.001.

Appendix A

Table A.1

Table A.1
Mean individual variance of rounded and non-rounded density forecasts.

Horizon	Definition	INFL		RGDP		UNEM	
		Rounded	Non-rounded	Rounded	Non-rounded	Rounded	Non-rounded
H1	M10	0.11	0.34	0.11	0.39	0.10	0.34
H1	M5	0.18	0.49	0.19	0.59	0.22	0.53
H1	M1	0.23	0.53	0.26	0.65	0.22	0.53
H2	M10	0.12	0.42	0.24	0.74	0.12	0.44
H2	M5	0.21	0.59	0.24	0.74	0.20	0.68
H2	M1	0.29	0.62	0.33	0.81	0.28	0.75

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. M10, M5 and M1 refer to multiple-of-ten, multiple-of-five and integer definitions of rounders.

Appendix B

Table B.1

Table B.1
Correlation coefficients of the mean 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.

Appendix C

Table C.1

Table C.1
Cumulative proportion of explained variance of the mean individual variance and the share of non-rounders.

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

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

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