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Uncertainty and Forecastability of Regional Output Growth in the United Kingdom: Evidence from Machine Learning

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Abstract

Utilizing a machine-learning technique known as random forests, we study whether regional output growth uncertainty helps to improve the accuracy of forecasts of regional output growth for twelve regions of the United Kingdom using monthly data for the period from 1970 to 2020. We use a stochastic-volatility model to measure regional output growth uncertainty. We document the importance of interregional stochastic volatility spillovers and the direction of the transmission mechanism. Given this, our empirical results shed light on the contribution to forecast performance of own uncertainty associated with a particular region, output growth uncertainty of other regions, and output growth uncertainty as measured for London as well. We find that output growth uncertainty significantly improves forecast performance in several cases, where we also document cross-regional heterogeneity in this regard.

JEL classification: C22; C53; D8; E32; E37; R11

Keywords: Regional Output Growth; Uncertainty; United Kingdom; Forecasting; Machine Learning

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1 Introduction

Theoretically, the effect of uncertainty on economic activity is generally explained by the real option theory (see for example, Bernanke (1983), Pindyck (1991), Dixit and Pindyck (1994), and more recently, Bloom (2009)), which suggests that decision-making is affected by uncertainty because it raises the option value of waiting. In other words, given that the cost associated with wrong investment decisions are very high, uncertainty makes firms and, in the case of durable goods, also consumers more cautious. As a result, economic agents postpone investment, hiring, and consumption decisions to periods of lower uncertainty (which results in cyclical fluctuations in macroeconomic aggregates). In other words, uncertainty is expected to negatively impact overall output (besides consumption investment). In the wake of the "Great Recession" and more recently the COVID-19 pandemic, the large empirical literature (see Castelnuovo et al., (2017), Gupta et al., (2018, 2019, 2020a, 2020b), Al-Thaqeb and Algharabali (2019), Caggiano et al., (2020), for detailed reviews) that has emerged involving the impact of uncertainty on output has overwhelmingly confirmed the negative association between these two variables as outlined in theory.

While the literature dealing with the influence of uncertainty on output primarily relies on in-sample-based structural analyses, more recently, quite a few studies (see for example, Karnizova and Li (2014), Balcilar et al., (2016), Junttila and Vataja (2018), Aye et al., (2019a, 2019b), Gupta et al., (2020c), Pierdzioch and Gupta (2020)) have also analyzed the role of uncertainty in forecasting economic activity (output growth and recessions) in out-of-sample analyses. This is an important line of research, since policymakers in general, and central banks in particular, would need accurate predictions of the future path of the economy following periods of heightened uncertainty while making their policy decisions. Understandably, precise forecasting of the macroeconomy is also important for investors. Finally, since in-sample predictability might not translate into forecasting gains, and the ultimate test of any predictive model (in terms of econometric methodologies and the predictors being used) is primarily considered to be in its out-of-sample performance (Campbell, 2008), this area also forms a pertinent question for academic researchers.

Against this backdrop, the objective of this research is to analyze the forecasting ability of uncertainty for output growth in the United Kingdom, but from a regional perspective. In particular, we look at twelve regions of the UK (namely East Midlands, East of England, London, North East, North West, Northern Ireland, Scotland, South East, South West, Wales, West Midlands, Yorkshire and the Humber) over the quarterly period from 1970:02 to 2020:02. In the process, we not only study the predictive role of uncertainty associated with a particular region, but also incorporate the effect of uncertainty of the other regions, given the widespread evidence of international uncertainty spillovers (see for example, Gupta et al., (2016), Gabauer and Gupta (2018), Antonakakis et al., (2018, 2019), Christou et al., (2020a)), and evidence of which we also provide in our particular data set. We also control for other standard aggregate macroeconomic predictors (inflation rate, financial stress, and interest rate), as well as lagged values of the growth rate of the specific-region under investigation and the other regions, which have also been shown to depict interconnectedness (Koop et al., 2020a).

At this stage, we must point out that Junttila and Vataja (2018), Aye et al., (2019b), and Gupta et al., (2020c) have highlighted the important role played by uncertainty in forecasting alternative measures of the performance of the aggregate real economy of the UK, but our paper makes the first attempt to analyze the forecastability of output growth due to uncertainty at the regional level, based on a newly constructed high-frequency (quarterly) novel data set of regional Gross Value Added (GVA) by Koop et al., (2020b, 2020c). As highlighted by Mumtaz (2018) and Mumtaz et al., (2018), based on in-sample analyses of state-level data for the United States (US), the impact of uncertainty is heterogeneous and depends on the underlying conditions of the regions at the time the uncertainty shock originates. Naturally, one cannot generalize the role of uncertainty for the aggregate economy to the various regions comprising the overall country, thus making our regional study of tremendous importance from the policy perspective for determining the nature and size of policy intervention to counteract the negative influence of an uncertainty shock, especially given the well-established heterogeneity involving business-cycle fluctuations and, in general, across regions of the UK (Barrios et al., (2003), Beenstock and Felsenstein (2008)). Note that, while we could have studied the states of the US, which does indeed have widespread availability of regional data, and could indeed be an area of future research, our decision to look at the UK emanates from the persistent uncertainty witnessed by its regions ever since the Brexit referendum that took place in (23rd) June, 2016, besides the impact of the global financial and European sovereign debt crises that took place earlier. Hence, the UK, which has witnessed waves of crises including the current Coronavirus episode, forms an interesting case study of the uncertainty-growth nexus.

As far as the econometric approach is concerned, we rely on a machine-learning approach, known as random forests (Breiman, 2001), which in turn has two main advantages. First, random forests can accurately analyze the links between regional GVA growth and a large number of predictors in a full-fledged data-driven manner. Second, random forests automatically capture potential nonlinear links between output growth and its predictors, including uncertainty, as shown to exist historically for the UK by Christou et al., (2020b) and Bredin et al., (2021),[1] as well as any interaction effects between the predictors.

We structure the remainder of this research as follows. In Section 2, we briefly describe how a random forest is grown. In Section 3, we describe our data and report our empirical results. Finally, in Section 4, we conclude with final remarks.

2 Random forests

A random forest consists of a large number of individual regression trees (see Hastie et al., (2009) for a for a textbook exposition; our notation follows theirs). A regression tree, T, in turn, consists of branches that subdivide the space of predictors, $\mathbf{x} = (x_1, x_2, ...)$, of the regional output growth rate (in the following: regional output growth, for short) into l non-overlapping regions, R_l. These regions are computed by applying a search-and-split algorithm in a recursive top-down fashion.

Application of this search-and-split algorithm to grow a regression tree requires, starting at the top level of the tree, iterating over the various predictors, s, and the all possible splitting points,

[1] For a detailed review of the international literature on the nonlinearity between uncertainty and economic activity, the reader is referred to Caggiano et al. (2021).

p, that can be formed using the data on a predictor. For every combination of a predictor and a splitting point, the search-and-split algorithm forms two half-planes, $R_1(s,p) = \{x_s | x_s \leq p\}$ and $R_2(s,p) = \{x_s | x_s > p\}$ so as to minimize the standard squared-error loss criterion:

$$\min_{s,p} \left\{ \min_{\bar{RG}_1} \sum_{x_s \in R_1(s,p)} (RG_i - \bar{RG}_1)^2 + \min_{\bar{RG}_2} \sum_{x_s \in R_2(s,p)} (RG_i - \bar{RG}_2)^2 \right\}, \tag{1}$$

where the index i denotes those observations on regional output growth, RG, that belong to a half-plane, and $\bar{RG}_k = \text{mean}\{RG_i \,| x_s \in R_k(s,p)\}, k = 1,2$ denotes the half-plane-specific mean of regional output growth. The objective function given in Equation (1), thus, requires (i) searching over all combinations of s and p, and, (ii) for any given combination of s and p, minimizing the half-plane-specific squared error loss by an optimal choice of the half-plane-specific means of regional output growth. The solution of this minimization problem gives the top-level optimal splitting predictor and optimal splitting point, and the two $\bar{RG}_k$. The resulting simple regression tree that has two terminal nodes.

In order to grow a larger tree, the next step of the search-and-split algorithm requires to carry out the minimization problem in Equation (1) for the two top-level half-planes, $R_1(s,p)$ and $R_2(s,p)$, yielding, up to two second-level optimal splitting predictors and optimal splitting points, and four second-level region-specific means of regional output growth. Solving the minimization problem over and over again gives an increasingly complex regression tree. Finally, the search-and-split algorithm is terminated when a regression tree has a preset maximum number of terminal nodes or every terminal node has a minimum number of observations. In our empirical research, we a cross-validation technique to determine the optimal minimum number of observations per terminal node (see Section 3.2 for details).

Once the the search-partition algorithm has stopped, the regression tree sends the predictors of regional output growth from its top level to its leaves along the optimal partitioning points (that is, the nodes of the tree) and branches. A forecast of regional output growth can then be computed by its region-specific mean. For a regression tree made up of L regions, this forecast is formed as follows ($\mathbf{1}$ denotes the indicator function):

$$T\left(\mathbf{x}_i, \{R_l\}_1^L\right) = \sum_{l=1}^{L} \bar{RV}_l \mathbf{1}(\mathbf{x}_i \in R_l). \tag{2}$$

The search-and-split algorithm can be used in principle to grow an increasingly complex regression tree. However, the resulting complex hierarchical structure of a regression tree gives rise to an overfitting and data-sensitivity problem. and, thereby, implies that forecasting performance deteriorates. It is at this stage that a random forest enters the scene. A random forest solves the overfitting problem in two steps. In the first step, a large number of bootstrap samples (sampling with replacement) is drawn from the data. In the second step, a random regression tree is fitted to every bootstrap sample. Such a random regression tree differs from a classic regression tree in that for every splitting step only a random subset of the predictors is being used. In this way, a random regression tree mitigates the effect of influential predictors on tree building. Moreover, growing a large number of random trees lowers the correlation of forecasts from the individual trees. Finally, averaging the decorrelated forecasts computed by means of the individual random regression trees stabilizes the forecasts of realized output growth.

3 Empirical analysis

3.1 Data

The annualized GVA growth of the regions (East Midlands, East of England, London, North East, North West, Northern Ireland, Scotland, South East, South West, Wales, West Midlands, Yorkshire and the Humber) is obtained from the nowcasting project of Koop et al., (2020b, 2020c) associated with the Economic Statistics of the Centre of Excellence.[2] Koop et al., (2020b, 2020c) develop a mixed frequency Vector Autoregressive (MF-VAR) model and use it to produce estimates of quarterly regional output growth. Temporal and cross-sectional restrictions are imposed in the model to ensure that the quarterly regional estimates are consistent with the annual regional observations and the observed quarterly UK totals. Koop et al., (2020b, 2020c) use a machine-learning method based on the hierarchical Dirichlet-Laplace prior to ensure optimal shrinkage and parsimony in the overparameterised MF-VAR. Because this data set is available

[2]The data is dowlodable from: `https://www.escoe.ac.uk/regionalnowcasting/`.

from 1970:02 onward, our analysis starts from this period and ends in 2020:02, based on data availability at the time of writing of this paper.

Uncertainty is a latent variable, and hence one requires ways to measure it. In this regard, besides the various alternative metrics of uncertainty associated with financial markets (such as the implied-volatility indices, realized volatility, idiosyncratic volatility of equity returns, corporate spreads), there are primarily three broad approaches to quantify uncertainty: (1) A news-based approach, with the main idea behind this method being to perform searches of major newspapers for terms related to economic and policy uncertainty, and then to use the results to construct indices of uncertainty. (2) Measures of uncertainty derived from stochastic-volatility estimates of various types of small and large-scale structural models related to macroeconomics and finance. (3) Measures of uncertainty obtained from dispersion of professional forecaster disagreements. As far as our metric of uncertainty is concerned, motivated by the recent work on the nexus between growth and growth-uncertainty by Balcilar and Ozdemir (2020), we use the second approach, due to unavailability of the first and third avenues associated with regional data. In other words, our measure of regional uncertainty is derived from stochastic volatility (SV) estimates of the regional output growth. In particular, as in Kastner and Früwirth-Schnatter (2014), given observed growth rates for a particular region denoted by $y = (y_1, y_2, ..., y_T)'$, the SV model is specified as: $yt = e^{ht/2}\varepsilon_t$, with $h_t = \mu + \psi(h_{t-1} - \mu) + \sigma\nu_t$, where it is assumed that the iid standard normal innovations ε_t and ν_s are independent for $t, s \in \{1, ..., T\}$. The unobserved process $h = (h_0, h_1, ..., h_T)$ appearing in the state equation is usually interpreted as the latent time-varying volatility process (our measure of uncertainty) with initial state distributed according to the stationary distribution, i.e., $h_0|\mu, \psi, \sigma \sim \mathcal{N}(\mu, \sigma^2/(1-\psi^2))$. Simulation efficiency in state-space models can often be improved through model reparameterization. Given that, centered parameterization has several disadvantages, following Kastner and Frühwirth-Schnatter (2014), the (fully) non-centered parameterization of the model is given through: $y_t \sim \mathcal{N}(0, \omega E_t^{\sigma\tilde{h}})$, with $\tilde{h}_t = \psi\tilde{h}_{t-1} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0,1)$, where $\omega = e^{\mu}$, is of particular importance. The initial value of $\tilde{h}_0|\psi$ is drawn from the stationary distribution of the latent process, i.e., $\tilde{h}_0|\psi \sim \mathcal{N}(0, 1/(1-\psi^2))$, and note that, $\tilde{h}_t = (h_t - \mu)/\sigma$. Figure 1 shows the estimated regional stochastic volatilities.

– Please include Figure 1 about here. –

Our forecasting exercise also includes Consumer Price Index (CPI)-based annualized inflation rate, with the CPI data obtained from the Main Economic Indicators (MEI) Database of the Organisation for Economic Co-operation and Development (OECD). To measure the stance of monetary policy, we consider the official bank rate derived from the Bank of England (BoE) until 1989, and then we use the shadow short rate (SSR) developed by Wu and Xia (2016) from 1990 onwards,[3] given that our period of analysis involves the zero lower bound (ZLB) scenario in the wake of the Great Recession and the global financial crisis, and more recently following the outbreak of the Coronavirus in 2020. Given that a range of unconventional monetary policies (such as large scale asset purchases, a maturity extension program and efforts of forward guidance in order to manage expectations of a prolonged period of low policy rates) are pursued during the ZLB situations, we would need a uniform and coherent measure of the monetary policy stance. Thus we use the SSR, which measures the nominal interest rate that would prevail in the absence of its effective lower bound.[4] Finally, we incorporate the information of the Financial Stress Index (FSI) derived from the Statistical Data Warehouse of the European Central Bank.[5] The index includes six market-based financial stress measures that capture returns and (realized) volatility of three financial market segments, i.e., equity, bond and foreign exchange. In addition, when aggregating the sub-indices, the FSI takes the co-movement across market segments into account. The reader is referred to Duprey et al., (2017) for further details. Note that data that is available at higher (monthly frequency), is converted to quarterly values by taking three-month averages.

[3]The data is available for download from the website of Professor Jing Cynthia Wu at: https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0.

[4]The SSR is based on models of the term-structure, which essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical “shadow yield curve" that would exist if physical currency were not available. The process allows one to answer the question: “what policy rate would generate the observed yield curve if the policy rate could be taken negative?" The “shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero. The main advantage of the SSR is that it is not constrained by the ZLB and thus allows us to combine the data from the ZLB period with that of the the non-ZLB era, and use it as the common metric of monetary policy stance across the conventional and unconventional monetary policy episodes.

[5]The data can be downloaded from: https://sdw.ecb.europa.eu/quickview.do;jsessionid=D122B96CF06237259EFEBFB2ADCA10F0SERIES_KEY=383.CLIFS.M.GB._Z.4F.EC.CLIFS_CI.IDX.

3.2 Empirical results

We carry out our empirical analysis by using the statistical computing program R (R Core Team 2019), where we make use of the add-on package “grf” (Tibshirani et al., 2020). Our results are based on estimates of random forests for rolling-estimation windows of length 40, 60, and 80 quarters (that is, 10, 15, and 20 years). While shifting the rolling-estimation windows across the data set, we optimize, by means of cross validation, the number of predictors randomly selected for splitting, the minimum node size of a tree, and the parameter that governs the maximum imbalance of a node, where we use 2,000 regression trees to grow a random forest. We study three forecast horizons: $1, 2, 4$ quarters, where the target variable in case $h > 1$ is the arithmetic average of the regional output growth rates under scrutiny over the respective forecast horizon.

We estimate random forests for four different models. Model 1 features, in addition to the the inflation rate, the monetary policy-related interest rate, and the FSI as proxies of monetary and financial conditions, as predictors only the own lagged regional output growth of a region along with the regional output growth of all other regions, given the evidence of spillovers of regional growth as shown by Koop et al., (2020a). Model 2 features the predictors of Model 1 plus the own stochastic volatility of a region, capturing the associated uncertainty of that region. Comparing Models 1 and 2 sheds light on whether today’s regional output growth uncertainty helps to improve the accuracy of forecasts of subsequent regional output growth. Model 3 features all predictors of Model 2 and, in addition, the regional stochastic volatilities of all other regions.

To motivate the formulation of Model 3, we would like to formally highlight the importance of interregional stochastic volatility spillovers. In this regard, we utilize a full-fledged time-varying version of the spillover approaches of Diebold and Yilmaz (2012, 2014), as proposed based on a time varying parameter-vector autoregressive (TVP-VAR) model by Antonakakis et al., (2020). This framework is based on the generalized forecast error variance decomposition for a VAR, but the biggest drawback of the generalized spillover method is that it provides misleading information when it comes to aggregate spillover as the associated index is bounded between 0 and 100 percent, and so when a shock is introduced to the individual variable it brings most of the variation in other factors than the factor to which shock was introduced. In light of this, we also the joint spillover method by following Lastrapes and Wiesen (2021) capable in gauging the system-wide spillovers, as developed in a TVP-VAR context by Balcilar et al., (2020).

Both approaches provide qualitatively similar results, illustrating the robustness of our findings with respect to the spillover analysis. Figure 2 represents the dynamic total connectedness, which describes the average amount of shock spillover one series has to all others in the network. We see that the Antonakakis et al., (2020) results are constantly smaller in magnitude than those of Balcilar et al., (2020). Besides the fact that the high degree of dynamic total connectedness highlights the importance of uncertainty shock spillovers when it comes to regional UK output growth, it further points out significant economic events that had a substantial effect on its dynamic behavior such as the mid-1970s recessions that was marked by the 1973 oil crisis, and stagflation, as well as the early 1980s recession characterized by the transition from a manufacturing to a services economy and a period of considerable spending cuts. More recent dynamics cover the time of the global financial crisis, the European sovereign debt crisis, and the Coronavirus pandemic that has spread over to the European continent in the beginning of 2020.

– Please include Figure 2 about here. –

But even more to the point is the direction of the transmission mechanism as it lays out a more in-depth analysis of the regional shock propagation. Figure 3 depicts the relative strength of each region in a time-varying behavior underlining the significant and permanent effect the global financial crisis of 2009 had on most UK regional dynamics. In particular, regions such as London, East of England, North West, and Scotland decreased in its net transmission power until the end of the sample period. Furthermore, similar but less severe adjustments can be observed during the Coronavirus pandemic. In general, our results reveal that Yorkshire and the Humber, East of England, and London have been permanent transmitters of shocks whereas East Midlands, West Midlands, South West, and Wales have been permanent receivers of shocks. Two notable evolutions are that the North West has become an essential transmitter after 2009, whereas Scotland has become a receiver of shocks. It should also be mentioned that our findings indicate the importance of economic weight London has in the evolution of UK's regional uncertainty by its persistent net transmission characteristic, the unprecedented magnitude in its transmitting power prior the global financial crisis of 2009, and its still continuing - even though not as significant - role afterwards. Thus, this analysis shows that the UK regional stochastic-volatility spillovers are strong, as its dynamics explain between 75% and 90% of the evolution of uncertainty.

– Please include Figure 3 about here. –

Going back to our Model 3, given the evidence of output growth volatility spillovers across regions, upon comparing Models 2 and 3, we can assess whether regional uncertainty spillovers onto other regions helps t0 predict regional output growth of a particular region. Finally, Model 4 features the own stochastic volatility of a region plus the stochastic volatility of output growth estimated for London, given its importance as a transmitter of uncertainty shocks. When we compare Models 2 and 4 model, we can study the contribution of the capital city to forecasting regional output growth over and above the own uncertainty of a region.

Turning next to our out-of-sample forecasting analysis, Table 1 summarizes results for root-mean-squared forecast-errors (RMSFE) ratios. A RMSFE ratio larger than unity implies that the alternative model outperforms out-of-sample in terms of the RMSFE the corresponding baseline model. The first bloc of results obtains when the baseline model features only regional output growth as predictors (Model 1), while the alternative model features, in addition, the own stochastic volatility of a region (Model 2). We observe in general RMSFE ratios that exceed unity for Yorkshire and The Humber, East of England, Scotland, and Northern Ireland. Results for North East and Wales are mixed, and for East Midlands, London, South East, South West, West Midlands, and North West we observe RMSFE ratios smaller than unity or hovering around unity for several combinations of the length of the rolling-estimation window and forecast horizon. On balance, however, the results suggest that taking into account regional output growth uncertainty over and above regional output growth and monetary and financial conditions helps to improve the accuracy of forecasts of regional output growth, where the results certainly display a certain degree of cross-regional heterogeneity.

– Please include Table 1 about here. –

The second bloc of results in Table 1 compares Model 2 and Model 3. This comparison sheds light on the contribution of uncertainty that originates in other regions for the accuracy of output growth forecasts. We observe in the majority of cases RMSFE ratios smaller than unity when we study the short 40-quarters rolling-estimation window. For the two longer rolling-estimation windows, in contrast, we often observe RMSFE ratios that exceed unity, with evidence that regional spillover effects help to improve the accuracy of output growth forecasts being somewhat weaker for London and especially for East of England than for the other regions. Hence, it appears that accounting for output growth uncertainty that has its origins in other regions implies that Model 3 for several regions and model configurations has a better forecast performance than Model 2 in terms of the RMSFE criterion.

The third bloc of results in Table 1 sheds light on the role of uncertainty as measured for London. The RMSFE ratios show that accounting for the "London effect" leads to more accurate forecasts for the following regions, especially when we consider the two longer rolling-estimation windows: North East, East Midlands, South East, South West, West Midlands, North West, and Wales. The "London effect" is either small or even deteriorates the accuracy of forecasts when we consider Yorkshire and the Humber, East of England, Scotland, and Northern Ireland.

We use the test proposed by Clark and West (2007) of equal mean-squared prediction errors to shed light on the statistical significance of differences in forecast performance across the various models. The null hypothesis is that the alternative model has the same out-of-sample forecasting performance as the baseline model. The alternative hypothesis is that the alternative model performs better than the baseline model. Table 2 summarizes the results (p-values).[6]

– Please include Table 2 about here. –

[6] As an additional analysis, we decomposed the regional output volatility into common and idiosyncratic components using the non-parametric and model-free two-step general dynamic factor approach of Barigozzi and Hallin (2016) to check whether such a decomposition adds value to the forecasting exercise. Based on the Tables A1 at the end of the paper (Appendix), we find that such a decomposition gives largely insignificant results. This result is possibly an indication of the strong evidence of overall output growth volatility spillovers and interconnectedness across the regions, whereby distinguishing between common and idiosyncratic volatilites corresponding to common and local factors that drive these respective volatilities, result in loss of information that tends to add value to the forecasting analysis.

We find relatively strong evidence (in terms of the significance of the test results, using roughly a 5% threshold) that adding own regional uncertainty to Model 1 improves forecast accuracy for Yorkshire and the Humber, East of England, Scotland, and Northern Ireland. The test results are occasionally significant for North East, London, North West, and Wales. Hence, there is evidence that output growth uncertainty matters for forecasting regional output growth, though our results clearly show that it is important to differentiate between regions in this regard. As far as a comparison of Models 2 and 3 is concerned, we find that the model that includes the other regions stochastic volatilities as predictors produces significantly better forecasting results for Wales, Scotland, and Northern Ireland than the model that dismisses uncertainty originating in other regions, mainly for the two longer rolling-estimation windows. There is also some, albeit weaker, evidence that regional uncertainty spillover-effects matter in some model configurations for Yorkshire and the Humber, South East, South West, and North West. Finally, we find strong evidence that accounting for the "London effect" significantly improves forecast accuracy in the case of East Midlands, South East, and South West. We also find a few significant test results for North East, West Midlands, North West, and Wales.

As a further extension, and as a robustness check, we replicated the analysis given in Table 2 for forecasts of the regional output growth rate $h-$periods ahead, given data when a forecast has to be made, rather than its arithmetic average over the forecast horizon. The results (not reported to safe journal space, but available from the authors upon request) in some cases strengthen the evidence of a role of uncertainty. Specifically, evidence of predictive value of own regional output uncertainty strengthens for North East, London, and North West, while including the regional output uncertainty of all regions gives significant results for all regions at the two longer forecast horizons, that is, for $h = 2, 4$ for the intermediate forecast horizon, and in the overwhelming majority of regions for the long forecast horizon. Finally, evidence of the "London effect" strengthens for the West Midlands and Wales. In sum, these results further back our conclusion that uncertainty matters for forecasting regional output growth, and that it is important to carefully take into account regional heterogeneity in this regard.

4 Concluding Remarks

We have used random forests and a stochastic-volatility model to study the out-of-sample predictive value of regional output growth uncertainty for regional output growth in twelve regions of the UK over the sample period from 1970 to 2020, where we have accounted for a region's own uncertainty, the uncertainty of other regions, and uncertainty as measured for London, given evidence of regional volatility connectedness. We have reported evidence that uncertainty helps to improve forecast accuracy, and that spillover effects of uncertainty onto other regions as well as the "London effect" is beneficial in this regard too. The results, however, turned out to display a non-negligible extent of cross-regional heterogeneity.

From the perspective of policymaking, our results highlight primarily two issues: First, due to the evidence of volatility spillovers of output growth across regions, policymakers need to take into account the growth uncertainty of other regions beyond its own when making predictions about the future path of growth of a specific region, and accordingly deciding on policy choices to negative the adverse effect of uncertainty. Second, given the underlying heterogeneity, understandably, policy decisions, both in terms of the type of intervention and its associated strength, cannot be uniform at the aggregate UK level , but needs to be conducted on a region-specific manner.

In future research, it would be interesting to use the methodology to study the output growth-uncertainty nexus at the regional level for other countries (such as the US). Another promising avenue for future research is to use alternative machine-learning techniques to study the output growth-uncertainty nexus. Such a comparison can also be used to trace out which machine-learning technique performs best when applied to regional output growth data.

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Figure 1: Regional stochastic volatilities

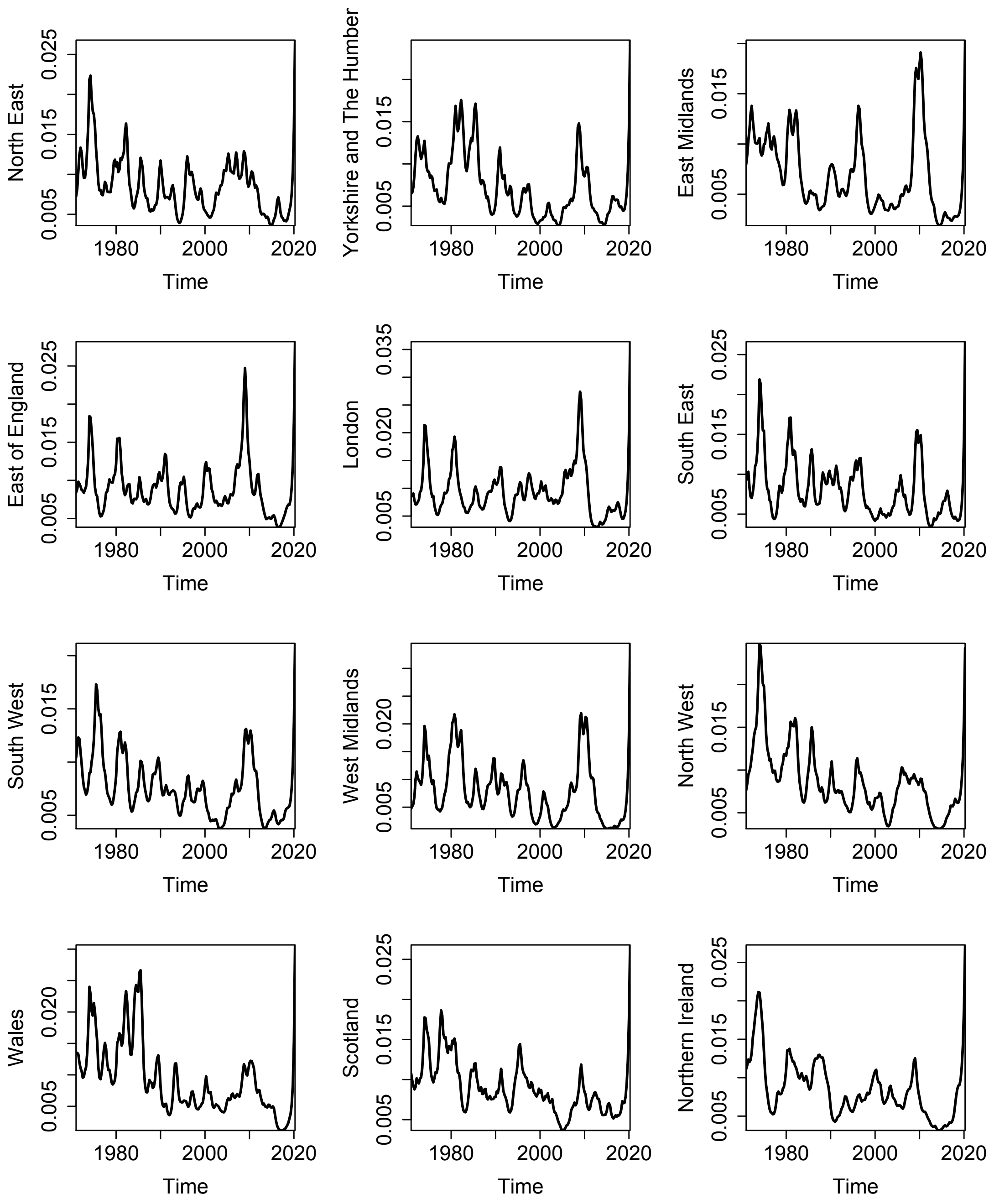
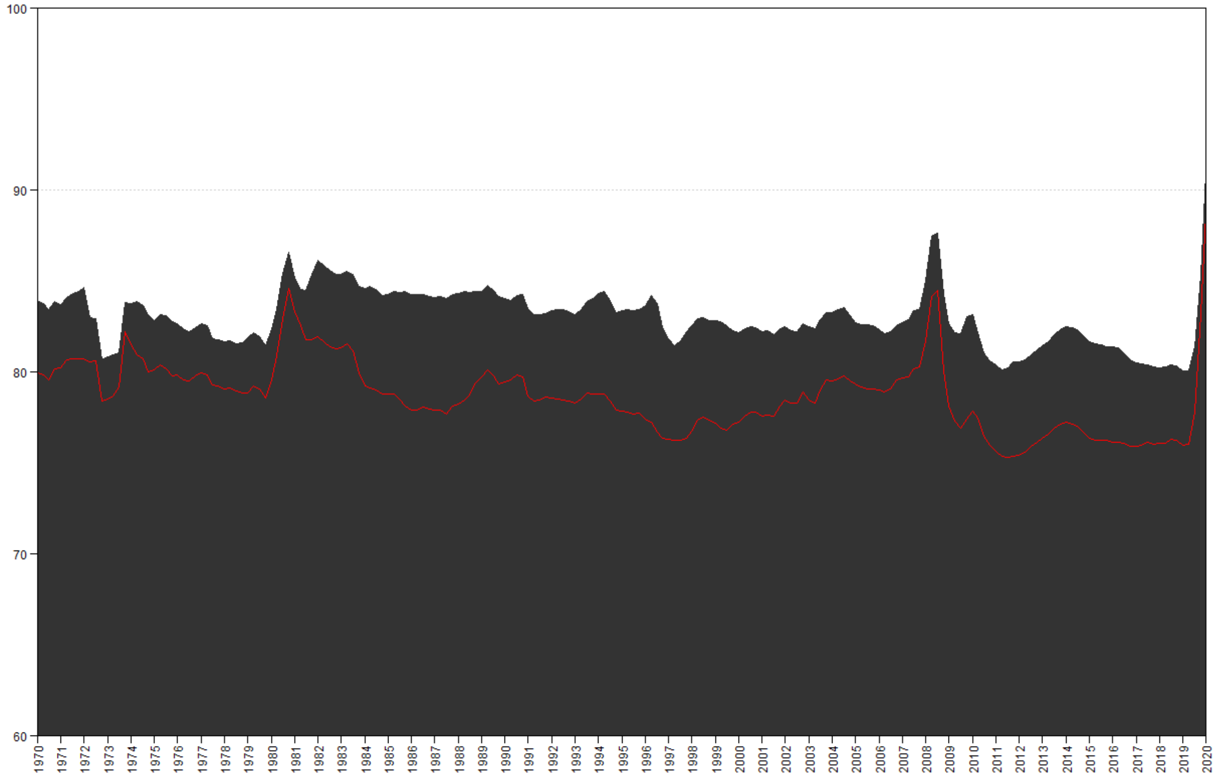
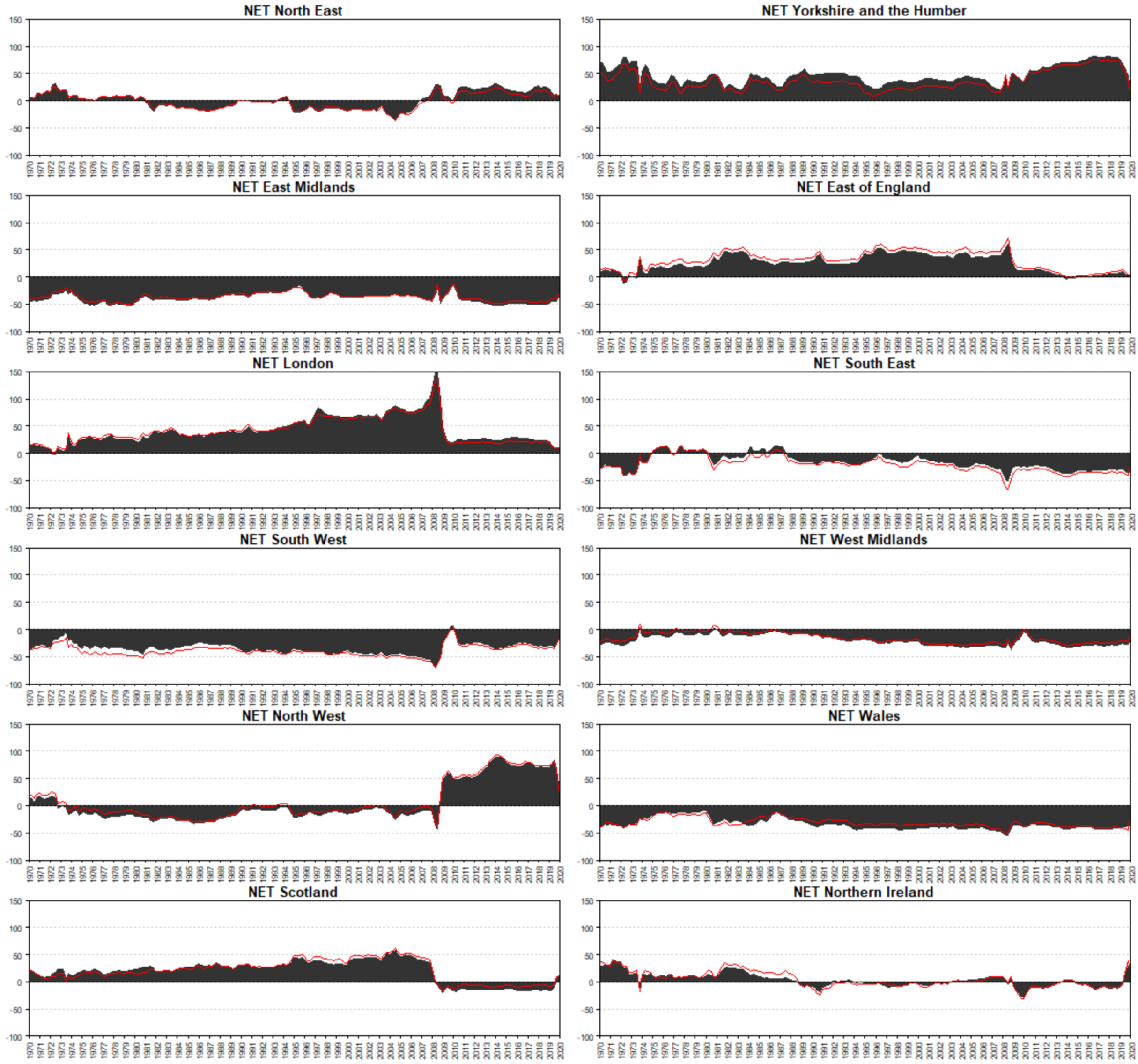


Figure 2: Dynamic total connectedness



Note: Black area illustrates Balcilar et al. (2020) whereas red line demonstrates Antonakakis et al. (2020) results based upon a 20-quarter ahead forecast horizon. Both approaches are based on a TVP-VAR with a lag length of as suggested by the Bayesian information criteria.

Figure 3: Net total directional connectedness measures



Note: Black area illustrates Balcilar et al. (2020) whereas red line demonstrates Antonakakis et al. (2020) results based upon a 20-quarter ahead forecast horizon. Both approaches are based on a TVP-VAR with a lag length of as suggested by the Bayesian information criteria.

Table 1: Comparing models by means of root-mean-squared-forecast-error ratios

Model combination	Region	Window length = 40 h=1	Window length = 40 h=2	Window length = 40 h=4	Window length = 60 h=1	Window length = 60 h=2	Window length = 60 h=4	Window length = 80 h=1	Window length = 80 h=2	Window length = 80 h=4
Base vs. Base + own SV	North East	0.9991	1.0090	1.0067	0.9985	1.0151	0.9889	1.0151	0.9966	1.0125
Base vs. Base + own SV	Yorkshire and the Humber	1.0162	1.0073	1.0216	1.0195	1.0350	1.0245	1.0747	1.0670	1.0558
Base vs. Base + own SV	East Midlands	1.0062	1.0022	0.9823	1.0078	0.9771	1.0138	0.9934	0.9916	1.0079
Base vs. Base + own SV	East of England	1.0286	1.0287	1.0269	1.0570	1.0407	1.0381	1.0683	1.0413	1.0224
Base vs. Base + own SV	London	1.0077	0.9970	1.0062	1.0348	1.0073	1.0061	0.9985	1.0065	0.9973
Base vs. Base + own SV	South East	0.9768	0.9941	0.9889	0.9698	0.9893	0.9843	0.9923	0.9934	0.9741
Base vs. Base + own SV	South West	0.9796	0.9925	0.9969	1.0007	1.0068	0.9962	1.0070	1.0073	1.0001
Base vs. Base + own SV	West Midlands	0.9956	1.0026	0.9956	0.9891	0.9686	1.0088	1.0387	0.9959	1.0096
Base vs. Base + own SV	North West	0.9767	1.0029	0.9906	0.9904	0.9914	0.9823	1.0183	1.0080	1.0097
Base vs. Base + own SV	Wales	0.9959	0.9869	1.0175	0.9874	0.9979	1.0000	1.0105	1.0206	0.9976
Base vs. Base + own SV	Scotland	1.0206	1.0332	1.0360	1.0128	1.0216	1.0301	1.0200	1.0364	1.0354
Base vs. Base + own SV	Northern Ireland	1.0077	1.0097	1.0277	1.0322	1.0117	1.0078	1.0326	1.0256	1.0112
Base + own SV vs. Base + all SVs	North East	0.9530	0.9414	0.9521	0.9847	1.0135	1.0241	1.0247	1.0349	1.0295
Base + own SV vs. Base + all SVs	Yorkshire and the Humber	0.9514	0.9466	0.9538	1.0375	1.0407	1.0239	1.0641	1.0603	1.0650
Base + own SV vs. Base + all SVs	East Midlands	0.9812	0.9763	0.9678	0.9904	1.0092	1.0006	1.0671	1.0856	1.0565
Base + own SV vs. Base + all SVs	East of England	0.9596	0.9235	0.9526	1.0070	0.9798	0.9966	0.9979	0.9988	1.0253
Base + own SV vs. Base + all SVs	London	0.9613	0.9514	0.9671	0.9998	1.0071	0.9976	1.0555	1.0108	1.0263
Base + own SV vs. Base + all SVs	South East	0.9360	0.9311	0.9371	1.0276	0.9911	1.0196	1.0203	1.0186	1.0258
Base + own SV vs. Base + all SVs	South West	0.9801	0.9596	0.9690	1.0303	1.0210	1.0279	1.0317	1.0195	1.0346
Base + own SV vs. Base + all SVs	West Midlands	0.9374	0.9257	0.9646	1.0933	1.0812	1.0542	1.0445	1.0448	1.0840
Base + own SV vs. Base + all SVs	North West	0.9801	0.9706	0.9676	1.0687	1.0537	1.0694	1.0671	1.0536	1.0424
Base + own SV vs. Base + all SVs	Wales	0.9718	0.9833	0.9618	1.1280	1.1218	1.1384	1.1719	1.1428	1.1602
Base + own SV vs. Base + all SVs	Scotland	0.9964	0.9836	0.9984	1.0400	1.0340	1.0176	1.0272	1.0267	1.0057
Base + own SV vs. Base + all SVs	Northern Ireland	1.0095	1.0098	1.0122	1.0422	1.0290	1.0249	1.0720	1.0593	1.0647
Base + own SV vs. Base + own SV + London SV	North East	0.9802	0.9600	0.9739	1.0242	1.0220	1.0119	1.0157	1.0228	1.0375
Base + own SV vs. Base + own SV + London SV	Yorkshire and the Humber	0.9938	0.9783	0.9579	1.0288	1.0387	1.0055	1.0009	1.0086	1.0086
Base + own SV vs. Base + own SV + London SV	East Midlands	1.0193	1.0150	1.0379	1.0328	1.0754	1.0436	1.0557	1.0619	1.0568
Base + own SV vs. Base + own SV + London SV	East of England	0.9956	0.9977	0.9892	0.9563	0.9713	0.9801	0.9682	0.9741	0.9869
Base + own SV vs. Base + own SV + London SV	London	–	–	–	–	–	–	–	–	–
Base + own SV vs. Base + own SV + London SV	South East	1.0200	1.0073	1.0163	1.0563	1.0448	1.0204	1.0294	1.0366	1.0347
Base + own SV vs. Base + own SV + London SV	South West	1.0399	1.0231	1.0327	1.0553	1.0461	1.0415	1.0490	1.0297	1.0326
Base + own SV vs. Base + own SV + London SV	West Midlands	1.0019	1.0019	1.0354	1.0205	1.0556	1.0155	1.0051	1.0636	1.0054
Base + own SV vs. Base + own SV + London SV	North West	0.9972	0.9844	0.9889	1.0385	1.0403	1.0463	1.0396	1.0412	1.0196
Base + own SV vs. Base + own SV + London SV	Wales	1.0126	1.0020	0.9953	1.0689	1.0664	1.0565	1.0594	1.0413	1.0734
Base + own SV vs. Base + own SV + London SV	Scotland	0.9792	0.9594	0.9734	1.0120	0.9969	0.9983	0.9890	0.9995	0.9914
Base + own SV vs. Base + own SV + London SV	Northern Ireland	0.9971	1.0060	0.9764	1.0071	0.9975	1.0070	1.0171	1.0055	1.0093

Note: This table reports RMSFE ratios, computed for out-of-sample forecasts. The columns entitled "Model combination" gives the baseline and the alternative model. A ratio larger than unity indicates that the alternative model outperforms the corresponding baseline model. Estimation is by a rolling window. The parameter h denotes the forecast horizon (in months). The random forests are built using 2,000 trees.

Table 2: Comparing models by means of the Clark-West test

		Window length = 40			Window length = 60			Window length = 80		
Model combination	Region	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Base vs. Base + own SV	North East	0.1449	0.0960	0.1146	0.3079	0.0082	0.5515	0.0184	0.3374	0.0687
Base vs. Base + own SV	Yorkshire and the Humber	0.1167	0.1499	0.1064	0.0072	0.1024	0.0198	0.0126	0.0220	0.0364
Base vs. Base + own SV	East Midlands	0.0888	0.2081	0.9196	0.2424	0.7090	0.2370	0.4868	0.5810	0.1388
Base vs. Base + own SV	East of England	0.0236	0.0644	0.0093	0.0501	0.0174	0.0249	0.0188	0.0469	0.1545
Base vs. Base + own SV	London	0.1352	0.1955	0.0810	0.0522	0.1323	0.1844	0.3726	0.1170	0.3882
Base vs. Base + own SV	South East	0.8660	0.3921	0.5136	0.9002	0.7210	0.7700	0.6152	0.5538	0.9237
Base vs. Base + own SV	South West	0.8836	0.5086	0.3793	0.1916	0.1983	0.1673	0.1068	0.0933	0.2785
Base vs. Base + own SV	West Midlands	0.3562	0.2565	0.3339	0.5375	0.8371	0.1938	0.0363	0.3473	0.1423
Base vs. Base + own SV	North West	0.9370	0.1751	0.5156	0.3702	0.5320	0.8608	0.0236	0.0296	0.0088
Base vs. Base + own SV	Wales	0.3756	0.8414	0.0036	0.6842	0.2994	0.3234	0.1373	0.0114	0.3734
Base vs. Base + own SV	Scotland	0.0262	0.0349	0.0401	0.0610	0.0594	0.0301	0.0603	0.0233	0.0377
Base vs. Base + own SV	Northern Ireland	0.1075	0.0903	0.0049	0.0139	0.0590	0.1401	0.0463	0.0893	0.0714
Base + own SV vs. Base + all SVs	North East	0.6158	0.7604	0.6484	0.2274	0.1364	0.0642	0.1762	0.1198	0.1588
Base + own SV vs. Base + all SVs	Yorkshire and the Humber	0.6158	0.7011	0.6055	0.0544	0.0446	0.0808	0.1000	0.0878	0.0783
Base + own SV vs. Base + all SVs	East Midlands	0.4621	0.5421	0.6730	0.3120	0.2357	0.2204	0.1109	0.0774	0.1069
Base + own SV vs. Base + all SVs	East of England	0.6829	0.9334	0.7179	0.1386	0.4851	0.2452	0.3141	0.3271	0.1431
Base + own SV vs. Base + all SVs	London	0.8059	0.8116	0.6572	0.3023	0.2444	0.3062	0.1564	0.2440	0.2176
Base + own SV vs. Base + all SVs	South East	0.9491	0.9657	0.9405	0.1452	0.4718	0.1676	0.0474	0.0748	0.0563
Base + own SV vs. Base + all SVs	South West	0.4345	0.6713	0.6190	0.0037	0.1031	0.0473	0.1560	0.2081	0.1150
Base + own SV vs. Base + all SVs	West Midlands	0.8332	0.8714	0.5153	0.0516	0.0460	0.0704	0.1481	0.1191	0.0665
Base + own SV vs. Base + all SVs	North West	0.4127	0.5153	0.5234	0.0426	0.0786	0.0535	0.1224	0.1024	0.1539
Base + own SV vs. Base + all SVs	Wales	0.1989	0.1636	0.3371	0.0312	0.0527	0.0429	0.0618	0.0683	0.0542
Base + own SV vs. Base + all SVs	Scotland	0.2496	0.6024	0.1652	0.0231	0.0042	0.0347	0.0134	0.0268	0.0930
Base + own SV vs. Base + all SVs	Northern Ireland	0.0446	0.0640	0.0527	0.0323	0.0755	0.0756	0.0655	0.0514	0.0631
Base + own SV vs. Base + own SV + London SV	North East	0.4086	0.6125	0.5637	0.0571	0.0538	0.0561	0.1179	0.0846	0.0924
Base + own SV vs. Base + own SV + London SV	Yorkshire and the Humber	0.3238	0.4966	0.6781	0.0350	0.0157	0.1600	0.1422	0.0831	0.1033
Base + own SV vs. Base + own SV + London SV	East Midlands	0.0303	0.0533	0.0113	0.0601	0.0158	0.0497	0.0518	0.0877	0.1133
Base + own SV vs. Base + own SV + London SV	East of England	0.4066	0.2511	0.5480	0.9097	0.8580	0.8682	0.9325	0.9237	0.6650
Base + own SV vs. Base + own SV + London SV	London	–	–	–	–	–	–	–	–	–
Base + own SV vs. Base + own SV + London SV	South East	0.0111	0.1297	0.0593	0.0113	0.0048	0.0336	0.0092	0.0075	0.0168
Base + own SV vs. Base + own SV + London SV	South West	0.0199	0.0558	0.0221	0.0080	0.0203	0.0201	0.0041	0.0223	0.0086
Base + own SV vs. Base + own SV + London SV	West Midlands	0.2695	0.2699	0.0503	0.0489	0.0227	0.1737	0.1254	0.0576	0.2154
Base + own SV vs. Base + own SV + London SV	North West	0.2328	0.3585	0.3058	0.0120	0.0308	0.0044	0.1026	0.1049	0.1457
Base + own SV vs. Base + own SV + London SV	Wales	0.1143	0.2257	0.4043	0.0426	0.0552	0.0681	0.1457	0.1654	0.1283
Base + own SV vs. Base + own SV + London SV	Scotland	0.6258	0.9833	0.8155	0.0610	0.3072	0.2529	0.4343	0.1971	0.4014
Base + own SV vs. Base + own SV + London SV	Northern Ireland	0.1151	0.0341	0.4862	0.1497	0.2771	0.1049	0.1057	0.1959	0.1988

Note: This table reports the results (p-values) of the Clark-West test of equal mean-squared prediction errors. The null hypothesis is that the alternative model has the same out-of-sample forecasting performance as the baseline model. The alternative hypothesis is that the alternative model performs better than the baseline model. Results are based on Newey-West robust standard errors. Estimation is by a rolling window. The parameter h denotes the forecast horizon (in months). The random forests are built using 2,000 trees.

Appendix

Table A1: Comparing models by means of the Clark-West test (Common and Idiosyncratic SV)

Model combination	Region	Window length = 40			Window length = 60			Window length = 80		
		h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Base + own common SV vs. Base + all common SVs	North East	0.9260	0.9238	0.7897	0.0962	0.3503	0.4106	0.2633	0.6132	0.1626
Base + own common SV vs. Base + all common SVs	Yorkshire and the Humber	0.8923	0.0831	0.5789	0.8078	0.3046	0.4302	0.7728	0.5921	0.6482
Base + own common SV vs. Base + all common SVs	East Midlands	0.2932	0.8874	0.9171	0.5802	0.1182	0.6902	0.7778	0.7568	0.8170
Base + own common SV vs. Base + all common SVs	East of England	0.9075	0.5945	0.9321	0.7421	0.7662	0.4901	0.9032	0.6979	0.2521
Base + own common SV vs. Base + all common SVs	London	0.5024	0.1272	0.1024	0.0629	0.7455	0.8593	0.1545	0.8658	0.9004
Base + own common SV vs. Base + all common SVs	South East	0.8536	0.4284	0.4352	0.8736	0.8716	0.9396	0.1674	0.8654	0.4115
Base + own common SV vs. Base + all common SVs	South West	0.9214	0.3237	0.8152	0.9311	0.2439	0.8402	0.4269	0.0370	0.0478
Base + own common SV vs. Base + all common SVs	West Midlands	0.8177	0.9311	0.7658	0.0965	0.8599	0.1974	0.8897	0.3949	0.6176
Base + own common SV vs. Base + all common SVs	North West	0.3446	0.2017	0.2304	0.8078	0.5765	0.9017	0.3044	0.2616	0.8997
Base + own common SV vs. Base + all common SVs	Wales	0.5409	0.6926	0.3185	0.4314	0.2716	0.4528	0.7098	0.0947	0.2783
Base + own common SV vs. Base + all common SVs	Scotland	0.2266	0.2406	0.0502	0.8405	0.2355	0.3606	0.1266	0.7845	0.3899
Base + own common SV vs. Base + all common SVs	Northern Ireland	0.8664	0.6499	0.0895	0.6944	0.5397	0.3688	0.7931	0.7773	0.5115
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	North East	0.7320	0.8830	0.3756	0.5591	0.2748	0.1926	0.0784	0.5278	0.5941
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	Yorkshire and the Humber	0.2516	0.2633	0.2833	0.7261	0.8589	0.8295	0.0788	0.5910	0.5827
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	East Midlands	0.7034	0.8850	0.7679	0.8928	0.2210	0.8584	0.5180	0.5234	0.5119
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	East of England	0.0441	0.0237	0.0368	0.8560	0.2125	0.6577	0.3037	0.0261	0.2261
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	London	0.8726	0.9540	0.9504	0.9381	0.9462	0.8857	0.9822	0.9679	0.8304
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	South East	0.9246	0.7471	0.9634	0.8385	0.6620	0.8995	0.9296	0.8770	0.3674
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	South West	0.8742	0.9490	0.3543	0.8570	0.9348	0.9015	0.3765	0.0854	0.6314
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	West Midlands	0.8773	0.8698	0.9101	0.8663	0.8628	0.8394	0.8374	0.8599	0.6480
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	North West	0.9539	0.9317	0.1141	0.1051	0.4884	0.4078	0.4192	0.1826	0.4324
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	Wales	0.5805	0.9457	0.6132	0.7806	0.8692	0.9056	0.3568	0.0572	0.0656
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	Scotland	0.7093	0.6521	0.0545	0.4434	0.7771	0.3940	0.0170	0.6431	0.1671
Base + own idiosyncratic SV vs. Base + all indiosyncractic SV	Northern Ireland	0.0261	0.2226	0.2460	0.0666	0.1314	0.1347	0.0075	0.2043	0.0072

Note: This table reports the results (p-values) of the Clark-West test of equal mean-squared prediction errors. The null hypothesis is that the extended model has the same out-of-sample forecasting performance as the baseline model. The alternative hypothesis is that the full model performs better than the baseline model. Results are based on Newey-West robust standard errors. stimation is by a rolling window. The parameter h denotes the forecast horizon (in months). The random forests are built using 2,000 trees.