Reconciled Estimates and Nowcasts of Regional Output in the UK*

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Abstract: There is renewed interest in "levelling up the regions" of the UK. The combination of social and political discontent, and the sluggishness of key UK macroeconomic indicators like productivity growth, has led to increased interest in understanding the regional economies of the UK. In turn, this has led to more investment in economic statistics. Specifically, the Office for National Statistics (ONS) recently started to produce quarterly regional GDP data for the 9 English regions and Wales that date back to 2012Q1. This complements existing real GVA data for the regions available from the ONS on an annual basis back to 1998; with the devolved administrations of Scotland and Northern Ireland producing their own quarterly output measures. In this paper we reconcile these two data sources along with UK quarterly output data that date back to 1970. This enables us to produce both more timely real–terms estimates of quarterly economic growth in the regions of the UK and a new reconciled historical time-series of quarterly regional real output data from 1970. We explore a number of features of interest of these new data. This includes producing a new quarterly regional productivity series and commenting on the evolution of regional productivity growth in the UK.

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1 Introduction

Boris Johnson's government has committed to "levelling up the regions" of the UK[1] and issues of regional inequality have played a key role in recent policy debates (e.g. Nguyen, 2019 and McCann, 2020). To achieve this aim and to evaluate different policies reliable and consistent data measuring the economic performance of the regions are required. This is the over-arching purpose of this paper. As we will explore in this paper, there are a number of different and overlapping data sources for sub-national output growth in the UK, and this has important implications for our understanding of regional economic performance, including productivity.

Historically, the Office for National Statistics (ONS) only produced data on Gross Value Added (GVA) for the UK regions at an annual frequency and with a release delay of nearly a year. But data on GVA (and other macroeconomic variables) for the UK as a whole are produced at a quarterly frequency and with a much shorter release delay. Koop, McIntyre, Mitchell and Poon (2020) exploited this frequency mismatch and difference in release delays to produce more timely nowcasts (which can be interpreted as flash estimates) and higher frequency historical estimates of UK quarterly regional GVA growth back to 1970.

Recently, in September 2019, the ONS began to produce quarterly output data for the regions of the UK - their so-called "Regional Short Term Indicators" (RSTIs). But these data date back only to 2012. They are released with a delay relative to UK GVA, but the delay is shorter than for the annual regional GVA data. Hence, we now have three data sources (i.e. annual regional GVA, quarterly UK GVA and the new RSTI data) which can be used to improve our understanding of regional output growth. They all have different release timings and one of them is only available for a short period of time at the end of our sample. The issue addressed in this paper is how to reconcile these three data sources to improve the flash estimates and historical high frequency regional output estimates of Koop et al. (2020).[2]

Koop et al. (2020) use a Mixed Frequency Vector Autoregression (MF-VAR) to nowcast and produce their regional GVA estimates. This model contains two restrictions which play important roles. We refer to these as the "inter-temporal" and "cross-sectional" restrictions. The inter-temporal restriction reflects the fact that a quarterly output measure such as GVA should add up to the corresponding annual output measure over the year. The cross-sectional restriction is based on the fact that the output estimates of the regions in any quarter should add up to the corresponding UK output estimate for that quarter.

In this paper, we begin by investigating the properties of the new RSTI data in the context of these restrictions. We next modify the MF-VAR of Koop et al. (2020) to incorporate the RSTI data. We carry out three empirical exercises. The first of these produces historical estimates of real quarterly regional output growth and discusses their properties with a particular focus on a

[1] For example, see https://www.ft.com/content/8af414d2-2c86-11ea-bc77-65e4aa615551.

[2] Similar issues are faced in other countries, as emphasised by Stock (2005): "an important practical challenge facing regional economists is combining...different sources of data to provide a timely and accurate measure of regional economic activity".

comparison with Koop et al. (2020). The second uses our new regional output data set along with regional employment data to investigate regional patterns in productivity. The third is a nowcasting exercise where we show how the incorporation of the RSTI data can be used to improve the accuracy of regional nowcasts.

2 The MF-VAR Model

The reader is referred to Koop et al. (2020) for: i) a complete description of the MF-VAR model incorporating the inter-temporal and cross-sectional restrictions; ii) a description of the Markov Chain Monte Carlo (MCMC) algorithm used to carry out Bayesian estimation and prediction in the model and iii) a description of the Bayesian shrinkage prior used to ensure parsimony in this otherwise over-parameterised model. Here we offer a summary of the model and how we adapt it to incorporate the RSTI data. MF-VARs which, like Koop et al. (2020), use state space methods have also been used in many mixed-frequency data applications to the US including Eraker, Chiu, Foerster, Kim and Seoane (2015), Schorfheide and Song (2015) and Brave, Butters and Justiniano (2019).

We begin by describing some variable definitions, relationships and notational conventions used in this paper.

- $t = 1, .., T$ runs at the *quarterly* frequency.
- $r = 1, .., R$ denotes the R regions in the UK.
- Y_t^{UK} is GVA for the UK in quarter t.
- $y_t^{UK} = log(Y_t^{UK}) - log(Y_{t-1}^{UK})$ is the quarterly change (log difference) in GVA in the UK.
- Y_t^r is GVA for region r in quarter t. It is not observed before 2012.
- $Y_t^{r,A} = Y_t^r + Y_{t-1}^r + Y_{t-2}^r + Y_{t-3}^r$ is annual GVA for region r. It is observed in quarter 4 of each year, but not in other quarters.
- $y_t^{r,A} = log(Y_t^{r,A}) - log(Y_{t-4}^{r,A})$ is annual GVA growth in region r. It is observed, but only in quarter 4 of each year. $y_t^A = \left(y_t^{1,A}, .., y_t^{R,A}\right)'$ is the vector of annual GVA growth rates for the R regions.
- $y_t^r = log(Y_t^r) - log(Y_{t-1}^r)$ is the quarterly change in GVA in region r. It is not observed before 2012. $y_t^Q = \left(y_t^1, .., y_t^R\right)'$ is the vector of quarterly GVA growth rates for the R regions.

Any VAR involves the choice of a set of dependent variables. In our case, the main variables in our VAR are the quarterly GVA growth rates for the UK and its regions.[3] Thus we work with

[3] In our empirical work and following Koop et al. (2020), we augment this vector with four additional UK quarterly predictors: inflation, interest rates (the Bank Rate), the exchange rate and the change in the oil price. Koop et al. (2020) also included additional regional predictors as exogenous variables. These did little to improve forecast performance and, accordingly, they are not used in any of the models used in this paper.

$y_t = \left(y_t^{UK}, y_t^{Q\prime}\right)'$ as the vector of dependent variables in a VAR. What makes the VAR a MF-VAR is the fact that we have a frequency mismatch (prior to 2012) in that only annual regional data are available before 2012, whereas quarterly UK data are always available. Thus, the y_t^Q variables in the VAR are unobserved and our goal is to estimate them.

In a MF-VAR involving a quarterly/annual frequency mismatch over the entire sample, a key feature of the model is the inter-temporal restriction. It ensures that the estimated quarterly regional data add up to the observed annual regional data. In our regional UK application, we have an additional restriction to exploit: the cross-sectional restriction. This ensures that regional GVA values add up to UK GVA. When working with log-differenced variables, as we do in this paper, Koop et al. (2020) show that the inter-temporal and cross-sectional restrictions take the form:

$$y_t^{r,A} = \frac{1}{4}y_t^r + \frac{1}{2}y_{t-1}^r + \frac{3}{4}y_{t-2}^r + y_{t-3}^r + \frac{3}{4}y_{t-4}^r + \frac{1}{2}y_{t-5}^r + \frac{1}{4}y_{t-6}^r \tag{1}$$

and

$$y_t^{UK} \approx \frac{1}{R}\sum_{r=1}^{R} y_t^r, \tag{2}$$

respectively. Given that the inter-temporal restriction involves seven quarters, we also use $p = 7$ lags in our VAR. As we motivate and explain further below and in the Appendix, we impose the cross-sectional restriction, (2), allowing for a stochastic (mean zero) error.

The MF-VAR of Koop et al. (2020), thus, involved three components: the VAR itself, the inter-temporal restriction and the cross-sectional restriction. But, in our earlier work, the frequency mismatch existed for the entire sample from 1970 - with y_t^Q always unobserved. In the present paper, the frequency mismatch ends in 2012 as the new RSTI data become available; i.e. towards the end of our sample y_t^Q is observed. So from 2012 onwards we can work with the VAR itself and no longer need the inter-temporal restriction; and the cross-sectional restriction is also trivially satisfied (subject to the aforementioned error) in-sample, i.e. when estimating the model. Informally speaking, we need a method for turning off the restrictions near the end of the sample (dating back to 1970) when estimating the model. Econometric details of how this is done are provided in the Appendix. But we should note that when, as in section 6 below, using the model out-of-sample to produce nowcasts, we do use the cross-sectional restriction to exploit the fact that the UK data, y_t^{UK}, for quarter t are published ahead of the RSTI regional data, y_t^r, for quarter t. Koop et al. (2020) found that conditioning regional nowcasts on more timely information from the UK aggregate, acknowledging that the UK aggregate itself comprises the regional disaggregates via (2), helps delivers improved regional nowcasts.

3 Regional Output Data in UK

In the UK at present there are two main sources of regional real output growth data produced by the ONS: 1) annual real GVA data produced for all NUTS1 regions of the UK (GVA(B)),[4] and 2) new quarterly regional short term indicators which were first produced in September 2019 (and provide historical coverage back to 2012). The first data set is the "National Statistics" publication, while the second is classed as an "experimental statistic". The RSTIs are based on VAT turnover data, which are now used to produce the headline UK GDP estimates.[5] Since the VAT turnover data are effectively a census, data with complete coverage exist for each region meaning there is no sampling error. The VAT turnover data are apportioned across regions based on each firm's employment share within that region (using the Inter-Departmental Business Register). These RSTIs are referred to by ONS as "Regional GDP" which they argue "complement" the existing publication of regional GVA. Recall that GVA plus taxes (less subsidies) on products is GDP, and that in chained volume terms the growth rates of real GVA and real GDP are the same rates at a regional level.[6]

The annual GVA(B) data are released approximately a year after the end of the year to which they relate; thus, e.g., in December 2019 we received new data covering the year 2018. The RSTI data have a release delay of around 6 months, and only cover the 9 English regions and Wales. The reason for this is that Scotland produces its own quarterly GDP measure, released with a delay of just under 3 months, and Northern Ireland has its growth indicator which is released with a delay of slightly more than 3 months. For comparison, UK GDP is released on a quarterly basis with a delay of around 6 weeks after the end of the quarter. The release pattern for these data is described in the figure below, taking 2020 as our example. In our nowcasting exercise presented in Section 6 below, we produce estimates of regional output growth coincident with and conditioning on the latest release of the quarterly UK output data. Thus, e.g., upon receipt of the UK estimate for growth in 2019Q4 released in February 2020, we re-run our model and produce estimates for 2019Q4 allocating this national growth to the regions of the UK. This timing reflects our current understanding of the expected release pattern.

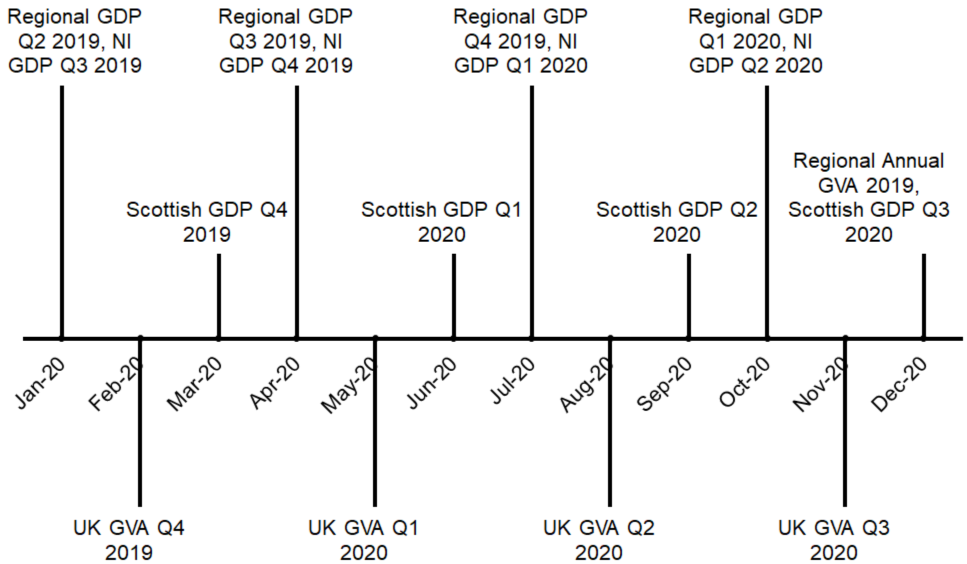
The ONS's intention is that these two data sources will align over the period where data are available on both, with the GVA(B) data being the preferred measure, and the RSTI data constrained to it. Thus, and subject to delays in data release and data revisions, the RSTI data on a quarterly basis will aggregate (temporally) to annual growth in the GVA(B) data. This landscape is only complicated by the data for Scotland and Northern Ireland. Due to methodological differences, the annual growth estimates produced by these devolved administrations do not constrain to those of the ONS. Of course, the devolved administrations' own quarterly estimates, which are the equivalent

[4] The ONS produce a wider range of GVA data on an annual basis, including production and income based approaches, but they have the same timelines and frequency as the GVA(B) data which is the ONS's 'balanced' version of these other data sets. Accordingly, we focus on GVA(B) data in our analysis.

[5] See: `https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/vatturnoverdatainnationalaccountsbackgroundandmethodology` for more detail on this.

[6] `https://www.ons.gov.uk/ons/rel/elmr/economic-trends--discontinued-/no--627--february-2006/methodology-notes--links-between-gross-domestic-product--gdp--and-gross-value-added--gva-.pdf2`.

Figure 1: Release calendar for regional and national output data in the UK in 2020



RSTIs for these nations, will constrain to their own annual estimates.

In the case of the Scottish Government data, the differences in method are of two main types. The first is that the Scottish Government takes a different approach to the calculation of output in the construction sector.[7] The second, and more important, is that the Scottish Government produce their real terms series differently to how the ONS produce their equivalent real terms series for Scotland. In essence, they take different approaches to deflation. The Scottish Government approach is closer to that of the ONS for the UK as a whole.[8] This accounts for most of the difference between the two series as illustrated by Figure 2 showing the ONS and Scottish Government series in nominal terms (i.e. before deflation). In real terms, see Figure 3, we can see that there are more substantial differences between the two series.

The data for Northern Ireland, produced by the Northern Ireland Statistics and Research Agency (NISRA), are a "Composite Economic Index", which is an experimental measure of economic activity. These data are in effect treated as the RSTI measure for Northern Ireland. We compare these data (while produced on a quarterly basis we focus here on the annual data) to the annual GVA data produced for Northern Ireland by the ONS in Figure 4 below. While there is a high degree of commonality, there are again clearly periods where they differ.

On the regional data side, therefore, the situation can be summarised as follows. ONS RSTI data for the English regions and Wales will in general, but subject to data release delays, constrain to the ONS's annual regional data contained in the GVA(B) release. The Scottish Government and NISRA

[7] See the Scottish Government GDP sources catalogue here: `https://www2.gov.scot/Resource/0054/00540467.xlsx`.

[8] For more on this, see the Scottish Government GDP methodology document here: `https://www2.gov.scot/Resource/0054/00542708.pdf`.

Figure 2: Comparison of Nominal ONS and Scottish Government (SG) Output Estimates

quarterly data, while internally consistent on a quarterly and annual basis, differ from the annual ONS regional GVA(B) data. These regional GVA(B) data, in turn, are consistent with published "Blue Book" estimates for the UK as a whole.

The consistency between the RSTI data, the GVA(B) data, and the UK GDP data is conveniently summarised in this extract from the ONS:[9]

> "...[RSTIs] will align with the annual growth rates determined by regional accounts, while fitting a quarterly path based on the underlying [RSTIs] data. Since regional accounts themselves are constrained to national estimates of GDP, this process of benchmarking ensures that [RSTIs] are also broadly in line with the national estimates. However, there may still be inconsistencies between our [RSTIs] data, post regional accounts benchmarking, and our short-term estimates of GDP. This is because there are some clear differences in the data sources and methods used (for example, in the extent to which VAT data is used). This means that while [RSTIs] aims to produce the best estimates at a regional level, the sum of the regions (adding in published estimates for Scotland and Northern Ireland) may not equal the national total in the time period following the regional accounts benchmarking."

So ONS annual GVA(B) for the regions add up to the annual UK total and, subject to release delays, the RSTI data will therefore also constrain to the quarterly UK total. But where the annual GVA(B) data are not available - or while we await alignment to the RSTI data following publication of new GVA(B) data: "the sum of the regions (adding in published estimates for Scotland and Northern

[9] https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/introducinggdpforthecountriesoftheukandtheregionsofengland

Figure 3: Comparison of Real ONS and Scottish Government (SG) Output Estimates

Ireland) may not equal the national total". For this reason the ONS constrain the RSTI data "in such a way that minimises changes to the region by industry quarter on quarter growth rates". So, in short, the RSTIs should be broadly consistent with the relevant UK data.

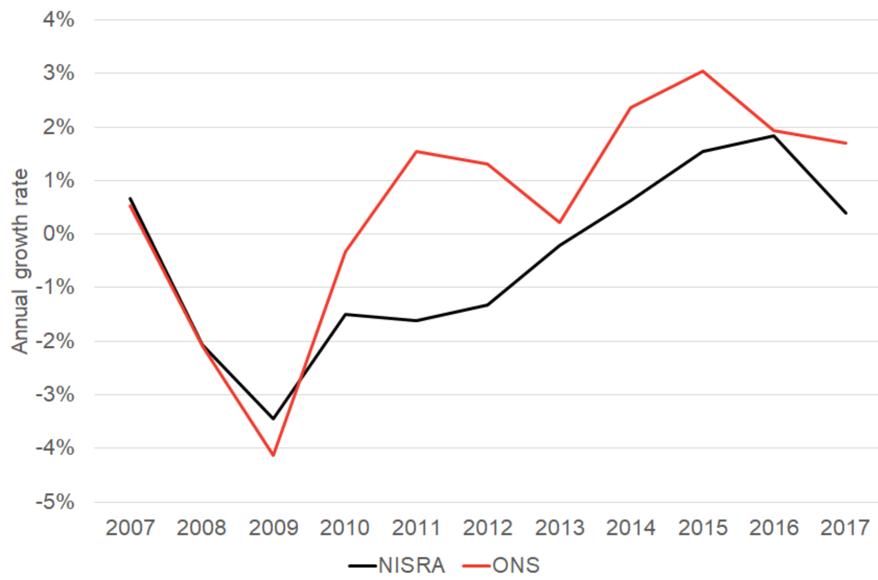
In the context of our model, this means that the inter-temporal restriction will generally hold for the English Regions and Wales in the underlying quarterly/annual data. It will also hold (albeit, as discussed above, post 2012 against the data from the Scottish Government and NISRA) for the Scottish and Northern Irish series. The cross-sectional restriction is satisfied in the annual ONS data; and, given the discussion above, it is broadly satisfied with the quarterly RSTI data – but since we are working in a model which excludes the UK's continental shelf (UKCS), as in Koop et al. (2020), we in any case impose the cross-sectional restriction allowing for an error (see the Appendix for details). In practice, our model conditions, over the available period, on the ONS annual data where these are available and the RSTI data are not, and on the RSTI data where these are available. This means that our model takes the Scottish Government and Northern Ireland Government data to be the 'true' estimates of quarterly (regional) output post 2012.

4 Empirical Results: Quarterly Regional Growth Estimates

Figures 5 and 6 plot reconciled historical quarterly estimates of output growth, y_t^Q, for each of the 12 regions having estimated the MF-VAR model using the RSTIs as summarised in section 2 (labelled "KMMP+RSTI" in the figures). For comparison purposes, we also plot regional output growth estimates from the KMMP model of Koop et al. (2020) that does not make use of the ONS's new quarterly RSTI data (labelled "KMMP").

Comparison of the new estimates KMMP+RSTI with KMMP reveals that the two sets of estimates

Figure 4: Comparison of Real ONS Output and NISRA Composite Economic Index



do track each other fairly well (simple correlation coefficients between these series are mostly between $0.94 - 0.99$, the only exception is Northern Ireland (0.89)). But there are some differences, especially since 2012 - which is when the RSTIs date back to. For the East Midlands and the East of England our new estimates indicate slightly stronger output growth in recent quarters. However, even though the RSTIs date back only to 2012Q1, comparison of the two sets of estimates reveals some differences pre-2012. This is explained by updated parameter estimates in KMMP+RSTI relative to KMMP. While these differences do not perhaps change one's overall impression of regional economic performance since 1970, it is interesting that our new estimates indicate that the contractions in economic growth in the East of England, the South East, the South West, the West Midlands, the North West and Scotland in the aftermath of the global financial crisis of 2007-8 were slightly less acute than KMMP suggested. We next explore further features of these new regional output growth data by focusing on their implications for inference about regional productivity.

5 Empirical Results: Regional Labour Productivity

Headline UK productivity performance over the past decade or so has been exceptionally weak. Having witnessed steady growth, comparable with our international competitors, over the decades before the financial crisis, UK labour productivity growth has seemingly lost its momentum. Indeed a recent paper (Crafts and Mills, 2020) argues that by some criteria "the slowdown [in productivity in the UK] is unprecedented in the past 250 years". Under the moniker 'the productivity puzzle', many hypotheses have been proposed as explanations for this 'puzzle'. These range from labour hoarding by firms (Martin and Rowthorn, 2012) (although it has been argued that some of this in fact represents firms employing people creating 'intangible' assets (Goodridge et al., 2013)), through weaknesses in

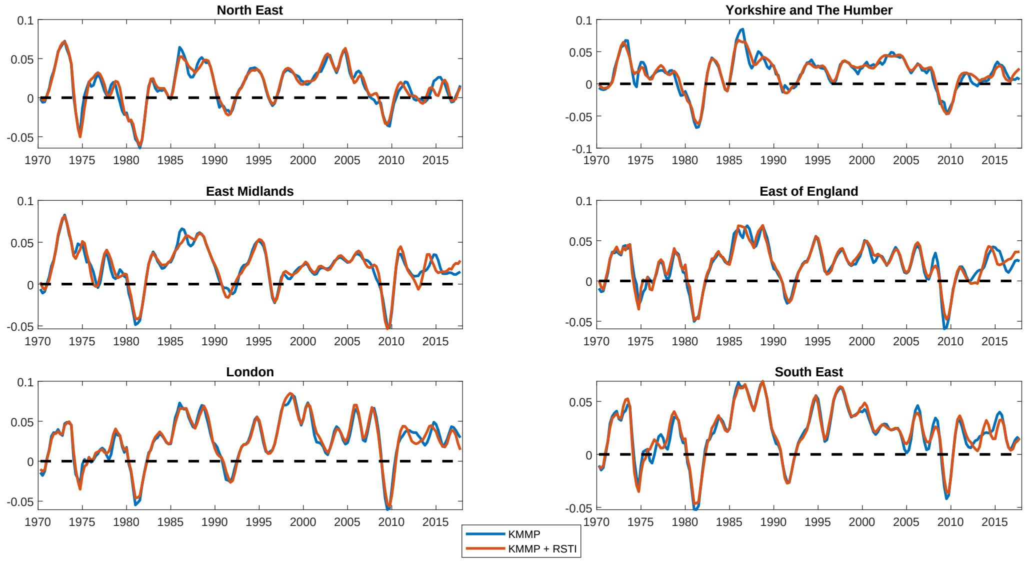


Figure 5: KMMP vs KMMP + RSTI annualised estimates of quarterly real output growth

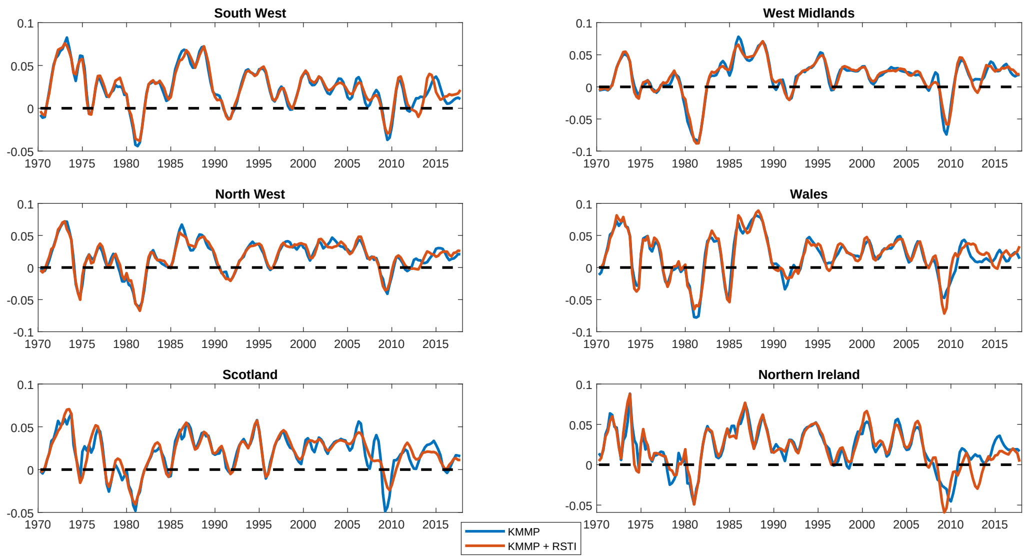


Figure 6: KMMP vs KMMP + RSTI annualised estimates of quarterly real output growth

management practice (for an overview of the role of management practice in productivity see: Bender et al. (2018)), mis–measurement and changes in the production boundary (e.g., Coyle (2017)), and many others. A good assessment of a number of different hypothesis can be found in Goodridge et al. (2018).

Whatever the reasons, the consequences are reflected in regional productivity performance which has been similarly dire. There has long been an interest in regional economic performance in the UK (e.g., Rice, Venables and Patacchini, 2006); but this interest has received a new impetus through the recent emphasis on "levelling up" of regional economic performance. Zymek (2020) summarises four main reasons why regional productivity performance might differ. These are: 1) differences in the workforce (skill, motivation, health, etc.); 2) differences in regional capital stock; 3) geography and local institutions; and 4) sectoral specialisation. Within the UK the well documented 'brain drain' out of some regions towards London and the South East of England has long been considered as a factor in explaining differences in regional economic performance. It is difficult to comment too much on differences in regional capital stock given a lack of data - although data on FDI do suggest that such investments can boost regional productivity. While some features of an area (e.g. its remote location) are easy to capture, many of the intangible characteristics associated with different locations are difficult to capture; although there is some evidence that place characteristics do not explain much of the difference in productivity performance (e.g., see Gibbons et al. (2014)). Work by the ONS[10] has shown that controlling for differences in industry mix does not really explain differences in regional productivity, but differences between firms within industries do appear to be important.

While some of these explanations and hypotheses require detailed firm-level data to explore, many instead require more aggregated productivity data. The challenge here in the UK is that these data are available over a relatively short time span, and historically these have only available at an annual frequency. The advent of new regional quarterly data for the English regions and Wales, combined with existing data for Scotland and Northern Ireland, offer the opportunity to change some of that. In this section we produce a set of regional productivity indices at the quarterly frequency, reconciling data from these different sources. At this stage, we cannot take this series back further given the limited time series of regional quarterly hours data, although we hope to address this in subsequent work.

Here we restrict ourselves to investigating differences in regional productivity since 1997. This can be done using our new estimates of quarterly regional output growth. We can do this at the quarterly frequency because, while official estimates of quarterly regional output growth for the English regions and Wales are limited (they are only available back to 2012Q1), the ONS provide a time series of number of hours worked (which they call 'productivity hours') and employment (called 'productivity jobs') at the regional level on a quarterly basis back to 1997Q2. These 'productivity hours' and 'productivity jobs' measures are refinements to raw job and hour counts to produce a consistent measure of labour input.[11] ONS currently report regional productivity measures, but these are only

[10] https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/compendium/economicreview/april2018/regionalfirmlevelproductivityanalysisforthenonfinancialbusinesseconomygreatbritainapril2018

[11] For more details on these refinements see: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwor

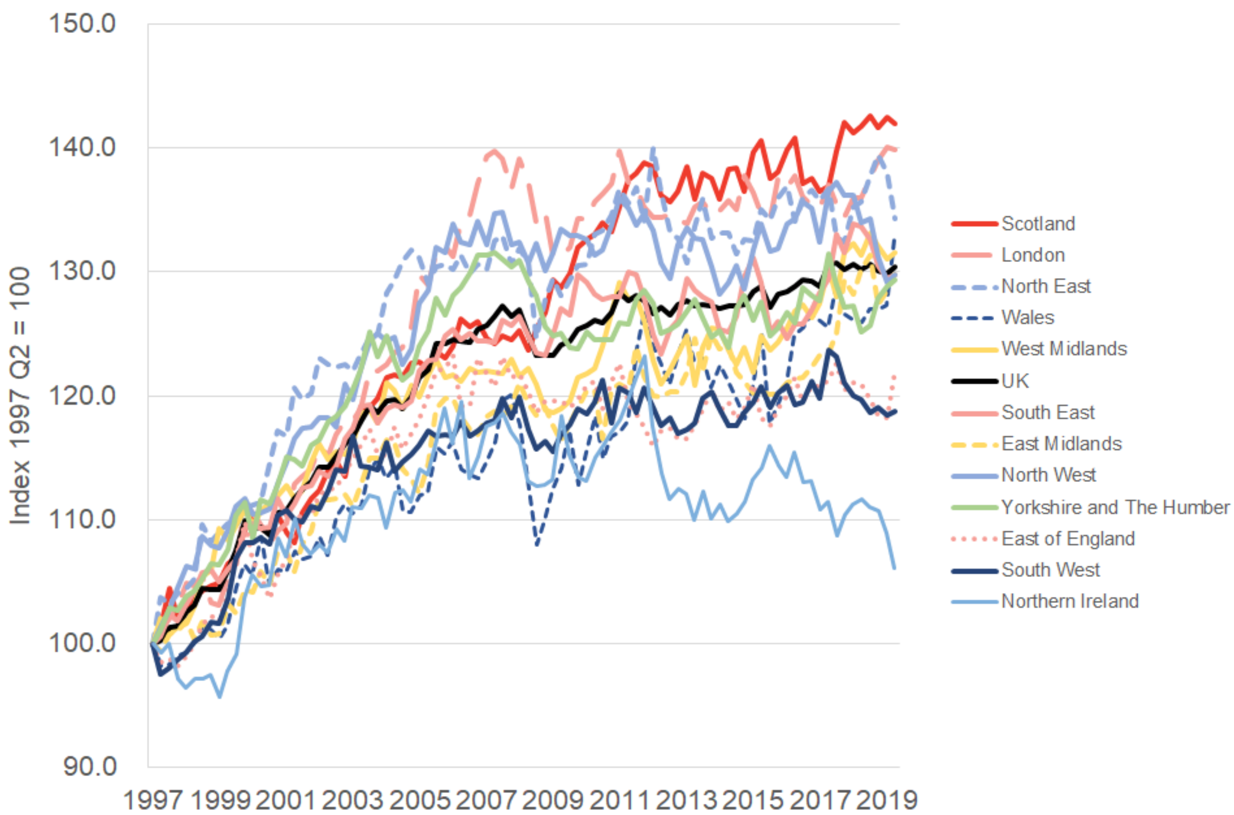


Figure 7: Regional labour productivity index (1997 - 2019)

available on an annual basis back to 1998.[12] These data are also available at various spatial scales (including city–regions) back to 2004.[13]

Combining our new quarterly regional output growth estimates with the ONS's release of quarterly regional labour input measures, we construct our measure of productivity growth for each region; these are plotted in Figure 7. A few things stand out in Figure 7. First, the fastest and slowest productivity growth over this period is in Scotland and Northern Ireland, respectively. Second, productivity experiences across a batch of regions are fairly similar (East Midlands, West Midland and Wales, for instance).

In Table 1, we calculate the average annual growth rate of labour productivity across each region of the UK using our estimates from Figure 7 over the period for which full year estimates are available, as well as for two sub–sample periods. Over the period 1998–2018, Scotland had the fastest average annual growth in labour productivity, increasing by 1.69% on average, compared to only 0.67% on average in Northern Ireland. Table 1 also contains the equivalent growth rates computed from the

k/labourproductivity/bulletins/labourproductivity/julytoseptember2019.

[12]See https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/bulletins/regionallabourproductivityincludingindustrybyregionuk/2018 for the latest version of these data at the time of writing.

[13]See https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/articles/regionalandsubregionalproductivityintheuk/february2019 for the latest version of these data at the time of writing.

ONS annual productivity series. These are broadly similar, although with some differences - the largest of which is for Northern Ireland - in part reflecting data and seasonal-adjustment revisions and in part different output measures for Northern Ireland (and Scotland). We examine the Northern Ireland data in more detail below.

Table 1 also explores how these average annual growth rates across regions differ in the years leading up to the financial crisis (1998 – 2006) as well as in an equivalent period afterwards (2010 – 2018). We can see clearly that there are only three regions (Wales, East Midlands and West Midlands) registering average growth in labour productivity in the later period which exceeds 1% a year. This contrasts with only three regions (Northern Ireland, East Midlands and Wales) registering less than 2% growth on average in labour productivity over the earlier period. The average and standard deviation of these average annual growth rates underline that it is not greater dispersion in performance, but a big difference in the level of labour productivity growth, that separates the performance of regions in the earlier and later periods.

Table 1: Average Annual Growth Rate of Labour Productivity

	ONS (A)	KMMP (Q)	KMMP (Q)	KMMP (Q)
	1998 - 2018	1998 - 2018	1998 - 2006	2010 - 2018
UK	1.20%	1.27%	2.58%	0.52%
Scotland	1.59%	1.69%	2.62%	0.98%
London	1.45%	1.46%	3.41%	0.31%
West Midlands	1.29%	1.38%	2.37%	1.16%
North West	1.27%	1.26%	2.98%	0.13%
South East	1.23%	1.33%	2.60%	0.26%
North East	1.16%	1.42%	2.82%	0.68%
Northern Ireland	1.13%	0.67%	1.94%	-0.27%
East of England	1.11%	0.99%	2.45%	0.00%
East Midlands	1.09%	1.32%	1.88%	1.23%
South West	1.07%	0.93%	2.13%	-0.03%
Yorkshire and The Humber	0.93%	1.01%	2.98%	0.18%
Wales	0.91%	1.25%	1.74%	1.49%
Regional Mean	1.19%	1.23%	2.49%	0.51%
Regional St. Dev	0.19%	0.27%	0.49%	0.55%

To see more clearly what is driving these changes (recalling that productivity here is the ratio of growth in output to growth in labour input) we show the results for some individual regions, starting with London in Figure 8. From here we can see that while London has experienced fast overall

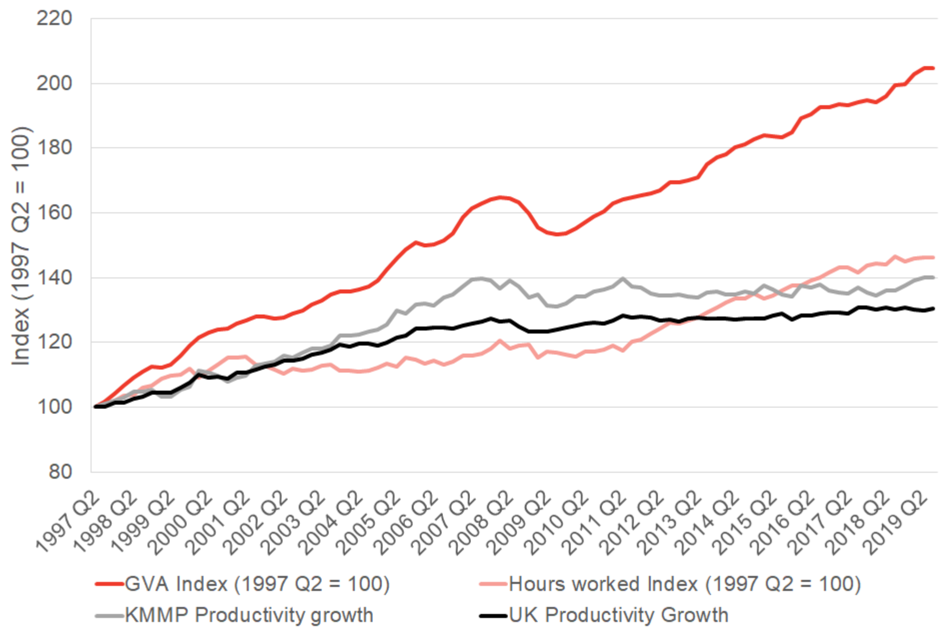


Figure 8: London labour productivity (1997 - 2019)

growth over this period, this has largely been matched by changes in hours worked. The result is that London's overall productivity (as measured by our new quarterly series, "KMMP") has tracked that of the UK as a whole, with the exception of an apparent 'level' shift just prior to the financial crisis.

Another interesting region to consider is North West England, shown in Figure 9. Again over this period output has grown steadily, but for much of this period hours worked was stagnant, only increasing in any meaningful way from around the end of 2013. The effect of this is that productivity in the North West grew more quickly than the UK as a whole, with only the recent rise in hours worked leading to convergence in productivity towards the UK average.

We discussed earlier that there are differences between the ONS's estimate of output in Scotland and Northern Ireland and comparable estimates from the devolved administrations. We also noted that, in Figure 7, it was Scotland that had the fastest productivity growth over this period and Northern Ireland which had the weakest.

In order to explore this further, we set out the data for each in turn, starting with Scotland. The Scottish Government publish their own estimate of quarterly labour productivity using their own GDP data and the ONS hours worked data (which they do some smoothing to, but which is essentially the same). This chart starts from 1998Q1 rather than 1997Q2 because the Scottish Government data start in 1998.

We can see from Figure 10 that our estimate of labour productivity growth in Scotland is substantially higher than that of the Scottish Government's over this period. Given that our estimate and that of the Scottish Government use hours worked data that are basically the same, the difference here is driven by what is thought to have happened to output growth. And, as discussed earlier, our estimates of growth in Scotland are higher than those estimated by the Scottish Government

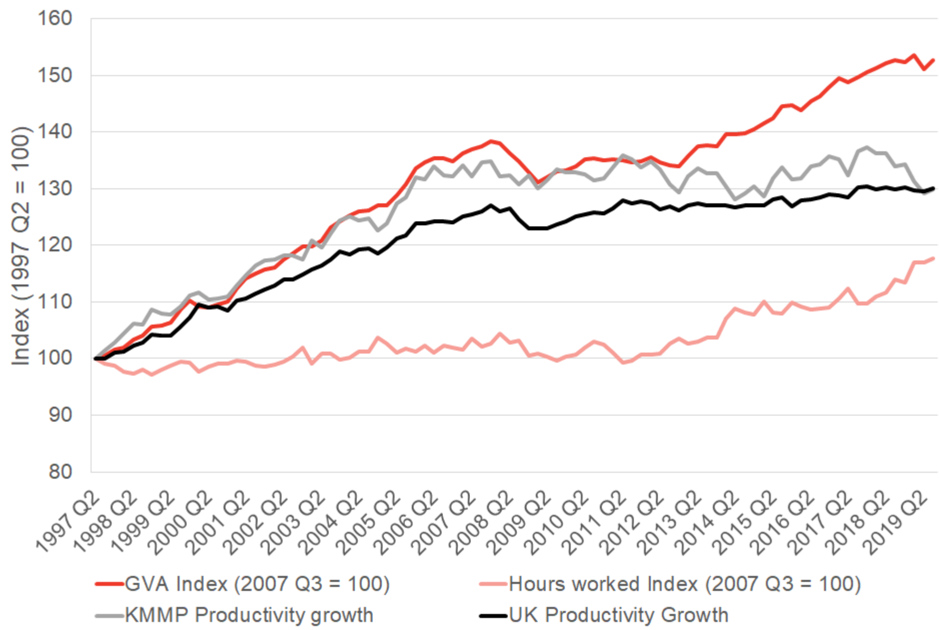


Figure 9: North West England labour productivity (1997 - 2019)

(reflecting the underlying (annual) ONS data).

The net effect of this is that the Scottish Government estimate that productivity growth in Scotland tracked that of the UK as a whole fairly well over the available period, dropping around the financial crisis; but with a subsequent fall in hours worked, productivity catches up again. On our measure, we have a somewhat different post financial crisis story, with fast growth in output driving faster growth in productivity. This results in us estimating productivity growth to have been much faster than suggested by the Scottish Government. It is important to be clear though - this is only because the ONS have output growing faster in Scotland over this period than the Scottish Government estimate.

For Northern Ireland, looking at Figure 11, we see something different. There has been greater movement in hours worked in Northern Ireland over this period than in Scotland. This has driven a lot of the variation in productivity. Labour productivity in Northern Ireland is now around its level in the early 2000s, with growth over the last twenty years substantially behind that of the UK as a whole. While output has grown, this has been matched closely by movements in hours worked since the early 2000s.

While NISRA do not report their own labour productivity measures, as we mentioned earlier, there are differences in the estimates of output growth produced by NISRA and the ONS. In order to explore this in more detail, Figure 12 shows the NISRA and ONS measures of output, the ONS measure of hours worked, and our "KMMP" measure of productivity against a measure based on combining the NISRA output growth measure with the ONS hours data. NISRA only report output growth from 2006Q1, so we focus on the period since then.

Figure 12 emphasises that since 2006Q1, regardless of whether one focuses on the NISRA or ONS

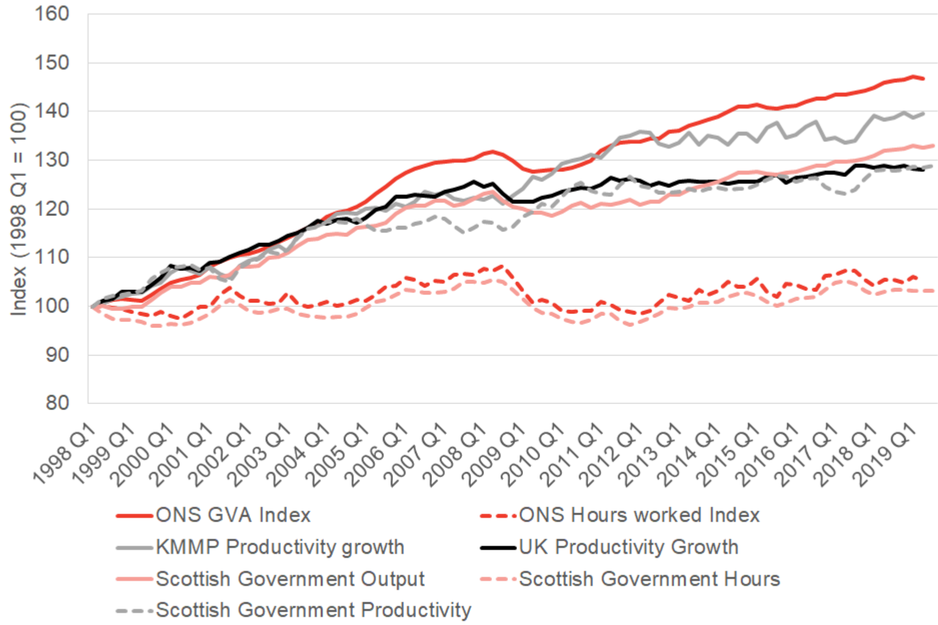


Figure 10: Scotland labour productivity (1998 - 2019)

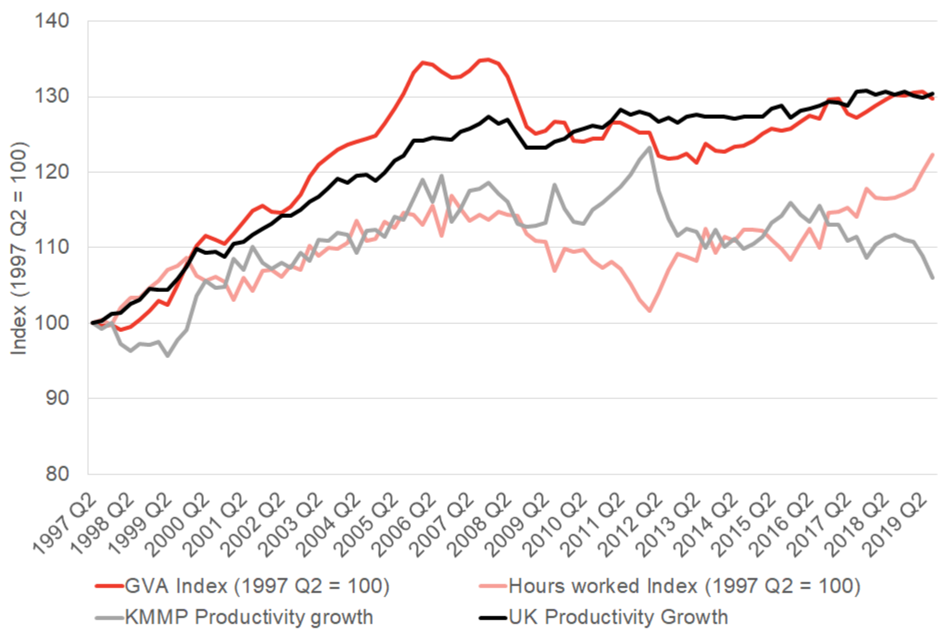


Figure 11: Northern Ireland labour productivity (1997 - 2019)

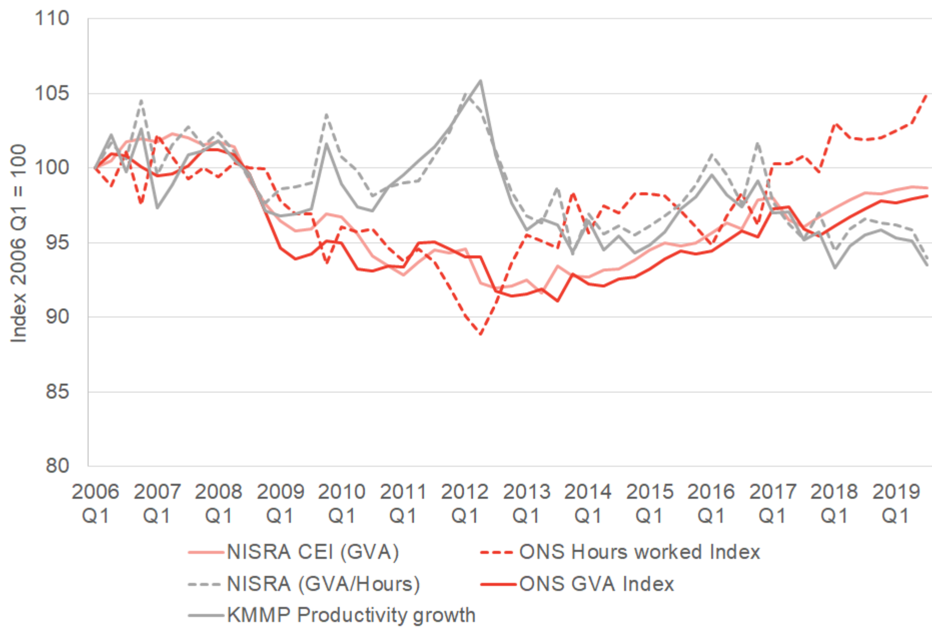


Figure 12: Northern Ireland labour productivity (2006 - 2019)

measure of output growth, productivity in Northern Ireland has fallen substantially. While output is down over the period as a whole, it is the substantial increase in hours worked that is driving this deterioration in labour productivity.

Contrasting estimates of regional output growth are a feature of the sub–national statistical landscape in the UK. Both the Scottish Government and NISRA data represent attempts by the devolved administrations to produce 'better' regional output data than those otherwise available from the ONS (initially in terms of frequency and timeliness), leveraging local insight and data. With the recent addition of higher frequency and more timely data from ONS for the English regions (the RSTIs), and continued production by the ONS of the 'benchmark' National Statistics regional data on an annual basis, some means is needed to reconcile these into a consistent series - which is what we do here. This is important because, as we have seen, the underlying economic story about productivity that you draw can be sensitive to different measures. In a similar way, our understanding of regional productivity would be enhanced by extending these data back further in time.

In this section we have explored the implications of our new reconciled quarterly output growth estimates for the understanding of regional labour productivity over the past two decades. We find that there are substantial differences in productivity performance over the post 1997 period. Some of this movement is being driven by changes in hours worked rather than in output, like in Northern Ireland. But differences in economic data - specifically contrasting estimates of output growth - can have a substantial impact on our understanding of regional productivity performance, as was the case in Scotland. It is important to be aware of these data uncertainties when using them to comment on regional economic performance.

6 Empirical Results: Nowcasting Regional GVA Growth

In this section we investigate the out-of-sample nowcasting (and backcasting) performance of our MF-VAR model with the RSTI data included. We evaluate the accuracy of the probabilistic nowcasts and backcasts from the model by comparing them against the (subsequent) RSTI outturns over the out-of-sample period 2012Q2 - 2019Q2.

All nowcasts and backcasts are produced recursively (i.e. produced using an expanding window of data) and involve re-estimation of the MF-VAR. Given that the RSTI data date back only to 2012Q1, we start our out-of-sample evaluation in 2012Q2. Given that vintage RSTI data do not exist, our analysis is "quasi real-time", i.e. it involves use of the latest (at the time of writing this was February 2020) RSTI data vintage.

We adopt a timing convention where we update our nowcasts and backcasts each time there is a new release of UK GVA, expecting information on this aggregate to be informative about the regional disaggregates that it comprises (cf. (2)). Given the 6 month release delay for the RSTIs, regional data for the previous two quarters will not have been released at this point in time. Our estimate for the previous quarter is therefore what we call a *now*cast; and our estimate for two quarters ago we call the *back*cast. The following discussion elaborates on this point; and the reader may find it useful to refer back to the release calendar in Figure 1. We emphasise that both *now*casts and *back*casts are produced ahead of the quarterly RSTI outturns subsequently published by ONS.

The nowcast is an updated estimate of regional output growth timed to be coincident with the latest quarterly estimate of UK GVA growth from the ONS, currently published around 45 days after the end of the reference quarter. In a given calendar year, the first set of nowcasts and backcasts are made in (mid) February on receipt of the latest UK quarterly GVA estimate (for Q4 of the previous year). These are the nowcast for regional growth in Q4 of the previous year and a backcast for Q3 of the previous year. This nowcast is available 5 months ahead of the RSTI data, as only in July will the RSTIs provide estimates for Q4 of the previous year; and the backcast for Q3 of the previous year is available 2 months ahead of the Q3 RSTI data release in April. As Figure 1 shows, these nowcasts and backcasts made in February condition on RSTI data up to Q2 of the previous year and Q3 data for Scotland and Northern Ireland. But as the ONS publish their estimates for annual regional GVA in the fourth quarter of each year, the latest annual regional GVA data used in estimation are for the year before the last. The second set of nowcasts and backcasts (respectively, for Q1 of the current year and Q4 of the previous year) are then made in May on receipt of the UK GVA estimate for Q1 of the current year; and so on for the nowcasts and backcasts made in August and November. Thus, an advantage of our approach is that nowcasts and backcasts of quarterly regional growth can be produced respecting and acknowledging the staggered publication and release of intra-year data on the regional and UK-wide variables. That is, we produce nowcasts and backcasts of regional output growth acknowledging the fact that in real-time data have a ragged-edge at the end of the sample.

Figures 13 and 14 plot our backcasts (predictive means along with 68% credible intervals) against the outturn (i.e. the actual RSTI realisation) for each region. Figures 15 and 16 do the same for the nowcasts. The point nowcasts and backcasts follow the outturns well, indicating that our model is

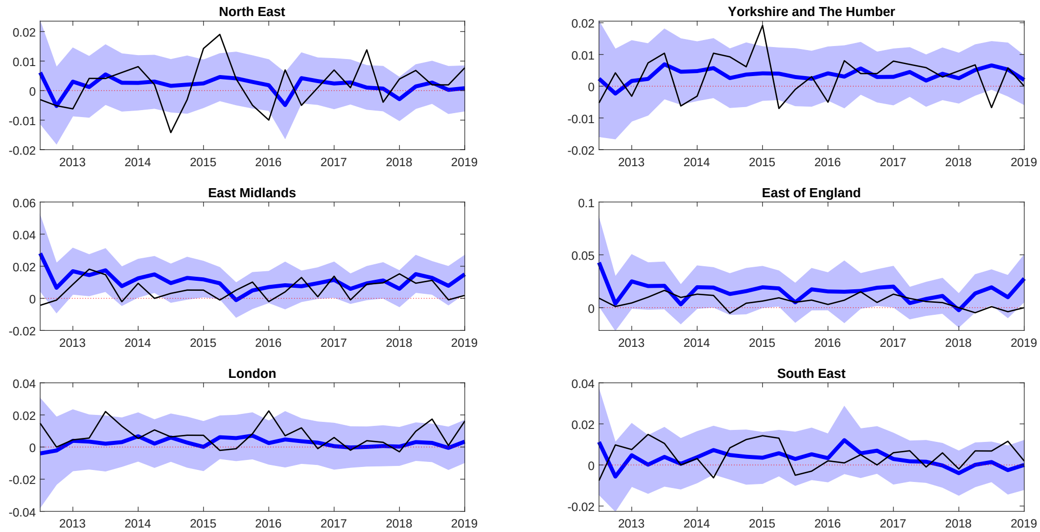


Figure 13: Backcasts versus RSTI data. The blue line plots the recursively computed backcasts from the KMMP + RSTI model; and the shaded blue area is the corresponding 68% credible interval. The black line represents the actual RSTI data (the "target").

forecasting well. The credible intervals are fairly narrow and suggest a reasonably good coverage rate. It is interesting to note that the credible intervals for the backcasts tend to be narrower than for the nowcasts. This is sensible, reflecting the fact that the backcasts condition on additional information than available for the nowcast.

In Koop et al. (2020) we demonstrated that the MF-VAR, based on quarterly UK data and annual regional data (but not the new quarterly regional RSTI data from 2012), nowcasted well. Tables 2 and 3 present evidence that also including the RSTI data, using the model as set out in section 2, offers substantial additional improvements. Table 2 reports cumulative log scores (i.e. sums of log predictive likelihoods) as a measure of performance of the entire predictive density. Table 3 contains root mean square forecast errors (RMSFEs) as a measure of the quality of the point (mean) nowcasts and backcasts. These tables directly compare the performance of our new nowcasts and backcasts to those produced using the model and data of Koop et al. (2020) that did not exploit the RSTI data. Again we label the two models' nowcasts and forecasts "KMMP+RSTI" and "KMMP".

KMMP+RSTI is clearly nowcasting and backcasting much better than KMMP alone. This is particularly noticeable with the log scores, seen in Table 2, where major improvements are found from incorporating the RSTI data.[14] But even the RMSFEs, shown in Table 3, indicate the benefits of incorporating the RSTI data. RMSFEs using KMMP tend to be 5 or 10 percent higher than those produced by KMMP+RSTI.

[14] To aid in interpretation for the Bayesian, note that cumulated log scores over the entire sample equal the log marginal likelihood. For the non-Bayesian, the log marginal likelihood is asymptotically equivalent to the Schwarz criterion. Increases of either the log marginal likelihood or Schwarz criterion of 5 or 10 are very large and we are finding improvements of our log scores to be of this magnitude.

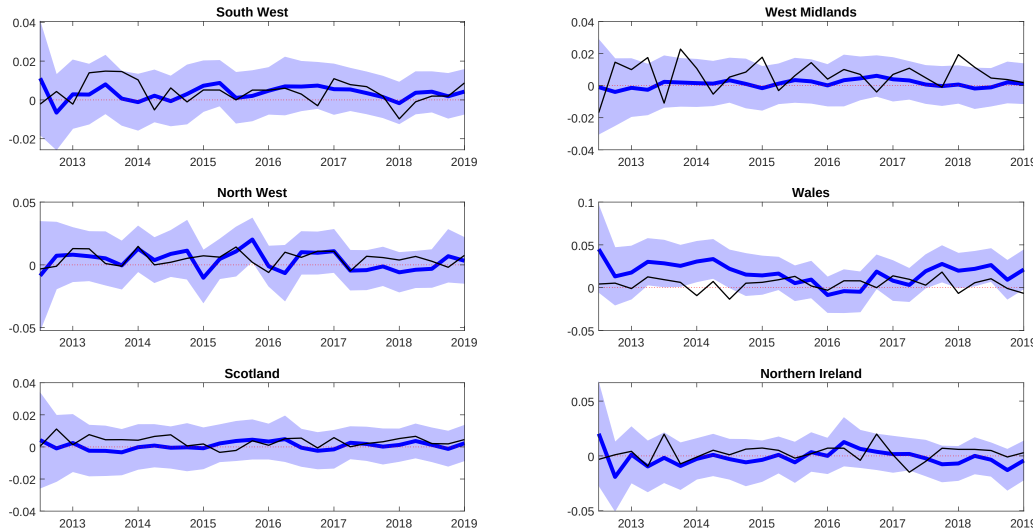


Figure 14: Backcasts versus RSTI data (cont.). The blue line plots the recursively computed backcasts from the KMMP + RSTI model; and the shaded blue area is the corresponding 68% credible interval. The black line represents the actual RSTI data (the "target").

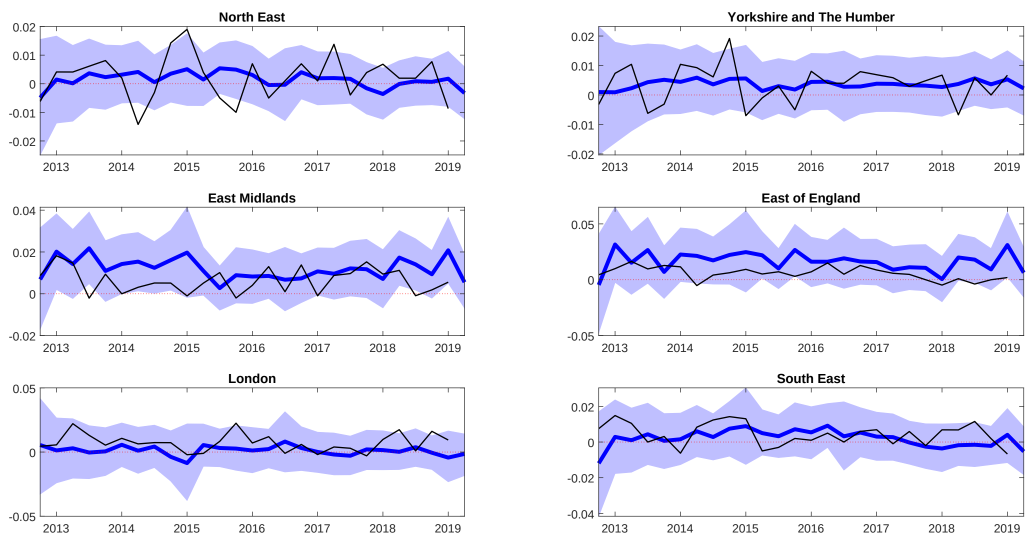


Figure 15: Nowcasts versus RSTI data. The blue line plots the recursively computed nowcasts from the KMMP + RSTI model; and the shaded blue area is the corresponding 68% credible interval. The black line represents the actual RSTI data (the "target").

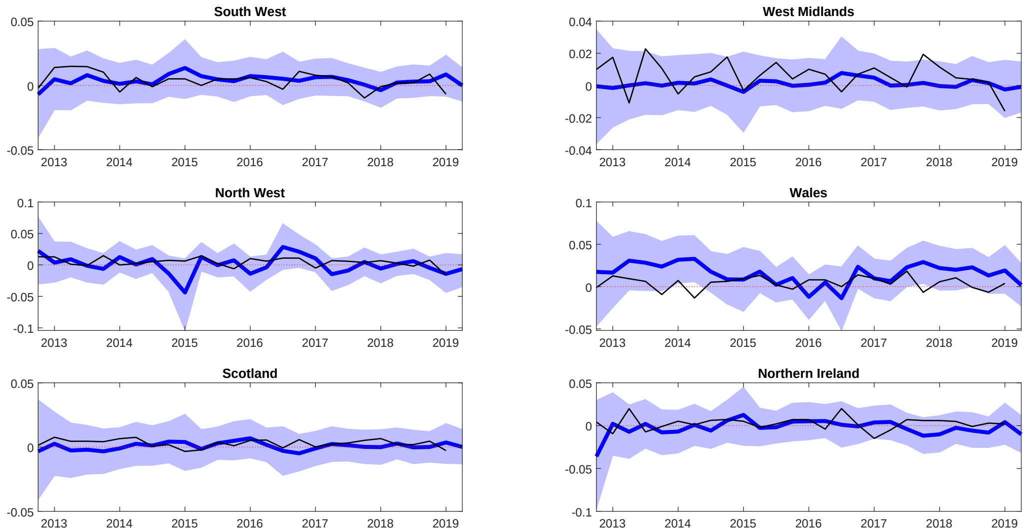


Figure 16: Nowcasts versus RSTI data (cont.). The blue line plots the recursively computed nowcasts from the KMMP + RSTI model; and the shaded blue area is the corresponding 68% credible interval. The black line represents the actual RSTI data (the "target").

7 Conclusions

Regional economic performance, partly as a result of the "levelling up" agenda, but also a reflection of the emergent economic crisis generated by the Coronavirus pandemic, is going to be central to economic policy and debates in the UK for some time to come. Regional economies reeling from the after–effects of the Coronavirus 'lockdown' are expected to face a shakeout in businesses and in the labour market. What this means for regional output and productivity will depend on a range of factors, not least the policy response that is put in place, but also changes in sectoral composition and the workforce across regions. Our understanding and tracking of this will require us to reconcile the different output measures that we have, both at a national and regional level, and to do so in a timely fashion. One cannot reliably base policy *today* on regional output data that are two years out-of-date. Furthermore, our ability to explore key hypotheses about differences in regional productivity is impeded without access to more timely, higher frequency and longer time spans of consistent regional economic data.

This paper has developed an econometric model to help remedy these data shortcomings. It has extended the model of Koop et al. (2020) to produce reconciled quarterly real output growth estimates for the UK regions. The reconciliation involves incorporating into the model (of UK quarterly data and annual regional output data) the ONS's recently produced RSTI data, as well as quarterly data from the devolved administrations in Scotland and Northern Ireland. We have used this model to produce a new historical time-series of reconciled regional quarterly real output growth from 1970 to the present day. And we have explored a number of features of interest of these new data. In particular, we use the data to understand some properties of regional productivity growth. We have also investigated whether incorporating (historical) RSTI data into the model can be useful in producing timely, high frequency, flash estimates (our “nowcasts” and “backcasts”) of regional output growth (which in turn can be used to provide more timely insights into regional productivity performance). The outcome of this investigation was strongly positive. The flash estimates produced are substantially better than those produced using only the annual regional data and quarterly UK data. With the flash estimates available 2 to 5 months ahead (for the backcasts and nowcasts, respectively) of the subsequently published RSTI data, they facilitate policymaking based on more up-to-date regional data. Our approach also provides a higher frequency dataset on which we can explore a range of hypothesis about differences in regional productivity. While this productivity dataset currently covers a shorter time period than we should like, due to limitations in the quarterly regional labour input series rather than regional output, we hope to remedy this in future research.

Table 2: Cumulative Log Scores for Real GVA Growth Forecasts, 2012Q2-2019Q2

	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
KMMP + RSTI												
backcast	83.17	83.70	80.18	72.29	76.57	79.45	79.50	75.70	73.83	65.21	80.75	72.49
nowcast	82.21	82.71	78.45	69.63	73.97	77.96	77.44	73.66	69.96	63.54	78.22	69.60
KMMP												
backcast	74.70	74.34	73.80	62.56	63.41	69.36	64.94	63.52	61.19	50.79	62.18	52.88
nowcast	72.84	72.70	70.25	58.03	60.22	66.11	62.26	60.65	53.78	46.10	58.79	48.47

Table 3: RMSFEs for Real GVA Growth Forecasts, 2012Q2-2019Q2

	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
KMMP + RSTI												
backcast	0.0077	0.0065	0.0096	0.0133	0.0088	0.0085	0.0068	0.0110	0.0081	0.0195	0.0052	0.0108
nowcast	0.0074	0.0060	0.0090	0.0141	0.0100	0.0080	0.0063	0.0112	0.0148	0.0180	0.0055	0.0118
KMMP												
backcast	0.0083	0.0071	0.0098	0.0127	0.0111	0.0104	0.0080	0.0121	0.0230	0.0215	0.0080	0.0170
nowcast	0.0079	0.0059	0.0111	0.0168	0.0128	0.0128	0.0081	0.0120	0.0483	0.0258	0.0111	0.0341

8 Appendix: The MF-VAR when the Frequency Mis-Match Ends in 2012

The MF-VAR of Koop et al. (2020) can be written as:

$$\begin{bmatrix} y_t^{UK} \\ y_t^{Q} \end{bmatrix} = \begin{bmatrix} \Phi_{qc} \\ \Phi_{ac} \end{bmatrix} + \begin{bmatrix} \Phi_{qq,1} & \Phi_{qa,1} \\ \Phi_{aq,1} & \Phi_{aa,1} \end{bmatrix} \begin{bmatrix} y_{t-1}^{UK} \\ y_{t-1}^{Q} \end{bmatrix} + \ldots + \begin{bmatrix} \Phi_{qq,7} & \Phi_{qa,7} \\ \Phi_{aq,7} & \Phi_{aa,7} \end{bmatrix} \begin{bmatrix} y_{t-7}^{UK} \\ y_{t-7}^{Q} \end{bmatrix} + \epsilon_t, \tag{3}$$

where ϵ_t is i.i.d. $N(0, \Sigma_t)$. Σ_t follows the same multivariate stochastic volatility process as in Koop et al. (2020).

If we group the coefficients in the MF-VAR into blocks as:

$$\Phi_{qq} = \begin{bmatrix} \Phi_{qq,1}, & \Phi_{qq,2}, & \Phi_{qq,3} & , \ldots, \Phi_{qq,7} \end{bmatrix}, \tag{4}$$

$$\Phi_{qa} = \begin{bmatrix} \Phi_{qa,1}, & \Phi_{qa,2}, & \Phi_{qa,3} & , \ldots, \Phi_{qa,7} \end{bmatrix}, \tag{5}$$

$$\Phi_{aq} = \begin{bmatrix} \Phi_{aq,1} & , \Phi_{aq,2} & , \Phi_{aq,3} & , \ldots, \Phi_{aq,7} \end{bmatrix}, \tag{6}$$

$$\Phi_{aa} = \begin{bmatrix} \Phi_{aa,1} & , \Phi_{aa,2}, & \Phi_{aa,3} & , \ldots, \Phi_{aa,7} \end{bmatrix}, \tag{7}$$

then we can define the part of the MF-VAR relating to the regional data as:

$$\mathbf{s}_t = \Gamma_s \mathbf{s}_{t-1} + \Gamma_z \mathbf{y}_{t-p:t-1}^{UK} + \Gamma_c + u_{a,t}, \tag{8}$$

where $\mathbf{s}_t = (y_t^{Q'}, y_{t-1}^{Q'}, y_{t-2}^{Q'}, \ldots, y_{t-7}^{Q'})'$ is a $z \times 1 = R \times 7$ vector containing the regional variables and their lags and $\mathbf{y}_{t-p:t-1}^{UK} = (y_{t-1}^{UK}, \ldots, y_{t-7}^{UK})'$ contains lags of the UK variables. The coefficient matrices in this equation have the form:

$$\Gamma_s = \begin{bmatrix} \Phi_{qq} & 0 \\ \mathbf{I} & 0 \end{bmatrix}_{z \times z}, \Gamma_z = \begin{bmatrix} \Phi_{aq} \\ 0 \end{bmatrix}_{z \times p}, \Gamma_c = \begin{bmatrix} \Phi_{ac} \\ 0 \end{bmatrix}_{z \times 1}. \tag{9}$$

For UK GVA growth, we have

$$y_t^{UK} = \Lambda_{qs} \mathbf{s}_t + \Phi_{qq} \mathbf{y}_{t-p:t-1}^{UK} + \Phi_{ac} + u_{q,t}, \tag{10}$$

where

$$\Lambda_{qs} = \begin{bmatrix} 0 & \Phi_{qa} \end{bmatrix}_{1 \times z}.$$

Combining these together into one MF-VAR we have

$$y_t = \Lambda_{as}\mathbf{s}_t + \Lambda_z \mathbf{y}^{UK}_{t-p:t-1} + \Phi_{qc}, \tag{11}$$

where

$$\Lambda_{as} = \begin{bmatrix} 0 & \Phi_{qa} \\ & M \end{bmatrix}, \Lambda_z = \begin{bmatrix} \Phi_{qq} \\ 0 \end{bmatrix}, \tag{12}$$

$$M = \begin{bmatrix} \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 & 0 \\ 0 & \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 \end{bmatrix}. \tag{13}$$

Note that the matrix M imposes the inter-temporal restriction.

Finally, the cross-sectional restriction gives us an additional measurement equation for the MF-VAR. We have

$$y^{UK}_t = \mathbf{R}\mathbf{s}_t + \eta_t, \eta_t \sim N(0, \sigma^2_{cs}), \tag{14}$$

where

$$\mathbf{R} = \begin{bmatrix} \frac{1}{R} & \dots & \frac{1}{R} & 0 & \dots & 0 \end{bmatrix}_{1\times z}. \tag{15}$$

As discussed in Koop et al. (2020), the cross-sectional restriction can be expected to only hold approximately and this explains the presence of the error, η_t, added to this restriction (e.g. GVA from the UK's continental shelf, UKCS, is included in UK GVA but not in any of our regions). We use the same prior for σ^2_{cs} as in Koop et al. (2020) which reflects a view that the approximation error is small.

The model just described is that of Koop et al. (2020). It can be seen that y^Q_t, which is regional quarterly GVA growth, appears in the vector of variables y_t (and, thus, in $\mathbf{s_t}$). It is not observed and, thus, treated as states to be estimated by the MF-VAR. In the present paper, the same holds true, prior to 2012. However, from 2012 onwards the RSTI data exist and y^Q_t is observed. This can be accommodated by having the M matrix in (13), which imposes the inter-temporal restriction, change in 2012. To be specific, prior to 2012 the model is as above. From 2012 onwards, we use the same model but with:

$$M = \begin{bmatrix} 1 & 0 & \dots & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 & 0 & 0 & 0 & 0 \\ & & & & & & & \end{bmatrix}. \tag{16}$$

That is, the first R columns of M are now an identity matrix (and the remaining columns are zeros). The inter-temporal restriction, which specifies the relationship between quarterly and annual output figures, is no longer needed since the quarterly figures are directly observed. That is, from 2012 we have quarterly RSTI data and the quarterly output data from NISRA and the Scottish

Government; so if we were to want any annual regional data, the annual data they add up to would simply be their annual aggregation. For the English regions, these annual data will be the same as the annual regional data that the ONS report. For Northern Ireland and Scotland, as explained in section 3, the quarterly output data will aggregate to annual estimates from NISRA and the Scottish Government.

In summary, we use a model which is the same as Koop et al. (2020), and all specification, prior and computational details are as described there. But we then extend it, as described above, to allow for the change in 2012 when the quarterly RSTI data also become available.

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